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TECHNOLOGICAL UNEMPLOYMENT IN THE AGE OF GENERATIVE AI: A BIBLIOMETRIC REVIEW

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ABSTRACT

This study maps the intellectual, conceptual, and social structure of research on technological unemployment in the age of generative artificial intelligence (GenAI), with a focus on labor market disruption, job exposure, and reskilling. Unlike prior reviews that address artificial intelligence and employment in broad terms, this study integrates these three dimensions within the specific context of GenAI, offering a more focused perspective on the evolving future-of-work literature. Using a bibliometric review approach, the study analyses 810 documents published between 2022 and 2026 across 538 sources. The findings reveal a sharp increase in publication output after 2023, indicating a rapid expansion of the field following the widespread diffusion of large language models and related generative technologies. The intellectual structure of the field is organised around four main domains: automation and displacement economics, AI and digital transformation, organisational and human resource management, and sociotechnical perspectives on digital work. Conceptually, the field is shifting from general concerns about automation toward themes such as the future of work, decision-making, generative AI, occupational exposure, and adaptive capabilities. Overall, the results suggest that technological unemployment in the GenAI era is increasingly understood not simply as job loss, but as a broader process involving task transformation, workforce vulnerability, and institutional adaptation, with important implications for research, policy, and organisational strategy.

Introduction

The rapid emergence of generative artificial intelligence has transformed contemporary debates on employment, labor markets, and the future of work (Makridis 2026; Artz and Ren 2025). Unlike earlier waves of automation, which were primarily associated with routine manual and repetitive clerical tasks, generative AI extends technological capability into domains traditionally linked to cognition, communication, writing, analysis, and creative production (Wong et al. 2025; Chertow et al. 2024). This shift has revived longstanding concerns about technological unemployment, but in a form that is analytically more complex than classic mechanisation narratives. The current debate no longer revolves solely around whether technology replaces labor. It increasingly asks which occupations are exposed, which tasks are reconfigured, how inequalities may

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deepen or shift, and what forms of reskilling are needed to sustain employability (Engberg et al. 2025).

The resurgence of technological unemployment as a research topic is driven by the distinctive character of GenAI systems. Large language models, foundation models, and generative applications can summarise information, produce text, generate code, support decision-making, and augment various forms of knowledge workAs a result, exposure to technological disruption is no longer confined to industrial labor. White-collar occupations, service roles, educational tasks, human resource functions, and professional work have all become part of the emerging conversation (Agarwal 2025). This development complicates the traditional assumption that higher-skilled workers are naturally insulated from technological substitution. At the same time, the scholarly literature on AI and work has expanded rapidly across multiple disciplines, including labor economics, organizational behavior, human resource management, information systems, education, sociology of work, and policy studies (Al-Nabhani et al. 2025; Parteka et al. 2024).

This expansion has produced conceptual richness, but also fragmentation. Studies often examine job displacement, labor market disruption, occupational exposure, or reskilling separately, even though these dimensions are tightly interwoven in the context of GenAI. As a result, the field lacks an integrated overview that can clarify its intellectual foundations, thematic priorities, leading contributors, and emerging directions (Lobel 2024). This study addresses that gap through a bibliometric review of research on technological unemployment in the age of generative AI. The study focuses on three interconnected lenses: labor market disruption, job exposure, and reskilling (Carter and Wynne 2024) . The aim is to map how the field has developed, identify the most influential contributors and outlets, examine the intellectual and conceptual structure of the literature, and highlight directions for future research. The topic is both theoretically timely and practically urgent, as governments, firms, universities, and workers are increasingly forced to respond to AI-driven transformation without a fully consolidated evidence base (Kim and Lee 2024a).

The contribution of this article is threefold. First, it narrows the analytical focus from AI and work in general to the more specific nexus between technological unemployment and generative AI. Second, it integrates labor market disruption, job exposure, and reskilling within a single bibliometric framework, thereby linking concerns that are often treated separately in the literature. Third, it combines performance analysis and science mapping to show not only who and what dominates the field, but also how the literature is conceptually and intellectually organized. In doing so, the study offers a structured foundation for understanding how the future-of-work debate is being reshaped in the era of generative AI (Sharma et al. 2024).

