## *SECTION ECONOMICS, BUSINESS ADMINISTRATION, TOURISM AND STATISTICS*

# THE RELATIONSHIP BETWEEN DIGITALIZATION AND THE LABOR MARKET: A BIBLIOMETRIC ANALYSIS

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**Abstract:** *This paper aims to analyze recent scientific research on digitalization and the labor market. The development of robotic process automation, artificial intelligence and digital platforms has contributed to the increasing digitalization of the labor market. The COVID-19 pandemic has further developed the usefulness of digital technologies in the workplace. The objectivity of the bibliometric analysis allowed the identification of literature of interest for the connection between digitalization and the labor market. Given the context, this paper provides a bibliometric analysis of the literature on digitalization, employment, and the digital economy of the labor market for the period 2020-2025. The relevant literature was collected from the Web of Science Core Collection of Clarivate Analytics. 463 documents, such as articles, early access documents, and book chapters (predominantly in English), were registered and evaluated in the bibliometric analysis of the fields of Economics, Management, Business, Education, and related fields in the social sciences. Evaluative bibliometrics was used, coupled with scientific mapping techniques, such as keyword co-occurrence, bibliographic linkage, co-citation, and co-authorship. The thematic structures were refined using the VOSviewer software. The results obtained show that publications and citations are increasing (from 36 in 2020 to 114 in 2025; a total of 4321 citations). The thematic axes focus on thematic topics regarding digital skills and human capital, digital transformation at the firm level, productivity and distribution of earnings, employment in the ecosystem, inequality, and public policies in the digital transition. In conclusion, the results show that the implications of digitalization on the labor market are specific; they must be considered when developing public policies.*

**Keywords:** *digitalisation; labour market; bibliometric analysis; digital skills; employment.*

**JEL Classification:** *J21; J24; O33*

## 1. Introduction

Digital transformation has become a primary driver of structural change in modern economies, with technologies like artificial intelligence (AI) and digital platforms fundamentally reshaping work organization, competency demands, and labor market outcomes. This process was significantly accelerated by the COVID-19 pandemic, which forced firms to rapidly adapt to a shifting technological landscape.

Despite the intense academic focus on this intersection across fields like economics, management, and education, there is a need for a systematic synthesis of the rapidly evolving research produced in recent years.

This topic has generated a wide range of papers in a few fields that mainly include the fields of economics, management, information systems, and education. From an economic perspective, the focus has been on the aggregate and distributive consequences of technological advances on employment, wages, productivity, and the structure of occupations in the labor market. In this context, the published works have used analyses based on quasi-experimental approaches.

The specialized literature in the field of management and organization analyzes changes in digital capacity and work reconfiguration processes at the firm level. Publications in educational studies analyze digital skills and modified training systems.

This paper contributes to the literature by applying an objective scientific mapping methodology (VOSviewer), managing to clearly delineate four major thematic pillars of the digital transition. The added value of our research lies in identifying critical gaps in the current literature, such as the underrepresentation of platform work and the gig economy, thus providing an essential foundation for public policy development and for guiding future econometric research efforts.

In this context, bibliometric analysis has identified a series of research trends, emerging themes, and research gaps in different fields of knowledge. This paper used evaluative bibliometrics and scientific mapping to analyze the most recent research literature on digitalization and the labor market. This study addresses the following *research questions:*

Q1: *What is the overall structure, dynamics, and intellectual architecture of scientific literature concerning the intersection of digitalization and the labor market between 2020 and 2025?*

Q2: *Which thematic clusters and research gaps have emerged within this interdisciplinary body of work?*

To answer these questions, the paper pursues several *research objectives*: describing the bibliometric characteristics of the current research dataset; evaluating the dynamics of publications and citations to identify high-impact sources and authors; reconstructing the relational structure of the field through co-occurrence and co-citation analysis synthesizing the main thematic axes of the literature.

