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The Impact of Technological Change and Automation on Income Distribution and Labor Income Share: A Bibliometric Analysis (1975–2024)

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ABSTRACT

Recently, topics regarding the link between technological advancement, automation, income distribution and labor income share have been receiving much attention. However, a comprehensive bibliometric analysis of this field has yet to be conducted. Hence, this paper aims to fill that gap by examining the development and trends in research focusing on automation, technological change, and their impact on income distribution and labor income share. Bibliometric data sourced from the Scopus database were used, covering articles published between 1975 and 2024 based on several predefined criteria. The analysis was performed using Biblioshiny, incorporating a total of 509 articles. A significant increase in annual publications was observed from 2010 to 2024. The United States and China were the dominant countries in this field, accounting for 14.15% (72 articles) and 10.61% (54 articles) of the publications, respectively. Besides that, University of California and Daron Acemoglu were identified as the most influential institution and author, respectively. *Technological Forecasting and Social Change* journal stands out as the most prolific source with 19 publications in this field, while the *Journal of Development Economics* has garnered the most citations. Key terms such as "technological change" and "income inequality" were frequently used by authors, with thematic trends indicating a growing focus on "automation" and "artificial intelligence". These findings reflect an increasing academic and policy-driven interest in understanding how technological disruption reshapes labor markets. Overall, this study provides an overview of the most influential publications, authors, countries, and topics in the field, shedding light on the evolving research landscape surrounding the intersection of technological change and labor market dynamics.

Keywords: Income distribution; Labor income share; Automation; Technological change; Bibliometric analysis

INTRODUCTION

The factors that define the distribution of income have garnered the attention of scholars. Research analyzing the effects of technological innovations on income distribution has experienced considerable expansion of late (Hötte et al., 2023). Scholars have focused on how technological progress, especially through automation and digitalization, affects economic structures and reshapes the dynamics of labor markets. In this regard, most of the literature seems to agree on the notion that productivity and economic growth tend to increase with technological change. Nonetheless, it tends to expand the income distribution gap, as some groups, such as capital-intensive businesses, skilled labour, and capital holders, are disproportionately favored by such developments. (Choudhary & Kumar, 2024; Kharlamova et al., 2018; Tong, 2024; Wahiba & Dina, 2023). Furthermore, human capital plays a critical role in determining the extent to which the effects will be mitigated. One prominent example of such advancement is the growth of automation technologies, which continues to rapidly reshape labor market dynamics. Therefore, understanding the relationship between technology, inequality, and labor institutions has become increasingly important for guiding inclusive economic policy and future research.

It would be reasonable to claim that one could extend the discussion regarding inequality by analyzing the labor income share of a particular nation. The labor income share is defined as the value of national income that is earned by labor, and this measurement has become a barometer of income distribution dynamics. The International Labour Organization (ILO) views it as a key indicator that reflects the distributional dynamics between capital and labor in an economy. Its decline frequently indicates structural shifts caused by globalization, technological advancement, and policy interventions. Thus, this suggests that it is important to understand how these changes affect the distribution of income and the social relations within the capital and labor system, within the broader context of equity and ethical sustainability. Notably, many studies have been conducted to assess the decline of labor income share in various economic settings (Autor et al., 2020; Dao et al., 2017; Heer et al., 2023; Paul, 2020), highlighting the growing concern and increased scholarly focus on this issue.

In the contemporary context of technology, automation is central to the transformation of labor markets and reshaping the distribution of income. This involves the process of replacing human labor through the use of sophisticated technologies such as industrial robots, artificial intelligence (AI), and machine learning. Automation is undoubtedly useful in production, as it enhances productivity while lowering operational costs. Despite this advantage, it also brings significant challenges. One of the primary concerns is its impact on employment structure, particularly through the displacement of routine and low-skilled jobs. A study on high-level automation countries by Erkişi & Çetin (2025) found that robotic capital has a persistent negative impact on the share of labor income. This is largely due to substitution effect, where robots displace human labor thereby causing a reduction in income share going to labor. Consequently, this phenomenon exacerbates income inequality by increasing the demand for high-skilled labor while reducing opportunities for lower-skilled workers, thereby influencing the distribution of income between labor and capital. Therefore, it is crucial to understand the role of automation in reshaping income distribution and labor income share, to grasp the broader implications of technological change.

Given the increasing academic interest in the implications of technical change and automation for income distribution and labor income share, a systematic overview of the evolution and structure of this body of scholarship is clearly warranted. Although numerous empirical and theoretical studies on this subject have been made, a comprehensive synthesis of the field's intellectual and thematic development over time remains limited. Therefore, this study addresses that gap by utilizing a bibliometric analysis to investigate the trajectory of scholarly output from 1975 to 2024. Several assessments such as identifying key trends, influential contributors, most cited literature, and frequently used keywords were carried out. This study is significant, as the findings shall provide insights into existing knowledge and directions for further research at the intersection of technology, labor markets, and income distribution by giving an evidence-based overview of how the discourse has been progressed up until now.

This paper is organized as follows. The next section explains the methodology used in the study. This is followed by the results from the bibliometric analysis, along with the discussion. Then, the subsequent section highlights the limitations of this study. Finally, the last section provides the conclusion.

METHODOLOGY

Study design

In this paper, we employed a bibliometric analysis to present a comprehensive overview of research carried out in the last 5 decades addressing the impact of technological changes and automation on income distribution and labor income share. The use of bibliometric analysis has gained more recognition in recent years. It has also become a widely used tool across academic disciplines, as it moves beyond its traditional roots in library science. Bibliometric analysis is a quantitative method used to evaluate research patterns, trends, and influential contributions within a specific field (Donthu et al., 2021). At its core, it proceeds in a more structured and analytical way than a normal review-based approach. Given this, it is designed to explore and map how the scientific knowledge has developed over time using the techniques of performance analysis (Cobo et al., 2011), science mapping (Baker et al., 2021) and network analysis (Cisneros et al., 2018). Like meta-analysis, bibliometric analysis has inherent advantages, such as the ability to process large volumes of academic literature and reduce the interpretation bias due to its quantitative nature. These strengths are often a way to overcome the problems generally associated with traditional systematic literature reviews (Ramos-Rodrígue & Ruíz-Navarro, 2004).