Conceptual Background

Technological unemployment has long been associated with the displacement of labor by technological innovation. In its classical formulation, the concept refers to a situation in which machines or new production systems reduce the demand for human labor faster than new forms of employment can emerge. Yet this traditional view has become less adequate in the context of generative AI. Rather than simply removing occupations wholesale, GenAI often alters the internal composition of jobs by automating certain tasks, augmenting others, and changing the competence profile required for continued participation in the labor market. This implies that technological unemployment in the current era should be analyzed not merely as an employment quantity problem, but also as a work redesign problem. Generative AI represents a qualitatively important development because it introduces automation into domains of language, reasoning, communication, and symbolic production. Its influence therefore extends beyond manual substitution and into cognitive automation. This matters because many contemporary occupations are built around the manipulation of information, interpretation of text, and generation of knowledge outputs. Such tasks are now increasingly susceptible to algorithmic support or substitution, thereby expanding the range of workers exposed to technological change. (Lian et al. 2024)

This exposure is closely tied to labor market disruption. Labor market disruption refers to changes in occupational demand, wage structures, employment trajectories, and forms of work organization caused by technological or institutional shifts. In the GenAI context, disruption may involve partial job automation, changing expectations of productivity, downward pressure on some occupational groups, and the creation of hybrid human–AI roles. Importantly, disruption does not always mean immediate job elimination. It may instead manifest as task reallocation, work intensification, deskilling, skill upgrading, or new performance demands (Schwarz 2024). The concept of job exposure helps capture this nuance. Exposure-based approaches recognize that occupations differ not simply in whether they survive or disappear, but in the degree to which their constituent tasks can be codified, predicted, automated, or augmented by AI systems. Consequently, a highly exposed occupation may still remain viable if its non-automatable elements retain value or if AI complements rather than replaces human judgement. Exposure is therefore a bridge concept between technological capability and labor market outcome. (Kim and Lee 2024b)

Reskilling emerges as the central adaptive response within this conceptual landscape. If GenAI changes the structure of tasks rather than merely erasing jobs, then workers, firms, and institutions must respond by updating capabilities, redesigning training systems, and developing mechanisms for transition. Reskilling is not only an individual responsibility but also an institutional challenge involving education systems, labor market policy, organizational strategy, and digital infrastructure. This makes it a critical component of the broader debate on how societies can absorb technological change without exacerbating exclusion and inequality (Lian et al. 2024). Taken together, these concepts suggest an integrative logic in which generative AI increases occupational exposure, exposure contributes to labor market disruption, disruption raises the risk of technological unemployment or insecurity, and reskilling functions as a key adaptive mechanism. This conceptual framing informs the bibliometric mapping conducted in the present study (Bankins et al. 2024).

Method

This This study employs a bibliometric review design to map the development of research on technological unemployment in the age of generative AI. Bibliometric review is especially appropriate for fast-growing and interdisciplinary fields because it enables the systematic analysis of publication patterns, citation structures, thematic relationships, and collaboration networks. Unlike a purely narrative review, bibliometric analysis allows the literature to be examined at scale while preserving analytical transparency.

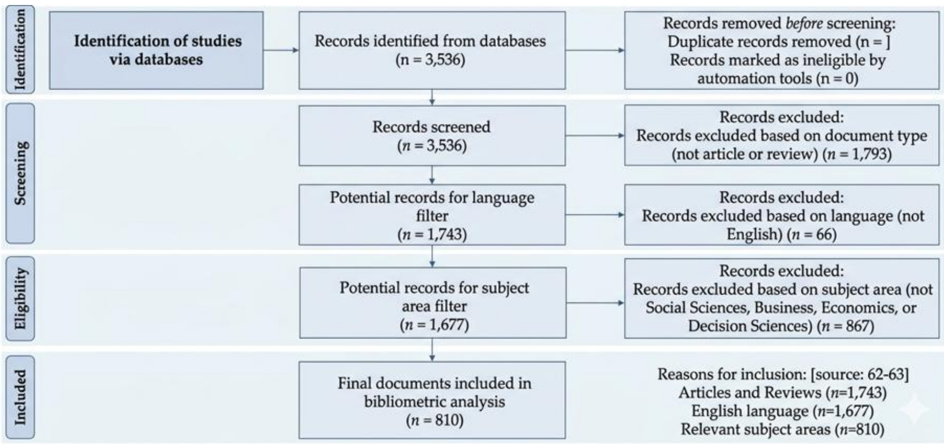

Figure 1. PRISMA Flowchart

Source: Scopus Database

The data collection process followed a structured screening strategy. The initial search identified 3,536 documents. Restricting the dataset to article and review document types reduced the corpus to 1,743 records, limiting the language to English reduced it to 1,677 records, and filtering by the most relevant subject areas—Social Sciences, Business/Management, Economics/Econometrics/Finance, and Decision Sciences—resulted in a final dataset of 810 documents. These screening stages are documented in the uploaded file.

