Research Article

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The Evolution of Job Displacement in the Age of AI and Automation: A Bibliometric Review (1984–2024)

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Abstract: This study presents a comprehensive bibliometric analysis of the scientific literature about artificial intelligence (AI), automation, and job displacement from 1984 to 2024. Utilizing the Scopus database, 225 relevant documents were retrieved and analysed using R Studio and VOSviewer. The analysis reveals significant trends in publication growth, citation metrics, and collaborative networks among researchers and institutions. Notable findings indicate a marked increase in research output during key technological advancements, highlighting the evolving discourse surrounding the implications of AI and automation on the workforce. This study identifies prevailing themes within the literature through keyword analysis and explores the interconnectedness of research contributions across various domains. This bibliometric review aims to provide a foundational understanding of the current landscape and future directions in studying AI, automation, and job displacement.

Keywords: artificial intelligence, automation, job displacement, bibliometric analysis, technological displacement, sustainable employment

1 Introduction

The rapid advancement of artificial intelligence (AI) and automation technologies over the past four decades has sparked significant discussions regarding their implications for the labour market. As businesses and organizations increasingly integrate these technologies, there is a growing concern about the potential for job displacement, reshaping the workforce landscape across various sectors. This bibliometric review aims to analyse the evolution of scientific literature surrounding AI, automation, and job displacement from 1984 to 2024, offering insights into the trends and themes that have emerged within this critical area of research.

This study aims to comprehensively analyse the scientific production related to AI and job displacement using bibliometric tools. By examining a robust dataset of 225 documents extracted from the Scopus database, this analysis will highlight key trends in publication growth, citation metrics, and collaborative networks among researchers and institutions. The study will reveal how major technological advancements have influenced the volume and focus of academic output in this domain, emphasizing the shifting discourse around AI's impact on employment.

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Through a systematic examination of keyword occurrences and citation patterns, this study aims to identify the prevailing themes and research trajectories in the literature on AI and job displacement. Key research questions include: What are the dominant topics and keywords associated with AI and automation concerning job displacement? How have international collaborations evolved in this field of study? Furthermore, this review will assess the influence of major journals and authors, shedding light on the leading contributors to this growing body of knowledge.

The findings from this bibliometric analysis will provide a foundational understanding of the current research landscape on AI, automation, and job displacement. Additionally, this review will serve as a resource for future researchers exploring the intersections of technology, labour markets, and socio-economic implications. As the discourse around the future of work continues to evolve, understanding the past and present trends in this field is crucial for anticipating and addressing the challenges posed by AI and automation in the coming years.

1.1 Study Objectives

- To analyse the scientific production related to AI, automation, and job displacement over 40 years (1984–2024).
- Using bibliometric tools to identify trends and patterns in annual scientific output on AI and job displacement.
- To evaluate the impact of published works through citation analysis and average citations per year.
- To determine the most influential journals and sources publishing research on AI, automation, and workforce displacement.
- To identify key authors and institutions contributing to research on job displacement and automation.
- To assess international collaboration trends in AI and job displacement research.
- To analyse core sources of AI and job displacement research through Bradford's law.

2 Literature Review

2.1 Theoretical Framework on Job Displacement Due to Technological Advancements

Technological advancements have long been viewed as a threat to human labour, as seen during the first Industrial Revolution when the introduction of power looms and mechanical knitting frames led to the Luddite movement, which opposed this shift (Mokyr, Vickers, & Ziebarth, 2015). During the nineteenth century, prominent economists Karl Marx and David Ricardo supported the idea that technology could render workers obsolete (Keynes, 2010). According to research, technological advancements are disrupting labour markets, leading to a growing polarization of employment opportunities into low-skilled and high-skilled positions (Cirillo, Evangelista, Guarascio, & Sostero, 2021). The rapid advancements in robotics and AI are anticipated to significantly alter the labour market (Katz & Murphy, 1992). The rapid growth of new technologies raises concerns about the potential displacement of high-skill, high-wage jobs, potentially putting previously secure positions at risk (Lloyd & Payne, 2019). By 2025, these transformations will create 97 million new jobs and eliminate 85 million existing ones globally (Susskind, 2020). Studies predict significant job losses in automation-prone roles, influencing on-going discussions on the impact of technological advancements on the labour market (Arntz, Gregory, & Zierahn, 2017; Frey & Osborne, 2017). Recent studies have challenged this perspective, highlighting the positive effects of technology on employment (Aghion, Antonin, Bunel, & Jaravel, 2022).

The theoretical framework on job displacement due to AI and automation draws on multiple essential perspectives from economics, sociology, and labour theory. Central to this framework is the theory of skills-biased technological change; technological advancements are believed to enhance the necessary for skilled labour, leading to wage inequality, the polarization of the workforce (Bolli & Pusterla, 2023), and increased wages (Card & DiNardo, 2002). The theory suggests that technology boosts the productivity of highly skilled jobs, replacing low to medium-skilled employment, leading to an increase in income inequality (Cirillo et al., 2021). Complementing this is routine-biased technological change, which explains how AI and automation replace human labour in routine tasks, contributing to the decline of mid-skilled jobs (Autor, Levy, & Murnane, 2003; Goos & Manning, 2007), and highlights the disappearance of the "middle" in manual and cognitive jobs, which machines can replace due to predictable and routine tasks (Goos & Manning, 2007). This displacement of routine work is further contextualized by Schumpeter's creative destruction, wherein technological innovations disrupt traditional industries, eliminating specific jobs while creating new opportunities (Susskind, 2020). Marxist labour theory also offers critical insights, emphasizing how technological advancements can generate surplus labour and exacerbate socioeconomic inequality, mainly as low-skill jobs disappear and high-skill jobs become more secure (Keynes, 2010).

2.2 Examination of the Relationship Between AI/Automation and Labour Market Dynamics

The interplay involving AI, automation, and labour market intricacies is continuously changing. This relationship substantially affects productivity levels, job displacement, income disparity, workforce competencies, and the overall economic framework. Technological advancements have varying societal impacts, with some arguing that they lead to job losses while others argue that they do not. This perspective is rooted in labour sociology and economics, but historical evidence since the Industrial Revolution suggests otherwise (Zhang, 2023). The rapid progress of AI technologies drives industrialization and commercialization processes while the industry continues exploring its application across various domains. AI is revolutionizing intelligent manufacturing, fostering a high-quality employment model based on effective human-machine collaboration, thereby generating and fulfilling job opportunities (Shen & Zhang, 2024).

Robots are often seen as rivals to humans, but this perspective is materialistic. The relationship between humans and machines should not be zero-sum. Focusing on collaboration can alleviate production limitations, enhance productivity, and create more employment opportunities and innovative roles rather than viewing robots as rivals (Duan, Deng, & Wibowo, 2023). Implementing materialized AI technology can improve production efficiency, aligning with the existing factor endowment structure. It can optimize production between upstream and downstream enterprises, facilitating production scaling and reproduction. This synergy fosters growth in labour demand across various skills, leading to a creative impact and concurrent increase in labour demand (Liu, Gu, & Lei, 2022). AI, a vital component of the fourth industrial revolution, significantly impacts human social status and workforce composition (Chen, 2023). AI and machinery are revolutionizing labour productivity by automating repetitive tasks, enhancing employee skills, and increasing the value of work. This shift may lead to the disappearance of low-skilled positions and new job opportunities (Polak, 2021).