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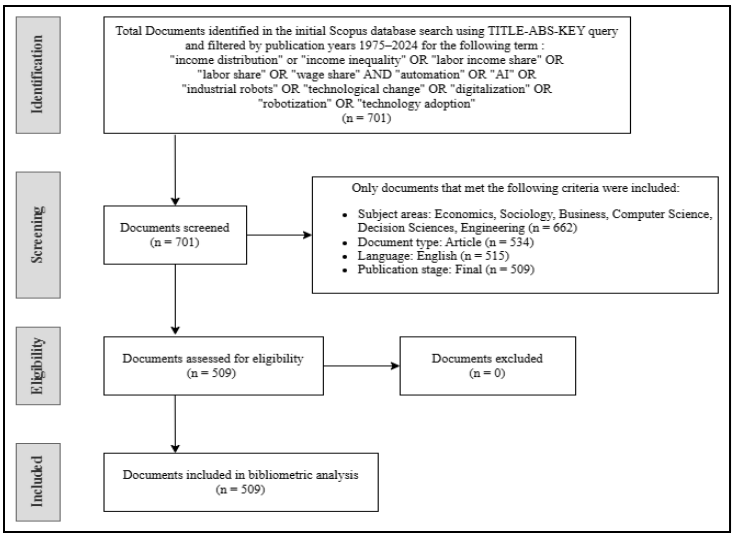
The analysis focuses on publications indexed in the Scopus database, which was selected due to its comprehensive coverage of peer-reviewed scholarly output (Baas et al., 2020). Specifically, both performance analysis and science mapping were employed to achieve the objective of this study. In addition, the extraction of bibliometric data from the Scopus website was guided by a well-defined set of inclusion and exclusion criteria. This was done to ensure a comprehensive and focused overview of the literature. Previous research has performed bibliometric analysis to explore related topics such as income inequality and policy (Rodriguez et al., 2023), automation, and labor market dynamics (Thi et al., 2024), as well as job displacement due to artificial intelligence (Subaveerapandiyan & Shimray, 2024). Yet, comprehensive bibliometric research into the impact of technological change and automation on income distribution and labor income share remains limited. Hence, having identified this gap, this study seeks to address it by systematically mapping the scientific landscape within this specific research area.

Search strategy

The search strategy for this bibliometric study was carefully designed to systematically capture relevant scholarly literature from the Scopus database, which is widely recognized for its comprehensive coverage of peer-reviewed academic publications. The search query was formulated to specifically target studies related to the topic of interest, ensuring the inclusion of high-quality and pertinent research. Specifically, the search query employed was: TITLE-ABS-KEY("income distribution" or "income inequality" OR "labor income share" OR "labor share" OR "wage share" AND "automation" OR "AI" OR "industrial robots" OR "technological change" OR "digitalization" OR "robotization" OR "technology adoption") AND PUBYEAR > 1974 AND PUBYEAR < 2025 AND (LIMIT-TO(SUBJAREA,"ECON") OR LIMIT-TO(SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"COMP") OR LIMIT-TO (SUBJAREA,"DECI") OR LIMIT-TO (SUBJAREA,"ENGI")) AND (LIMIT-TO(DOCTYPE,"Ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (PUBSTAGE, "Final").

To ensure comprehensive coverage of the relevant literature and encompass diverse terminologies used across disciplines, we incorporate a range of synonyms and related terms for both income distribution and technological change in the search query. In addition, to capture long-term trends and scholarly evolution, studies published from 1975 to 2024 were considered for the analysis, thus providing a comprehensive historical overview leading up to the present. The dataset was further refined using several filters to ensure quality and disciplinary relevance. For instance, only final-stage, peer-reviewed journal articles written in English were included in the analysis. In terms of subject coverage, we only considered publications within the scope of economics, sociology, business, computer science, decision sciences, and engineering, to ensure an interdisciplinary perspective while still staying on track with the study’s objectives. Notably, the final dataset was retrieved from Scopus on 31 March 2025, forming the empirical foundation for both the performance analysis and science mapping techniques used in this bibliometric study. For clarity, Figure 1 presents a PRISMA flow diagram that outlines the process of extracting and selecting bibliometric data for inclusion in the analysis.



Source(s): Authors' own elaboration

Figure 1. PRISMA flow diagram of literature search process

Data analysis

This study conducted a set of comprehensive bibliometric analyses to explore the intellectual and thematic landscape of research on automation, technological change, income distribution and labor income share. The analysis began by identifying trends in publication output over time, which can be examined from the annual scientific production output. Next, key sources of scholarly output were assessed to highlight the most influential journals and publication venues. Furthermore, this paper also identified the top contributing authors and institutions, providing insight into the leading figures and academic centers driving research in this field. To map the global landscape of research activity and collaboration, country-level contributions were evaluated. Besides that, we also examined the most influential papers in the field to assess their bibliometric impact and identify foundational contributions to the literature. Moreover, a keyword frequency analysis was performed to find out the commonalities and hot topics in literature, indicating the central interest of researchers in the literature. In addition, a co-citation network was presented, offering insight into the underlying architecture of seminal studies and intellectual connections, and how knowledge is built across investigations in the field. Lastly, global collaboration network analysis was conducted to explore international collaborative research patterns, emphasizing the range and strength of cooperation across nations in this area.

The analyses were conducted using Biblioshiny, an interactive web interface for the bibliometrix R package. This tool was selected for its user-friendly design and ability to support comprehensive bibliometric analysis. Biblioshiny is frequently chosen for bibliometric studies in various fields such as education, bioinformatics, sports tourism, cultural heritage, and organic chemistry (Pabuçcu-Aklş, 2024; Salleh & Bushroa, 2022; Yang et al., 2024; Zhang et al., 2025), demonstrating its versatility and broad acceptance among researchers. Moreover, this tool does not require advanced coding skills, thereby offering a systematic science-mapping and visualization for scholars across disciplines (Aria & Cuccurullo, 2017). More specifically, the word cloud, co-citation network and global collaboration map presented in the subsequent section of this paper were all generated using Biblioshiny. Metrics like betweenness centrality, closeness centrality, and PageRank scores were employed to observe the relative influence of countries, authors, and keywords within the research landscape. On the other hand, the trends of annual scientific production were plotted by using Microsoft Excel, instead of using the chart produced by Biblioshiny.

To provide a clearer institutional and regional analysis, this study presented several metrics. For example, to observe the 10 most productive institutions in the literature, we calculated the relative contribution percentage (%), which represents the proportion of articles published by each affiliation relative to the total number of articles produced by the top 10 affiliations. The formula is given by Equation (1),

$$\text{Relative contribution percentage (\%)}_i = \left(\frac{\text{Articles}_i}{\sum_{i=1}^{10} \text{Articles}_i}\right) \times 100 \quad (1)$$

where Articles_i represents the number of articles by the i-th affiliation and $\sum_{i=1}^{10} \text{Articles}_i$ is the total numbers of article produced by the top 10 affiliations. This approach highlights the institutions that have made the most significant impact within the field, thus ensuring a clearer interpretation of dominant research patterns. Using the full set of articles would dilute the comparative visibility of leading affiliations, whereas concentrating on the top 10 offers a more meaningful assessment of research concentration and leadership. Then, the accumulated percentage formula is given by Equation (2),

$$\text{Accumulated \%}_i = \sum_{k=1}^{i} \text{Relative contribution percentage (\%)}_k \quad (2)$$

where, $\text{Relative contribution percentage (\%)}_k$ is the individual contribution percentage of k-th affiliation for all ranks from 1 to i. This cumulative percentage reflects the progressive sum of individual contribution percentages, allowing for an understanding of the cumulative research influence of the top institutions.

