



Intelligence and the Future of Work: A Bibliometric Analysis of Job Displacement, Skills Transformation, and Workforce Adaptation

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ABSTRACT

Artificial intelligence is reshaping work through automation, augmentation, algorithmic management, and new demands for skills, yet the literature remains dispersed across management, technology, education, economics, and labor studies. This study maps the development and conceptual structure of research on intelligence and the future of work, with particular attention to job displacement, skills transformation, and workforce adaptation. Bibliographic records were retrieved from Scopus and Web of Science using a structured query combining artificial intelligence, future-oriented terms, work and employment concepts, automation and digital transformation, and impact-related terms. Following the documented screening process, eligibility, and inclusion stages, adapted from the PRISMA 2020 flow diagram, 469 publications covering 1994 to 2025 were analyzed using BiblioSpy®. The corpus recorded 14,537 citations, an annual growth rate of 17.86%, 1,363 unique authors, and an international co-authorship rate of 15.99%. Publication output accelerated sharply after 2019, reaching 163 documents in 2025. The United States led publication output and total citations, while the United Kingdom showed the highest average citation rate among the ten leading countries. Keyword co-occurrence mapping of 469 eligible records identified four connected clusters centered on artificial intelligence, automation, machine learning, and digital transformation. Together, these clusters show that the field links technological capability to changes in employment, human-AI collaboration, education, digital skills, productivity, ethics, and labor-market adjustment. The study provides an integrated map of the field, distinguishes productivity from influence, and identifies a research agenda that emphasizes longitudinal evidence, occupation-level transitions, inclusive reskilling, responsible deployment, and broader participation from underrepresented labor-market contexts. This synthesis offers a basis for comparing how technological change, labor-market institutions, and organizational responses shape workforce outcomes across contexts.

Keywords: Artificial Intelligence, Future of Work, Job Displacement, Skills Transformation, Workforce Adaptation, Bibliometric Analysis

INTRODUCTION

Artificial intelligence (AI) has moved from a specialized computing domain into the organization of everyday work. Machine learning, robotics, generative AI, and algorithmic decision systems increasingly shape how tasks are allocated, how performance is monitored, and how firms design jobs (Jetha et al., 2025; Lozie et al., 2024). The consequences depend partly on the deployment strategy. In a survey of 3,015 large firms across ten countries, Bughin (2025) found that early AI adoption generally favored advanced skills, whereas an automation-oriented strategy made prospects for basic skills negative. This distinction places organizational choice between technical capability and labor-market outcomes.

Three connected issues anchor the debate. Job displacement concerns the exposure of tasks and occupations to automation and the uneven distribution of transition risks (J. Wang et al., 2025). Skills transformation concerns

the digital, analytical, interpersonal, and adaptive capabilities needed as task boundaries change (Morandini et al., 2023). Workforce adaptation extends beyond individual training to job redesign, mobility, worker voice, and institutional support. Evidence from 214 Italian regions indicates that advanced digitalization and platformization can expand different occupational groups while sustaining employment polarization (Capello et al., 2025). Displaced tasks, therefore, do not translate mechanically into displaced workers; sectoral structures and labor-market institutions shape the pathway from technological change to employment outcomes.

The literature spans management, technology, education, economics, ethics, and labor studies. This range is analytically valuable but makes it difficult to see how substitution, augmentation, learning, and inclusion fit together. Chigbu & Makapela (2025) integrative review connects Industry 5.0, Education 5.0, and Work 5.0 through human-centered and sustainability goals, while also identifying tensions between automation and inclusion. A field-level map can complement such content-based synthesis by locating publication activity, influential contributions, collaboration patterns, and the vocabulary used to study employment and adaptation.

This study, therefore, provides a bibliometric analysis of research on intelligence and the future of work. Using Scopus records and BiblioSpy®, it evaluates publication and citation trends, leading sources, influential documents, productive authors, institutions, and countries, and the co-occurrence structure of author keywords. The study contributes a reproducible overview of the field and interprets its intellectual organization around job displacement, skills transformation, and workforce adaptation. Its purpose is to support researchers, employers, educators, and policymakers in locating mature research streams and identifying questions that require stronger longitudinal, comparative, and worker-centered evidence.

LITERATURE REVIEW

AI, Automation, and Job Displacement

Research on AI and employment distinguishes technical capability from realized labor-market outcomes. Technologies may automate specific tasks without eliminating an entire occupation (Agarwal, 2025). Organizational choices determine whether the resulting system substitutes for workers or augments their capabilities (Katsamakos et al., 2024). The meaning of work also matters. Drawing on Hannah Arendt, Waelen (2025) argues that debates about automation should consider whether technological systems erode craftsmanship, durable contribution, and opportunities for human action, rather than treating job counts as the only outcome. Job displacement is therefore best understood as a transition process involving task recomposition, bargaining power, job quality, and the distribution of economic and experiential benefits and risks.

Skills Transformation and Human Capital

AI adoption changes the content and value of skills. Technical competence increasingly combines with problem solving, communication, creativity, and the capacity to evaluate automated outputs (Zhang et al., 2024). In a mixed-methods chemical-engineering course, Keith et al. (2025) found that structured use of ChatGPT could develop ethical and critical competencies, while students' confidence sometimes exceeded the quality of their evaluations. This gap shows why exposure to a tool is an inadequate proxy for readiness. Skills transformation requires learning designs that connect AI literacy with domain knowledge, verification, judgment, and transfer into redesigned jobs (Krakowski, 2025; Reeves Huapaya et al., 2025). Education systems, employers, and public agencies therefore share responsibility for anticipating skill demand and evaluating whether training improves actual performance and mobility.

Workforce Adaptation and Human-AI Collaboration

Workforce adaptation includes individual learning as well as changes in work design, management, and institutional support. Generative systems broaden the issue because they can participate in exploratory and creative work rather than only prediction and optimization. Krakowski (2025) conceptualizes this shift as a shift toward human-AI agency and argues that human judgment remains central to how organizational and social gains are created and distributed (Katsamakos et al., 2024). Adaptation consequently requires more than

technical implementation. It involves mechanisms for participation, explanation, retraining, and mobility, especially where AI changes professional judgment or creates information asymmetries between workers and management (Bankins & Formosa, 2023; Chigbu & Makapela, 2025; J. Wang et al., 2025). Research must therefore examine how workers shape systems in practice and how organizations distribute authority in collaborative workflows.

Ethics, Inclusion, and Meaningful Work

The future of work is also a normative and organizational question. AI can expand access to information and support decisions, but it can reproduce discrimination, weaken accountability, or narrow opportunities for meaningful judgment (Kolbjørnsrud, 2024; Stahl et al., 2023). Agarwal (2025) had analyzed multi-criteria to identify innovativeness, productivity, and customer experience as prominent considerations when firms redesign employee roles. At the same time, adaptive structures and specialized AI teams rank among the preferred organizational responses. Because that evidence rests on seven experts, the priorities require broader testing. Ethical evaluation must address whose tasks are automated, who can challenge an automated decision, and whether productivity gains translate into better work, equitable access to training, and credible routes into new roles.