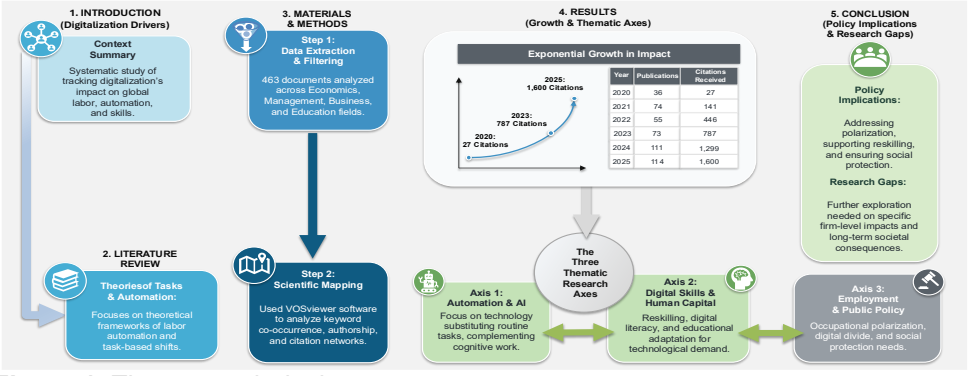


**Figure 1**: The research design
Source: Authors' own elaboration

Regarding the research stages, they are included in the form of a research design in Figure 1.
The paper's structure includes the Introduction as the first section. In Section 2, the literature review is presented. Section 3, the materials and methods, is presented. Section 4 presents the results and discussions. In Section 5, the conclusion is presented.

**2. Literature Review**

The theoretical background of this paper draws on several scientifically interconnected research areas. Thus, labor market theories, both classical and neoclassical, postulate that the level of wages and employment is the result of the interaction between demand and supply. In terms of employment, technological progress has both substitution and complementarity impacts by increasing the demand for cognitive tasks.
The task-based framework formalized by Autor et al. (2003) provides a widely used analytical lens, distinguishing between routine and non-routine tasks and showing how computerization affects each category differently.
Subsequent contributions extended this framework to address polarization – the simultaneous growth of high-skill and low-skill employment at the expense of middle-skill occupations (Autor and Dorn, 2013; Goss et al., 2014). The robotics literature introduced firm and sector-level evidence on the labour market consequences of automation (Acemoglu and Restrepo, 2018, 2019; 2020; Graetz and Michaels, 2018), while Frey and Osborne (2017) stimulated a broader debate by estimating the susceptibility of occupations to computerization. Brynjolfsson and McAfee (2014) contributed an influential narrative on the second machine age, highlighting both the productivity potential and the distributional risks of general-purpose technologies.
The concept of digital transformation at the firm level has been theorized in management and information systems literature (Vial, 2019; Verhoef et al., 2021), with increasing attention to the complementarity between digital technologies and skilled labour, and to the role of digital capabilities in enabling firms to convert technology investments into productivity gains (Shakina et al., 2021).
According to Akerman et al. (2015), Nunez-Canal et al. (2022), and He et al. (2022), digital skills and human capital are mediated both individually and collectively. Recent studies exemplify the digital economy's phenomena of rising inequality, particularly during the COVID-19 pandemic, where inequities were exacerbated (Matthess and Kunkel, 2020). Numerous studies have recently analyzed the digital economy's consequences, especially its ramifications for the labor share of the value added and the capital-labor value distribution (Autor et al. 2020, Li et al., 2023; Wu and Yang, 2022).
As digitalization permeates all sectors of activity, it generates a new form of economic activity - the digital economy - which can no longer be viewed as a distinct sector, but as an expanding ecosystem that reconfigures markets, value chains and interactions between economic actors (Bukht & Heeks, 2017; OECD, 2020). As digitalization expands, the phenomenon of sectoral convergence emerges, whereby traditional boundaries between industries blur. Services such as telemedicine, online education or fintech have a predominantly digital component and interconnect with several domains simultaneously, contributing to the reshaping of the economic landscape (Bharadwaj, Sawy, et al., 2013). Measuring the degree of digitalization

through dedicated tools, such as the European Commission's DESI scoreboard or the IMD World Digital Competitiveness Ranking, provides useful quantitative benchmarks on connectivity, digital skills and the integration of technologies in the business environment and the public sector (IMD, 2025).

## 3. Materials and Methods

The empirical basis of this study used a set of 463 documents, which were extracted from the *Web of Science Core Collection* (Clarivate Analytics). The method known as topic search (TS method) was used. The data retrieval strategy was based on the following three thematic pairs:

*TS = (("digital transformation" AND "labor market") OR ("digitalization" AND "employment") OR ("digital economy" AND "skills"))*

The document set was limited to the period 2020–2025 and to the specific categories within the Web of Science that refer to the research field of interest, namely: Economics, Business, Management, Business Finance, Education, Educational Research, Education Scientific Disciplines, and Social Sciences Interdisciplinary. Document types were limited to Article, Early Access, and Book Chapters, corresponding to the final exported dataset used for the bibliometric analysis. The export date is 22.11.2025. For consistency, a record with PY=2026 (Early Access 2025) is classified as 2025. To make the corpus-selection procedure more transparent, Table 1 reports the documented filtering flow from the initial topic-and-time-window search to the final exported corpus. The table also specifies the concrete selections applied at each stage of the Web of Science filtering process.