As for the analysis of key contributing countries and their collaboration patterns, metrics such as percentages of articles produced by each country relative to the total number of publications in the literature were presented. Besides that, the multiple-country publication (MCP) percentage for each country was also reported, representing the proportion of a country's publication that involve multiple countries. These measurements were extracted from the Biblioshiny output, which can be calculated using the formula in Equation (3) and Equation (4), respectively.

$$\text{Articles } \%_i = \frac{\text{Articles}_i}{\text{Total number of articles}} \times 100 \tag{3}$$

$$\text{MCP } \%_i = \frac{\text{MCP}_i}{\text{Articles}_i} \times 100 \tag{4}$$

Articles_i here represents the number of total publications by the i-th country and MCP_i represent the number of multiple-country publications for the i-th country. Notably, the total number of articles included in the study is equal to 509. The MCP % provides insight into the extent of international collaboration in research, thereby indicating the country's level of participation.

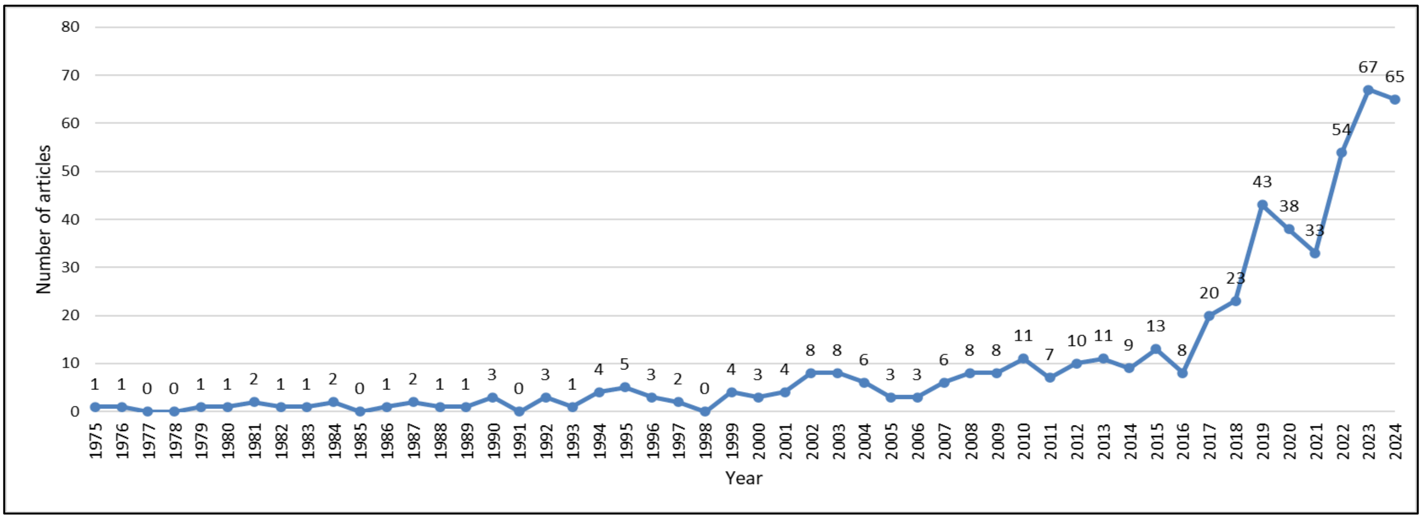
RESULTS AND DISCUSSION

Overview of trends and characteristics

The bibliometric analysis encompasses a comprehensive collection of 509 scholarly documents published between 1975 and 2024, derived from 278 distinct sources. This sample exceeds the recommended minimum of 200 documents, ensuring stable and reliable bibliometric results (Rogers et al., 2020) . The field has experienced a robust and consistent expansion, with an annual growth rate of 8.89%, indicating increasing academic attention to the relationship between technological change, automation, income distribution, and labor income share over the last five decades. The average age of documents in the dataset is approximately 9.08 years, suggesting a healthy mix of foundational and more recent contributions. These documents have garnered an average of 24.47 citations each, reflecting a moderate to high level of scholarly impact and ongoing relevance in related academic domains. In terms of document content, the dataset includes 1,214 Keywords Plus and 1,172 Author Keywords, reflecting a rich and diverse thematic landscape.

The study involves 983 unique authors, indicating a broad research community engaged in exploring the effects of automation and technological change on income distribution and labor income share dynamics. Of these, 161 authors contributed single-authored documents, and the dataset includes 170 single-authored papers in total. Collaboration appears to be a common feature in the field, with an average of 2.16 co-authors per document. Notably, 22.99% of the publications involved international co-authorships, pointing to a significant degree of cross-border scholarly collaboration, which may reflect the global implications and interest in this topic. It should be emphasized that all 509 documents included in the analysis are peer-reviewed journal articles with finalized publication, ensuring a consistent level of academic rigor and comparability across the dataset.

The annual scientific production reveals a clear and accelerating upward trend over the past five decades. As shown in Figure 2, from 1975 to the early 2000s, publication output remained relatively modest, with fewer than 10 articles per year and occasional years with no publications at all. This suggests that scholarly interest in the topic was initially limited and perhaps overshadowed by other economic concerns. However, starting in the early 2000s, particularly after 2002, a steady increase is observable, which intensifies significantly from 2010 onward. A sharp rise begins in 2017, culminating in a remarkable surge between 2019 and 2024. An obvious peak can be observed in 2019, with 43 articles published. However, the following years, 2020 and 2021, saw a slight decline to 38 and 33 articles, likely due to disruptions caused by the COVID-19 pandemic, though the output remained well above historical averages, showing continued interest in the topic. From 2022 to 2024, publication numbers surged again, reaching 54 in 2022, 67 in 2023, and 65 in 2024. This increase reflects a renewed focus on the impact of automation, driven by ongoing technological change and its effects on labor markets, with the topic gaining even more attention from both academics and policymakers.