Previous Bibliometric Studies, Research Gaps, and Future Directions

Previous reviews provide important but partial views of this domain (Table 1). Jacob Fernandes França et al. (2023) combined systematic review and bibliometric techniques for 35 studies on AI in potential assessment and talent management, emphasizing HR applications, bias, ethics, and law. C Conceição et al. (2023) examined 1,770 papers, combining Scopus and Web of Science records, on future work competencies and technological transformation. Fouad (2025) analyzed 276 records from Scopus, Web of Science, and OpenAlex on AI and Big Data for workforce-demand prediction. These studies establish relevant foundations, but their scopes respectively privilege human-resource applications, competency identification, or labor-market forecasting. The present study broadens the analytical lens by jointly mapping job displacement, skills transformation, and workforce adaptation across the multidisciplinary field of future work literature. It also integrates performance indicators with analyses of sources, documents, authors, institutions, countries, and keyword clusters. Accordingly, RQ1 through RQ5 assess the field's scale, evolution, dissemination, contributors, and influential documents, while RQ6 examines how its conceptual structure connects technological change with employment and adaptation. Future research should use longitudinal and occupation-level designs to test transitions suggested by these bibliometric patterns, compare outcomes across institutional settings, and examine whether reskilling and augmentation strategies improve mobility, job quality, and inclusion.

Table 1. Summary of several key past studies that have employed bibliometric methods to map the Intelligence and the Future of Work research landscape.

Authors (Year)	Objective (Summary)	Data Source & Year Coverage	TDE	Bibliometric Attributes Examined
França et al. (2023)	Examine the application of AI in human resource management, particularly employee potential assessment and talent identification, while addressing AI bias, ethics, and legal concerns.	EBSCO Academic Search Complete, Business Source Complete, ERIC, LISTA, and Regional Business News, with supplementary Google Scholar searching, included studies published from 2015 to 2022.	35	Publication trends, journal distribution and quartiles, h-index and SJR, author affiliations and countries, citation analysis, keyword co-occurrence, and co-authorship networks.
Conceição et al. (2023)	Identify the key competencies that the future labor market will require and explore how workers can adapt to	Scopus and Web of Science, publications up to 2021	1770 (897 Scopus + 873 WoS)	Annual publication trends, productive authors and sources, subject areas, co-authorship by authors, organizations, and countries,



	technological and organizational transformations.			citation patterns, country productivity and impact, keyword co-occurrence, and bibliometric network mapping.
El Massi & Elouadi (2025)	Map the global scientific landscape at the intersection of AI, Big Data, and labor-market prediction, and identify research trends, intellectual structures, influential contributors, and emerging directions.	Scopus, Web of Science, and OpenAlex (2003-2025)	276	Scientific production and growth, citation impact, authors and sources, institutional and country productivity, international collaboration, keyword frequency and co-occurrence, trend topics, thematic evolution and thematic mapping, conceptual structure, factorial analysis, and collaboration networks.

Note. TDE = Total Documents Examined.

RESEARCH QUESTIONS

The study addresses six research questions aligned with the available bibliometric evidence:

RQ1: What is the current bibliometric profile of research on intelligence and the future of work?

RQ2: How have publication output and citation patterns evolved?

RQ3: Which journals and publication sources are central to disseminating this research?

RQ4: Which highly cited documents have shaped the field's scholarly visibility?

RQ5: Who are the leading authors, institutions, and countries contributing to the field?

RQ6: What conceptual themes connect job displacement, skills transformation, and workforce adaptation?

Together, these questions link the field's performance structure to its conceptual organization and provide the basis for interpreting future research priorities.

METHODS

The study used a quantitative bibliometric design to map the development, scholarly influence, and conceptual structure of literature on intelligence and the future of work. Scopus provided the bibliographic metadata, and BiblioSpy® was the sole platform for cleaning, performance analysis, and keyword network analysis.

The analysis covered publication output, citations, source titles, highly cited documents, authors, institutions, countries, and author-keyword co-occurrence. These indicators were selected to address RQ1-RQ6 without treating citation impact as a direct measure of research quality.

Results are reported at the metadata level. Interpretations of thematic structure are bounded by the terms that passed the network threshold and do not substitute for a full-text systematic synthesis of every publication in the corpus.

Search Strategy

Scopus was searched on September 4, 2026, using the following query: ("artificial intelligence" OR "ai" OR "machine learning" OR "deep learning") AND ("future" OR "prospects" OR "trends" OR "outlook") AND

("work" OR "employment" OR "labor" OR "job") AND ("automation" OR "robotics" OR "digital transformation" OR "workplace") AND ("impact" OR "effect" OR "influence" OR "change"). The query operationalized the study's concern with technological change, employment, and future-oriented consequences.

Fig. 1 shows the identification and screening stages, adapted from the PRISMA 2020 flow diagram. The diagram reports 3,271 Scopus records and 1,499 Web of Science records, for a total of 4,770 records initially identified. Of these, 3,978 were removed before screening, leaving 792 screened records. The document-type and language filters then excluded 238 and 47 records, respectively, leaving 507 reports assessed for eligibility. Of these, 27 duplicates and 11 publications after 2025 were excluded, yielding 469 publications for the 1994 - 2025 bibliometric corpus.

Records were included when they matched the defined search concepts and the documented Scopus filters. The procedure supports transparent reporting of the corpus construction while recognizing that database coverage and query formulation delimit the resulting research landscape.