The final dataset spans the years 2022–2026 and was analyzed using Bibliometrix/Biblioshiny. The descriptive indicators show that the corpus covers 538 sources, includes 2,351 authors, contains 101,014 references, and reflects an annual growth rate of 18.63%. The dataset also records 2,576 author keywords, an average document age of 1.44 years, and an average of 16.24 citations per document. These metrics indicate that the field is recent, rapidly expanding, and already attracting substantial citation attention. The analytical approach is divided into two complementary components: performance analysis and science mapping. Performance analysis examines annual publication trends, leading authors, sources, affiliations, countries, and highly cited documents. Science mapping investigates the field's intellectual, conceptual, and social structure through co-citation analysis, keyword co-occurrence analysis, thematic mapping, thematic evolution, collaboration networks, and three-field linkages. Together, these techniques provide a multidimensional portrait of how the field is growing, what themes dominate, and how the literature is being organized. As with all bibliometric studies, the analysis is shaped by database scope, keyword standardization, and threshold selection. However, by combining transparent screening criteria with multiple mapping techniques, the study seeks to provide a robust and analytically coherent representation of the current research landscape.

Result and Discussion

Descriptive Overview of the Dataset

The final dataset comprises 810 documents published between 2022 and 2026, indicating that the literature on technological unemployment, generative AI, labour market disruption, job exposure, and reskilling is both recent and rapidly expanding. These documents are distributed across 538 sources, which suggests that the field has developed through a wide and interdisciplinary publication landscape rather than through a narrow concentration in a few specialised outlets. The dataset records an annual growth rate of 18.63%, confirming a strong upward trajectory of scholarly interest during the period under review. In terms of authorship structure, the corpus involves 2,351 authors, reflecting a large and diverse research community. Of these, 162 authors produced single-authored documents, while the mean number of co-authors per document is 3.05, indicating that collaborative authorship is the dominant mode of knowledge production. International co-authorship reaches 26.17%, which suggests that more than one-quarter of the publications were generated through cross-country collaboration. Overall, the field is not only expanding but also becoming increasingly collaborative and internationally connected. The knowledge base underlying the dataset is substantial. The 810 documents collectively contain 101,014 references and 2,576 author keywords, indicating both dense citation linkages and considerable thematic diversity. At the same time, the average document age is only 1.44 years, confirming the high recency of the literature. Despite this youth, the dataset already records an average of 16.24 citations per document, showing that the topic has rapidly achieved scholarly visibility. Taken together, these indicators portray a young, fast-growing, interdisciplinary, and increasingly international field with strong citation momentum.