Source(s): Generated by the authors using Microsoft Excel

Figure 2. Annual scientific production from 1975 to 2024

Key publication sources and their impact

According to Table 1, the analysis of key publications reveals a diverse range of influential journals contributing to the field of technological change, automation, and their implications for income distribution and labor income share. Among them, *Technological Forecasting and Social Change* stands out with the highest number of publications (19) and a strong citation impact (452 total citations), reflecting its sustained relevance and broad engagement with future-oriented socio-economic research. Although *Journal of Development Economics* has fewer publications (10), it boasts the highest total citation count (738), indicating the lasting influence of its contributions despite a lower publication volume. This suggests that articles published in this journal are particularly impactful and foundational to the discourse.

Table 1. Metrics of key publication sources from 1975 to 2024

Source	ISSN (Print)	H index	G index	M index	TC	NP	PY (Start)
Technological Forecasting and Social Change	0040-1625	11	19	0.41	452	19	1999
Journal of Development Economics	0304-3878	7	10	0.17	738	10	1984
Structural Change and Economic Dynamics	0954-349X	7	10	0.23	193	10	1995
Socio-Economic Review	1475-1461	6	6	0.55	272	6	2015
Technology in Society	0160-791X	6	7	1.00	84	7	2020
World Development	0305-750X	6	6	0.19	200	6	1995
Economic Modelling	0264-9993	5	5	0.71	119	5	2019
Economics of Innovation and New Technology	1043-8599	5	6	0.83	113	6	2020
Journal of Evolutionary Economics	0936-9937	5	6	0.28	91	6	2008
Journal of Monetary Economics	0304-3932	5	5	0.50	318	5	2016
Note(s): TC represents total citation, NP is the number of publications and PY stands for publication year							
Source(s): Table by authors							

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Journals such as S*tructural Change and Economic Dynamics*, *Socio-Economic Review*, and *World Development* also demonstrate consistent scholarly interest, each contributing significantly to both theoretical and empirical discussions. Notably, *Technology in Society* and *Economics of Innovation and New Technology* both exhibit high M-indices (1.00 and 0.83, respectively), indicating strong recent productivity and growing influence despite being relatively newer contributors to the field. The presence of journals with different disciplinary orientations, ranging from economics and innovation studies to social change, underscores the interdisciplinary nature of the research. Collectively, these publication sources form a solid intellectual foundation for understanding the evolving dynamics of technology-driven labor and income transformations.

Leading authors and their contributions

The citation analysis of top authors illustrated in Table 2 highlights the key intellectual contributors to the discourse on technological change, automation, and their socioeconomic impacts. Here, we presented the 10 most influential authors in this field, based on the number of total citations. Acemoglu leads with 1485 citations from just four publications since 2002, underscoring his foundational and widely recognized work in the field. His long-standing influence is further evidenced by the depth and longevity of citations, indicating that his research continues to shape the academic dialogue. With 473 citations from only four publications since 2020, Restrepo has seen a remarkable rise in a short period, likely due to close collaboration with Acemoglu on automation and labor market dynamics that has clearly resonated with a broader audience.

Table 2. Top 10 most cited authors in the literature

Ranks	Author	Total Citation	Number of Publications	Publication Year (start)
1	Acemoglu D.	1485	4	2002
2	Restrepo P.	473	4	2020
3	Prettner K.	218	3	2019
4	Ciarli T.	157	3	2010
5	Lorentz A.	157	3	2010
6	Savona M.	157	3	2010
7	Valente M.	157	3	2010
8	Balland P.-A.	154	2	2022
9	Broekel T.	154	2	2022
10	Alene A.	144	2	2009
Source(s): Table by authors				

Authors such as Prettner, Ciarli, Lorentz, Savona, and Valente, with three publications and citation counts exceeding 150, belong to another cohort of researchers producing a substantial body of modelling and empirical studies of continuous transitions in the economy and technology. Finally, it is noteworthy that authors such as Balland and Broekel, who entered the field more recently (2022), already have high citation counts. This indicates the work of these authors reflects current trends and resonates well with the academic community. Overall, the distribution of citations across both established and emerging scholars suggests a dynamic and evolving research landscape, enriched by both longstanding theoretical contributions and recent innovative insights.

Institutional and regional analysis

Table 3 illustrates the 10 most productive institutions based on the number of articles published, with University of California, leading by contributing 17 articles, representing 20% of the total output in this group. Following closely is Zhejiang Gongshang University with 14 publications, accounting for 16.47%. Other key contributors, including Chongqing University, Fujian Agriculture and Forestry University, and Southwestern University of Finance and Economics, each with 7 articles, contribute 8.24% each to the total output of the top 10. The institutions ranked 9th and 10th, Delhi Technological University and Huazhong University of Science and Technology, each contribute 6 articles, representing 7.06% of the total, further highlighting the diversity and regional engagement in this area of research. This strong representation from both Western and Chinese institutions emphasizes the global and diverse interest in the field.

Table 3. Top 10 most productive institutions in the literature

Rank	Affiliation	Articles	%	Accumulated %
1	University of California	17	20.00	20.00
2	Zhejiang Gongshang University	14	16.47	36.47
3	Chongqing University	7	8.24	44.71
4	Fujian Agriculture and Forestry University	7	8.24	52.94
5	Southwestern University of Finance and Economics	7	8.24	61.18
6	University College London	7	8.24	69.41
7	University Of Porto	7	8.24	77.65
8	Xinjiang University	7	8.24	85.88
9	Delhi Technological University	6	7.06	92.94
10	Huazhong University of Science and Technology	6	7.06	100.00

Note(s): % is the relative contribution percentage, calculated by using Equation (1). Accumulated % is calculated using Equation (2)

Source(s): Table by authors

Next, an analysis of corresponding authors' countries and collaboration patterns was carried out to offer further insights into country-level patterns of article production. Table 4 reveals that the United States (US) leads in overall publications, contributing 14.15% of total output with 72 articles, primarily driven by domestic collaborations, with 56 single-country publications. China ranks second, accounting for 10.61% of the total publications, and stands out for its strong engagement in international collaborations, where 31.5% of its articles are co-authored with foreign institutions. The United Kingdom (UK) also demonstrates a high degree of international cooperation, with nearly half of its publications involving cross-country partnerships. Germany, Italy, and Spain contribute significantly to lead research within the field, with varying levels of collaboration. Notably, Korea shows the highest international collaboration rate among the top contributors, with 50% of its publications being multi-country works. These findings not only identify the primary drivers of research in this domain, but also highlight the critical role of cross-border collaboration in advancing comprehensive and interdisciplinary research in technological change and income distribution.