**Table 1**. Selection flow of the bibliometric corpus

| Step | Filtering stage | Concrete selections applied | Records |
|---|---|---|---|
| 1 | Initial topic search and publication window | Topic search: ((“digital transformation” AND “labor market”) OR (“digitalization” AND “employment”) OR (“digital economy” AND “skills”)); Year Published: 2020–2025 | 1070 |
| 2 | Web of Science Categories filter | Economics; Business; Management; Education Educational Research; Social Sciences Interdisciplinary; Business Finance; Education Scientific Disciplines | 569 |
| 3 | Final document-type filtering and export | Document Types: Article; Early Access; Book Chapters. Database: Web of Science Core Collection. Retrieval/export date: 22 November 2025 | 463 |

Source: Authors' own elaboration based on the Web of Science Search History and the exported citation report retrieved on 22 November 2025.

The final bibliometric corpus was exported from the Web of Science Core Collection on 22 November 2025 (N = 463). Intermediate search-history entries generated during repeated document-type refinements were not used as analytical datasets.

Therefore, the table reports only the relevant selection stages leading to the final exported corpus.

Because the Web of Science Core Collection is dynamically updated, later reruns of the same query may return a different number of records; consequently, all bibliometric indicators reported in this article refer strictly to the frozen dataset exported on 22 November 2025.

The analysis was based on the use of two methods. The first method was evaluative bibliometrics, which used standard indicators such as the number of publications, total citations, citation distribution, and rankings of sources, authors, organizations, and countries to describe the performance and structure of scientific production. The second method was scientific mapping, which was carried out using the VOSviewer software and four of the relational methods: (i) keyword co-occurrence (Author Keywords) to determine the thematic structure; (ii) co-authorship by country to map collaborative networks; (iii) bibliographic linkage by country to study research fronts; and (iv) co-citation of cited references to map intellectual structure.

To answer the research question, the bibliometric search in WOS was restricted to articles published in the period 2020-2025, obtaining 1,070 articles. We consider that this time interval provides relevant information, both quantitatively and qualitatively, by weighing the number of articles in relation to the total. After applying the selected Web of Science Categories — Economics, Business, Management, Education, Educational Research, Social Sciences Interdisciplinary, Business Finance, and Education Scientific Disciplines — the dataset was reduced to 569 records. Finally, after applying the document-type filter and retaining Article, Early Access, and Book Chapters, the final exported corpus consisted of 463 records.

The selection procedure confirms that the final dataset was not restricted to a single disciplinary category, because the relationship between digitalization and the labour market requires a multidisciplinary and integrated approach. Digital transformation intersects with economics, management, education, social sciences, business finance, and technological change, which justifies the inclusion of several Web of Science Categories. Figure 2 presents the paper selection process used to construct the final bibliometric corpus. Figure 2 presents the article selection process.

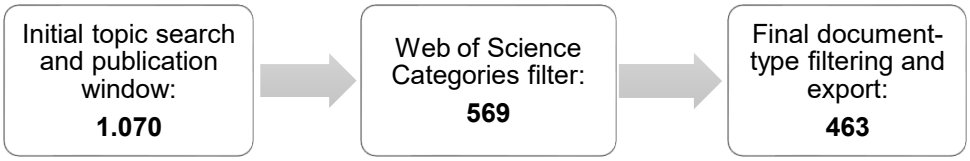


**Figure 2:** The process of selecting specialized literature
Source: Authors' own elaboration based on the Web of Science Search History and the exported citation report retrieved on 22 November 2025

Table 2 summarizes the VOSviewer analysis configurations. To ensure methodological transparency and reproducibility, the VOSviewer settings were explicitly reported. Table 1 presents the configurations used for each bibliometric network, including the type of analysis, unit of analysis, counting method, operational thresholds, and the number of items retained after threshold application.