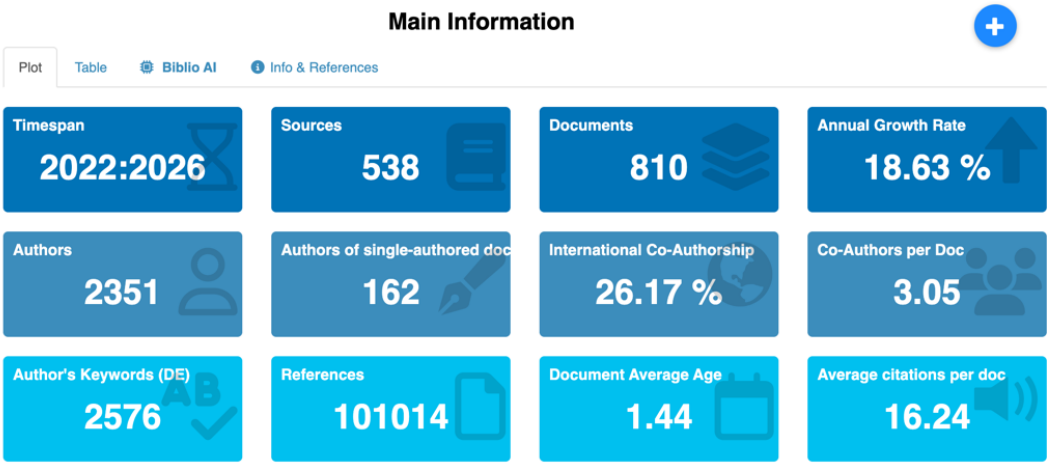

Figure 2. Descriptive Overview of the Dataset
Source: Biblioshiny

Annual Scientific Production

The annual scientific production reveals a steep upward trend in publication output. The field produced 51 articles in 2022, 67 in 2023, 171 in 2024, 420 in 2025, and 101 in 2026. This trajectory demonstrates that the field entered a pronounced growth phase after 2023, with 2025 representing the peak year of publication in the present dataset. The acceleration between 2023 and 2025 is particularly striking. Output more than doubled between 2023 and 2024 and then surged again in 2025. This pattern strongly suggests that the rise of large language models and public attention to generative AI has acted as a catalyst for scholarly production. The lower count in 2026 should be interpreted cautiously because it likely reflects an incomplete publication year rather than a substantive decline in research interest. Overall, the annual production pattern indicates that research on technological unemployment in the GenAI era is moving rapidly from early formation toward expansion and consolidation. The publication curve suggests that the field is not stabilising yet; rather, it remains in an active growth stage.

Annual Scientific Production

Plot Table

Show 10 rows Excel

Year	Articles
2022	51
2023	67
2024	171
2025	420
2026	101

Showing 1 to 5 of 5 entries Previous 1 Next

Figure 3. Annual Scientific Production
Source: Biblioshiny

Leading Authors and Their Local Impact

Author-level analysis shows that the field is characterised by a relatively dispersed but visible set of contributors. Sarah Bankins emerges as the most prominent author in terms of combined productivity and impact, with an h-index of 3, a g-index of 4, an m-index of 0.750, 690 total citations, and 4 publications since 2023. Her position indicates both sustained publication activity and strong recognition within the field. Arup Varma records the highest citation volume among the leading authors, with 901 citations, an h-index of 3, a g-index of 3, and 3 publications since 2022. Herman Aguinis also displays substantial influence, with 735 citations from 2 publications. Greg J. Bamber similarly contributes high citation impact, while Amany Elbanna and Lorentsa Gkinko represent early and stable contributors, each with 3 publications and 327 citations. Szufang Chuang and Shahriar Akter stand out for their high m-index values, indicating rapid citation accumulation over a relatively short publication window. These results suggest that the field is still open and not monopolised by a very small core of scholars. Influence is distributed across authors from human resource management, labour economics, management, information systems, and digital work studies, reinforcing the interdisciplinary nature of the literature.

Authors' Local Impact

Plot Table

Show 10 rows Excel Search:

Author	h_index	g_index	m_index	TC	NP	PY_start
BANKINS SARAH	3	4	0.750	690	4	2023
CHUANG SZUFANG	3	3	1.000	59	3	2024
ELBANNA AMANY	3	3	0.600	327	3	2022
GKINKO LORENTSA	3	3	0.600	327	3	2022
VARMA ARUP	3	3	0.600	901	3	2022
ACEMOGLU DARON	2	2	0.400	380	2	2022
AGUINIS HERMAN	2	2	0.500	735	2	2023
AKTER SHAHRIAR	2	2	1.000	17	2	2025
ANDALIBI NAZANIN	2	2	0.500	64	2	2023
BAMBER GREG J.	2	2	0.500	634	2	2023

Previous 1 2 3 4 5 ... 157 Next

Figure 4. Leading Authors and Their Local Impact

Source: Biblioshiny

Authors Production over Time

The temporal production pattern of leading authors further supports the interpretation of the field as recent and rapidly developing. The earliest visible author activity appears in 2022, with contributors such as Amany Elbanna, Lorentsa Gkinko, and Pascual Restrepo. A second and more concentrated wave emerges from 2023 onward, particularly around Sarah Bankins and related contributors. The year 2024 appears as the key point of author-level acceleration. Several influential scholars—including Bankins, Chuang, Kim Byung-Jik, Lee Julak, Mauricio Marrone, and Simon Lloyd D. Restubog—show visible publication activity during this period, with some extending into 2026. This continuity suggests that the field is moving toward a more cumulative and stable pattern of contribution rather than being driven solely by isolated publications.