AI has both a positive and negative impact on employment, as it streamlines complex tasks and represents a human-like intelligence. Like early industrial technologies, automation technologies like AI present opportunities and concerns about machine replacement. The rise in technology leads to increased capital composition and a surplus population, highlighting the complex relationship between technology and employment (Shen & Zhang, 2024). Artificial intelligence has significantly enhanced productivity in healthcare, transportation, and production environment management, leading to increased leisure time (Shen & Zhang, 2024). Despite the widespread use of AI, several industrialized nations have experienced declining labour income and slower productivity growth (Autor, 2019). Workers with low skills and those who are incapacitated are at a high risk of being replaced by automation (Ramos, Garza-Rodríguez, & Gibaja-Romero, 2022). AI and robotics significantly impact the manufacturing job market, leading to a significant unemployment issue in industry-related positions due to their disruptive nature (Bian, 2024).

2.3 Empirical Studies on AI and Job Displacement

Job displacement due to automation often results in individuals transitioning from stable, high-quality employment to less secure, lower-quality roles in the secondary labour market. This shift can lead to diminished job security, limited social mobility, and a decline in social standing. Over the past years, numerous studies have examined the impact of automation on employment, revealing significant concerns about job displacement.

A study by Frey and Osborne (2017) suggests that AI could replace 47% of the 702 US job categories within the next two decades, particularly as digitization accelerates post-pandemic. Similarly, research across various countries indicates that automation is poised to significantly impact employment. For instance, 60% of jobs in Brazil are expected to be affected by automation in the coming decades, with eight out of the ten most common occupations being highly susceptible (Lima et al., 2021). In the UK, 35% of jobs are projected to be substantially impacted (Frey & Osborne, 2014), while in Canada, 42% of jobs are at risk (Lamb, 2016).

The influence of technology on professions is also evident. A survey of technology professionals found that 48% believe robots can effectively perform routine tasks (Ngo et al., 2014). The rise of AI is expected to exacerbate high-tech unemployment by transforming traditional industries into routine tasks that technology will eventually replace (Susskind & Susskind, 2016). Research indicates that 55% of jobs at high risk of AI substitution face no gender disparity (David, 2017). Additionally, the introduction of robots has significantly reduced the responsibilities of low-skilled labour compared to medium-skilled and high-skilled labour (Graetz & Michaels, 2018). The increased use of robots in US labour markets has led to a 0.2% decrease in the employment-to-population ratio and a 0.42% decrease in wages (Acemoglu & Restrepo, 2020).

A study by Arntz, Gregory, and Zierahn (2016) found that, on average, 9% of jobs in 21 Organization for Economic Cooperation and Development (OECD) member nations face significant automation risk. This risk varies across countries, ranging from 12% in Germany to 6% in Estonia (Arntz et al., 2016). A broader analysis of 32 OECD nations revealed that 14% of jobs are highly susceptible to automation, with a 70% probability, while 32% face a 50–70% automation risk (Nedelkoska & Quintini, 2018).

Despite these concerns, several studies highlight the potential benefits of AI implementation. A study on a Spanish manufacturing company found that adopting robots led to a 10% net job increase, while firms that avoided investing in robotic technology experienced job losses (Koch, Manuylov, & Smolka, 2021). Graetz and Michaels (2018) also found that the use of robots increased annual labour productivity by 0.36 percentage points, positively impacted total factor productivity, and decreased output prices, although it did not significantly affect overall employment levels except for low-skilled workers. Nobel laureate Boden (1987) argues that the advancement of AI creates new jobs that surpass those lost, making long-term unemployment concerns unwarranted. Researchers suggest that while AI may initially impact the job market, its enhanced production efficiency will ultimately lead to increased production and employment opportunities (Guliyev, 2023).

2.4 Workforce Adaptation Strategies, Including Reskilling and Upskilling Initiatives

AI is not meant to substitute human labour wholly but to complement and improve human abilities, ensuring a smooth transition and fostering growth in the workforce (Idrisi, Geteye, & Shanmugasundaram, 2024). AI can automate roles previously performed by humans, potentially leading to job displacement in specific sectors (Idrisi et al., 2024). Automation in certain positions presents new opportunities and increased requirements for skills in developing sectors. The integration of AI requires the acquisition of the necessary skill sets (Baral, Rath, Goel, & Singh, 2022), such as education and training by utilizing innovative educational approaches, emphasizing experiential learning, and addressing a range of competencies, encompassing essential technical, leadership, and digital technology implementation skills (Babashahi et al., 2024). Workers must develop digital skills, higher education, technical expertise, and strong literacy and numeracy skills to adapt to technological advancements and reduce the risk of automation replacement (Filippi, Bannò, & Trento, 2023).

The industry domain (Jurczuk & Florea, 2022) emphasizes the importance of digital skills in future manufacturing, including process design, automation, creativeness, critical imagining, digital material development, data assessment, and cybersecurity. In the legal domain, law students need to understand AI to integrate legal expertise with technological insights, advocating for AI-focused modules in academic programs and on-going professional development opportunities (Beebeejaun & Gunputh, 2023). Chirgwin (2021) emphasizes the significance of integrating technical and emotional competencies in mine controllers, stressing the necessity for a blend of hard and soft skills in AI adoption. Meanwhile, Kumar, Naveen, Kumar Illa, Pachar, and Patil (2023) emphasize the importance of software engineers continuously enhancing their skills in AI tools like language processing, machine vision, machine learning, big data, and IoT technologies to stay applicable in the progressively developing AI landscape. Further, Faraj (2022) highlighted the relevance of developing technical competencies in digital, technological, scientific, mathematical, engineering, and programming fields and soft skills like continuous learning and digital culture proficiency for success in AI.

It is crucial to prepare the workforce for this transition and generate new employment openings in developing industries. AI adoption is vital for successfully integrating AI tools into their methodologies. To effectively incorporate AI into the educational sector, a robust infrastructure, reassessment of academic curricula, future-oriented training for faculty and students, collaboration with relevant institutions, and integration of AI technologies are crucial (Faraj, 2022). For successful implementation of AI, practical strategies include gathering employee feedback, fostering constructive attitudes, supporting job crafting, and tailoring AI training to improve performance can be conducted (He, Teng, & Song, 2024).

The workforce must adapt by acquiring new competencies and knowledge. Collaboration between governments, educational institutions, and organizations is crucial for offering training programs and resources that prepare individuals for the age of automation, fostering creativity, critical thinking, problem-solving capabilities, and technical skills related to AI and emerging technologies. Governments and organizations should allocate resources towards research and development initiatives to generate new employment opportunities in emerging industries like AI development. By leveraging these areas and fostering entrepreneurship, a sustainable future can be established where humans and AI coexist in a balanced manner (Idrisi et al., 2024). Finally, while there are concerns about job displacement from AI automation, viewing this transition as an opportunity is crucial. By providing upskilling programs, creating new employment potentialities in developing sectors, and guaranteeing a seamless transition into a future where humans collaborate with AI technology for shared benefits (Idrisi et al., 2024).