**Table 2:** VOSviewer Analysis Configurations

| **Analysis Type** | **Unit of Analysis** | **Counting Method** | **Number of operational thresholds** *Min= Minimum and Max= Maximum* | **Items included** |
|---|---|---|---|---|
| *Keyword co-occurrence* | Author Keywords | Full counting | Min=5 (occurrences of a keyword) | 49 out of 1,695 keywords |
| *Co-authorship* | Countries | Full counting | Min=5(documents of a country); Min=0(citations of a country); Max=25(countries per document) | 28 out of 84 countries |
| *Bibliographic coupling* | Countries | Full counting | Min=2(documents of a country); Min=0(citations of a country); Max=25 (countries per document) | 59 out of 84 countries |
| *Co-citation* | Cited references | Full counting | Min=5 (citations of a cited reference) | 145 out of 21,751 cited references |

Source: Authors' own elaboration based on VOSviewer

Maps were created in VOSviewer and were based on full counting. In country-based analyses, documents co-authored by 25 countries or fewer were included. Table 2 shows the VOSviewer configurations and operational thresholds for the scientific mapping analyses. All maps were created with the full counting method. In the keyword co-occurrence analysis, the Author Keywords were the unit of analysis, and a minimum of five occurrences was required. Out of a total of 1,695 keywords, 49 keywords met the requirement. For the country co-authorship network, the inclusion thresholds were set at a minimum of 5 documents per country and 0 citations per country; 28 out of 84 countries met these thresholds. For the bibliographic coupling analysis by country, the minimum threshold was set at 2 documents per country and 0 citations per country; 59 out of 84 countries were included. For the co-citation analysis, Cited References were used as the unit of analysis, with a minimum threshold of 5 citations per cited reference; 145 out of 21,751 cited references met the threshold. In the country analyses, reports with many co-authored countries were neglected, with a limit of 25 countries per document. Table 3 provides a summary of the key features of the Web of Science database.

**Table 3:** General Dataset Characteristics (Web of Science)

| **Indicator** | **Value** |
|---|---|
| Total documents (N) | 463 |
| Publication years (PY) | 2020–2025 (plus 1 record PY=2026, Early Access 2025) |
| Export date (DA) | 2025-11-22 |
| Total citations (TC sum) | 4321 |
| Documents with 0 citations | 135 / 463 (29.2%) |
| Primary language | English (422; 91.1%), Russian (22; 4.75%), Spanish (10; 2.16%) |
| Dominant WoS indices | ESCI (n=242), SSCI (n=195), BKCI-SSH (n=22), SCI-Expanded (n=18) |

Source: Authors' own elaboration based on the Web of Science.

Table 3 shows that the 463 sample documents have a total of 4,321 citations at the time of export, with 29.2% of the sample receiving no citations because a dataset with a substantial number of more recent documents was considered. The largest index is the Emerging Sources Citation Index (ESCI, n= 242), followed by the Social Science Citation Index (SSCI, n= 195). The dominant language of publication is English (91.1%). Publications in languages other than English include 4.75% Russian, 2.16% Spanish, and 1.08% Ukrainian, which is consistent with the geographical distribution of the countries of origin of the authors.

## 4. Results and Discussions

The distribution of the disciplinary categories analyzed reflects the interdisciplinary nature of specialized literature. The field of Economics tops the list with 169, followed by the fields of Management with 102 and Business with 95. The fields of Education and Educational Research, with 79, and Interdisciplinary Social Sciences, with 63 demonstrate the increasing fusion of competence and policy perspectives. This distribution is illustrated in Figure 3 in a treemap format.