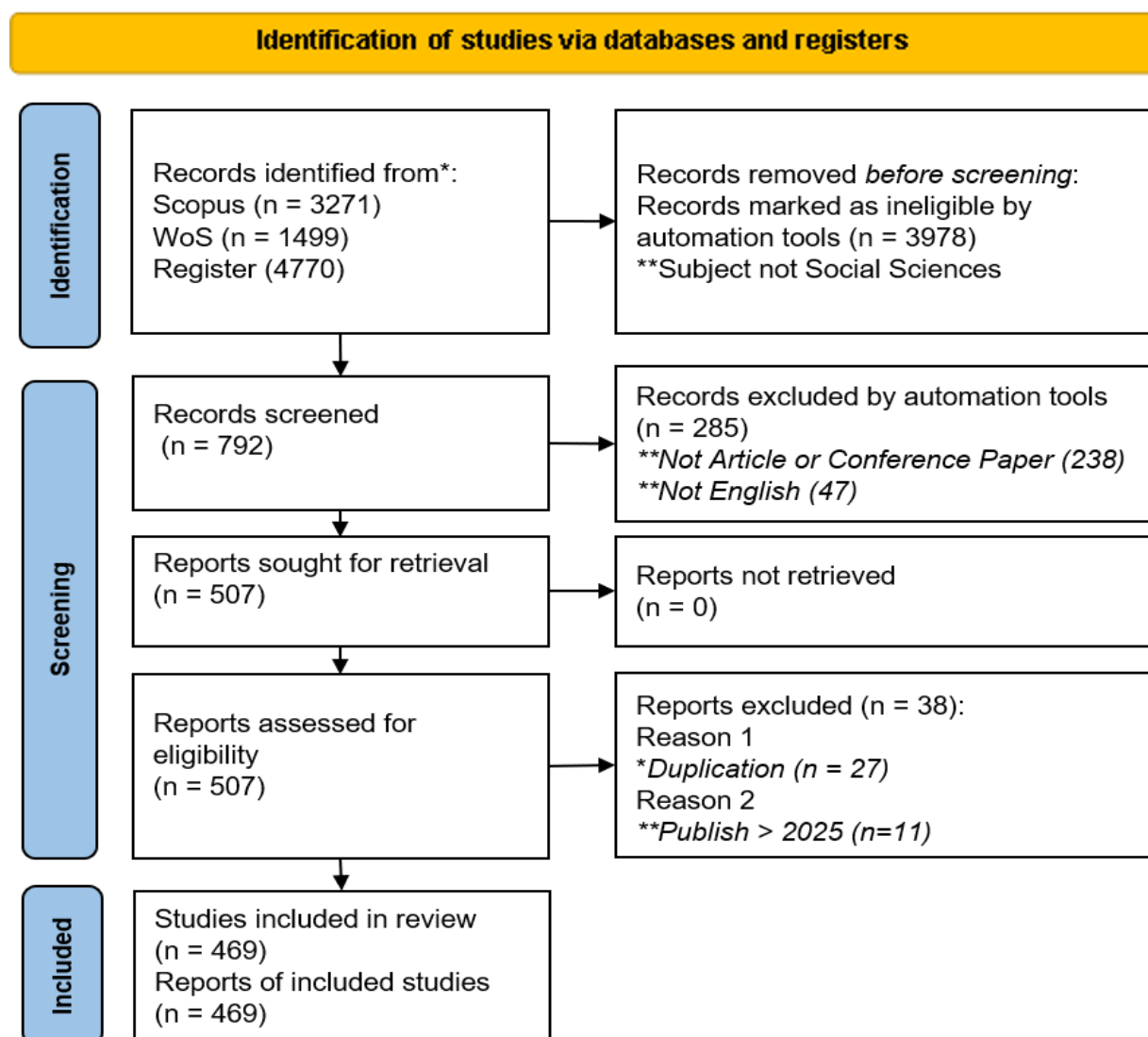


Figure 1. Flow diagram of the search and screening strategy

Data Cleaning and Harmonization

BiblioSpy® (Ahmi, 2026) was used to inspect and harmonize bibliographic fields required for the analysis, including author names, affiliations, countries, source titles, publication years, citations, and author keywords. Duplicate or inconsistent labels were reviewed before calculation. Keyword variants were handled in the supplied BiblioSpy workflow so that the co-occurrence network reflected consistent terms while preserving the original metadata's meaning.

Data Analysis

Performance analysis used total publications (TP), contributing and unique authors, cited publications (NCP), total citations (TC), citations per publication (C/P), citations per cited publication (C/CP), and the h-, g-, and m-indices. Results were summarized by year, source, document, author, institution, and country. Full counting was used for the author-keyword network, with association normalization, a minimum of five occurrences, and a minimum cluster size of five. The supplied network export used a clustering resolution of 1.0 and identified four thematic clusters.

Tools

BiblioSpy® (Ahmi, 2026) was the sole bibliometric platform used for data cleaning, harmonization, performance analysis, and visualization. The reported performance indicators, network, and maps were generated from the supplied BiblioSpy outputs.

RESULTS

The results address the six RQs through descriptive performance indicators and science mapping. Each subsection distinguishes research productivity from citation visibility and interprets recent cohorts with attention to their shorter citation exposure.

Current State of Research

Table 2 presents a corpus spanning 1994 to 2025, comprising 469 publications and an annual growth rate of 17.86%. The accumulated documents received 14,537 citations, with 396 publications cited, resulting in an average of 31 citations per publication and 36.71 citations per cited paper. The corpus involved 1,363 unique authors, 623 institutions, and 71 countries. An average of 2.98 authors per paper and an international co-authorship rate of 15.99% shows that cross-country collaboration occurred in fewer than one-fifth of the publications, indicating considerable scope for expanding international research partnerships. The h-index of 59 and g-index of 109 show that influence is distributed across a substantial group of publications rather than a single highly cited work. These indicators answer RQ1 by depicting a mature historical base with rapid recent expansion.

Table 2. Bibliometric summary

Indicator	Value
Timespan	1994:2025
Total Publications (TP)	469
Citable Year Span	32 years
Annual Growth Rate	17.86%
Document Average Age	3.22 years
Total Citations (TC)	14537
Average Citations per Document	31
Number of Cited Papers (NCP)	396
Average Citations per Cited Paper	36.71
Average Citations per Year	454.28
Total Contributing Authors	1398
Total Unique Authors	1363
Total Institutions	623
Total Countries	71
Single-Authored Documents	100
Average Authors per Paper	2.98

International Co-authorship Rate	15.99%
Unique Author Keywords	1603
Total References	61815
h-index	59
g-index	109

Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Publication Trends

Figure 2 and Table 3 answer RQ2. Annual output remained sparse before 2017, then rose from 13 publications in 2018 to 20 in 2019 and 44 in 2020. Growth remained uneven through 2021 and into 2023, then accelerated to 98 publications in 2024 and 163 in 2025. Citation totals peaked at 3,167 for the 2020 cohort and remained high for 2022 and 2023, but year-based citation totals combine field interest with exposure time. The lower total of 1,258 citations for the much larger 2025 cohort should therefore not be interpreted as a decline in influence.

