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Original article

TRENDS AND GAPS IN AI RESEARCH RELATED TO LABOR MARKET AND PRODUCTIVITY: A BIBLIOMETRIC PERSPECTIVE

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Abstract: *This study investigates the evolving structure of scientific research at the intersection of artificial intelligence (AI), labor markets and productivity. As economies continue to change and new technologies influence how people work and how efficiently tasks are completed, it is important to understand how these developments are reflected in academic studies. The main goal of this research is to identify major trends, key contributions, and areas that are still underexplored.*
The study is based on a selection of academic articles retrieved from the Web of Science database. A bibliometric analysis was carried out using the Bibliometrix package in R, through the Biblioshiny interface. The analysis focused on the evolution of publications, collaboration among author, and the most common research topics in the field. The results show a growing interest in how technology affects jobs and productivity, especially in recent years. However, the research in this area is still fragmented, with limited connections between different fields. This study offers a useful overview for researchers and decision-makers who want to better understand the relationship between technology, employment and economic performance. The findings suggest the need for more interdisciplinary work and highlight research directions that deserve more attention.

Keywords: Artificial Intelligence, Labor Market, Productivity, Bibliometric Analysis

JEL classification: J21, J24, O33, D83

1. Introduction: Background and Literature Review

Technological change has long influenced how economies function, how work is organized, and how productivity is achieved. In recent years, the rapid advancement of digital tools and automated systems has intensified academic and policy interest in the relationship between technology, the labor market, and productivity (Drydakis, 2022; Acemoglu & Restrepo, 2018). Artificial intelligence (AI), in particular, presents both opportunities and challenges: it enhances operational efficiency, but also disrupts traditional job structures and workforce dynamics (Jiao et al., 2023; Khushk et al., 2024). Studies have examined themes such as job automation, technological Jiao et al., 2023 unemployment, changes in required workforce skills, and improvements in efficiency and decision-making. At the same time, concerns have emerged regarding inequality in access to digital tools and the uneven distribution of productivity gains across sectors and regions. For instance, Anser et al. (2025) highlight national strategies for AI development as key determinants of economic performance, while Fares (2025) documents the duality in public perception, excitement about innovation coexisting with fear of job loss due to conversational AI. In higher education, Leite (2025) notes that generative AI is reshaping institutional priorities and workforce preparation. Similarly, Schneider-Kamp and Godono (2025) discuss how AI is transforming professional identity and skill profiles in modern work environments. Researchers have investigated the effects of AI across various sectors, including manufacturing, healthcare, finance, transportation and customer service. These studies reveal how AI technologies are being deployed not only to assist human workers but also to fully automate tasks previously

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thought to require uniquely human skills (Aguilera & Ramos Barrera, 2016; Tschang & Almirall, 2021; Morandini et. al., 2023). For instance, in manufacturing, robotics and predictive systems have replaced repetitive, low-skill tasks to reduce costs and improve precision (Arents & Greitans, 2022; Moore et. al., 2021). In customer service, chatbots and virtual assistants are handling vast volumes of routine inquiries (Xie et al., 2021), while in logistics and transportation, AI facilitates autonomous vehicle development and real-time route optimization (Mohsen, 2024; Adeoye et.al., 2025). The financial sector has embraced AI for tasks such as fraud detection, credit scoring, and algorithmic trading, significantly enhancing processing speed and accuracy (Oko-Odion, 2025; Heidari, 2023; Dhawas, 2025). In healthcare, AI algorithms now assist in diagnostics, image interpretation, and patient monitoring, contributing to greater efficiency and accuracy (Koski & Murphy, 2021; Shaheen, 2021). Even creative industries have adopted AI tools for content generation, campaign optimization and digital design (Anantrasirichai & Bull, 2022; Xue, 2024).

Several drivers explain the growing role of AI in replacing or transforming labor. Key among these is cost reduction (Dewangan et al., 2022; George et. al., 2023), productivity gains (Drydakis, 2022), demographic labor shortages (Yusuf, 2024), and advances in data availability and computational capabilities (Zhu et al., 2023; Hwang, 2018). Moreover, the COVID-19 pandemic acted as an accelerator, forcing organizations to adopt automation and remote systems to remain operational (Amankwah-Amoah, Wickramasinghe, 2022).

Despite the transformative potential, these technologies raise complex social and economic issues. Studies show increasing concerns about job displacement, skill mismatches, and inequality in digital access and productivity distribution (Kayode, 2023; Vasilescu et.al., 2020). In response, researchers advocate for inclusive digital policies, reskilling programs and reforms in education systems to ensure a balanced human-AI relationship (Miao & Holmes, 2021; Ramkissoon, 2024; Joshi, 2025).

Given the complexity and multidimensionality of the topic, this study employs bibliometric methods to map the evolution of academic research linking AI with labor market and productivity outcomes. Based on a dataset of 650 articles indexed in the Web of Science, the analysis was conducted using Biblioshiny, the graphical interface of the Bibliometrix package in R. This tool enables the extraction of trends, identification of collaboration networks and detection of thematic clusters across time.

Preliminary results reveal an intensifying scholarly interest over the last decade, especially with the rise of generative AI tools. However, the literature remains fragmented, marked by varying disciplinary perspectives and regional imbalances. Some contributions focus on sector-specific innovation and economic efficiency, while others explore psychological, educational, or ethical implications. By synthesizing these strands, the current research highlights both converging themes and existing gaps, offering guidance for future interdisciplinary work and informed policy strategies. Furthermore, by offering a structured and quantitative overview of current research dynamics, this paper contributes to a deeper understanding of how technological change, particularly through AI, influences the future of labor and productivity.

2. Methodology

This study employs a bibliometric methodology to quantitatively analyse the scientific literature on artificial intelligence (AI) in the context of labor markets and productivity. Bibliometric methods are suitable for mapping the structure and development of a research field, as well as for identifying emerging topics, influential contributions and collaboration patterns. The analysis was conducted using the Biblioshiny interface of the Bibliometrix R package.

2.1 Data Collection and Processing

The dataset used in this research was extracted from the Web of Science (WoS) Core Collection using a targeted query that combined AI-related terms (“artificial intelligence” OR “AI”) with labor and productivity-related terms (“labor” OR “employment” OR “workforce” and “productivity” OR “efficiency”). The search was applied to the topic fields such as title, abstract, author keywords and KeyWords Plus, for documents published between 2014 and 2025.

A total of 615 documents were identified and exported in BibTeX format. These records were then processed using Biblioshiny, allowing both quantitative evaluation and visual exploration of the research approach.

2.2 Main Descriptive Indicators

Basic descriptive statistics provide an overview of the dataset that are presented in *Figure 1*.

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Figure 1: Overview of the Bibliometric Dataset – General Statistics

Source: Author's own elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data.