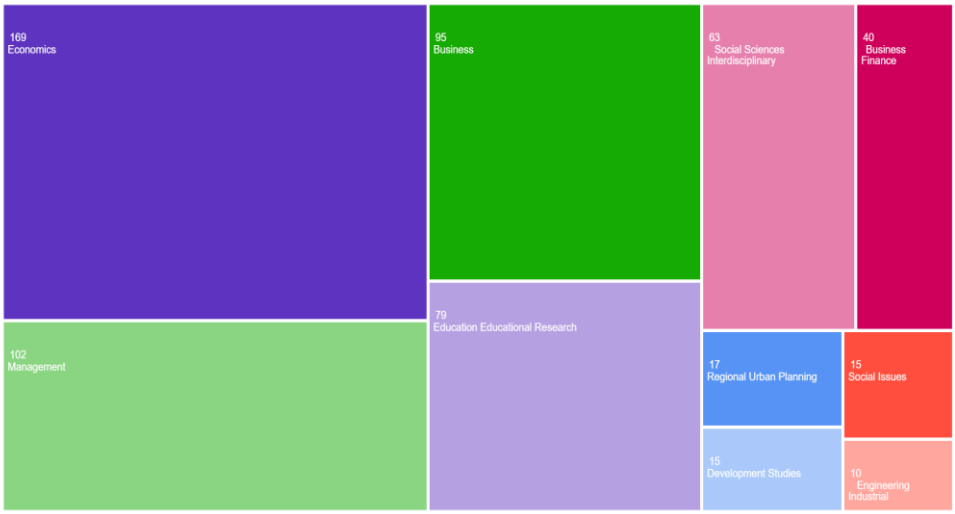


**Figure 3:** WoS Category Distribution (Treemap)
Source: Authors' own elaboration based on the Web of Science

From 2020 to 2026, the total amount of publications grew from 36 to 114; this means they are still headed for growth, however, the growth is uneven, the numbers for 2021 showed a spike (74 publications), 2022 had a dip (only 55 publications), then there are steady increases for the publication's numbers in 2023 (73), 2024 (111), and 2025 (114). The annual number of citations obtained has also increased for each year of this interval, from 27 in 2020 to 1600 for the year 2025.

Table 4 presents the number of publications and citations in the period 2020-2025.

**Table 4:** Publications and citations by year (2020–2025)

| Year | Publications (number) | Citations received in the year (number) | Cumulative citations 2020–y |
|---|---|---|---|
| 2020 | 36 | 27 | 27 |
| 2021 | 74 | 141 | 168 |
| 2022 | 55 | 446 | 614 |
| 2023 | 73 | 787 | 1,401 |
| 2024 | 111 | 1,299 | 2,700 |
| 2025 | 114 | 1,600 | 4,300 |

Source: Authors' own elaboration based on the Web of Science

Figure 4 presents the evolution of publications and citations in the period 2020–2025.

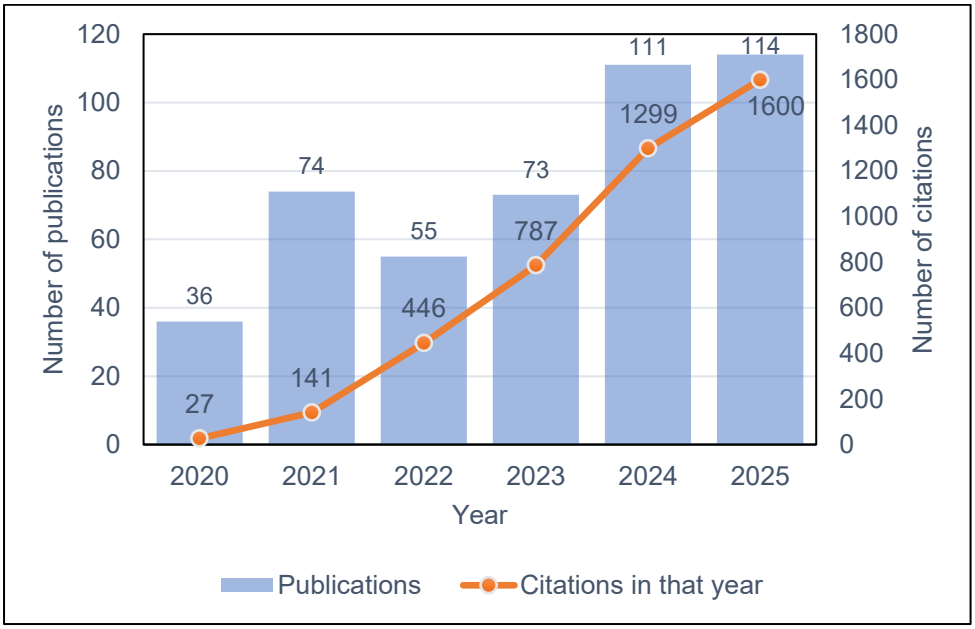


**Figure 4:** Annual Evolution of Publications and Citations Received (2020–2025)
Source: Authors' own elaboration based on the Web of Science

The data identified for 2022 showed a parallel increase in both the number of publications and citations. This is clear evidence of the transition from a conceptual to a consolidation phase, in which empirical studies that can be replicated continue to underpin subsequent studies.

The other publications that have a very high volume (based on the number of published documents) are “Financial and Credit Activity - Issues in Theory and Practice” (14 publications), “Technological Forecasting and Social Change” (13 publications) and “Technology in Society” (12 publications). However, if we consider the impact of citations, here the ranking tells us a completely different story. At the top of the citation impact figures are “Technological Forecasting and Social Change” (558 total citations; 42.9 average citations per document) and “Technology in Society” (513 citations; 42.8 average impact). Followed by the Journal of Business

Research (304 citations). This contrast between impact and volume shows us that visibility depends on the position of publications in citation networks and not just on the frequency of published documents.