2.5 Global Policy Responses and Frameworks Addressing the Challenges of Automation

The gradual progress of automation and AI poses significant challenges to global labour markets, economies, and societies. As a response, numerous international policy frameworks and initiatives have been established to mitigate risks and capitalize on these technologies' benefits. The OECD AI Principles, established in 2019 and revised in May 2024, reflect recent technological advancements and policy changes, ensuring their relevance and effectiveness in the field. These principles aim to promote the development and application of AI in a reliable, innovative, and democratic manner, ensuring human rights and democratic principles are upheld. These principles consist of "inclusive growth, sustainable development, and well-being," "human rights and democratic values, including fairness and privacy," "transparency and explainability," "robustness, security, and safety," and "accountability." Its recommendations comprise "investing in AI research and development," "fostering a digital ecosystem for AI," "Shaping an enabling policy environment for AI," "building human capacity and preparing for labour market transformation," and "international cooperation for trustworthy AI." Nations widely adopt these principles to guide their national AI policies (OECD, 2024).

The G20 countries emphasized the significance of global collaboration on AI strategies, pledging to promote the digital economy and AI through international cooperation in policy and governance to foster international collaboration and advance discussions on AI governance to fully realize its benefits and mitigate associated risks with aims to distribute AI's economic benefits equitably and mitigate labour market risks. The G20 AI Principles, established in 2019, aim to enhance AI solutions in the digital economy. They advocate for a regulatory framework that promotes innovation, addresses potential risks, and promotes responsible AI practices to accomplish the Sustainable Development Goals (SDGs) (G20, 2019). The United Nations Development Program (UNDP) emphasizes the importance of inclusive and sustainable economic growth in automation, aiming to align AI and automation with the UN's SDGs, particularly in job creation, education, and reducing inequality (UNDP, 2024).

The International Labor Organization (ILO) promotes international policies to improve social protection systems and facilitate worker reskilling and upskilling, especially in at-risk sectors, in response to the effects of automation on employment, aiming to reduce displacement and maximize job opportunities (ILO, 2024). The EU AI Act is a pioneering regulation of AI. The European Union has managed automation by implementing regulatory measures such as the General Data Protection Regulation and the forthcoming AI Act. These regulations are designed to oversee the application of AI in critical sectors while fostering innovation. Additionally, the EU has prioritized reskilling efforts, offering financial support through initiatives like the Digital Europe Programme (EU, 2024). Global policy responses to automation challenges emphasize integrating innovation, economic development, social safety nets, and workforce preparedness. Countries are addressing this by allocating resources for reskilling, implementing AI regulations, and promoting international cooperation. However, challenges persist in ensuring equal benefits for all demographic groups while addressing associated risks.

Preceding studies have examined the evolution of AI and automation such as examining the effects of automation on labour demand (Aghion et al., 2022), Risk of automation for jobs in OECD countries (Arntz et al., 2016), revisiting the risk of automation (Arntz et al., 2017), skill content of recent technological change (Autor et al., 2003), influence of AI and Its challenges (Beebeejaun & Gunputh, 2023), impact of AI on the labour market (Bian, 2024), computer technology and probable job destructions (David, 2017), impact of digital work on work–life balance and job performance (Duan et al., 2023), automation technologies and their impact on employment (Filippi et al., 2023), robots at work (Graetz & Michaels, 2018), AI and unemployment in high-tech developed countries (Guliyev, 2023), dynamics of job displacement and evolution of AI (Idrisi et al., 2024), impact of automation on Canada's workforce (Lamb, 2016), effects of digital technology on banking, production, and employment (Liu et al., 2022), technological anxiety and the future of economic growth (Mokyr et al., 2015), automation of employment in the presence of industry 4.0 (Ramos et al., 2022), and impact of AI on employment (Shen & Zhang, 2024). However, no study has been conducted to examine the evolution of job displacement in the age of AI and Automation for the last four decades. Therefore, this study was conducted to fill the literature gap.

3 Methodology

This study employs a bibliometric approach to analyse the literature on AI, automation, and job displacement over a 40-year period, from 1984 to 2024. The primary objective is to synthesize the evolution of research in this area and identify key trends, influential sources, and collaborative patterns.

3.1 Data Collection

The initial step involved selecting an appropriate database for the bibliometric analysis. The Scopus database was chosen due to its comprehensive coverage of peer-reviewed scientific literature and its robust citation indexing capabilities. A structured search query was carefully crafted to ensure the retrieval of relevant documents. This query combined keywords related to AI, machine learning, automation, and their impacts on job displacement and employment dynamics. The specific search string utilized was:

TITLE-ABS-KEY ((“Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Automation”) AND (“Job Displacement” OR “Workforce Displacement” OR “Job Loss” OR “Employment Impact” OR “Automation Risk”) AND (industry OR sector OR field OR discipline OR department)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “ch”) OR LIMIT-TO (DOCTYPE, “re”)) AND (EXCLUDE (PREFNAMEAUID, “Undefined”)).

This search was conducted on 9 September 2024, yielding a total of 225 documents that were deemed relevant for analysis. The selection criteria ensured that only articles published in English and classified as research articles, conference papers, or book chapters were included, providing a focused view of the literature.

3.2 Document Selection Criteria

To ensure a robust and relevant dataset, the following selection criteria were applied during the document retrieval process:
- **Database Selection:** Documents were sourced exclusively from the Scopus database due to its comprehensive indexing of high-quality, peer-reviewed journals across disciplines.
- **Time Frame:** The analysis covered the period from 1984 to 2024 to capture longitudinal trends in research on AI, automation, and job displacement.
- **Language:** Only documents published in English were included to ensure uniformity in content analysis and avoid potential translation inaccuracies.
- **Document Type:** The focus was on peer-reviewed journal articles, conference proceedings, and review articles to prioritize scholarly content with significant contributions to the field. Books, editorials, and grey literature were excluded.
- **Keyword Search:** A keyword search was conducted using terms such as “AI,” “automation,” “job displacement,” “workforce adaptation,” and “bibliometrics.” Boolean operators and wildcard symbols were used to refine search results and capture a broad range of relevant studies.
- **Exclusion Criteria:** Articles with insufficient bibliometric data, duplicate entries, or content outside the scope of AI and job displacement (e.g., focusing on unrelated industries or non-technological contexts) were excluded.
- **Rationale:** These criteria were designed to minimize bias, ensure data relevance, and provide a focused analysis of the most impactful research in this domain.

3.3 Selection Criteria and Limitations

The selection of documents was restricted to English-language publications indexed in the Scopus database. This approach introduces potential biases, particularly excluding non-English literature and grey literature, which may reflect diverse perspectives or emerging insights outside traditional publication channels.