The figure presents key descriptive indicators derived from the bibliometric dataset used in this study, offering a quantitative overview of the scientific output on artificial intelligence (AI) in relation to labor market and productivity.

The analysis spans the period 2014–2025, encompassing a total of 615 documents published in 388 distinct sources, including articles, journals and conference proceedings. These contributions originate from 2174 authors, with a relatively small share (74) being single-author publications, suggesting a strong trend toward collaborative research.

The collaborative nature of the field is further confirmed by an average of 3.96 co-authors per document and an international co-authorship rate of 24.72%, indicating a significant degree of cross-border collaboration.

The dataset includes 2260 author keywords, which reflect the thematic diversity and conceptual richness of the field. Collectively, these documents cite 30742 references, providing a robust basis for co-citation and knowledge diffusion analyses.

From an impact perspective, the average number of citations per document is 15.93, reflecting a moderate but growing academic interest in the topic. The average document age is 2.27 years, which implies that the majority of contributions are recent and aligned with current technological developments. The field shows a remarkable annual growth rate of 39.03%, underscoring the increasing relevance of AI-driven transformations in labor market and productivity in contemporary scientific discourse.

2.3 Analytical techniques

The study integrates multiple bibliometric techniques to explore the structure and trends in the literature, as presented below:

- ✓ *Annual Scientific Production* was used to assess temporal growth and interest in the field. Results confirm an upward trend, particularly after 2018, with projections continuing into 2025.
- ✓ *Three-Field Plots:* was used in order to identify the interconnections between countries, keywords, abstracts and source titles. For instance, one plot links countries to keywords and abstracts, while another connects countries to titles and keywords—revealing national research focuses and conceptual alignment.
- ✓ *Corresponding Authors' Countries* was used to highlight the geographic distribution of research contributions and international influence.
- ✓ *Most Cited Countries* was used to reflect the geographic impact of the literature based on citation performance.

2.4 Content and semantic analyses

To explore the conceptual structure of the field, several content-based techniques were applied and are described below:

- ✓ *Word Clouds* - generated from abstracts, these visualizations identify frequently recurring terms and concepts. Terms such as "automation," "technology," "employment," and "efficiency" dominate the thematic approach.

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- ✓ *Keyword Clustering (Coupling)* - revealed semantic groupings within the most frequently used keywords plus, pointing to subdomains such as workforce digitalization, decision-making processes and economic growth.
- ✓ Co-occurrence Networks - constructed separately for abstract terms and keywords plus, these networks map thematic proximity and strength of association between concepts.
- ✓ *Thematic Maps* - Two thematic maps—based on author keywords and keywords plus—classify research topics into four quadrants (motor themes, niche themes, emerging/declining themes, and basic themes). These diagrams show that AI-productivity relations are now situated among motor themes, while topics like algorithmic decision-making appear in emerging clusters.
- ✓ *Thematic Evolution* - focused on author keywords, this analysis traces the development of key themes over time. It shows a shift from general automation topics toward more specific ones like "generative AI" and "human-machine collaboration."
- ✓ Factorial Analysis (MCA) - applied to abstracts, this multivariate technique reveals latent dimensions in the literature and clusters of related publications.

2.5 Visualization and Tools

All analyses were performed using the Biblioshiny GUI, which offers interactive visualization capabilities, including network diagrams, Sankey flows and multidimensional scaling. The tool facilitated the generation of dynamic outputs such as word clouds, thematic maps, co-occurrence networks and factorial plots.

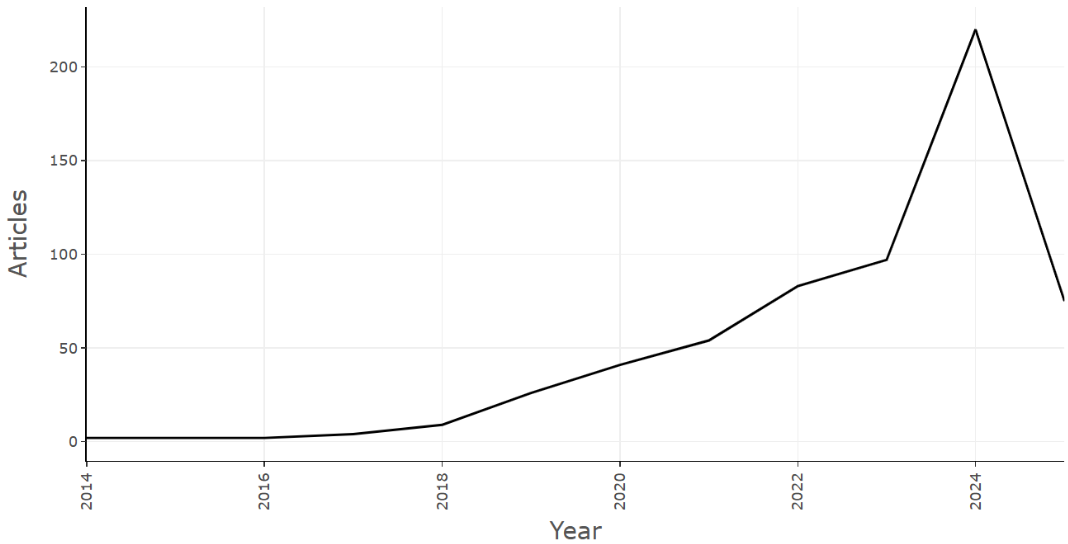
3. Results and discussions

3.1 Publication dynamics of scientific output

The evolution of scientific publications in the field of artificial intelligence (AI) in relation to labor market dynamics and productivity shows a significant upward trajectory during the period 2014 to 2025. This trend reflects both the growing interest of the academic community in the socio-economic implications of AI and the increased availability of digital tools for analyzing technological transformation.

As indicated by the bibliometric data, the field has experienced an annual growth rate of 39.03%, which is remarkably high and indicative of an emerging and dynamic research area, as shown in *Figure 2*.

Figure 2: Annual scientific production



Source: Author's own elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data

The acceleration in publication volume becomes particularly evident from 2018 onwards, coinciding with global discourse around the impact of automation on employment, as well as the proliferation of machine learning and generative AI applications in business and policy contexts.

This upward trend suggests that AI is increasingly being studied not only from a technological standpoint, but also through the lens of its interaction with labor economics, organizational change and productivity performance. The increase in scientific output also corresponds with key global developments, such as the digital acceleration

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caused by the COVID-19 pandemic, which intensified the need for automation, remote work systems and digital labor platforms.