Among the most cited individual papers by far are: Matthess and Kunkel (2020), Structural Change and Digitalization in Developing Nations (155 citations); Dutta et al. (2020) Digital Transformation Priorities of Indian Manufacturing SMEs (139 citations); and Wu and Yang (2022) The Impact of the Digital Economy on Employment Structure in China (138 citations). This analysis shows an increase in research interest in advanced and emerging economies.

Figure 5 displays the keyword co-occurrence network and author keywords. It is observed that the distribution of publications among authors is extremely uneven, with the highest number of publications by an author being three, and the rest being two or fewer publications. Fossen and Sorgner have two publications together and 183 citations. Sindhwani (Rahul) is also represented with two publications and 148 citations. We believe that this is because interdisciplinary fields are emerging.

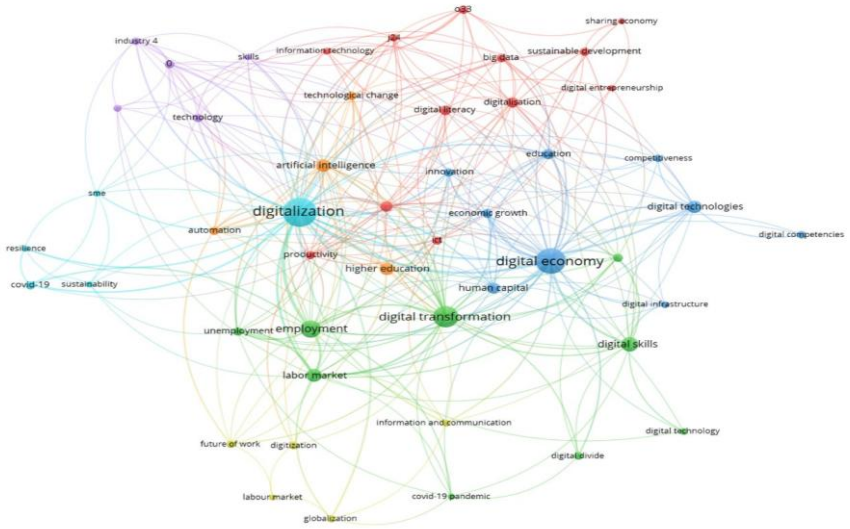


**Figure 5:** Keyword Co-Occurrence Network – Author Keywords (VOSviewer, network view)
Source: Authors' own elaboration in VOSviewer based on the Web of Science

By geographical affiliation, the most productive countries are, in order, China (66 documents), Russia (63), Ukraine (50), Spain (34), Germany (30), the United States (30), Italy (26), the United Kingdom (18), Romania (17), and India (15). At the institutional level, the Academy of Economic Studies has the most documents, with 10, followed by the University of Bucharest with 6. The analysis of the co-occurrence of keywords for the author identified seven thematic clusters, as shown in Figure 5.

Table 5 presents the thematic clusters in the author's key words co-occurrence and the thematic orientation.

**Table 5:** Thematic clusters in the author keywords co-occurrence network

| Cluster | Key words (occurrences) | Thematic Orientation |
|---|---|---|
| 1 – Red (12 terms) | digitalisation (13), entrepreneurship (13), digital literacy (12), productivity (9), big data (8) | Micro-level transformation and entrepreneurship |
| 2 – Green (9 terms) | digital transformation (54), employment (36), digital skills (24), labor market (21), unemployment (8) | Labour market outcomes and digital transition |
| 3 – Blue (9 terms) | digital economy (76), human capital (15), education (13), economic growth (10), innovation (8) | Macro-level growth, human capital and innovation |
| 4 – Yellow (5 terms) | future of work (7), globalization (6), ICT (6), labour market (5) | Future of work and globalization |
| 5 – Purple (4 terms) | industry 4 (7), fourth industrial revolution (6), skills (5) | Industry 4.0 and skill demand |
| 6 – Teal (5 terms) | digitalization (100), covid-19 (9), resilience (5), SME (5), sustainability (5) | Pandemic context, resilience, and SMEs |
| 7 – Orange (4 terms) | artificial intelligence (19), higher education (18), automation (9), technological change (8) | AI, automation, and educational adaptation |

Source: Authors' own elaboration based on VOSviewer

In the country co-authorship network (Figure 6), the USA (total link strength = 28) and Germany (22) act as collaboration hubs even though they do not have the highest document counts. China (66 documents), Russia (63), and Ukraine (50) have higher output volumes but weaker link strength, suggesting a greater proportion of their research output is nationally concentrated.