Table 4. Key contributing countries and their collaboration patterns

Country	Articles	Articles %	SCP	MCP	MCP %
United States	72	14.15	56	16	22.2
China	54	10.61	37	17	31.5
Germany	36	7.07	26	10	27.8
United Kingdom	31	6.09	17	14	45.2
Italy	22	4.32	19	3	13.6
Spain	14	2.75	10	4	28.6

Australia	11	2.16	10	1	9.1
India	11	2.16	10	1	9.1
Japan	10	1.96	9	1	10.0
Korea	10	1.96	5	5	50.0
Note(s): SCP represents single country publication. MCP represents multiple country publication Source(s): Table by authors					

Top cited papers and their impact

Table 5 illustrates the 10 most influential papers in the field based on the number of total citations. The analysis of the most cited publications underscores the foundational and influential works that have significantly shaped the academic discourse on automation, technological change, and income distribution. At the forefront is the paper titled "Directed Technical Change" by Acemoglu (2002), which has accrued 1,049 citations and continues to average 44 citations annually, reflecting its enduring theoretical impact. Other seminal works such as "Barriers to Technology Adoption and Development" by Parente and Prescott (1994) and "Financialization and U.S. Income Inequality" by Lin and Tomaskovic-Devey (2013) highlight the longstanding and evolving nature of economic inequality in the context of technological transitions. Notably, the more recent contributions by Acemoglu and Restrepo, in their papers titled "The Wrong Kind of AI?" (2020) and "Demographics and Automation" (2022), demonstrate the field's growing urgency and contemporary relevance, with strikingly high average citations per year (39 and 45, respectively). The diversity in publication years, ranging from the early 1990s to the 2020s, illustrates both the historical depth and the accelerating interest in this area. Collectively, these top-cited papers not only inform current academic inquiry but also guide policy debates by offering empirical and theoretical insights into the complex interplay between technology and labor market outcomes.

Table 5. Top 10 most influential studies on the literature

Rank	Title and DOI	Authors	Year	Total Citation	Total Citation per Year
1	Directed Technical Change (10.1111/1467-937X.00226)	Daron Acemoglu	2002	1049	44
2	Barriers to Technology Adoption and Development (10.1086/261933)	Stephen L. Parente and Edward C. Prescott	1994	594	19
3	Financialization and U.S. Income Inequality, 1970–2008 (10.1086/669499)	Ken-Hou Lin and Donald Tomaskovic-Devey	2013	397	31
4	Trade reforms and wage inequality in Colombia (10.1016/j.jdeveco.2003.07.001)	Orazio Attanasio, Pinelopi K. Goldberg, and Nina Pavcnik	2004	269	12
5	The wrong kind of AI? Artificial intelligence and the future of labour demand (10.1093/cjres/rsz022)	Daron Acemoglu and Pascual Restrepo	2020	234	39
6	Is Automation Labor Share-Displacing? Productivity Growth, Employment, and the Labor Share	David Autor and Anna Salomons	2018	200	25

	(10.1353/eca.2018.0000)				
7	Technology, trade, and factor prices (10.1016/S0022-1996(99)00016-1)	Paul R. Krugman	2000	188	7
8	Demographics and Automation (10.1093/restud/rdab031)	Daron Acemoglu and Pascual Restrepo	2022	180	45
9	The Care Economy? Gender, Economic Restructuring, and Job Polarization in the U.S. Labor Market (10.1177/0003122413487197)	Rachel E. Dwyer	2013	169	13
10	Determinants of the Wage Share: A Panel Analysis of Advanced and Developing Economies (10.1111/bjir.12165)	Engelbert Stockhammer	2017	165	18
Source(s): Table by authors					

The evolution of the literature over time is clearly reflected in the variety of themes covered in the top 10 most cited papers. The second most cited paper, which is the work by Parente & Prescott (1994) explored how differing barriers to technology adoption across countries influence economic development and income disparities. By modelling technology adoption as a costly process, it highlights that larger barriers to technology adoption require greater investments, which can prevent or delay economic progress. By comparing the US and postwar Japan, the paper explains how these barriers contribute to income gaps. Its findings remain relevant, emphasizing how institutional and infrastructural barriers shape technological advancement and long-term income inequality.

Moving to the early 2000s, the analysis of trade reforms in Colombia by Attanasio et al. (2004) expanded this view. Their paper highlighted how policy shifts, particularly tariff reductions, contributed to wage inequality, especially through skill-biased technological change and the growth of the informal sector. Additionally, the 2010s saw a shift in focus, with Dwyer (2013) exploring job polarization in the US. This particular work emphasized the growing significance of care work in reshaping job structures and highlighted the limitations of traditional theories explaining job growth and inequality. Then, the paper by Stockhammer (2017) further advanced this discourse by emphasizing the broader global trends of financialization, globalization, and welfare retrenchment. These aspects were identified as key drivers of wage share decline across both advanced and developing economies. Overall, these studies reflect a shift from examining the direct effects of technological adoption and trade policies on economic development to analyzing broader socio-economic factors like financialization, globalization, and labor market polarization in shaping income inequality and wage share.

As indicated by Table 5, Acemoglu's contributions are central to the discourse on technological change and income distribution. This is due to his multiple entries in the top-cited papers list. His seminal work in 2002 titled “Directed Technical Change” stands out with 1,049 citations in total and continues to have a significant theoretical impact. The paper provides a framework for understanding how technical change can favor certain factors, such as skilled labor, and how this bias is influenced by market forces like price effects, market size, and the elasticity of substitution, ultimately shaping income inequality and economic disparities (Acemoglu, 2002). Then, building on this foundation, Acemoglu’s recent work with Restrepo, in their paper titled “The Wrong Kind of AI?” and “Demographics and Automation”, further develops these themes while addressing the contemporary implications of automation and AI.

Acemoglu & Restrepo (2020) asserted that the increasing focus on automation through artificial intelligence has led to stagnating labor demand, causing a decline in labor share of national income and rising inequality. This highlights the need for a shift toward developing AI that also creates new, productive tasks for labor, so that these economic challenges can be addressed. Moreover, the other recent work by Acemoglu & Restrepo (2022)