3.4 Potential Biases in the Scopus Database

While the Scopus database offers comprehensive indexing of scholarly content across multiple disciplines, it is not without limitations. Language Bias is evident as Scopus primarily indexes English-language publications, potentially underrepresenting significant research published in other languages. Disciplinary Bias may occur, with certain fields like social sciences and humanities being underrepresented compared to STEM disciplines, leading to an incomplete view of interdisciplinary contributions to AI and job displacement. Regional Bias is another concern, as research outputs from developing countries or regions with limited publication infrastructure might be disproportionately excluded, skewing global representation. Additionally, Grey Literature such as policy reports, working papers, and government documents, which could provide valuable practical insights, is excluded from the database. Lastly, Recency Bias may arise due to the indexing process potentially delaying the inclusion of the most recent publications, omitting cutting-edge developments.

3.5 Mitigation Measures

To address these biases, efforts were made to diversify the dataset through the inclusion of multidisciplinary search terms, ensuring a wide range of subject areas. Future studies could complement Scopus-based analyses with data from other sources such as Web of Science, Google Scholar, or regional databases to improve representativeness and reduce bias. By incorporating these additional sources, researchers can gain a more comprehensive and balanced understanding of the impact of AI and job displacement across different disciplines, regions, and types of literature.

3.6 Data Analysis Tools

Two primary tools were utilized to analyse bibliometric data: R Studio and VOSviewer.

3.6.1 R Studio

R is a programming language, while R Studio serves as its integrated development environment, offering user-friendly interfaces for coding, visualization, and analysis. Bradford's law, which was employed in this study, categorizes journals into zones of relevance based on their citation distribution patterns, providing insight into core sources in a research field. R, unlike Python, maintains data objects in physical memory, requiring all data to be in a single memory space, which makes it less suitable for handling Big Data scenarios due to its higher memory consumption.

3.6.2 VOSviewer

This software tool specializes in constructing and visualizing bibliometric networks. It was instrumental in mapping the relationships between authors, institutions, and countries. VOSviewer enabled the creation of visual representations of co-authorship networks, keyword co-occurrences, and the most influential sources, which provided valuable insights into the structure of research within the field. VOSviewer is not suitable for citation analysis; cluster analysis is confusing, and no timespan selection.

3.7 Data Analysis Process

The data analysis process involved several steps.

3.7.1 Descriptive Analysis

The first step involved summarizing the overall scientific production related to AI, automation, and job displacement. Key metrics such as the total number of documents, annual growth rate, average citations per document, and document types were calculated. This descriptive analysis provided an overview of the research landscape over the past four decades.

3.7.2 Trend Analysis

Next, annual distributions of publications were examined to identify trends in scientific output over time. This included examining the number of publications per year and the average citations per year, highlighting significant spikes in activity, and correlating them with global events or technological advancements.

3.7.3 Co-authorship and Collaboration Analysis

Co-authorship patterns were analysed to determine the extent of collaboration among authors, institutions, and countries. VOSviewer was utilized to visualize these relationships, allowing for the identification of leading contributors and collaborative networks within the field.

3.7.4 Keyword Analysis

The frequency of keywords in the publications was examined to identify prevailing themes and topics of interest. This analysis helped in uncovering the evolution of research topics over time and understanding the focus areas within the literature.

3.7.5 Source Analysis

The most relevant sources were identified through citation analysis, highlighting the journals and conferences that have significantly contributed to the discourse on AI, automation, and job displacement. Bradford's law was applied to assess the core sources of research in this area, categorizing them into different zones based on their publication frequency.

The distribution of sources was analysed using Bradford's law, which posits that a small core of journals accounts for the majority of relevant articles in any given field, followed by larger groups of journals with progressively fewer relevant articles. According to Bradford's law, sources can be divided into three zones: the core zone, which includes highly relevant journals; the second zone, which consists of moderately relevant sources; and the third zone, which contains the least relevant sources. This stratification helps identify the most influential journals in the field (Bradford, 1985).

4 Result

Table 1 reveals a significant increase in scientific production regarding AI and job displacement over the years. From 1984 to 2024, a total of 225 documents have been published, reflecting an impressive annual growth rate of 11.28%. The average age of documents is relatively young at 2.84 years, indicating that research is current and evolving rapidly. Each document garners an average of 16.27 citations, suggesting that the works are well-regarded in the academic community. The diversity of the literature is evident, with a total of 10,798 references and a substantial number of keywords – 961 from the “Keywords Plus” category and 660 from “Author’s Keywords.” Collaboration is evident among 723 authors, with a small percentage (43) contributing single-authored works. Notably, international collaboration is present in about 20.89% of the documents, showcasing the global interest in this field.

Figure 1 shows that annual publication data exhibit a dramatic rise in research output, particularly in the last few years. The early years (1984–2014) show minimal activity, with sporadic publications – one in 1984 and a few in the following decades. However, starting in 2018, there’s a marked increase, culminating in a record of 72 publications in 2024. This upward trend indicates a growing recognition of the importance of AI’s impact on job displacement, likely driven by the rapid advancements in AI technology and its integration into various sectors.

Table 2 citation analysis highlights the changing influence of research over time. Early studies (1984–2000) received minimal citations, reflecting the nascent stage of the field. However, from 2014 onwards, a notable increase in average citations per article is observed, particularly in 2016 and 2017, with citations averaging over 100. This suggests that the body of literature is not only growing but also gaining traction and relevance in discussions surrounding AI and job displacement.

Citable Years refer to the number of years within a given period in which a publication is eligible to receive citations. For example, in a study conducted in 2024, the “citable years” could be from 2020 to 2024, reflecting the window during which the paper has the potential to be cited in other works. This metric helps in understanding the temporal relevance of the publication and its subsequent influence on the field.

Table 3 shows leading journals contributing to this body of research including “Lecture Notes in Computer Science,” “Sustainability (Switzerland),” and “AI and Society.” These sources are vital for disseminating findings and fostering discussions within the academic community. The prominence of these journals underscores the interdisciplinary nature of the research, bridging technology, ethics, and societal implications.