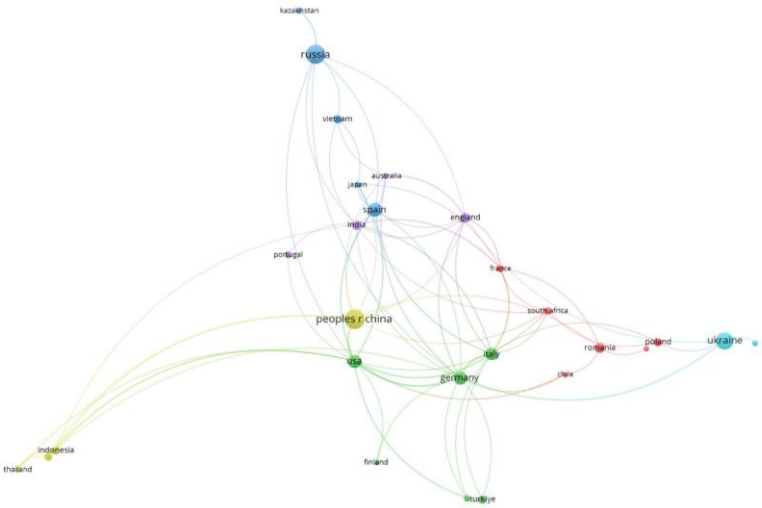


**Figure 6:** Country Co-Authorship Network (VOSviewer, network view)
Source: Authors' own elaboration in VOSviewer

Figure 7 displays the bibliographic coupling network by country. The bibliographic coupling network (Figure 7) counts the proximity of countries based on shared citations. China has the highest total link strength (7,177), followed by Italy (5,358), Germany (4,879), and the USA (4,057). This suggests they all converge around similar conceptual frameworks, in this case, the task-based approach and literature on digital transformation.

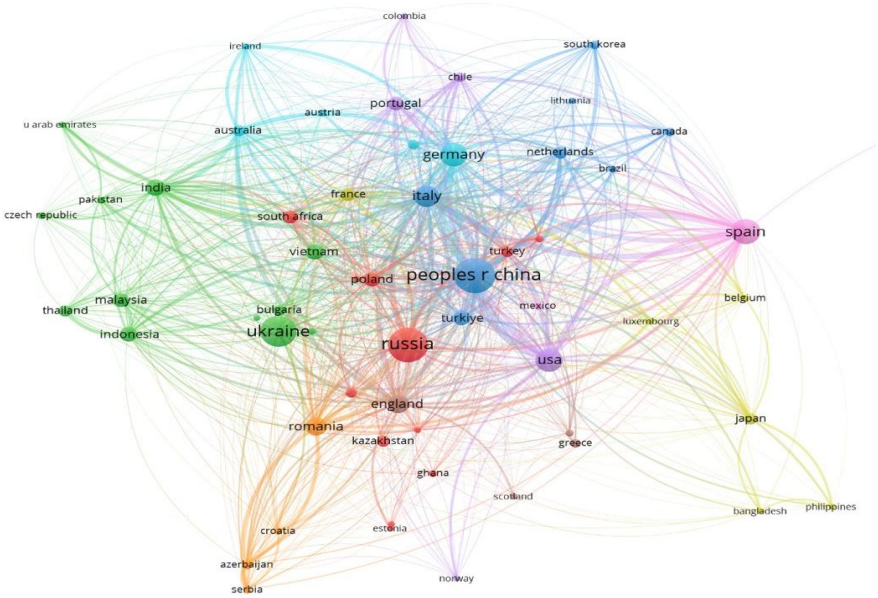


**Figure 7:** Bibliographic Coupling Network by Country (VOSviewer, network view)
Source: Authors' own elaboration in VOSviewer based on the Web of Science

Figure 7 presents Romania (total link strength = 2,104) in Cluster 7 (Orange), which suggests a relatively less influential research front, though still with strong activity, anchored in the European policy and economic spaces. Figure 8 presents the co-citation network and cited references.

From Figure 8, the co-citation network has six clusters. In cluster 3 (blue), the foundation of the discussion on automation and the labor market comes from the works of Frey and Osborne (2017) and Acemoglu and Restrepo (2018; 2019; 2020). Cluster 4 (yellow) is the task-based economic school, represented by Autor et al. (2003), Autor and Dorn (2013) and Goos et al. (2014). Digital transformation at the firm level is the focus of cluster 1 (red), with Vial (2019) and Verhoef et al. (2021). In cluster 2 (green), the digital economy area is represented by Goldfarb and Tucker (2019), and the area of econometric researchers is represented by Arellano and Bond (1991).