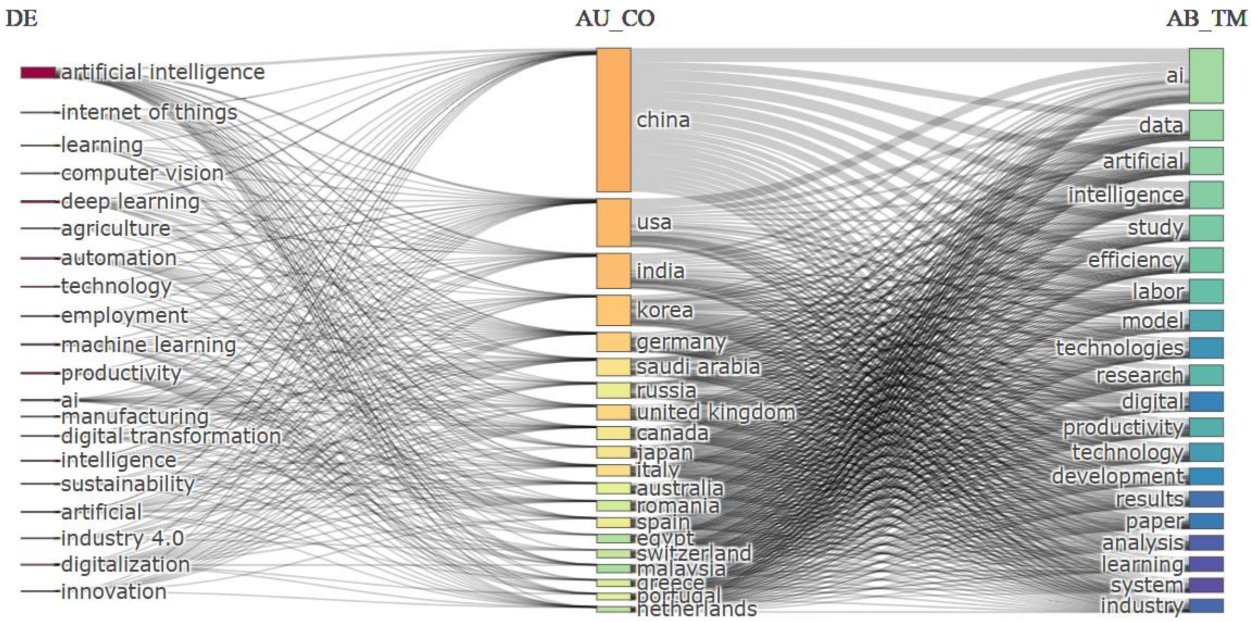
The concentration of recent publications also aligns with the average document age in the dataset (2.27 years) which supports the idea that this field is currently in a phase of rapid development, rather than academic maturity. The growing interest may be attributed to both theoretical debates and policy-driven initiatives around digitalization, labor transitions and inclusive productivity growth. The temporal analysis of publication patterns confirms that the topic of AI's influence on labor and productivity is not only relevant but also gaining momentum. The continued rise in academic engagement suggests that future research is likely to expand in both depth and thematic diversity, especially as AI technologies become more embedded in economic systems.

3.2 Interpretation of global research leadership and cooperation patterns

The three-field plot presented in *Figure 3* offers a comprehensive visualization of the relationship between author countries (AU_CO), author keywords (DE) and frequent terms in abstracts (AB_TM). This bibliometric tool enables the identification of national research priorities, semantic convergence between author-defined and contextualized concepts and the thematic distribution of contributions across countries.

At the national level, the most active contributors to the field are China, the United States, and India, followed by Germany, Korea, Saudi Arabia and the United Kingdom. These countries serve as major nodes in the central field, showing strong connectivity with both a diverse range of keywords and a rich set of abstract terms. The dense linkages suggest not only high productivity but also thematic diversity in how AI is related to labor market and productivity.

Figure 3: Three-Field Plot showing the Relationship between Author Keywords, Countries and Abstract terms



Source: Author's own elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data

From a conceptual standpoint, the most frequently used author keywords include: artificial intelligence, machine learning, productivity, employment, automation, digital transformation, industry 4.0, innovation. These terms reflect the dominant research concerns: technological integration in labor processes, economic efficiency, workforce restructuring and the digitalization of production and services. The presence of terms like *deep learning*, *computer vision* and *internet of things* indicates a strong focus on applied technologies with high automation potential.

In the rightmost dimension, the abstract terms reinforce and expand upon the keywords, offering insight into how research topics are contextualized within the body of each paper. Frequently occurring terms include: AI, data, technologies, efficiency; Labor, model, development, system; Productivity, digital, learning, industry. These abstract terms suggest that beyond mere labeling, authors are embedding AI in broader frameworks such as digital economic transformation, system-level integration and model-based performance assessment. The frequent occurrence of terms

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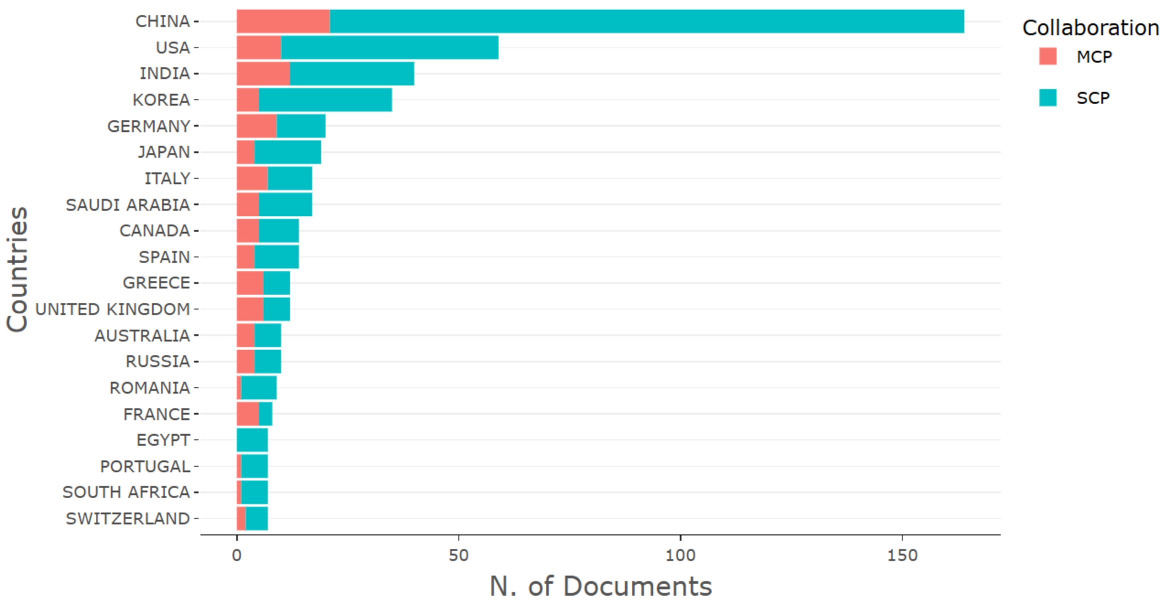
like *efficiency*, *technology*, and *development* reflects an emphasis on the functional and strategic dimensions of AI implementation in economic structures. One of the key observations from this analysis is the semantic alignment between countries and thematic priorities:

- China and India show strong ties to terms like *automation*, *machine learning* and *industry 4.0*, suggesting a focus on industrial modernization and economic scaling.
- The United States appears linked to a broader set of concepts, including *employment*, *digital transformation* and *innovation*, which indicates a more diversified approach.
- Germany and Korea are aligned with keywords such as *productivity* and *efficiency*, consistent with their industrial policy focus on smart manufacturing and technological competitiveness.