Table 4 shows Bradford’s law indicates that the primary sources of literature on AI and job displacement are concentrated in a few key journals, reinforcing the importance of these publications. With most of the

Table 1: Overview of scientific production in AI and job displacement (1984–2024)

Description	Results
Main information about data	
Timespan	1984–2024
Documents	225
Annual growth rate %	11.28
Document average age	2.84
Average citations per doc	16.27
References	10,798
Document contents	
Keywords plus (ID)	961
Author’s keywords (DE)	660
Authors	
Authors	723
Authors of single-authored docs	43
Authors collaboration	
Single-authored docs	43
Co-authors per doc	3.28
International co-authorships %	20.89
Document types	
Article	123
Book chapter	35
Conference paper	54
Review	13
Total	225

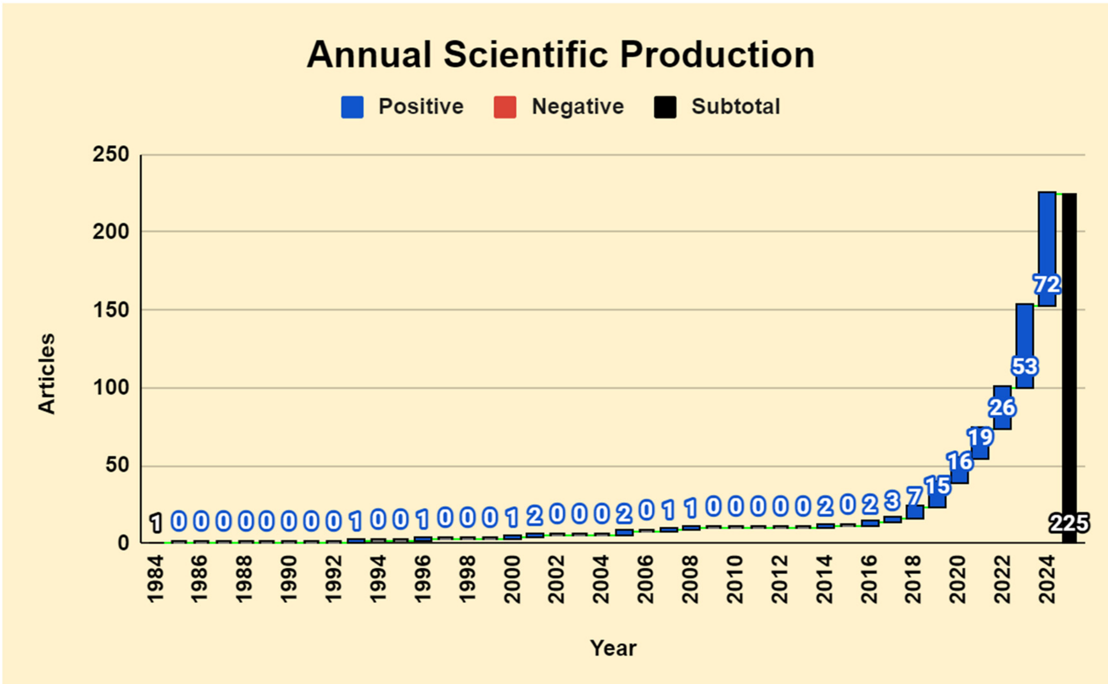

Figure 1: Annual publication trends on AI and job displacement.

Table 2: Citation metrics: average citations per year

Average citations per year				
Year	**MeanTCperArt**	***N***	**MeanTCperYear**	**CitableYears**
1984	3	1	0.07	41
1993	0	1	0	32
1996	2	1	0.07	29
2000	2	1	0.08	25
2001	7.5	2	0.31	24
2005	0	2	0	20
2007	0	1	0	18
2008	13	1	0.76	17
2014	79	2	7.18	11
2016	102.5	2	11.39	9
2017	134	3	16.75	8
2018	48.14	7	6.88	7
2019	25.27	15	4.21	6
2020	45.31	16	9.06	5
2021	12.58	19	3.14	4
2022	21.88	26	7.29	3
2023	10.4	53	5.2	2
2024	0.85	72	0.85	1

influential works appearing in a select number of journals, this highlights the need for researchers to focus on these key platforms for disseminating their findings.

The Bradford analysis categorizes journals into three zones based on the concentration of articles. Zone 1, also referred to as the “core zone,” contains a small number of journals that produce the majority of articles in a given field. The results indicate that these Zone 1 journals are central to scholarly discourse on AI and job

Table 3: Key sources of research on AI and job displacement

Most relevant sources	
Sources	**Articles**
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	5
Sustainability (Switzerland)	4
AI and Society	3
Technology in Society	3
Applied Sciences (Switzerland)	2
Communications in Computer and Information Science	2
E3S Web of Conferences	2
Economics Letters	2
Empowering the New Mobility Workforce: Educating, Training, and Inspiring Future Transportation Professionals	2
Foresight and STI Governance	2

Table 4: Core research sources identified by Bradford's law

Core sources by Bradford's law				
Source	**Rank**	**Freq**	**cumFreq**	**Zone**
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	1	5	5	Zone 1
Sustainability (Switzerland)	2	4	9	Zone 1
AI and Society	3	3	12	Zone 1
Technology in Society	4	3	15	Zone 1
Applied Sciences (Switzerland)	5	2	17	Zone 1
Communications in Computer and Information Science	6	2	19	Zone 1
E3S Web of Conferences	7	2	21	Zone 1
Economics Letters	8	2	23	Zone 1
Empowering the New Mobility Workforce: Educating, Training, and Inspiring Future Transportation Professionals	9	2	25	Zone 1
Foresight and STI Governance	10	2	27	Zone 1

displacement due to their high visibility, rigorous peer-review standards, and significant impact on academic and policy-making communities. While researchers are not obligated to submit exclusively to Zone 1 sources, doing so ensures greater reach, influence, and credibility for their work.

Submitting to Zone 1 journals enhances the visibility and dissemination of research findings, as these journals often have higher impact factors and wider readerships. However, contributions to Zone 2 and Zone 3 journals remain valuable for diversifying scholarly perspectives and fostering inclusivity in academic discourse.

TC (Total Citations): This metric represents the total number of citations received by a publication over its entire lifespan. It serves as an indicator of the overall impact and influence of the research within its academic and professional community.

TCpY (Total Citations per Year): This metric provides the average number of citations received per year since the publication date. It reflects the on-going relevance and timeliness of the research, offering insights into its sustained influence over time.

Table 5 reveals contribution of specific authors is crucial in shaping the field. Notably, several authors have multiple publications, particularly in recent years, showcasing their active role in advancing the discourse on AI and job displacement. The increasing number of citations for some authors indicates their work is influential and widely recognized.

Table 5: Author contributions to AI and job displacement research over time

Authors' production over time				
Author	**Year**	**Freq**	**TC**	**TCpY**
Akudjedu TN	2021	2	63	15.75
Antwi WK	2021	2	63	15.75
Arkoh S	2021	2	63	15.75
Botwe BO	2021	2	63	15.75
Chang C–H	2023	2	8	4
Cotten SR	2023	2	8	4
Kaur M	2023	1	0	0
Kaur M	2024	1	0	0
Lordan G	2018	1	82	11.714
Lordan G	2022	1	7	2.333
Pereira V	2016	1	2	0.222
Pereira V	2023	1	150	75
Sinha S	2023	2	0	0

Figure 2 reveals co-authorship analysis among leading organizations and highlights various institutions contributing to the research on AI, automation, and job displacement, with varying degrees of collaboration and citation impact. Institutions such as the Department of Geography, Planning and Recreation at Northern Arizona University, the PhD Institute of Socio-Economic Research at Duy Tan University, and the School of Geography and Ocean Science at Nanjing University all contributed one document, each garnering an impressive 422 citations, suggesting their significant influence in the field. However, their total link strength of 3 indicates moderate levels of collaboration. On the other hand, organizations like Aston University, Monash University, and King's College London contributed documents with 150 citations each. They showed strong collaborative networks, with a high total link strength of 24. This reflects a balance between citation impact and extensive partnerships. In contrast, German institutions such as the University of Heidelberg and ZEW Mannheim displayed fewer citations (270) and lower link strength (1), indicating limited collaboration despite