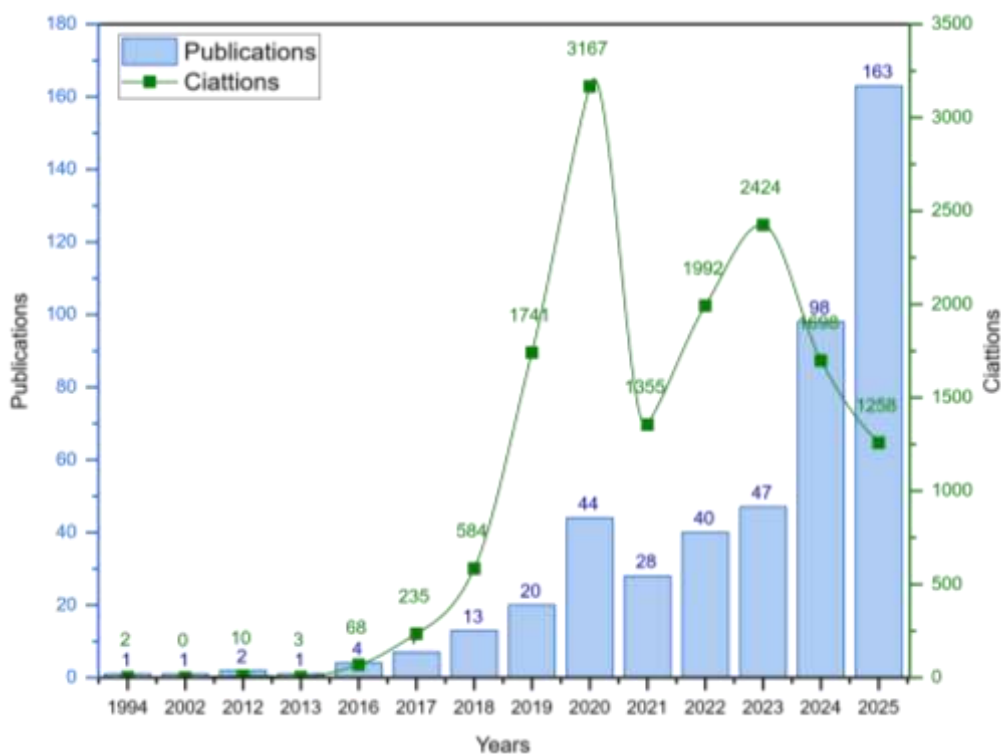


Figure 2. Annual publications and citations

Table 3. Yearly bibliometric statistics

YEAR	TP	NCA	NCP	TC	C/P	C/CP	h	g	m
2025	163	501	114	1258	7.72	11.04	19	30	9.5
2024	98	324	85	1698	17.33	19.98	21	38	7
2023	47	151	45	2424	51.57	53.87	20	47	5
2022	40	119	40	1992	49.8	49.8	19	40	3.8
2021	28	88	27	1355	48.39	50.19	15	28	2.5
2020	44	106	41	3167	71.98	77.24	24	44	3.429
2019	20	48	18	1741	87.05	96.72	13	20	1.625
2018	13	22	12	584	44.92	48.67	11	13	1.222
2017	7	14	7	235	33.57	33.57	5	7	0.5
2016	4	4	4	68	17	17	3	4	0.273
2013	1	1	1	3	3	3	1	1	0.071

2012	2	3	1	10	5	10	1	2	0.067
2002	1	2	0	0	0	0	0	0	0
1994	1	3	1	2	2	2	1	1	0.03

Note: TP = Total Publications, NCA = Number of Contributing Authors, NCP = Number of Cited Publications, TC = Total Citations, C/P = Citations per Publication, C/CP = Citations per Cited Publication, h = h-index, g = g-index, m = m-Quotient. Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Publications by Source Titles

Figure 3 and Table 4 address RQ3 by showing where the field is disseminated. Sustainability (Switzerland) is the most productive listed source with 17 publications and 557 citations. Technology in Society publishes 14 documents with 1,019 citations and 72.79 citations per publication, illustrating that productivity and influence do not necessarily coincide. Information Technology & People likewise has only four publications but 495 citations, producing the highest citations per publication among the listed sources, at 123.75. In contrast, engineering education proceedings publish several documents with comparatively low average citation counts. The distribution across management, technology, sustainability, human-computer interaction, education, and multidisciplinary outlets confirms that the future-of-work debate spans disciplinary boundaries rather than belonging to a single journal community.

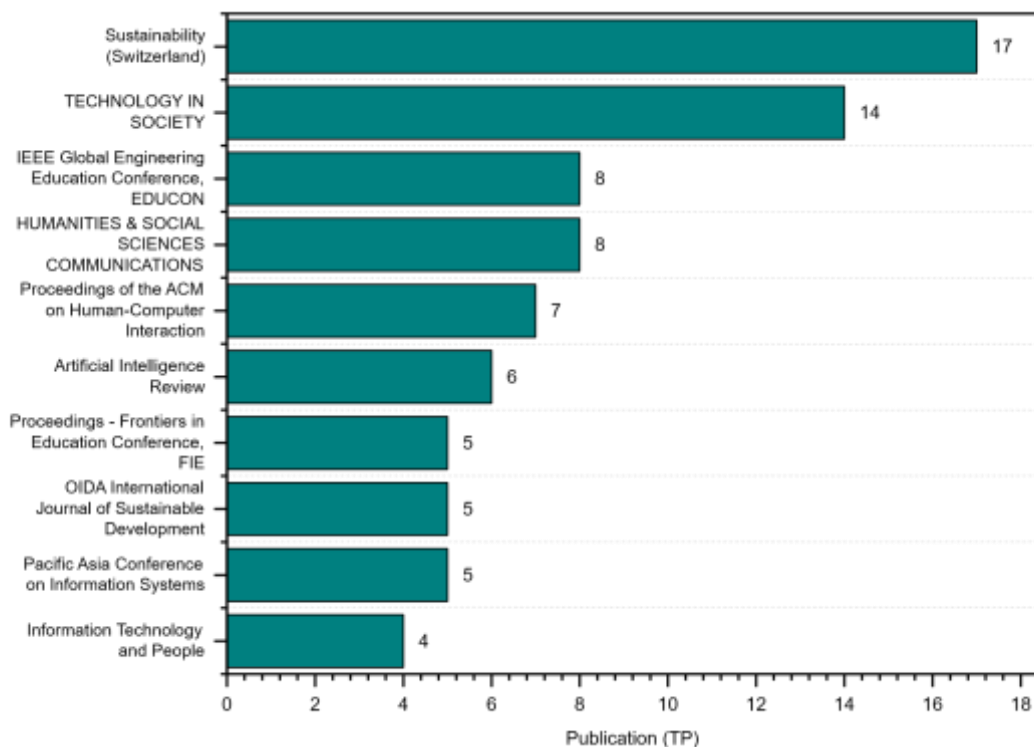


Figure 3. Top 10 most productive source titles

Table 4. Top 10 most active source titles

Source Title	Publisher	TP	TC	NCA	NC P	C/P	C/CP	h	g	m
Sustainability (Switzerland)	Multidisciplinary Digital Publishing Institute (MDPI)	17	557	63	16	32.765	34.812	10	17	1.25
TECHNOLOGY IN SOCIETY	ELSEVIER SCI LTD	14	1019	31	14	72.786	72.786	11	14	1.375
IEEE Global Engineering Education	IEEE Computer Society	8	44	30	7	5.5	6.286	3	6	0.6



Conference, EDUCON										
HUMANITIES & SOCIAL SCIENCES COMMUNICATIONS	SPRINGERNATURE	8	362	18	8	45.25	45.25	7	8	1.167
Proceedings of the ACM on Human-Computer Interaction	Association for Computing Machinery	7	524	40	7	74.857	74.857	5	7	0.625
Artificial Intelligence Review	Springer Nature	6	367	25	5	61.167	73.4	5	6	0.2
Proceedings - Frontiers in Education Conference, FIE	Institute of Electrical and Electronics Engineers Inc.	5	7	15	3	1.4	2.333	1	2	0.167
OIDA International Journal of Sustainable Development	Ontario International Development Agency	5	12	15	4	2.4	3	2	3	1
Pacific Asia Conference on Information Systems	Association for Information Systems	5	3	12	1	0.6	3	1	1	0.167
Information Technology and People	Emerald Publishing	4	495	9	4	123.75	123.75	4	4	0.8

Note: TP = Total Publications, TC = Total Citations, NCA = Number of Contributing Authors, NCP = Number of Cited Publications, C/P = Citations per Publication, C/CP = Citations per Cited Publication, h = h-index, g = g-index, m = m-Quotient, e = e-index, SJR = SCImago Journal Rank, SNIP = Source-Normalized Impact per Paper, JIF = Journal Impact Factor, ABDC = Australian Business Deans Council Rating, AJG = Academic Journal Guide. Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Highly Cited Documents

Table 5 addresses RQ4. Tussyadiah's (2020) review of automation in tourism leads with 877 citations, followed by Li et al. (2019) with 738 citations. Acemoglu and Restrepo's (2020) analysis of AI and labor demand ranks third with 447 citations, while Morandini et al. (2023) and Jarrahi et al. (2021) each record 415. The list combines sectoral, organizational, ethical, and socio-technical perspectives, showing that scholarly visibility is distributed across debates on automation awareness, labor demand, reskilling, algorithmic management, meaningful work, and human AI collaboration. Citation counts indicate influence within this corpus but do not, by themselves, establish methodological quality or practical effectiveness.