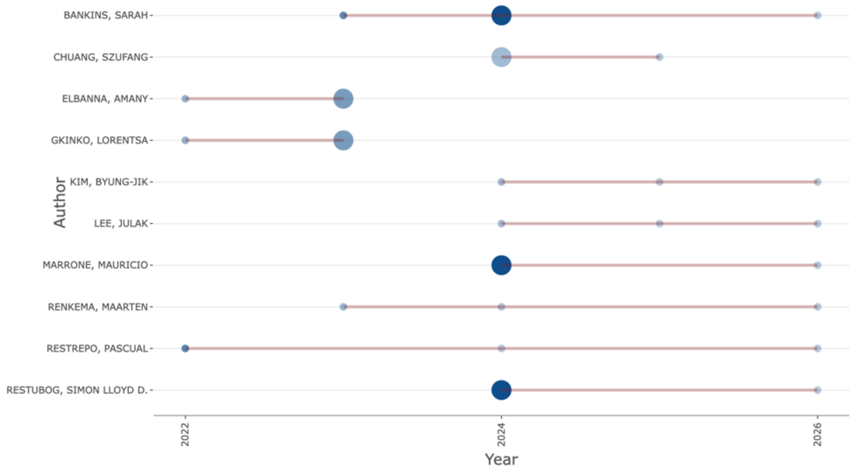

Figure 5. Authors Production over Time
Source: Biblioshiny

Most Relevant Sources

The source analysis confirms that the field is highly interdisciplinary. The most productive source is Sustainability (Switzerland) with 18 documents, followed by Proceedings of the ACM on Human-Computer Interaction with 16 documents and Technological Forecasting and Social Change with 10 documents. Other relevant outlets include International Journal of Human-Computer Interaction, Journal of Applied Learning and Teaching, Journal of Management Studies, and Societies, each contributing 6 documents, while Behavioral Sciences, Eurasian Business Review, and Frontiers in Education contribute 5 documents each. This distribution shows that the field is not dominated by a single disciplinary outlet. Instead, the conversation is spread across sustainability studies, human–computer interaction, technology forecasting, management, education, and behavioural science. Such dispersion reflects the fact that technological unemployment in the

GenAI era is simultaneously being examined as a labour issue, a management challenge, an educational problem, and a sociotechnical transformation.

Figure 6. Most Relevant Sources
Source: Biblioshiny

Most Relevant Affiliations

Institutional analysis reveals a globally distributed but moderately concentrated publication structure. Arizona State University is the most productive affiliation with 9 articles, followed by Macquarie University and Monash University with 8 articles each. Tsinghua University contributes 7 articles, while Symbiosis International (Deemed University) and the University of Oxford each produce 6. Lancaster University, RMIT University, the University of Bath, and the University of Johannesburg each contribute 5 articles. These results suggest that the field is not driven by a single institutional centre. Instead, it is shaped by multiple universities across the United States, Australia, China, the United Kingdom, India, and South Africa. This pattern reinforces the interpretation that the field is internationally visible but still institutionally dispersed.

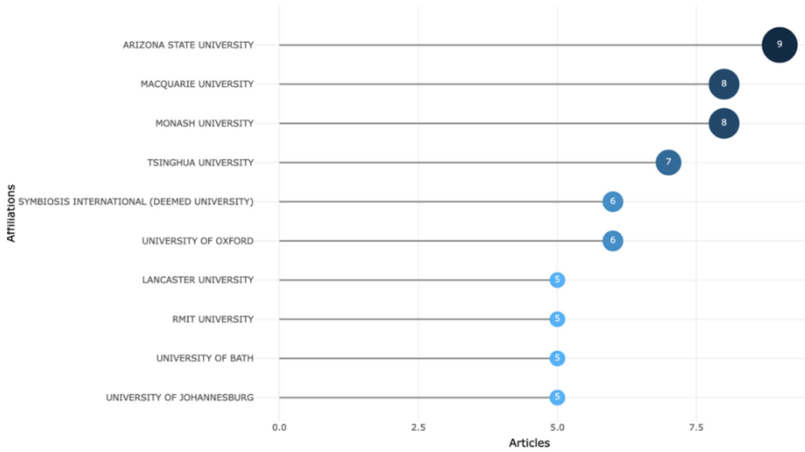

Figure 7. Most Relevant Affiliations

Source: Biblioshiny

Corresponding Authors' Countries

The country-level distribution shows that the United States is the leading contributor, followed by China, the United Kingdom, and India. A second tier includes Germany, Italy, Australia, and Spain, while Korea, Canada, Poland, France, the Netherlands, Saudi Arabia, Turkey, South Africa, Portugal, the United Arab Emirates, Hungary, and Romania also appear among the contributing countries. An important feature of the country chart is the visible dominance of single-country publications over multiple-country publications in several major contributing nations. This suggests that although the field is internationally distributed, much of its production still occurs within domestic research ecosystems. In other words, the field is global in participation but not yet fully internationalised in its collaboration structure.