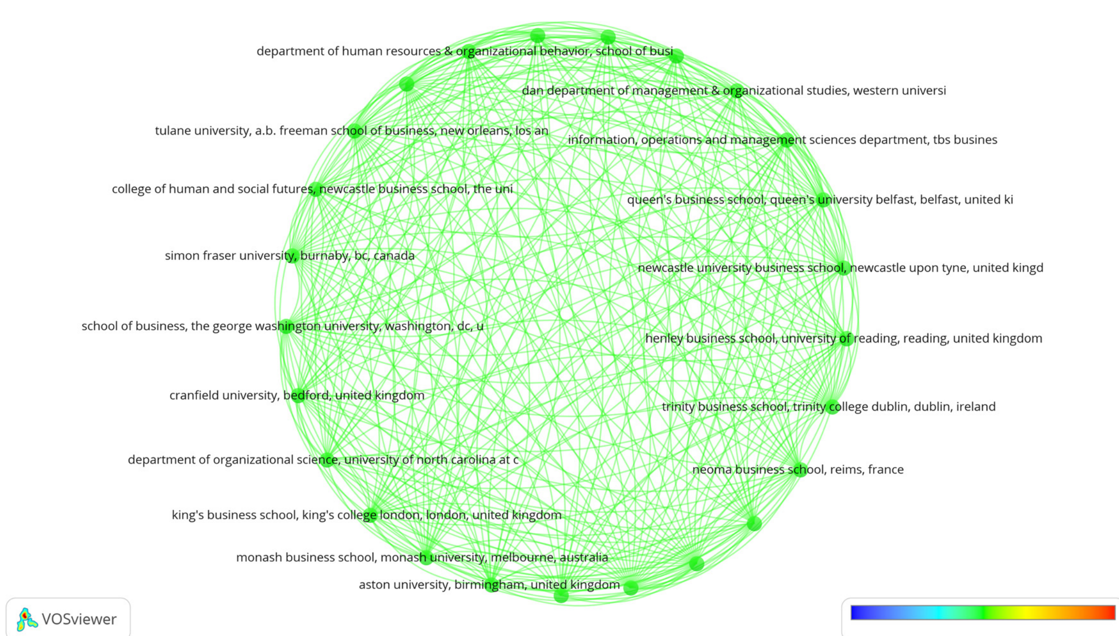

Figure 2: Co-authorship analysis among leading organizations.

contributing impactful research. The table underscores how certain organizations are pivotal for their academic contributions and ability to foster wide-reaching collaborations, which can be crucial in advancing complex, interdisciplinary topics like AI and automation's effect on job displacement.

Table 6 shows co-authorship analysis highlights the United States as the leader in AI and job displacement research, with the highest number of documents (55), citations (1,479), and strong collaborative networks (link strength 31). The United Kingdom follows closely, demonstrating significant partnerships and contributions. Germany, France, and Australia also show substantial research output, with varying degrees of collaboration. Countries like Vietnam and China are making a notable impact in citations but have limited global collaboration. Meanwhile, India leads among emerging economies with 31 documents, though with lower citation impact. African nations, including Nigeria and Ghana, are starting to contribute but have limited visibility. Overall, the analysis reflects a mix of established and emerging countries, with a potential for expanded global partnerships in this field.

Table 6: Co-authorship patterns by country in AI and job displacement research

Co-authorship countries			
Country	**Documents**	**Citations**	**Total link strength**
United States	55	1,479	31
United Kingdom	21	562	29
France	7	275	17
Australia	11	309	15
Germany	15	696	11
Italy	12	333	11
Netherlands	3	245	10
United Arab Emirates	10	129	10
Ireland	5	252	9
Canada	2	153	6
Denmark	2	90	6
Ghana	2	63	6
New Zealand	3	44	6
Vietnam	4	538	6
India	31	233	5
Malaysia	7	4	5
Nigeria	4	33	5
Switzerland	3	1	5
Uganda	3	59	5
Greece	4	3	4
Morocco	3	9	4
Turkey	5	7	4
China	6	428	3
Finland	2	193	3
Romania	4	10	3
Austria	4	28	2
Bangladesh	5	4	2
Poland	2	116	2
Portugal	6	7	2
Russian Federation	3	79	2
Saudi Arabia	5	53	2
South Africa	8	47	1
Spain	3	17	1
Thailand	2	61	1
Bulgaria	2	17	0
Mexico	2	21	0
South Korea	3	3	0
Sweden	2	115	0

Table 7: Author productivity analysed through Lotka's law

Author productivity through Lotka's law		
Documents written	**No. of authors**	**Proportion of authors**
1	708	0.979
2	15	0.021

Lotka's law is a foundational principle in bibliometrics that describes the frequency distribution of scientific productivity among authors. It states that the number of authors publishing nnn papers is approximately proportional to 1/n21/n^21/n2. In other words, a small number of authors produce a large portion of the total output, while the majority contribute only a few publications.

In the context of Table 7, Lotka's law is used to analyse the distribution of contributions among authors in the dataset. This helps identify prolific contributors and assess patterns of collaboration and productivity.

Table 7 shows according to Lotka's law, the overwhelming majority of authors contribute a single document to the literature. This pattern indicates that while there are many contributors to the field, a small number of researchers produce the majority of influential work. This finding suggests that the field may benefit from encouraging sustained engagement from a wider pool of authors.

Table 8 reveals institutional contributions highlight the prominent role of specific universities, particularly in South Africa, where multiple institutions have shown consistent publication output over the years. This indicates a growing institutional interest and investment in the research area, especially in 2024, with notable contributions from the University of Johannesburg and Universiti Malaysia Pahang Al-Sultan Abdullah.

SCF (Single-Country Fractionalized): SCF refers to publications authored by researchers from a single country. Fractionalization accounts for the proportional contribution of each author when determining the overall output, ensuring a fair representation in cases of multi-author works. This metric helps identify research efforts that are confined to individual nations, shedding light on localized studies or nationally funded initiatives.

MCP (Multiple-Country Publications): MCP represents publications that involve collaboration between authors from multiple countries. This metric indicates the extent of international research cooperation, reflecting trends in global partnerships and shared research priorities.

Table 9 reveals distribution of corresponding authors reveals that the USA has the highest number of articles published, followed by India and Germany. This suggests that these countries are leading the charge in producing research on AI and job displacement, although varying ratios of multi-author contributions indicate different collaborative practices among countries.