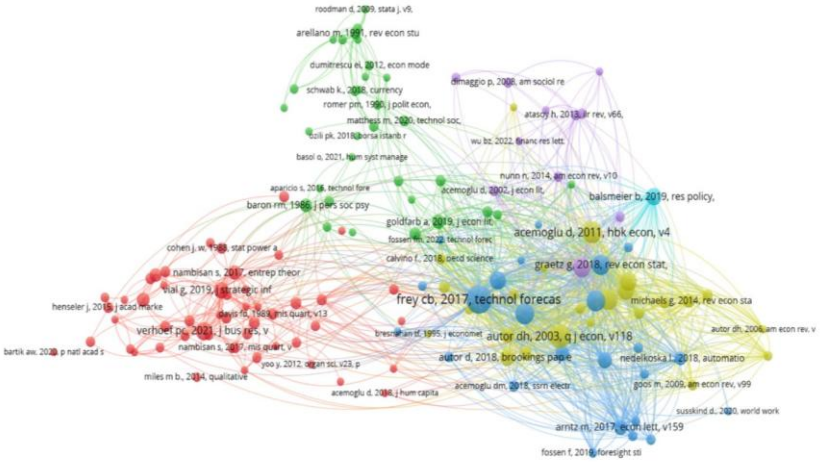


**Figure 8:** Co-Citation Network – Cited References (VOSviewer, network view)
Source: Authors' own elaboration in VOSviewer based on the Web of Science,

Triangulating the keyword clusters, co-citation structure, and highly cited works, four dominant thematic axes characterize the literature. *Axis 1 – Automation and Artificial Intelligence*. Grounded in the task-based framework (Autor et al. (2003)) and in the automation literature (Frey and Osborne, 2017; Acemoglu and Restrepo, 2019; 2020), this axis analyses how digital technologies substitute routine tasks and complement non-routine cognitive work, with distributional implications for wages and occupational structure. *Axis 2 – Digital Skills, Human Capital and Educational Adaptation.* Competency acquisition and development mediate the relationship between technology adoption and labour market performance. Research in this axis explores digital literacy, reskilling and upskilling, and the role of educational systems in matching skill supply to technological demand (Nunez-Canal et al., 2022; Shakina et al., 2021). *Axis 3 – Firm-Level Digital Transformation, Productivity and Earnings Distribution.* This axis focuses on the organisational dimensions of digitalisation, including investment in digital technologies, process reconfiguration, and the redistribution of value added between labour and capital (Li et al., 2023; Dutta et al., 2020; Vial, 2019, Fossen and Sorgner, 2021).*Axis 4 – Employment Structure, Inequality and Public Policy.* The fourth axis addresses the structural and distributional consequences of digital transition, including occupational polarisation, the digital divide, and the role of institutional frameworks and active labour market policies (Wu and Yang, 2022; He et al., 2022; Fossen and Sorgner, 2022).

## 5. Conclusions

This study focused on systematic bibliometric mapping in the period 2020-2025, related to the digitalization process and the labor market. In this regard, a total of 463 documents indexed by Web of Science were analyzed. The strong upward trend in both publications and citations demonstrates the consolidation of academic interest and, therefore, the interdisciplinary nature of the field. The disciplinary

distribution (Economics, Management, Business, Education), international connection, and co-citation networks illustrate the developing disciplinary character of the field.

The analyzed specialized literature was structured around four main thematic axes: employment structure with inequality and policies, automation and artificial intelligence, digital skills and human capital, as well as transformation and productivity at the firm level. Each of these axes covers specific, but interconnected, research directions and methods, and highlights the relevance of integrating economic and organizational approaches for future studies.

The results of this paper showed that the heterogeneity of digitalization measurements, endogeneity in the technology-work relationship, and distributional heterogeneity (by gender, age, space, and time) are some of the methodological challenges. There is also an underrepresentation of the analyzed keyword network for platform work, the gig economy and remote work, so these areas can be the subject of specific research efforts.

From a policy perspective, it was found that there is a considerable volume of literature studies that highlight the specific factors that the literature describes as relevant to the context. These factors are institutional framework, digital infrastructure, level of competence, firm size, and sectoral distribution. In response to the mentioned factors, future policies should focus on building a digital and social protection infrastructure.

The current research will be continued in the future through a more detailed and structured refinement of the specialized literature to identify empirical and econometric research that can explain the integration of AI in the labor market in the context of recently adopted legislation at the EU level.

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