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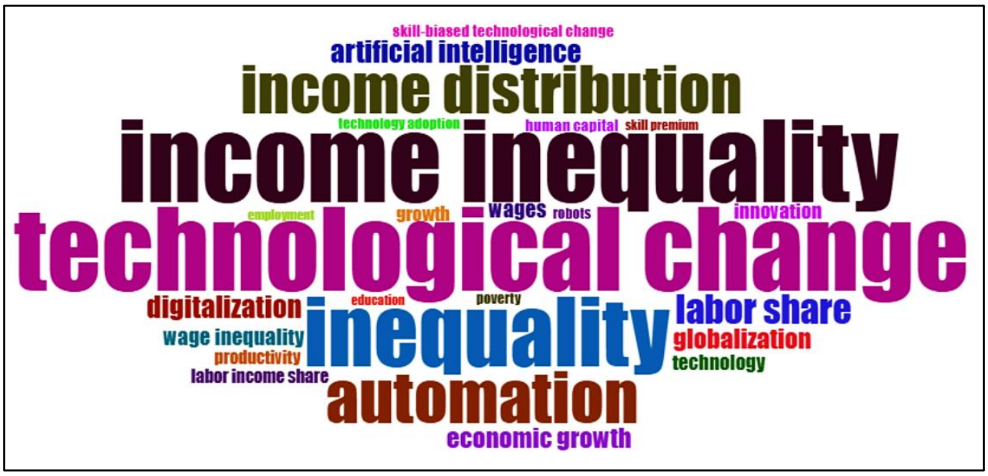
provides yet more evidence that older populations lead to increased automation utilization, particularly in industries that depend on middle aged workers. Consequently, such automation adoption pattern results in higher efficiency but lower labor share, with the effects being more pronounced in more automatable sectors. Altogether, these top cited papers clearly highlight the mounting crisis in understanding the effects of technological advancement on income inequality. Acemoglu's consistent contributions form an integrated body of work, starting from the foundations of the theory through to current matters of concern.

Thematic focus and keyword trends

Figure 3 illustrates a word cloud of several most used terms in the literature, based on authors' keywords. By using the author's keyword rather than keywords plus, the analysis captures the authors' intentional focus and thematic priorities more accurately, leading to more relevant and meaningful insights in the bibliometric study. Looking at the top 10 keywords with the highest number of occurrences, *technological change* and *income inequality* are the most dominant themes in the literature, with 74 and 73 occurrences, respectively. This underscores the central concern over how advances in technology influence disparities in income. Closely related, *inequality* (61) and *income distribution* (43) further highlight the scholarly emphasis on examining how economic gains are shared within societies. Furthermore, the role of *automation* (46), often seen as a direct consequence of technological progress, features prominently, reflecting concerns over labor market disruptions. In parallel, emerging technologies like *artificial intelligence* (20) and *digitalization* (20) are gaining traction as key forces shaping modern economies. Next, the term *labor share* (26) is also frequently discussed as a critical outcome of these transformations, with implications for wage stagnation and employment quality. Furthermore, the intersection of technological change with broader macroeconomic forces such as *economic growth* (18) and *globalization* (18) suggests a multifaceted inquiry into how global integration and innovation are reshaping the structure of work and wealth. Together, these findings demonstrate a robust scholarly interest in the complex, interdependent relationships among technology, inequality, and economic outcomes.



Note(s): The text size represents frequency, with larger text indicating higher frequency

Source(s): Generated by the authors using Biblioshiny

Figure 3. Most frequent words in the literature

Over the past few decades, there has been a marked and accelerating rise in scholarly attention to the term *automation* and *artificial intelligence*, especially from the late 2010s onward. While automation virtually absent from academic discussions before 2017, its frequency surged sharply from 1 mention in 2017 to 46 in 2024, reflecting growing concern over its economic and labor market implications. Similarly, *artificial intelligence* emerged only in 2018 and expanded rapidly from 2 mentions that year to 20 by 2024. This trend underscores a significant shift in the research agenda toward understanding the transformative effects of intelligent technologies on employment, income distribution, and economic structures. The parallel rise in keywords such as *technological change*, *income inequality*, and *labor share* suggests that automation and AI are increasingly studied not in isolation but as core drivers of broader socioeconomic changes. This evolving focus highlights how the academic discourse is responding to real-world disruptions, positioning AI and automation at the heart of debates on the future of work, productivity, and inequality.

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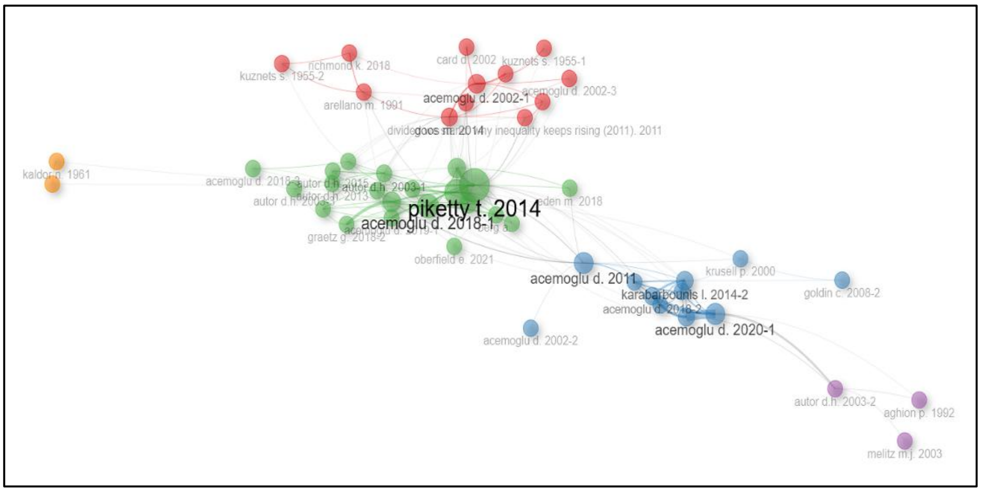
Co-citation analysis

The co-citation analysis reveals significant insights into the key authors and their contributions to the fields, by observing metrices like betweenness, closeness, and PageRank value. Betweenness measures how often a publication connects different clusters in the network, indicating its role as a bridge between research clusters. Central to the co-citation network illustrated by Figure 4 is Piketty (2014), with the highest betweenness value (496.775), signifying its pivotal role in connecting different clusters of literature. Then followed by Goos (2014) with a notably high betweenness value of 281.845. Furthermore, Acemoglu emerges as a dominant figure, with multiple key publications spanning across several years (2002, 2011, 2018-2020), reflecting the deep influence of his works on the discourse surrounding technological change and income distribution. His varied works are positioned across clusters 1, 2, and 3, with publications in 2002 (70.456 betweenness), 2011 (266.564 betweenness), and more recent ones, underscoring the consistency of his impact over time. Brynjolfsson (2014), another key contributor in Cluster 3, is another important figure, with betweenness 126.46 and a strong PageRank (0.039), indicating its relevance in discussions on automation and technological progress.