The plot presented in *Figure 3* illustrates how national contexts shape thematic emphases in research on AI and labor. While there is notable overlap in foundational concepts, such as AI, productivity, technology—differences in abstract language and keyword choices point to country-specific research agendas and policy drivers.

Figure 4 presents the distribution of the top 20 countries based on the number of documents authored by corresponding authors in the research field focused on artificial intelligence, labor market and productivity. The horizontal bar chart distinguishes between Single Country Publications (SCP) and Multiple Country Publications (MCP), offering insight into both national output and the extent of international collaboration.

Figure 4: Top 20 corresponding author countries with collaboration type



Source: Author's own elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data

The data reveal that China is the most prolific country in this domain, with over 160 publications, of which a significant proportion are SCP. This indicates a strong domestic research capacity and institutional prioritization of AI-related themes, particularly in economic and labor applications. However, the relatively lower proportion of MCP suggests that China's output is primarily nationally driven.

The United States follows as the second most active country, but with a much higher share of international collaboration (MCP). This implies a strong integration into global academic networks and a leadership role in fostering cross-border research partnerships. The balance between domestic and collaborative output is a distinguishing feature of the U.S. profile. India, Korea, and Germany complete the top five, each showing robust participation in the field. While India's contribution is largely based on SCP, countries like Korea and Germany demonstrate a higher involvement in internationally co-authored papers, reflecting their strategic position within global research consortia. Countries such as Saudi Arabia, Italy, Japan, and Canada also appear prominently, with moderate volumes and varied degrees of collaboration. Notably, European countries like Switzerland, Portugal, France, and Romania have a smaller document count but contribute consistently to international publications, indicating that while output may be limited, it is often embedded in collaborative scientific networks.

The data presented in *Figure 4* highlights the geographic concentration of knowledge production, with China

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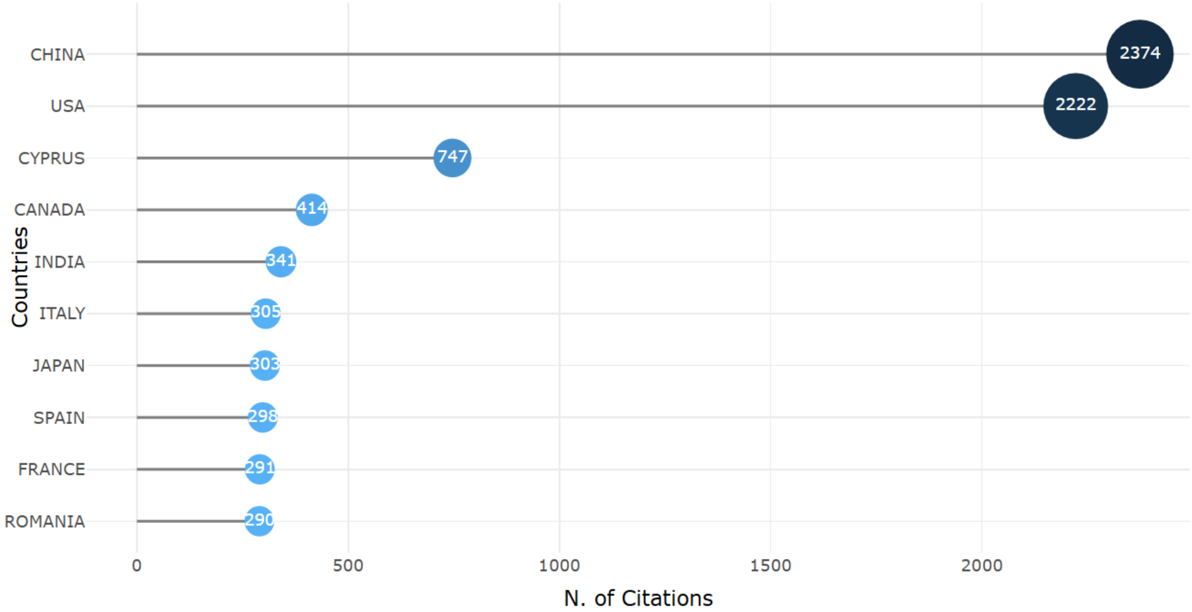
and the USA as dominant actors, but also reflects a healthy level of international collaboration, especially among European and Asian contributors. The distinction between SCP and MCP provides a deeper understanding of how countries position themselves: whether as autonomous research hubs or as active players in global academic ecosystems.

Figure 5 complements the analysis of publication output by illustrating the citation impact of contributions from the most active countries in the field of artificial intelligence (AI), labor market and productivity. While the previous figure focused on the quantity of documents published (with or without international collaboration), this figure shifts the focus toward the influence and visibility of those publications as measured by total citation count.

Figure 5: Total citations by country (Top 10)



Source: Author's own elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data

The data show that China and the United States are not only the most prolific in terms of publication volume but also dominate in terms of academic impact, with 2.374 and 2.222 citations respectively. This dual dominance indicates that these countries are not only producing more research, but their work is also more widely referenced, suggesting leadership in setting the research agenda and influencing subsequent studies. Interestingly, Cyprus emerges as a notable outlier. Although it was not among the top countries by document count in the previous figure, it ranks third in citations, with 747 total citations. This suggests that although Cypriot scholars contribute fewer publications, their work is highly impactful and frequently cited. This phenomenon may reflect concentrated expertise, strategic international co-authorship or high-quality outputs in niche areas.

Other countries such as Canada, India, Italy and Japan show moderate citation counts (290–414 citations), aligning with their mid-range positions in the document output chart. These results suggest a balanced combination of productivity and influence, though none match the citation density achieved by China or the United States. In contrast, countries such as Romania, France and Spain appear with relatively lower citation totals despite their visible presence in the academic output. This disparity may point to emerging research communities that are still building global visibility, or to the need for greater international dissemination and engagement.