Table 5. Top 9 highly cited documents

No	Authors	Title	Source	TC	C/Y	NTC
1	Tussyadiah (2020)	A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism	Annals of Tourism Research	877	125.29	12.18
2	Li et al. (2019)	Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate	TOURISM MANAGEMENT	738	92.25	8.48
3	Acemoglu &	The wrong kind of AI? Artificial	Cambridge Journal	447	63.86	6.21

	Restrepo (2020)	intelligence and the future of labour demand	of Regions, Economy and Society			
4	Jarrahi et al. (2021)	Algorithmic management in a work context	BIG DATA & SOCIETY	415	69.17	8.58
5	Morandini et al. (2023)	THE IMPACT OF ARTIFICIAL INTELLIGENCE ON WORKERS' SKILLS: UPSKILLING AND RESKILLING IN ORGANISATIONS	Informing Science	415	103.75	8.05
6	Bankins & Formosa (2023)	The Ethical Implications of Artificial Intelligence (AI) For Meaningful Work	Journal of Business Ethics	388	97	7.52
7	Wang et al. (2019)	Human-AI collaboration in data science: Exploring data scientists' perceptions of automated AI	Proceedings of the ACM on Human-Computer Interaction	343	42.88	3.94
8	Yu et al. (2023)	Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective	Information Technology and People	311	77.75	6.03
9	Khogali & Mekid (2023)	The blended future of automation and AI: Examining some long-term societal and ethical impact features	TECHNOLOGY IN SOCIETY	305	76.25	5.91
10	Howard & Borenstein (2018)	The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity	Science and Engineering Ethics	289	32.11	6.43

Note: TC = Total Citations, C/Y = Citations per Year, NTC = Normalized Total Citations

Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

The field's most prominent contributions address four interrelated issues (Table 5a). The first concerns the economics of automation and labor demand. Acemoglu & Restrepo (2020) argue that technological development has been biased toward automation, with insufficient emphasis on creating new tasks for workers. They associate this imbalance with stagnant labor demand, a declining labor share of national income, rising inequality, and weaker productivity growth. In tourism, Tussyadiah (2020) identifies limited empirical research on how intelligent automation is transforming production and consumption. The study proposes four research priorities: designing beneficial AI, facilitating its adoption, assessing the effects of intelligent automation, and creating a sustainable future with AI systems.

The second issue concerns worker perceptions, skills, and reskilling. Drawing on a survey of 468 full-time hotel employees, Li et al. (2019) find that awareness of AI and robotics is positively associated with turnover intention. Perceived organizational support weakens this relationship, whereas a competitive psychological climate strengthens it. Morandini et al. (2023) examine how AI is transforming professional skills, recommend mapping transversal skills, identify the competencies required for effective AI adoption, and provide targeted training and development. These measures can support upskilling and reskilling while promoting a more equitable distribution of AI's benefits.

The third issue concerns management, collaboration, and control. Jarrahi et al. (2021) conceptualize algorithmic management as a sociotechnical process that reshapes power relations between workers and managers, requires new roles and competencies, can generate opposition to algorithms, and creates technical and organizational opacity with implications for accountability. Based on interviews with 20 data scientists, D. Wang et al. (2019) find that participants regarded increasing automation as inevitable and expressed concerns about its effects, yet remained optimistic about their job security. They expected future data science work to combine automated capabilities with indispensable human expertise. Yu et al. (2023) develop a socio-technical

framework in which workplace AI adoption is shaped by personnel, technical, organizational-structure, and environmental subsystems, with proposed outcomes at the individual, organizational, and employment levels.

The fourth issue concerns ethics, meaningful work, and equity. Bankins & Formosa (2023) develop a conceptual framework showing how three AI deployment paths-replacement, tending the machine, and amplification-may enhance or diminish meaningful work. They evaluate these effects across task integrity, skill cultivation and use, task significance, autonomy, and belongingness, emphasizing that the consequences depend on the tasks automated and how AI is implemented. Khogali & Mekid (2023) synthesize prospective societal and ethical consequences of AI and automation, including job displacement, employee well-being, organizational dehumanization, fear of AI, inequality, and concerns surrounding autonomous vehicles.

These contributions connect the study's three central concerns: the relationship between technological capability and labor demand, the changing skill requirements associated with workforce adaptation, and responsibility for ensuring that AI-supported work remains inclusive and meaningful. They also demonstrate the multidisciplinary character of the literature, which draws on economics, tourism, information systems, human-computer interaction, organizational studies, and business ethics.

Table 5a. Content-based qualitative synthesis of the 9 most cited documents

No	Authors	Source	Core Focus	Key Contribution	Thematic Cluster
1	Tussyadiah (2020)	Annals of Tourism Research	Intelligent automation in tourism	Reviews how intelligent automation is changing the production and consumption of tourism. It identifies limited empirical research and proposes four priorities: designing beneficial AI, facilitating adoption, assessing the effects of intelligent automation, and creating a sustainable future with AI systems.	Economics of automation and labor demand
2	Li et al. (2019)	TOURISM MANAGEMENT	Employee awareness of AI and robotics in hospitality	Finds that employees' awareness of AI and robotics is positively associated with turnover intention. Perceived organizational support weakens this relationship, whereas a competitive psychological climate strengthens it.	Worker perceptions, skills, and reskilling
3	Acemoglu & Restrepo (2020)	Cambridge Journal of Regions, Economy and Society	AI and the future of labor demand	It explains that AI may automate tasks previously performed by labor or create new tasks for workers. It argues that excessive emphasis on automation has contributed to stagnant labor demand, a declining labor share, greater inequality, and weaker productivity growth.	Economics of automation and labor demand
4	Jarrahi et al. (2021)	BIG DATA & SOCIETY	Algorithmic management	Conceptualizes algorithmic management as a sociotechnical process that reshapes worker-manager power relations, requires new roles and competencies, can generate opposition to algorithms, and creates technical and organizational opacity with implications for accountability.	Management, collaboration, and control
5	Morandini et al. (2023)	Informing Science	AI and workers' skills	Examines how AI is transforming professional skills and recommends mapping transversal skills, identifying	Worker perceptions, skills, and

				competencies needed for effective AI adoption, and providing targeted training and development to support upskilling and reskilling and promote a more equitable distribution of AI's benefits.	reskilling
6	Bankins & Formosa (2023)	Journal of Business Ethics	AI and meaningful work	Develops a framework linking three AI deployment paths-replacement, tending the machine, and amplification to five dimensions of meaningful work: task integrity, skill cultivation and use, task significance, autonomy, and belongingness. The effects may enhance or diminish meaningful work, depending on which tasks are automated and how AI is implemented.	Ethics, meaningful work, and equity
7	Wang et al. (2019)	Proceedings of the ACM on Human-Computer Interaction	Human-AI collaboration in data science	Finds that data scientists viewed increasing automation as inevitable and expressed concerns about its effects, yet they remained optimistic about job security. They expected future data science work to combine automated capabilities with indispensable human expertise.	Management, collaboration, and control
8	Yu et al. (2023)	Information Technology and People	Antecedents and outcomes of workplace AI	Develops a socio-technical framework in which workplace AI adoption is shaped by personnel, technical, organizational-structure, and environmental subsystems. Its proposed outcomes operate at the individual, organizational, and employment levels.	Management, collaboration, and control
9	Khogali & Mekid (2023)	TECHNOLOGY IN SOCIETY	Long-term societal and ethical effects of AI	Synthesizes prospective societal and ethical consequences of AI and automation, including job displacement, employee well-being, organizational dehumanization, fear of AI, inequality, and concerns surrounding autonomous vehicles.	Ethics, meaningful work, and equity