Table 8: Institutional contributions to AI and job displacement research over time

Affiliations' production over time		
Affiliation	**Year**	**Articles**
University of Johannesburg	2024	9
Universiti Malaysia Pahang Al-Sultan Abdullah	2024	8
Michigan State University	2023	7
Michigan State University	2024	7
University of the Witwatersrand	2019	6
University of the Witwatersrand	2020	6
University of the Witwatersrand	2021	6
University of the Witwatersrand	2022	6
University of the Witwatersrand	2023	6
University of the Witwatersrand	2024	6

Table 9: Distribution of corresponding authors by country

Corresponding author's countries					
Country	**Articles**	**SCP**	**MCP**	**Freq**	**MCP_Ratio**
USA	25	17	8	0.111	0.32
India	10	9	1	0.044	0.1
Germany	9	6	3	0.04	0.333
United Kingdom	9	7	2	0.04	0.222
Australia	7	5	2	0.031	0.286
Italy	6	4	2	0.027	0.333
South Africa	6	6	0	0.027	0
China	4	3	1	0.018	0.25
France	4	2	2	0.018	0.5
Malaysia	4	3	1	0.018	0.25

Figure 3 shows global scientific output in AI and job displacement research is dominated by the USA with the highest frequency (137), followed by India with a substantial contribution (105). The UK (33), Australia (29), and Germany (28) also rank among the top contributors. European countries like Italy (23) and emerging regions such as South Africa (23) and Bangladesh (20) are increasingly participating in this research. Malaysia (17) and China (15) also show growing involvement, indicating the global nature and widespread interest in AI's impact on the labour market.

Table 10 reveals citation impact analysis illustrates that the USA not only produces the most articles but also has the highest total citations, indicating influential work. Countries like Germany and France follow, but their average citations suggest variations in the impact of their research, with Finland showing a remarkably high average citation rate.

Table 11 reveals an analysis of key terms indicating that "employment," "artificial intelligence," and "automation" are the most frequently used terms, underscoring the central themes of the research. This terminology reflects the critical issues being addressed in the literature, highlighting the intersection of technology and labour.

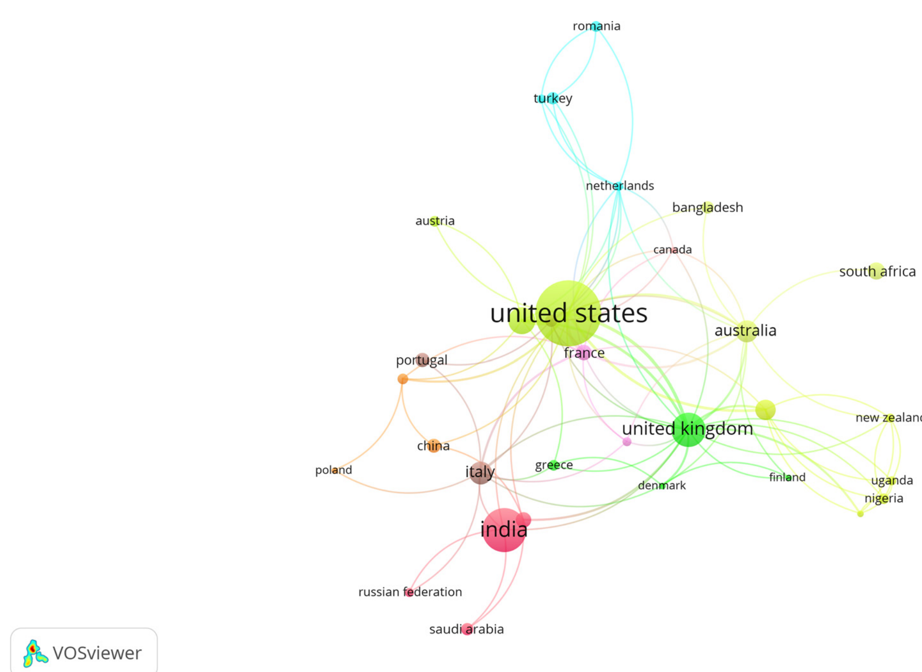

Figure 3: Global scientific output in AI and job displacement research.

Table 10: Citation impact of research by country

Most cited countries		
Country	**TC**	**Average article citations**
USA	798	31.9
Germany	394	43.8
France	266	66.5
Italy	203	33.8
Finland	193	96.5
United Kingdom	174	19.3
India	143	14.3
Sweden	115	57.5
Ghana	63	31.5
Thailand	61	30.5

Figure 4 shows author keywords that further emphasize the significance of terms like “artificial intelligence,” “automation,” and “job displacement.” The presence of keywords related to ethical considerations and emerging technologies indicates an awareness of the broader implications of AI on society and the labour market.

Table 12 lists the analysis of emerging trends reveals a shift towards topics like “technology adoption,” “engineering education,” and “ethical technology,” particularly in recent years. This suggests that researchers are increasingly focusing on the implications of AI technologies on various sectors and the necessity for ethical considerations as automation continues to evolve.

5 Discussion

This study presents a bibliometric analysis tracing the evolution of job displacement research in the context of AI and automation from 1984 to 2024. Key findings indicate a growing interest in the topic, marked by a rapid increase in publications post-2018, as well as an overall annual growth rate of 11.28%. The rise in AI-related research on job displacement coincides with the increasing influence of AI technologies across various industries. Our analysis also reveals significant international collaboration, with the United States, the United Kingdom, and Germany producing the most publications, while emerging economies such as India and South Africa are becoming notable contributors.

Table 11: Frequency of key terms in AI and job displacement research

Most frequent words	
Words	**Occurrences**
Employment	52
Artificial intelligence	43
Automation	37
Job loss	14
Robotics	14
Human	12
Article	11
Job displacement	11
Labour market	11
Decision-making	10

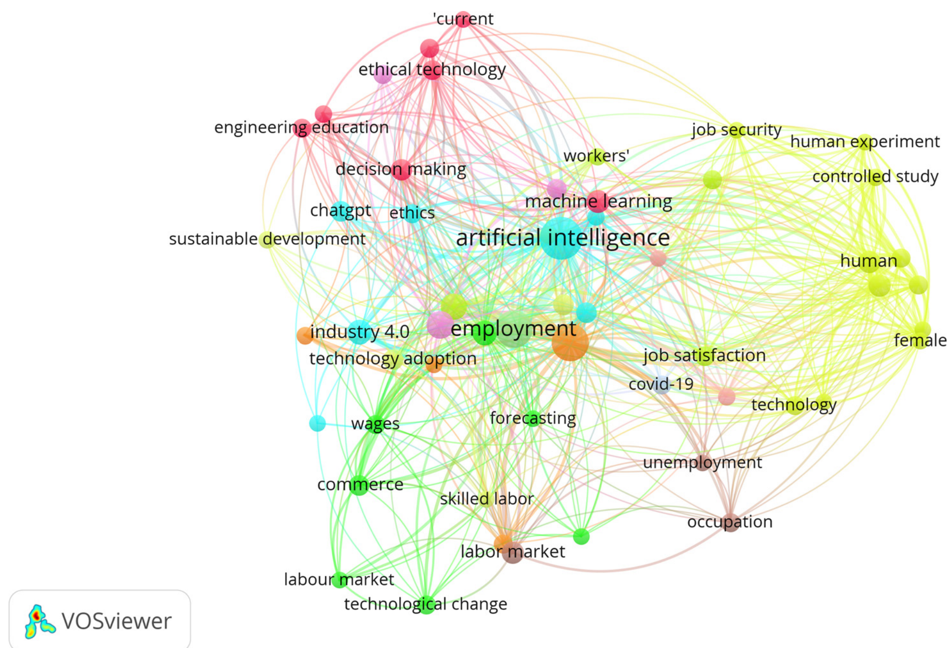

Figure 4: Analysis of author keywords in AI and job displacement studies.