Source(s): Generated by the authors using Biblioshiny

Figure 4. Co-citation network of foundational authors' papers

The centrality metrics reveal that Piketty not only has the highest betweenness but also maintains a reasonable closeness (0.006) and PageRank (0.043), suggesting that his work connects multiple fields of inquiry and is frequently cited across a broad spectrum of topics. This prominence in the network highlights the enduring influence of his theories on inequality. Furthermore, the analysis shows a clear division between authors who focus on technological and economic factors (Acemoglu, Goos, Autor) and those focused more specifically on the social and policy implications of these changes (Piketty, Goldin). Authors like Karabarbounis (2014) and Gollin (2002), with moderate betweenness values (121.823 and 90.322, respectively), further illustrate the divide between the economic and social dimensions of technological change. Lastly, the relatively lower betweenness and PageRank values for authors such as Kaldor (1961) and Nelson (1982) suggest that while they contribute foundational theories, their current influence within the co-citation network is more limited compared to the more recent works. This underscores the evolving focus on contemporary issues like automation, globalization, and their effects on labor markets and inequality.

There are several insights that can be observed from this co-citation analysis. At its core, this analysis uncovers the intellectual architecture of the research field, revealing how foundational theories, empirical methods, and contemporary debates interconnect. For instance, the centrality of authors such as Acemoglu, Autor, and Piketty suggests that discussions on automation, labor share, and income inequality are deeply rooted in a blend of structural economic theory and real-world labor market dynamics. Moreover, high betweenness scores for works by Piketty and Goos indicate their role as conceptual bridges linking diverse strands of literature, from inequality diagnostics to technological change. Additionally, the emergence of tightly knit clusters around newer publications highlights an evolving focus on the distributive consequences of automation and globalization, while continued references to classic works such as Kuznets (1955) and Kaldor (1961), reflect the field's theoretical continuity. Both authors are foundational figures in economic theory, particularly in discussions

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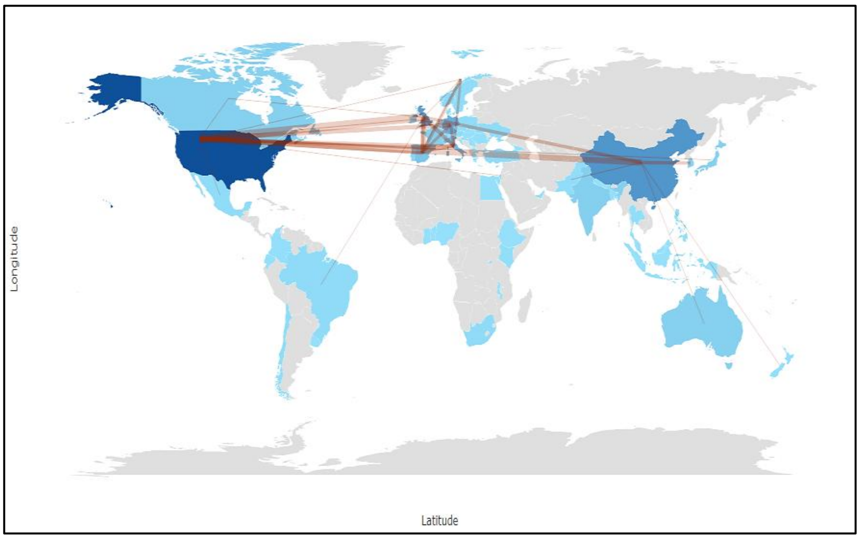
related to income inequality, economic development, and the relationship between technological change and economic structure. This structure portrays a maturing yet still active research agenda that integrates historical insight with modern policy relevance, providing a roadmap for scholars engaging with the socioeconomic impacts of technological transformation.

Global collaborative networks

The country collaboration map illustrated by Figure 5 highlights a dynamic and globally interconnected research landscape. The US stands out as the most collaborative hub, forming partnerships with 26 countries, including a particularly strong connection with the UK (11), followed by China (6), Germany (4), and Italy (3), and France (3). The UK also plays a central role, building robust links with France (8), Spain (5), and Italy (4), underscoring the depth of regional and transatlantic academic ties. China emerges as a key player in cross-border research, actively collaborating with Korea (3), the UK (3), and both Australia and New Zealand (2). Germany and Italy further contribute to this global web, engaging in multiple partnerships, particularly within Europe. Although many connections occur only once, the presence of frequent and multi-directional collaborations among leading economies reflects the increasingly international nature of research on automation, income distribution, and labor dynamics.



Source(s): Generated by the authors using Biblioshiny

Figure 5. Country collaboration map

China emerges as the most influential node in the collaboration network, with the highest betweenness centrality (349.935), closeness centrality (0.015), and a strong PageRank score (0.090), underscoring its pivotal role in bridging global research clusters and connecting diverse institutions. The US also demonstrates significant influence with a betweenness centrality of 250.123 and the highest PageRank score (0.117), reflecting its central position in the knowledge flow across countries. Germany and UK follow closely, with betweenness values of 181.639 and 178.567, respectively, highlighting their strong integration and collaborative reach within the network. Other countries such as Italy and Spain, exhibit moderate levels of centrality and influence, with betweenness values of 60.965 and 58.093 respectively, contributing steadily to international partnerships. Meanwhile, nations like Bangladesh and the Philippines, despite being part of smaller clusters, demonstrate notable betweenness centrality values (18.033 and 23.431, respectively), indicating their roles in linking underrepresented or region-specific research efforts. Overall, the network reveals a strong concentration of collaboration within clusters centered around China, the US, and leading European countries, while also indicating emerging contributions from some Asian nations.

The prominent position of China and the US as the most influential node in the country collaboration network is well-justified by their leadership in automation, robotics, and AI research. Both countries are recognized as major players in the global robotics markets. The US excels in the development of service robots that interact with humans, while China is advancing in industrial robotics, particularly through initiatives like "smart manufacturing" and "smart factories" (Reshetnikova & Tretyakova, 2024). Besides that, China has been the largest consumer of industrial robots over the past decade, surpassing the US in terms of robot intensity and aligning with developed countries in this metric (Lemutov, 2024). In the realm of AI, China and the US are the world leaders, with China leading in the volume of AI-related research papers. Additionally, it was found that collaborative efforts between China and the US in AI research have resulted in more impactful and highly cited work, highlighting the benefits of international cooperation in advancing automation technologies (Alshebli et al., 2024). Given these factors, it is unsurprising that China and the US occupied central positions in the global research collaboration network, as their technological leadership and academic output continue to shape the direction of automation and AI research worldwide.

Comparative Viewpoint within Broader Research

To provide an additional depth into our analysis, we compare our own findings with the work of Zhou et al. (2025), who conducted a bibliometric study on the impact of artificial intelligence on the labor market. Though their paper examines employment trends rather than income distribution directly, yet it squares neatly with the wider discussion on how technological advancement reshape wages and labor share dynamics. Notably, their analysis was based on data from the Web of Science database, gathering 1647 documents published between 2007 until 2024, and utilized CiteSpace as a tool for to perform bibliometric analysis.