When linked with the Collaboration chart, a few key insights emerge:

- ✓ Countries with higher MCP (international collaboration), like the USA, Germany and Switzerland in the previous figure, tend to produce research with greater citation impact, supporting the argument that international collaboration enhances scientific visibility.
- ✓ China's impact is exceptional despite its lower collaboration ratio, indicating strong national research infrastructure and global interest in its outputs.
- ✓ Countries with fewer publications but higher citation averages, like Cyprus, highlight the importance of quality over quantity and the strategic role of impactful contributions.

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3.3 Content analysis

By conducting these analyses we aimed to explore the semantic and conceptual structure of the literature using keyword analysis, term frequency mapping and co-occurrence clustering. The combination of word clouds, coupling clusters and network visualizations offers a multidimensional understanding of how the research field on artificial intelligence (AI), labor market and productivity is structured and evolves.

The word cloud generated from the abstracts of the analyzed documents *(Figure 6*) provides an initial overview of the most frequently used terms in the corpus. Not surprisingly, the dominant words are “intelligence”, “artificial” and “AI”, which confirms the centrality of artificial intelligence in the scope of this bibliometric study**.**

Figure 6: Word Cloud of Most Frequent Terms in Abstracts

Source: Author’s elaboration using Biblioshiny, based on Web of Science data

Other frequently occurring terms include “management”, “impact”, “productivity”, “learning”, “technology” and “system”. These terms suggest a strong alignment between AI technologies and themes such as decision-making processes, organizational transformation, digital infrastructure, and labor efficiency. Notably, terms such as “employment”, “labor” and “economic” appear less frequently but are present, indicating that labor-market implications, although addressed, may be more nuanced or specialized within the broader AI discourse. The presence of “sustainable”, “agriculture” and “industry” suggests expanding applications of AI beyond core technology sectors, reflecting a growing interest in cross sectorial impacts.

This word cloud provides evidence that abstract writing in this field emphasizes both technological promise and economic relevance, with increasing recognition of labor implications. It bridges the conceptual focus of keywords with the application-oriented narrative of empirical findings, supporting a comprehensive understanding of how the topic is positioned in scholarly discourse. Building on the word cloud analysis, which identified the most frequently used terms in abstracts, the next step involves examining how these keywords relate to one another conceptually. To achieve this, a clustering analysis based on Keyword Coupling was performed using the Keywords Plus field. This approach reveals deeper thematic structures within the literature, grouping closely related terms into conceptual clusters based on their co-occurrence patterns. The resulting thematic map presented in *Figure 7* allows us to explore not only which topics are common, but also how central and developed they are within the broader research field.

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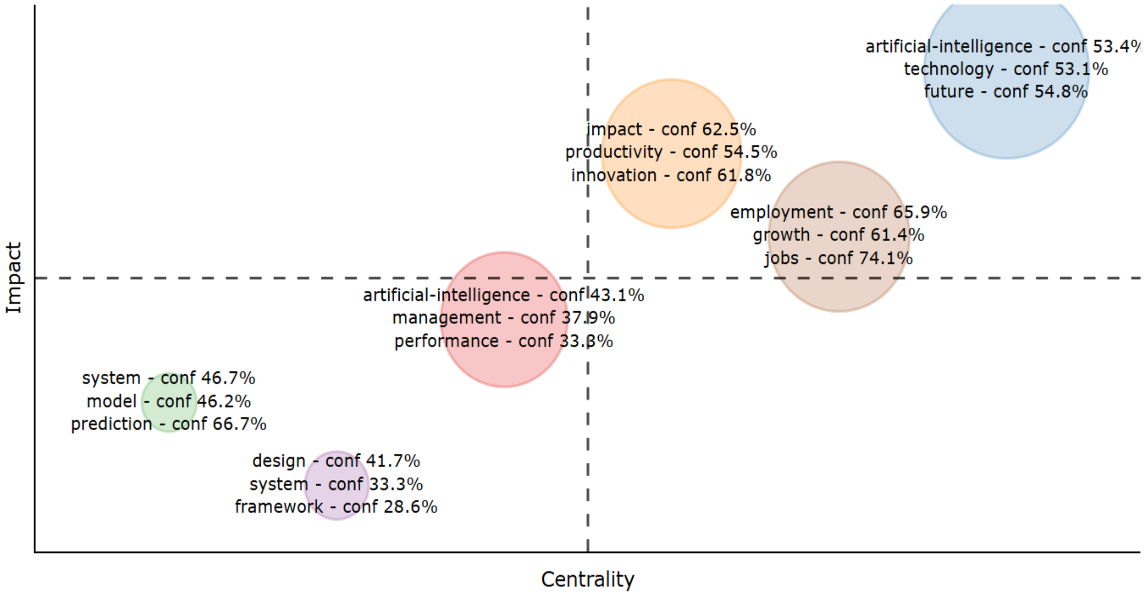
Figure 7: Thematic Map Based on Keyword Coupling (Keywords Plus)



Source: Author's elaboration using Biblioshiny, based on Web of Science data

The thematic map derived from Keywords Plus, illustrates the centrality and impact of clustered concepts in four quadrants. In the *upper-right quadrant*, we observe clusters such as “artificial-intelligence”, “technology” and “future”, which are not only conceptually central but also well-developed. These represent the intellectual core of the literature and include influential and frequently cited works. The *upper-left quadrant* includes clusters like “productivity”, “innovation” and “impact”. These are specialized but have high thematic density, indicating that while they may not be central to the entire field, they are internally cohesive and important within specific subdomains. The *lower-right quadrant* shows terms like “employment”, “growth” and “jobs”, which are foundational to the field's structure but still developing in complexity or citation strength. Their position suggests they are crucial to the discourse but may lack deep internal elaboration or coverage. In the *lower-left quadrant*, we find “model”, “design” and “framework”, which have low centrality and low density. These themes could represent underexplored or outdated areas, or emerging ones not yet fully integrated into mainstream research.

Analyzing the date provided in *Figure 7*, it can be concluded that this visualization reflects a conceptual hierarchy in which AI and productivity occupy high centrality, while employment-related terms maintain foundational relevance but require deeper elaboration. It also shows that research focused on the effects of AI and studies looking at its future role are coming together and that there is a need to better include labor-related topics in the main discussions about technology.

To complement the previous word frequency and thematic clustering analyses, a co-occurrence network was constructed to visualize the relational structure of the field. While word clouds and thematic maps highlight term prominence and conceptual density, co-occurrence analysis uncovers how key terms are interconnected across the literature. By examining how frequently keywords appear together within the same documents, this method provides insight into the main thematic groupings and intellectual linkages within the research field. *Figure 8* presents this network, based on Keywords Plus, with clusters revealing the dominant conceptual zones in the discourse surrounding AI, labor market and productivity.