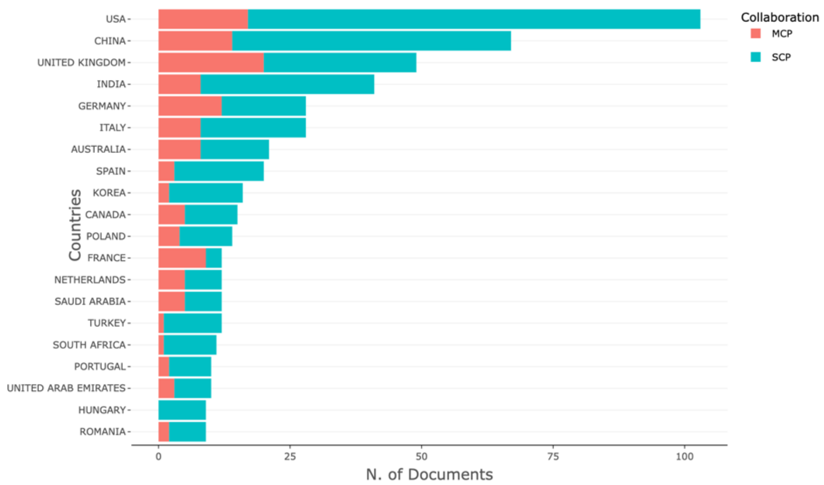

Figure 8. Corresponding Authors' Countries
Source: Biblioshiny

Most Globally Cited Documents

Citation analysis identifies a set of highly influential publications that anchor the field. The most globally cited document is Budhwar P. (2023) in Human Resource Management Journal with 630 citations, followed by Thornhill-Miller B. (2023) in Journal of Intelligence with 422 citations and Acemoglu D. (2022) in Journal of Labor Economics with 375 citations. Other highly cited works include Bankins S. (2024) in Journal of Organizational Behavior with 364 citations, Firat M. (2023) in Journal of Applied Learning and Teaching with 347 citations, and Dempere J. (2023) in Frontiers in Education with 346 citations. Additional influential documents include Fügener A. (2022) in Information Systems Research with 332 citations, Parent-Rocheleau X. (2022) in Human Resource Management Review with 316 citations, Malik N. (2022) in International Journal of Manpower with 299 citations, and Morandini S. (2023) in Information Sciences with 298 citations. The spread of these documents across HRM, labour economics, organisational behaviour, education, and information systems again underlines the interdisciplinary backbone of the field.

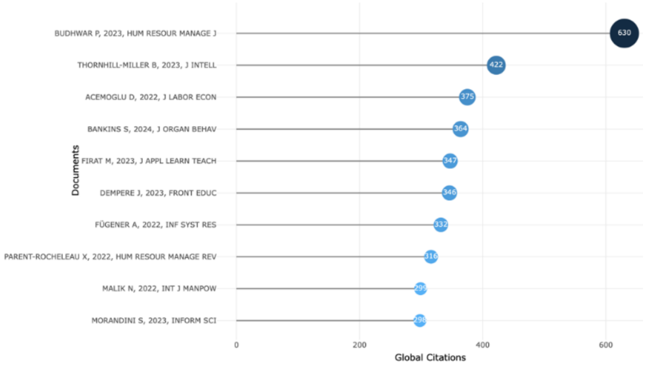

Figure 9. Most Globally Cited Documents
Source: Biblioshiny

Three-Field Linkage Between References, Authors, and Keywords

The three-field plot shows that the field is built on a combination of foundational references, emergent authors, and consolidating thematic keywords. On the reference side, classic works such as Osborne et al. on job computerisation and McAfee and Brynjolfsson on the second machine age remain highly connected to contemporary contributions. On the author side, names such as Kim Byung-Jik, Lee Julak, Sarah Bankins, Simon Lloyd D. Restubog, Mauricio Marrone, Arup Varma, and Greg J. Bamber are strongly linked to the keyword landscape. On the keyword side, the most prominent terms include artificial intelligence, future of work, generative AI, ChatGPT, employment, digital transformation, sustainability, automation, decision making, and machine learning. This linkage indicates that the field is being constructed through the interaction of classical automation debates, new generations of AI-and-work scholarship, and a rapidly stabilising vocabulary centred on work transformation, employment, and adaptation.