Publications by Authors

Table 6 contributes to RQ5 by distinguishing author productivity from citation impact. Kim, Soboleva, and Lee are the listed authors, with three publications each, while the remaining authors contribute two publications each. Kim and Lee's three publications received 145 citations each, while Soboleva's received only one citation, meanwhile, several authors with only two publications achieved considerably higher citation impact. The low maximum publication count indicates a dispersed authorship structure with limited concentration around individual prolific scholars. It also suggests that the field is assembled through contributions from multiple disciplinary communities rather than maintained by a small, stable core of authors.

Table 6. Most productive authors

Author	Affiliation	Country	TP	NCP	TC	C/P	C/CP	h	g	m
Kim, Byung-Jik	University of Ulsan	South Korea	3	3	145	48.33	48.33	3	3	1

Soboleva, Elena V.	Vyatka State University	Russia	3	1	1	0.33	1	1	1	0.333
Lee, Julak	Ang Univ	South Korea	3	3	145	48.33	48.33	3	3	1
Webster, Craig	Ball State University	United States	2	2	81	40.5	40.5	2	2	0.286
Ashton, Mark	University of Surrey	United Kingdom	2	2	430	215	215	2	2	0.286
Ek, Jackeline Iturbe	Tecnológico de Monterrey	Mexico	2	2	9	4.5	4.5	2	2	0.5
Skovsgaard, Morten	University of Southern Denmark	Denmark	2	2	55	27.5	27.5	2	2	1
Kediya, Shailesh	Symbiosis Skills and Professional University	India	2	2	6	3	3	1	2	0.333
Mansouri, Khalifa	Hassan II University	Morocco	2	1	5	2.5	5	1	2	0.25
Xu, Shi	University of Surrey	United Kingdom	2	2	430	215	215	2	2	0.286

Notes: TP = Total number of Publications, NCP = Number of Cited Publications, TC = Total Citations, C/P = average Citations per Publication, C/CP = average Citations per Cited Publication, h = h-index, g = g-index, m = index. Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Publications by Institutions

Institutional patterns in Table 7 further answer RQ5. Georgia Institute of Technology leads in productivity, with 5 publications and 700 citations. Carnegie Mellon University, Tecnológico de Monterrey, University of South Australia, University of Surrey, and University of Washington each contribute four publications, but their citation profiles differ substantially. Among these institutions, the University of Surrey records 1,382 citations, followed by the University of Washington with 427 and the University of South Australia with 205, demonstrating how a relatively small number of influential publications can shape institution-level citation performance. The presence of universities from the United States, the United Kingdom, Mexico, Australia, and Indonesia indicates geographically diverse participation, although research output remains thinly distributed across institutions.

Table 7. Most productive institutions

Institution	Country	TP	NCA	NCP	TC	C/P	C/CP	h	g	m
Georgia Institute of Technology	United States	5	9	5	700	140	140	4	5	0.444
Carnegie Mellon University	United States	4	7	3	43	10.75	14.33	2	4	0.4
Tecnologico De Monterrey	Mexico	4	6	4	15	3.75	3.75	2	3	0.5
University of South Australia	Australia	4	4	4	205	51.25	51.25	3	4	0.333
University of Surrey	United Kingdom	4	7	4	1382	345.5	345.5	4	4	0.571
University of Washington	United States	4	6	2	427	106.75	213.5	2	4	0.2
Arizona State University	United States	3	9	2	77	25.67	38.5	2	3	0.286
Ball State University	United States	3	5	2	81	27	40.5	2	3	0.286
Bina Nusantara University	Indonesia	3	9	3	7	2.33	2.33	2	2	0.667
Boston University	United States	3	4	3	557	185.67	185.67	3	3	0.429

Note: TP = Total Publications, NCA = Number of Contributing Authors, NCP = Number of Cited Publications, TC = Total Citations, C/P = Citations per Publication, C/CP = Citations per Cited Publication, h = h-index, g = g-index, m = m-Quotient. Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Publications by Countries

Figure 4 and Table 8 show the international distribution of research. The United States leads with 92 publications and 4,103 citations, followed by the United Kingdom with 41 publications and 2,805 citations. China contributes 34 publications, India 29, Germany 27, and Australia 20. The United Kingdom has the highest citations per publication among the ten leading countries (68.41), while the United States has the largest h-index of 29. These differences reinforce the distinction between volume and influence. Contributions from 71 countries signal global relevance, but the leading group remains concentrated in North America, Europe, Asia, and Australia, leaving scope for stronger participation from underrepresented labor-market settings.



Figure 4. Global distribution of publications

Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Table 8. Top 10 countries

Country	TP	NCA	NCP	TC	C/P	C/CP	h	g	m
United States	92	239	76	4103	44.6	53.99	29	63	0.879
United Kingdom	41	98	38	2805	68.41	73.82	21	41	0.636
China	34	88	28	1486	43.71	53.07	13	34	1.625
India	29	87	24	571	19.69	23.79	10	23	0.4
Germany	27	79	22	646	23.93	29.36	11	25	1.222
Australia	20	47	19	837	41.85	44.05	11	20	1.222
Russia	15	40	10	151	10.07	15.1	5	12	0.625
Italy	15	35	15	614	40.93	40.93	9	15	1.286
Malaysia	14	41	9	96	6.86	10.67	5	9	0.833
South Africa	14	20	12	161	11.5	13.42	8	12	0.533

Note: TP = Total Publications, NCA = Number of Contributing Authors, NCP = Number of Cited Publications, TC = Total Citations, C/P = Citations per Publication, C/CP = Citations per Cited Publication, h = h-index, g = g-index, m = m-Quotient. Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Keyword Co-occurrence Analysis

Figure 6 addresses RQ6 by mapping 54 author keywords that met the occurrence threshold across 469 eligible records. The keyword co-occurrence network reveals three major thematic clusters that structure the research domain. These clusters demonstrate that literature is primarily organized around artificial intelligence and work transformation, machine learning and digital transformation, and labor-market and educational adaptation.

The blue cluster is centered on artificial intelligence, which forms the largest and most connected node in the network. It includes keywords such as automation, work, productivity, innovation, technology, skills, human–AI collaboration, technological change, technological unemployment, robot, and the fourth industrial revolution. This cluster indicates that AI research is strongly associated with changes in work design, technological adoption, productivity, and the relationship between human capabilities and automated systems.