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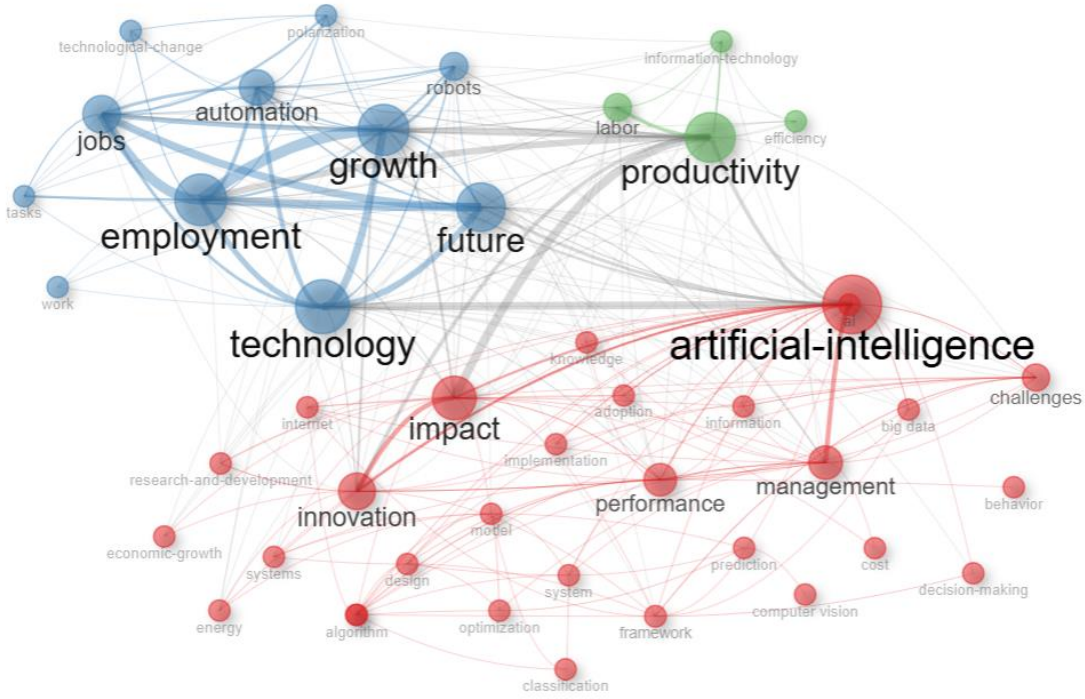
Figure 8: Co-Occurrence Network of Keywords Plus



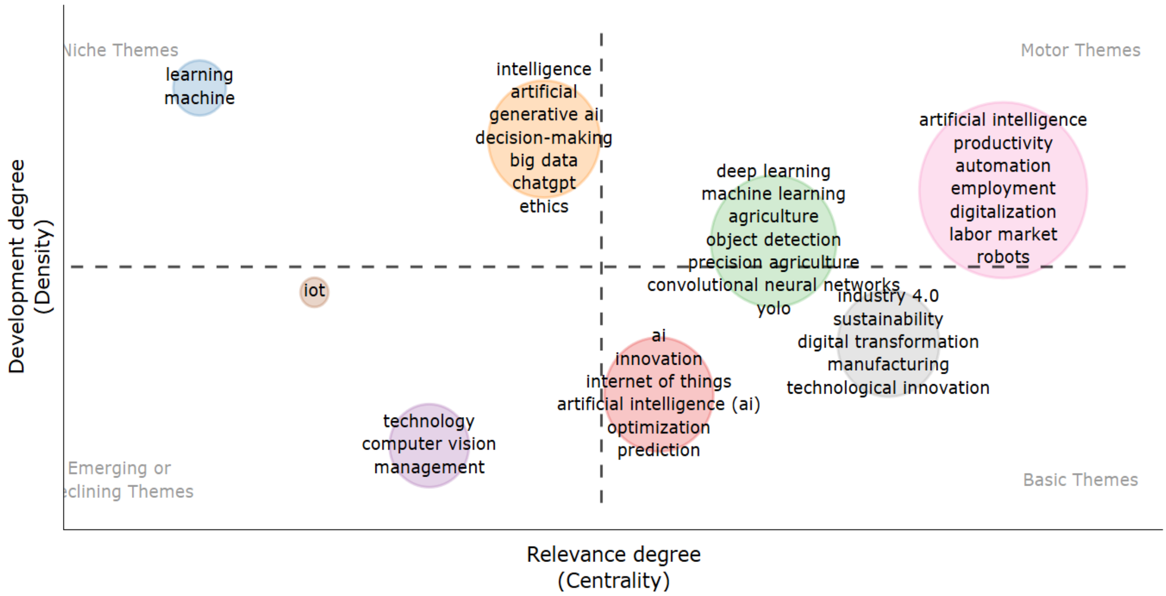
Source: Author's elaboration using Biblioshiny, based on Web of Science data

According to the data provided by the Co-Occurrence Network of Keywords Plus, three main clusters emerge, each represented by a distinct color. The *red cluster*, centered around "artificial-intelligence", includes related terms such as "management", "performance", "innovation," "impact" and "framework". This cluster reflects the technological and organizational dimensions of AI deployment, particularly in business contexts. The *blue cluster,* dominated by terms such as "employment", "jobs", "technology", "growth" and "automation", illustrates the socio-economic and labor market aspects of the discourse. These terms tend to co-occur in papers addressing the implications of AI on work, digital transition and labor structures. The *green cluster* is smaller but significant, anchored by terms like "productivity", "efficiency" and "labor", which points to performance-based studies measuring outcomes of AI integration. The network highlights "technology" and "impact" as central bridging terms that link otherwise distinct research communities, technological applications and socio-economic evaluations. This suggests that while the literature may be segmented, certain high-frequency terms serve as integrative concepts that cut across disciplinary lines.

3.4 Thematic mapping and evolution

To further explore the conceptual structure of the field, this section examines the development and evolution of themes over time using two advanced bibliometric visualizations: a thematic map based on authors' keywords and a thematic evolution diagram showing how key concepts have progressed across two major time intervals (2014–2020 and 2021–2025). The thematic map in Figure 9 categorizes concepts into four quadrants based on *density* (development) and *centrality* (relevance to the field). This structure provides information of both the importance and maturity of different research themes.