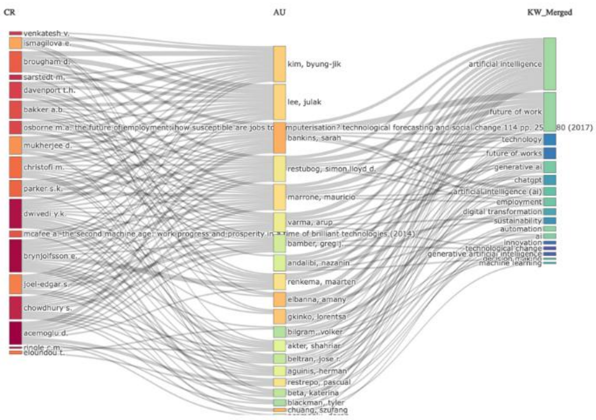

Figure 10. Three-Field Linkage Between References, Authors, and Keywords

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Source: Biblioshiny

Intellectual Structure of the Field

The co-citation network reveals that the field is organised around four broad intellectual clusters. The first cluster is centred on the economics of automation, technological change, and labour displacement. Key names in this cluster include Acemoglu, Brynjolfsson, McAfee, and Restrepo. This cluster represents the classical and neo-classical foundation of the field, where technological unemployment is primarily discussed in terms of productivity, labour substitution, and the long-run relationship between innovation and employment. The second cluster is organised around AI, digital transformation, and strategic management perspectives. Authors such as Dwivedi and Chowdhury appear prominently in this domain, suggesting that the field draws substantially from work on digital disruption, organisational transformation, and the societal implications of AI adoption. This cluster functions as an important bridge between technological capability and broader management discourse.

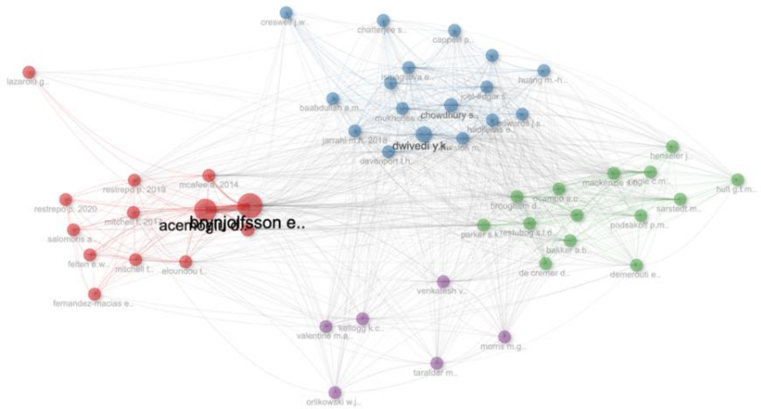

Figure 11. Intellectual Structure of the Field
Source: Biblioshiny

The third cluster reflects organisational and human resource management foundations. Here, the visible presence of authors associated with measurement, organisational behaviour, and management research suggests that the field is increasingly interested in how AI influences work design, employee experience, organisational capability, and management practice. This cluster also shows that the future-of-work debate is not confined to macroeconomic concerns but is being actively incorporated into firm-level and HRM-related scholarship. The fourth cluster points toward sociotechnical and digital work perspectives. The presence of authors such as Orlikowski, Kellogg, Tarafdar, and Venkatesh suggests a growing concern with digital work systems, technology-mediated adaptation, technostress, and the reorganisation of work under algorithmic conditions. This cluster is especially important for understanding the move from simple substitution models toward more complex interpretations of human–technology interaction. Taken together, the co-citation structure indicates that the field is intellectually plural. It brings together labour economics, management, organisational studies, and sociotechnical scholarship, thereby confirming that technological unemployment in the age of GenAI cannot be adequately understood through a single disciplinary lens.