There are several key points of convergence between the findings of Zhou et al. (2025) and this study. For instance, both analyses recognize the US and China as the leading contributors in the literature. From 2007 through early 2024, the US has produced a total of 372 articles on the relationship between AI and the labor market, but its proportion of annual output began declining after 2012. On the other hand, China's publication rate surged after 2015 and overtook the US by 2024 (Zhou et al., 2025). Furthermore, their study also identified *Technological Forecasting and Social Change* journal as the leading outlet, with 57 published articles. This shared finding suggests that certain trends remain robust across different databases.

On the other hand, keyword co-occurrence mapping in their analysis places the term *artificial intelligence* at the center of the network, suggesting that researchers now regard the technology as crucial to future labor markets and income flows. Meanwhile, the surrounding nodes point to related terms such as *technological change*, *job polarization*, *wage inequality*, and *automation*, which underscores rising concern about the distributional effects of technology on the workforce. As for the emerging research trends, there has been a clear temporal shift in research focus that was outlined in their paper. Specifically, during the period of 2007 until 2017, the number of literatures addressing AI and the labor market remained low, with research was predominantly concerned with substitutional effects of robots on employment. However, majority of the research still lacked in-depth analysis of mechanisms, industry-specific differences, and structural changes in the labor market. Then, from 2015 onwards, the research on AI and labor market has entered a more multidimensional an in-depth phase, including additional terms such as *wage inequality*, *technological unemployment,* and *job polarization*. Thus, this shift in scholarly focus, as demonstrated by Zhou et al. (2025), provides empirical evidence of technology's increasing influence on income distribution and labor income share.

Overall, this comparative discussion reveals both the robustness of certain trends across databases, namely Scopus and Web of Science and underscores the unique contribution of this study to the literature. That is, this provides a fresh perspective to the ongoing discussion by focusing directly on the distributional effects of automation and technological transformation on labor's income.

Policy Analysis

The findings of this study highlight a growing policy urgency to address the impacts of automation and technological change on income distribution and labor income share. The bibliometric analysis demonstrates that both public officials and researchers are growing more interested in tracing how technology is altering work routines and salary structures across various sectors and nations. Soaring number of publications throughout the year, together with an intensified emphasis on automation, widening pay gaps, and general labor-market disruptions, further mirror this urgency. If left unchecked, these technological forces may undermine workplace conditions, wage levels, and income distribution, weakening equity and economic stability. Accordingly, lawmakers should act on three fronts: provide education and training to help workers collaborate with machines, strengthen social safety nets to cushion abrupt layoffs, and design incentives that encourage firms to create decent, secure jobs in the evolving economy.

Furthermore, policy makers should consider regulations and strategies that directly reflect these empirical trends. Take for example, the US and China, two leading contributors in the literature have already recognized the policy implications of AI and are seeking ways to maximize its benefits while mitigating the harms. With this being said, several considerations can be taken to align policy with these trends. For instance, governments may launch upskilling packages, raise unemployment benefits and expand health coverage, and set transparent standards for gig and platform workers. On the global stage, officials can lean on the wide evidence outlined here, including the leading institutions, authors, and journals, to spur cooperation and smoother rules between nations. By curbing income gaps, fortifying education and training, and raising job quality, policy makers can help to build a working future of work where the benefits of automation and technology are broadly shared and contribute to a more equitable and resilient society.

LIMITATIONS

While this study offers valuable insights into the intersection of automation, technological change, and labor income share, it is also limited in some areas. For instance, the use of bibliometric data includes its own set of limitations, as it only includes published scientific literature and excludes other important dissemination formats of knowledge such as grey literature, policy reports, or industry-specific judgements. Therefore, the analysis is limited to only academic perspective, overlooking the practical and emerging side of non-academic stakeholders. Additionally, the impact or influence of the studies is determined by the number of citations, which it is highly possible that the number of citations may not truly reflect the actual influence of certain papers. This is because, there may be a variety of reasons for authors to cite certain papers. As a result, highly technical or experimental papers may be cited less frequently than broader review papers or lower-tech interventions that offer greater generalizability.

Another limitation stems from the lack of feasibility in conducting a global study on the top authors, institutions, and countries. The bibliometric approach can clearly provide a methodological approach for large scale mapping, but unfortunately, the mapping is often biased towards the publications from a few developed countries, mainly in the North America and Western Europe. Consequently, this may underrepresent research coming from emerging economies, where the effects of automation and technology on labor markets are likely to differ. Moreover, the co-citation and collaboration analysis methods used do not fully capture the interdisciplinary nature of the subject, as researchers often engage in cross-sectoral collaborations that are not necessarily formalized within formal citation networks.

CONCLUSION

This bibliometric study provides a thorough overview of the academic landscape surrounding the impact of technological change and automation on income distribution and labor income share. By observing publication trends, influential sources, prominent authors, and institutions, as well as country-level contributions, this paper addresses the growing and increasingly collaborative research field. Furthermore, key thematic focuses such as technological change, income inequality, and automation respond to the evolving nature of discourse shaped by both theoretical and empirical developments. Notably, the co-citation patterns revealed foundational intellectual structures, while the global collaboration network underscores the cross-border relevance of these socioeconomic challenges. Ultimately, the findings of this paper directly fulfil the objective of this study by providing valuable insights and guiding future investigations into the intersection of technological transformation and labor market dynamics.

Looking ahead, future research should delve into the various avenues regarding this topic, as the bibliometric analysis has identified emerging research gaps that empirical studies could address. Foremost, it is recommended that greater emphasis be placed on cross-country comparative studies that consider institutional diversity, labor market structures, and policy regimes, especially in emerging economies where data are often underrepresented. Following this, interdisciplinary approaches that bridge economics, sociology, and technology studies could offer more nuanced insights into the social dimensions of labor transformations. Moreover, as artificial intelligence and digital platforms continue to evolve, there is a need for more granular analysis at the sectoral and occupational levels to capture uneven impacts across different segments of the workforce. Besides that, future research could also further explore the role of digital platforms in shaping employment conditions and income distribution. A clear picture of these dynamics may guide policymakers and advocates in crafting fair, equitable policies for a workforce that is rapidly changing. For example, studies could focus on the people working in gig economy, freelance field, and delivery services by investigating how automation and algorithmic management alter their working hours, income, and sense of stability. Lastly, scholars should engage more directly with policy evaluation by linking empirical evidence to the design and assessment of interventions aimed at promoting inclusive growth. These directions will not only enrich the academic discourse but also enhance the practical relevance of research in informing equitable responses to ongoing technological disruption.

Ethical statement

This study did not involve human participants, human data, or human tissue. Therefore, ethical approval and informed consent were not required.

Declaration of Conflicting Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

The bibliometric data used in this study were obtained from the Scopus database. These data can be accessed by applying the search query outlined in the methodology section.

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