Figure 9: Thematic Map Based on Authors' Keywords



Source: Author's elaboration using Biblioshiny (Bibliometrix R package), based on Web of Science data

The thematic map reveals a diverse conceptual structure within the field, organized into four distinct quadrants. In the upper-right quadrant, we find the **motor themes**, which include highly developed and broadly connected concepts such as *artificial intelligence*, *productivity*, *automation*, *employment*, *digitalization*, *labor market* and *robots*. These topics represent the core drivers of scholarly inquiry, combining both theoretical maturity and strong empirical grounding. Moving to the upper-left quadrant, the map highlights a set of **niche themes**, notably *learning* and *machine*. Although these topics are well-developed internally, they exhibit lower centrality, suggesting that they function as specialized or technical subdomains. While coherent within themselves, they are less integrated into the broader discourse. The lower-left quadrant captures what are considered **emerging or declining themes**, including keywords such as *technology*, *computer vision*, *management*, *optimization* and *framework*. These may represent either new fields at the early stages of development or older concepts whose relevance is diminishing, something that can be inferred from shifts in publication volume and citation patterns. The lower-right quadrant encompasses the **basic themes**. Here we find foundational concepts like *industry 4.0*, *sustainability*, *digital transformation* and *technological innovation*. These themes hold a central place in the field and are essential for its structure, though they are not yet fully developed. Their positioning indicates high potential for future interdisciplinary research, particularly as they bridge technological advancements with broader socio-economic considerations. A distinctive feature in the center-left of the map is a **rapidly growing cluster** with terms like *generative AI*, *chatGPT*, *ethics*, *big data* and *decision-making*. These indicate newer conceptual directions gaining traction and have the potential to shift toward the motor theme quadrant in future cycles.

Following the static view provided by the thematic map, which captures the current structure and maturity of research themes, it is equally important to understand how these themes have evolved over time. The thematic evolution map, presented in *Figure 10*, tracks the progression of authors' keywords across two distinct periods: 2014–2020 and 2021–2025, highlighting both enduring topics and the emergence of new areas of interest. This dynamic analysis reveals how conceptual priorities have shifted, consolidated or diverged as the field has matured.

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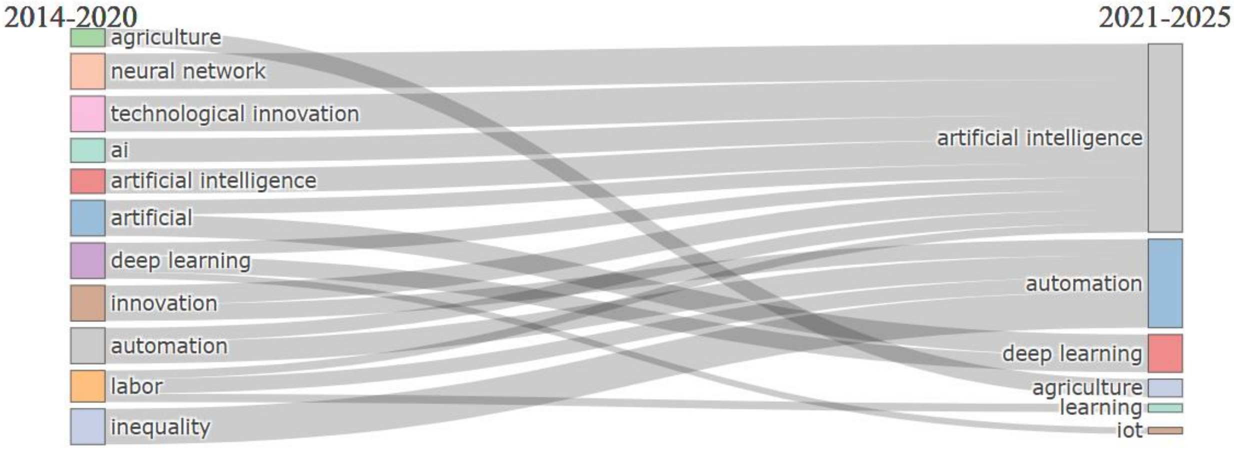
Figure 10: Thematic Evolution of Authors' Keywords (2014–2020 vs. 2021–2025)



Source: Author's elaboration using Biblioshiny (Bibliometrix R package) based on Web of Science data

One of the most notable patterns is the continuity and consolidation around the term *artificial intelligence*, which remains the dominant concept across both time intervals. This central theme increasingly absorbs related notions such as *AI*, *neural network*, *technological innovation* and *artificial*, reflecting a process of conceptual standardization and growing centrality in the field. The diagram also points to the emergence of new concepts in the more recent period, including *automation*, *deep learning*, *learning* and *IoT*. These keywords highlight the field's shift toward more applied and system-level implementations, suggesting that research is becoming more practice-oriented and technologically integrated. At the same time, certain themes from the earlier period, such as *inequality*, *innovation* and *labor*, appear to have faded or been reframed in the later phase. Their reduced visibility could indicate a repositioning of these topics within broader conceptual categories or a reorientation of research priorities. A particularly interesting case of specialized growth is seen in the consistent presence of *agriculture*, which remains visible across both time periods. This suggests a sustained scholarly interest in sector-specific applications of AI, especially in areas like precision agriculture and sustainable development.

Overall, the evolution diagram illustrates how the field has matured, consolidating around dominant concepts while expanding toward practical implementations and sectorial relevance. The present research that approached the analysis of thematic mapping and concepts evolution illustrate a clear thematic maturation in the literature. The field has evolved from fragmented discussions around "AI" and "automation" into more structured conversations centered on productivity, employment and labor market dynamics. Simultaneously, new research fronts are emerging around generative AI, ethical implications and machine learning applications, signaling the next phase of academic inquiry. The maps presented in *Figure 9 and 10*, suggest a growing alignment between technological advancement and socio-economic relevance, but also emphasize the need for deeper integration of ethical, labor-related and interdisciplinary themes to maintain conceptual richness as the field matures.

3.5 Factorial analysis of abstract terms

To complement the keyword-based analyses and further explore the semantic structure of the literature, a Multiple Correspondence Analysis (MCA) was performed on the terms extracted from article abstracts. MCA is a multivariate statistical technique used in bibliometrics to reduce complex textual data into two or more dimensions, revealing underlying patterns and conceptual clusters. This method helps uncover relationships between frequently occurring terms and offers insights into how distinct research topics are positioned in relation to one another. Additionally, it contributes to identifying areas of literature fragmentation or convergence by showing which themes are conceptually aligned or isolated.

The MCA map in *Figure 11* visually represents the spatial distribution of key terms derived from abstracts along two principal dimensions. Each point corresponds to a term and its proximity to others indicates semantic similarity based on co-occurrence patterns across documents.