The rising trend in publications, particularly after 2018, reflects the growing societal concern regarding AI's impact on labour markets, consistent with existing literature highlighting AI's disruptive potential across industries (Brynjolfsson & McAfee, 2014). The findings align with studies by Acemoglu and Restrepo (2020), which discuss how automation accelerates technological unemployment in certain sectors while offering opportunities for new job creation in others. Further integration of AI in surgical robotics improves oral cancer surgery precision, reduces complications, and offers personalized care, resulting in shorter procedures, fewer complications, and faster recovery times (Al-Raeei, 2024).

Interestingly, the concentration of research in a few dominant regions, such as the USA and Europe, is consistent with previous studies indicating that wealthier nations are better positioned to study and address

Table 12: Emerging trend topics in AI and job displacement research

Trend topics				
Item	**Freq**	**Year_q1**	**Year_med**	**Year_q3**
Technology adoption	8	2020	2020	2021
Engineering education	7	2020	2020	2023
Manufacturing	5	2007	2020	2023
Adult	8	2020	2021	2022
Humans	7	2020	2021	2022
Productivity	7	2013	2021	2022
Automation	37	2020	2022	2023
Robotics	14	2020	2022	2024
Human	12	2021	2022	2023
Employment	52	2020	2023	2024
Artificial intelligence	43	2021	2023	2023
Job displacement	11	2021	2023	2023
Job loss	14	2023	2024	2024
Decision-making	10	2022	2024	2024
Ethical technology	8	2023	2024	2024

the challenges of automation (Frey & Osborne, 2017). However, the growing involvement of countries like India suggests that the discourse is expanding to include more diverse perspectives, which is crucial as AI's impact on the labour force is global.

The prominence of key journals such as Lecture Notes in Computer Science and Sustainability (Switzerland), known for their interdisciplinary focus, points to AI research's complex, multifaceted nature. This is consistent with calls in the literature for more cross-disciplinary approaches to understanding AI's social and economic effects (Makridakis, 2017). Furthermore, the frequent appearance of terms such as "ethics" and "upskilling" in keyword analyses suggests that researchers are increasingly aware of the broader implications of automation beyond just economic disruption, such as ethical considerations and the need for reskilling the workforce. This corresponds with the findings of Bessen (2018), who emphasized that reskilling is critical for mitigating the negative effects of automation. Harari (2024) presents a critical perspective on the societal implications of AI and automation, emphasizing potential risks over opportunities. While our study aligns with Harari's cautionary tone regarding workforce displacement, it diverges in highlighting pathways for workforce adaptability through targeted reskilling and policy interventions. Uklańska (2023) study analyses frequently cited robotic process automation publications, focusing on AI and digital transformation, assessing methodology clarity and implementation model availability. While, Park, Kim, and Sung-Bum (2024) study highlights the need for future research on service robots in the hospitality and tourism sector, highlighting the importance of analysing customer experiences related to robotic services.

5.1 Significance of Findings

The findings of this study underscore the accelerating global interest in understanding and mitigating the impacts of AI-driven job displacement. The dominance of terms like "automation" and "ethics" reflects a broadening scope in the literature that extends beyond mere technological impacts to include social and ethical dimensions. As noted by Martini, Bellisario, and Coletti (2024), AI research is increasingly integrating human-centred concerns, recognizing that technological advancement should be managed to benefit society as a whole.

The increasing focus on ethical concerns and workforce adaptability in our study aligns with trends observed in recent literature. A shift from early concerns about job loss toward more nuanced discussions about human–AI collaboration, upskilling, and ethical AI deployment has been noted by Susskind (2020). This suggests that the academic discourse is evolving in a direction that balances technological advancement with human welfare, acknowledging the importance of proactive workforce adaptation strategies.

5.2 Policy Implications of the Findings

The findings of this bibliometric analysis carry significant implications for policymakers grappling with the challenges and opportunities posed by AI and automation in the workforce. The identification of emerging research themes, such as workforce adaptability and ethical considerations, underscores the need for proactive and adaptive policies. Policymakers should prioritize investment in large-scale reskilling and upskilling programs to mitigate the risks of job displacement while enabling workers to transition into new roles created by technological advancements.

Additionally, the global collaboration trends observed in this study suggest that international cooperation is essential for addressing the broader socio-economic impacts of automation. Governments could benefit from establishing cross-border agreements to share best practices and fund collaborative research initiatives. Ethical considerations, another key theme, call for the development of regulatory frameworks that ensure AI deployment respects privacy, equity, and human dignity.

5.3 Practical Implications

The implications of this study are both academic and practical. Policymakers need to consider the global trends identified in this study when crafting responses to the labour market disruptions caused by AI. As AI continues to evolve, reskilling initiatives and social safety nets must be prioritized to minimize the negative impacts on workers. This is consistent with policy recommendations from the OECD (2024), which emphasize the importance of education and continuous learning in an AI-driven economy.

5.4 Future Research

Future research should focus on more localized and sector-specific studies, particularly in emerging economies where the effects of automation may differ from those observed in more developed countries. Additionally, there is a need for deeper exploration of the ethical implications of AI on job displacement, particularly concerning inequality, as proposed by scholars like West (2018). More comprehensive studies could further illuminate the role of AI in job creation versus job destruction, helping to inform strategies that balance the two in the face of rapid technological advancement.

Finally, while this study highlights the global nature of AI-related job displacement research, future work should investigate whether the knowledge produced in developed countries is transferable to different socio-economic contexts. Such work could examine the scalability and applicability of workforce adaptation strategies across different industries and regions, an area highlighted by Davenport and Kirby (2016) as crucial for future research on AI's impact.

6 Conclusion

The bibliometric analysis conducted over the past four decades reveals significant trends and shifts in the academic discourse surrounding AI, automation, and job displacement. Notably, the results indicate a marked increase in scientific production, particularly in recent years, with a pronounced spike in research output coinciding with technological advancements. The data highlight various publication types, with articles being the predominant format, followed by conference papers and book chapters.

Furthermore, the citation metrics underscore the growing importance of this research area, with several key authors and institutions emerging as prominent contributors. The analysis also indicates a solid international collaboration trend, reflecting a collective effort among researchers to address the complex challenges posed by automation and job displacement on a global scale.

This bibliometric review provides a comprehensive overview of the evolving landscape of research on AI and job displacement, identifying critical themes and trends that will inform future inquiries in this vital area of study. The insights gleaned from this analysis will not only enhance our understanding of the implications of AI and automation for the workforce but also guide policymakers, educators, and industry leaders in navigating the transformative impact of these technologies on employment.

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