The green cluster is associated with machine learning and digital transformation. It includes deep learning, generative AI, natural language processing, chatbots, data science, cybersecurity, ethics, sustainability, and the future of work. The strong connections among these keywords indicate that machine-learning technologies are increasingly examined alongside organizational transformation, responsible AI, and emerging generative technologies. This cluster, therefore, represents the methodological and technological dimensions of future-of-work research.

The orange cluster reflects labor-market and workforce adaptation, incorporating keywords such as labor market, employment, Industry 4.0, workplace, higher education, ChatGPT, large language model, robotics, and sustainable development goal. This grouping highlights the relationship between technological change and broader employment, educational, and societal responses. The presence of higher education and emerging generative AI terms also indicates growing attention to workforce preparation and skills development.

Overall, Figure 6 demonstrates that the field is strongly interconnected across technological development, work transformation, and workforce adaptation. Artificial intelligence serves as the principal conceptual hub, while machine learning, digital transformation, employment, and education connect technical developments with their organizational and labor-market implications.

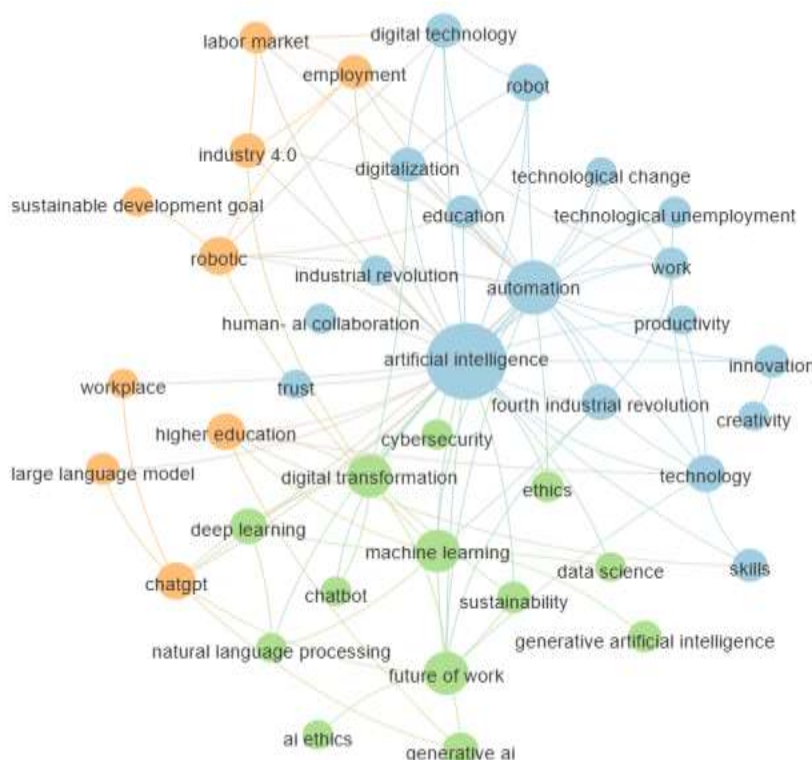


Figure 6. Co-occurrence network of author keywords with at least five occurrences

Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

Table 9: Classification of Main Research Teams

Cluster Color	Core Keywords	Research Theme
Blue	Artificial intelligence; automation; work; productivity; innovation; technology; skills; human–AI collaboration; technological change; technological unemployment; robot; fourth industrial revolution	AI, automation, and human-centered work transformation
Green	Machine learning; digital transformation; future of work; deep learning; generative AI; generative artificial intelligence; natural language processing; chatbot; data science; cybersecurity; ethics; sustainability	Machine learning, generative AI, and digital transformation
Orange	Labor market; employment; Industry 4.0; workplace; higher education; ChatGPT; large language model; robotic; sustainable development goal	Labor market, education, and workforce adaptation

Figure 7 plots the observed publication spans and relative frequencies of nine keywords meeting the five-occurrence threshold, showing when each term became prominent within the research domain. Horizontal lines represent the interquartile publication period, bubble positions the median year, and bubble sizes the keyword frequency; the spans describe timing, not year-by-year growth rates (RQ2, RQ6). Artificial intelligence is the dominant topic, with 189 occurrences and a median year of 2024; its interquartile range extends from 2021 to 2025, indicating sustained recent research attention. Automation records 68 occurrences, with a median year of 2023, spanning approximately 2020–2024, suggesting it became established slightly earlier. Robot is centered around 2022. Machine learning (30 occurrences) and digital transformation (31 occurrences) both peak in 2024. Earlier themes - fourth industrial revolution, digitalization, education, and the future of work - center on 2023. Overall, Figure 7 shows a thematic progression from robotics and industrial transformation toward artificial intelligence, machine learning, and digital transformation.

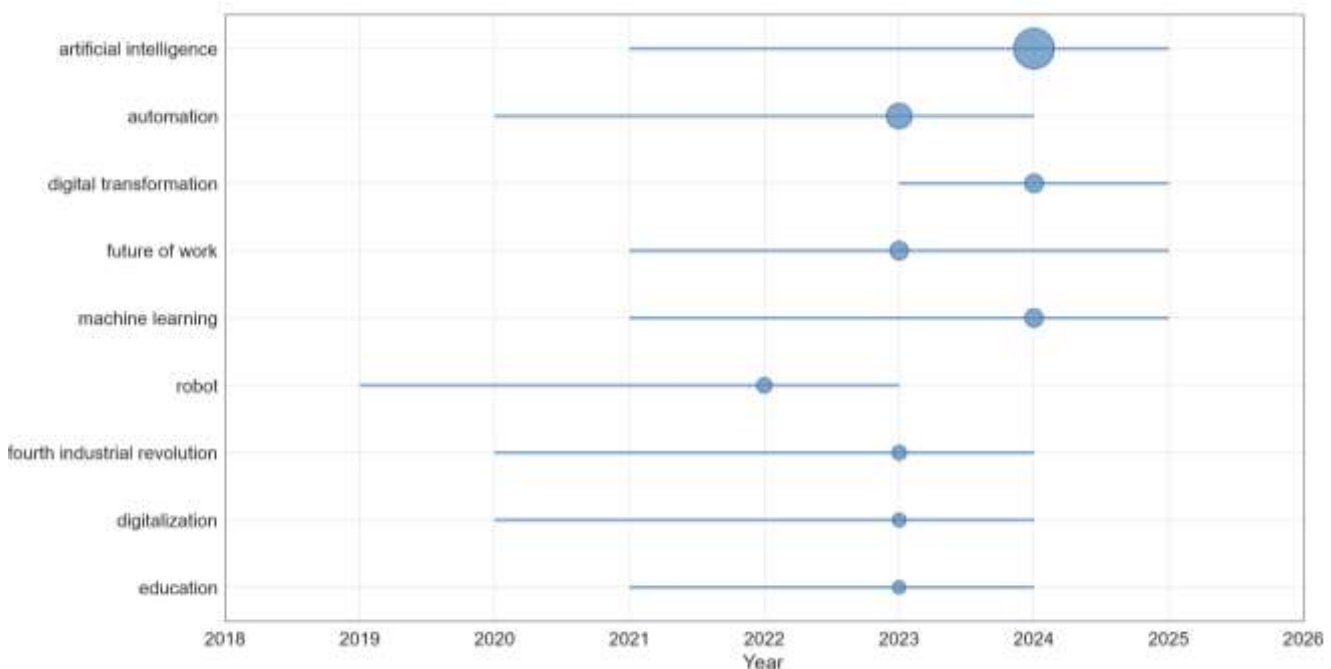


Figure 7. Keyword Trend Topics with at least five occurrences

Source: Generated by the author(s) using BiblioSpy® (Ahmi, 2026).