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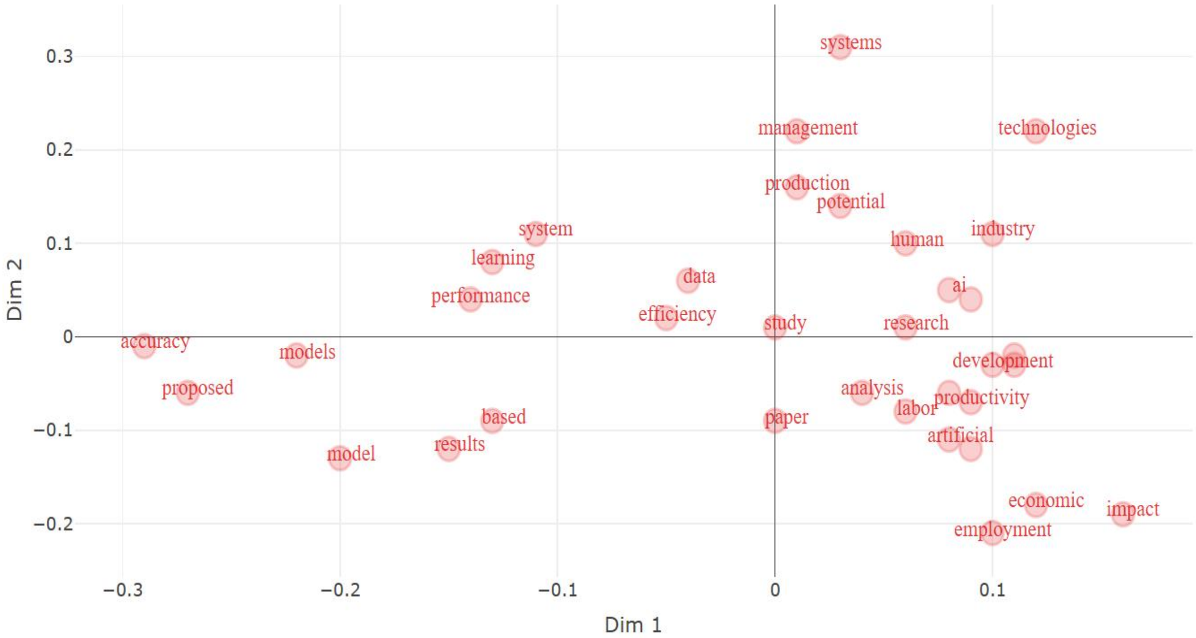
Figure 11: Multiple Correspondence Analysis (MCA) of abstract terms



Source: Author's elaboration using Biblioshiny (Bibliometrix R package), based on Web of Science data

The map in *Figure 11* reveals several conceptual groupings, indicating thematic affinities among commonly used abstract terms. In the central and right-hand region of the map, we observe a cluster of core terms such as *AI*, *development*, *artificial*, *labor*, *productivity*, *economic*, *impact* and *employment*. This grouping reflects the mainstream discourse in the field, where research focuses on the influence of artificial intelligence on labor market dynamics, economic outcomes and productivity. The tight arrangement of these terms suggests that this is a highly cohesive area of literature. In the upper-right quadrant, we find terms like *technologies*, *systems*, *management*, *production* and *potential*. These concepts form a distinct technological-management cluster, associated with applications of AI in industrial and organizational contexts. Their position suggests that they are conceptually linked, but slightly more peripheral than the central economic-employment themes. Toward the left-hand side of the map, we see a more dispersed grouping of technical and methodological terms such as *accuracy*, *models*, *proposed*, *results*, *model* and *based*. This area represents a more method-centric subfield, possibly reflecting studies focused on algorithmic performance, data models and validation techniques. The spread and marginal location of this cluster indicate a degree of thematic fragmentation, as these studies may not be fully integrated into the socio-economic or managerial discourse.

A few terms like *study*, *research*, *human* and *paper* occupy transitional spaces, connecting different thematic areas. These general-purpose terms often serve as bridges between more specific subfields, though their lack of tight clustering also reflects their broad, less-specialized usage. The overall findings of the factorial map illustrate a dual structure of the field: a dense, conceptually integrated cluster around AI and its labor-market and economic implications and a more fragmented zone composed of technical and methodological discussions. This configuration suggests that while the core of the literature is consolidating around policy and impact-related themes, there remains a need to better integrate computational and model-based research into the broader discourse.

4. Conclusions

This study conducted a comprehensive bibliometric analysis to explore how scientific literature addresses the relationship between artificial intelligence (AI), labor markets and productivity. By examining 615 publications indexed in the Web of Science over the period 2014–2025, the analysis revealed a fast-growing and increasingly influential research field. The topic has experienced a strong annual growth rate of 39.03%, with AI emerging as a central concept interlinked with productivity, automation, digitalization and labor-related themes.

The findings indicate that China and the United States lead in both publication output and citation impact. China contributes the highest number of documents, largely from single-country collaborations, while the United States demonstrates strong international research ties. This reflects different strategies for scientific engagement, one nationally concentrated, the other globally networked.

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The keyword and content analyses uncovered three primary conceptual areas within the literature. The first focuses on technological and organizational dimensions of AI implementation; the second addresses the socio-economic and labor market implications; and the third concentrates on measuring productivity and performance outcomes. Core keywords such as "artificial intelligence", "technology", "employment" and "productivity" consistently appeared across word clouds, co-occurrence networks and abstract term analyses, confirming their centrality. Thematic mapping further highlighted that while key technological themes are well-developed and central to the field, labor-related issues remain underdeveloped in terms of integration and density.

Thematic evolution analysis showed how literature has matured over time. Terms like "AI", "automation" and "deep learning" have become more prominent in recent years, while previously central concerns such as "inequality", "innovation" and "labor" have shifted or been absorbed under broader conceptual directions. Factorial analysis reinforced these patterns, revealing a tightly connected cluster around AI's economic and employment impacts and a more dispersed area of technical-methodological research, suggesting partial fragmentation in the field's intellectual structure. By quantifying research dynamics, this study contributes to a deeper understanding of how AI is conceptualized in relation to labor and productivity. It maps the intellectual structure of the field, highlights its interdisciplinary character and identifies both dominant and emerging research fronts. Furthermore, it offers valuable insights into geographic trends, collaboration patterns and the balance between theoretical development and applied focus. Nevertheless, the study has certain limitations. The analysis is based solely on data from the Web of Science, potentially excluding relevant contributions from other databases such as Scopus or Google Scholar. The reliance on bibliometric indicators also means that the study measures visibility and structure, but not the qualitative depth or methodological rigor of individual publications. Additionally, the use of keywords, titles and abstracts limits the semantic depth available for interpretation. To address these limitations, future research could broaden the scope to include multiple data sources and combine bibliometric methods with qualitative content analysis. Further exploration of citation networks, author influence and regional policy frameworks would offer a deeper understanding of the field. As AI technologies continue to evolve, especially with the emergence of generative models and advanced automation, there is a clear need to strengthen the integration between technical innovation and labor-oriented inquiry. In conclusion, the study reveals a topical but still structurally imbalanced research field. While AI and productivity are well-established in academic discourse, labor-related themes remain comparatively underexplored and insufficiently connected. Addressing this gap will be crucial for building a more holistic and socially responsive body of knowledge in the coming years.

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