DISCUSSION

The bibliometric evidence depicts a field that has moved from scattered early contributions to rapid expansion after 2019. This growth coincides with the wider deployment of machine learning, workplace automation, and generative AI. However, the results should be read as a shift in research attention rather than as proof of a

uniform labor market effect. The combination of management, technology, education, ethics, and economics sources reflects a field whose central problem is socio-technical: the consequences of AI depend on technical design, organizational choices, institutions, and worker capabilities.

AI, automation, and human-centered work transformation

This blue cluster connects artificial intelligence with automation, work, skills, productivity, technological change, technological unemployment, and human–AI collaboration. Its center of gravity is the relationship between technical adoption and work design. The most cited contributions illustrate the same concerns from different angles: automation-biased AI is argued to stagnate labor demand and lower labor's share of national income when insufficient attention is paid to creating new tasks in which labor can be productively employed (Acemoglu & Restrepo, 2020); algorithmic management is conceptualized as a sociotechnical phenomenon that reshapes power relations between workers and managers and introduces technical and organizational opacity (Jarrahi et al., 2021); and socio-technical frameworks situate adoption outcomes within personnel, technical, organizational, and environmental subsystems (Yu et al., 2023). Worker perceptions also fall within this theme: awareness that one's job could be automated is associated with lower commitment and career satisfaction, and with higher turnover intentions, cynicism, and depression; such appraisals shape employees' intentions to stay with or leave organizations (Rezapouraghdam et al., 2025). The theme, therefore, frames human-centered transformation as a design and governance problem rather than purely a technical one, and future work should examine how task discretion, coordination, workload, and the distribution of productivity gains change in practice.

Machine Learning, Generative AI, and Digital Skills Transformation

This cluster pairs technical vocabulary (deep learning, natural language processing, chatbot, generative AI, data science, cybersecurity) with responsibility and sustainability constructs (ethics, sustainability), representing the technological and methodological dimension of the field. Figure 7 confirms the currency of this vocabulary: machine learning and digital transformation are both centered on 2024, while artificial intelligence is the dominant topic overall, with 189 occurrences and a median year of 2024. Research attention is increasingly coupling technical capability with responsible deployment, as reflected in the corpus's most visible documents: the long-term societal and ethical impacts of blended automation and AI - including job losses, employee well-being, the dehumanization of jobs, and fear of AI - are the object of explicit synthesis (Khogali & Mekid, 2023); bias encoded in, or learned by, AI systems is treated as a category of harm users experience day-to-day and as inseparable from design and deployment (Krakowski, 2025); and sectoral research agendas prioritize designing beneficial AI, facilitating adoption, assessing the impacts of intelligent automation, and creating a sustainable future with AI systems (Tussyadiah, 2020). For skills, this cluster implies that readiness cannot be equated with exposure to tools: the ethical and critical capacity to evaluate automated outputs must accompany the use of generative systems.

Labor market, education, and workforce adaptation

This cluster links labor market, employment, Industry 4.0, workplace, higher education, ChatGPT, large language model, and sustainable development goal, framing adaptation as an educational and institutional process rather than an individual employability concern. Workforce preparation now includes AI literacy and familiarity with large language models. The most cited documents specify what adaptation requires: mapping transversal skills to close skill gaps and providing targeted training so that the benefits of AI are equitably distributed; anticipating futures in which automation and human expertise are both indispensable; and evaluating whether AI deployment paths - replacing, tending the machine, or amplifying - preserve opportunities for meaningful work (Khogali & Mekid, 2023). The temporal pattern in Figure 7 - from robot (median 2022) toward automation (2023) and then AI, machine learning, and digital transformation (2024) - suggests a thematic progression from industrial robotics toward general-purpose and generative AI, which gives this theme its comparative agenda across education systems and labor-market institutions.

Structural Barriers to Workforce Adaptation in Underrepresented Labor Markets

Knowledge production remains concentrated in North America, Europe, Asia, and Australia; India (29

publications; 19.69 citations per publication) is its most visible Global South contributor (Fig. 4, Table 8). Barriers in developing economies differ unreliable connectivity, inadequate power supply, AI-skilled professional shortages, and education systems lacking AI literacy. A systematic review of 100 studies finds adoption hindered by infrastructural deficiencies, skill shortages, and complex policy landscapes, while smaller, credit-constrained firms face higher adoption costs (Chigbu & Makapela, 2025; Morandini et al., 2023).

Generative AI sharpens this asymmetry: automation-vulnerable workers face displacement while augmentation is blocked by infrastructure gaps—"disruption without dividend". Robot adoption lowers labor income shares in developing, but not in developed, economies, benefiting middle- or advanced-educated workers. Technologies optimized for skill-abundant economies impose a productivity penalty, though catch-up remains feasible via leapfrogging or learning-oriented strategies. High-income countries dominate AI policy discourse (Yu et al., 2023); future research should compare how infrastructure investment, reskilling systems, and governance capacity enable inclusive adaptation, especially in informal labor markets and rural–urban divides.

IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

Theoretically, the four clusters support an integrated view in which technological capability, task change, skills formation, and institutional adaptation interact. Practically, employers should pair AI investment with transparent work redesign, worker consultation, and accessible development pathways. Policymakers should support portable skills, transition assistance, data rights, and evaluation of distributional outcomes. The study is limited to Scopus and to the supplied search formulation, so relevant work indexed elsewhere or using different terminology may be absent. Citation indicators favor older publications, author keywords vary across disciplines, and co-occurrence maps do not establish causality or research quality. Future work should combine bibliometric monitoring with systematic content analysis and longitudinal labor-market evidence.

CONCLUSION

This study maps 469 Scopus and Web of Science-indexed publications on AI and the future of work from 1994 to 2025. The field expanded rapidly after 2019, accumulated 14537 citations, and involved authors from 71 countries. Research is disseminated across management, technology, sustainability, education, and human-computer interaction outlets, while productivity and citation influence remain distinct across sources, authors, institutions, and countries. Three keyword clusters link AI, automation, and human-centered work transformation; machine learning, generative AI, and digital transformation; and labor market, education, and workforce adaptation. Together, these findings answer the six RQs by showing a multidisciplinary, internationally collaborative, and conceptually interconnected field. The evidence also exposes priorities for stronger research: longitudinal measurement of task and job transitions, comparative evaluation of reskilling pathways, attention to job quality and worker voice, and wider coverage of underrepresented labor-market contexts. Future studies should connect bibliometric monitoring with systematic content analysis and occupation-level evidence to evaluate whether AI deployment produces inclusive augmentation, durable mobility, and meaningful work.

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