Conceptual Structure of the Field

The keyword co-occurrence network shows that artificial intelligence is the central conceptual anchor of the field. Around this term, several thematic groupings become visible. One cluster focuses on employment, job displacement, technological change, labour market, innovation, and robotics. This grouping reflects the classical concern with labour market disruption and the economic consequences of technological change. A second cluster revolves around future of work, decision making, ChatGPT, large language model, language model, human–computer interaction, behavioural research, and ethical technology. This suggests that the field is increasingly moving toward more refined discussions of cognitive automation, AI-supported decision systems, and the role of emerging generative tools in work settings. The presence of both future of work and ChatGPT in this cluster is especially telling: it indicates that the literature has begun to connect abstract future-of-work debates with specific technological artefacts. A third cluster highlights human, occupational exposure, workplace, skill, risk assessment, and perception. This grouping points toward a more human-centred and occupational perspective within the literature, where the focus is not simply on AI as a technological object but on its effects on exposure, capability, and vulnerability. The inclusion of skill in this cluster is consistent with the study's broader focus on reskilling and adaptation.

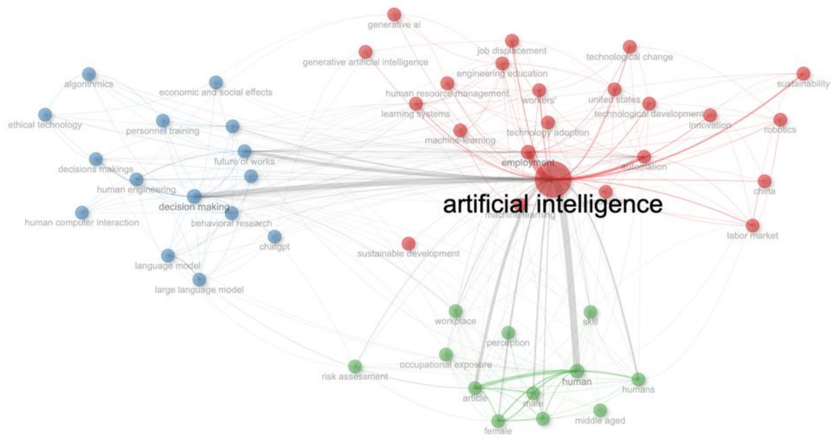

Figure 12. Conceptual Structure of the Field

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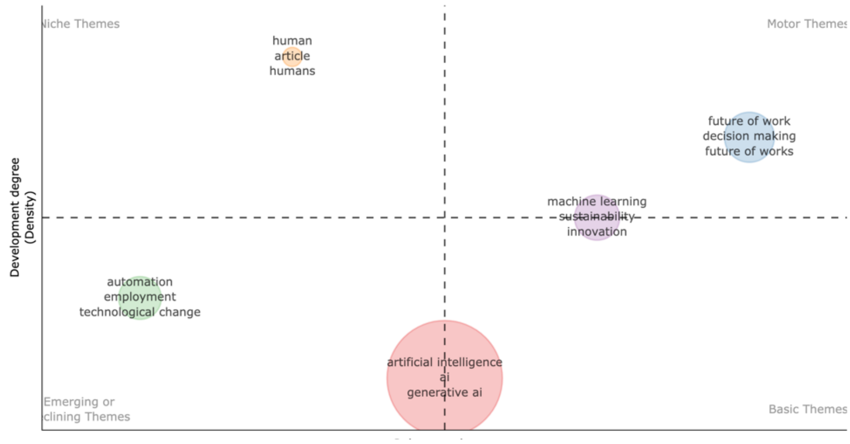

Figure 13. Thematic map
Source: Biblioshiny

The thematic map adds another layer of interpretation. Future of work and decision making appear as motor themes, indicating that they are both highly developed and central to the field. By contrast, artificial intelligence, AI, and generative AI occupy the basic theme quadrant, suggesting that they are central to the field but still in a process of conceptual consolidation. Machine learning, innovation, and sustainability are positioned near the basic-to-motor boundary, reflecting their supportive but still evolving role. Meanwhile, automation, employment, and technological change appear in the emerging-or-declining quadrant, which may indicate that while these concepts remain important, they are increasingly being reinterpreted through newer AI-specific vocabularies. Overall, the conceptual structure suggests that the field is undergoing a thematic transition: from broad and familiar terms such as automation and technological change toward more specific concepts such as generative AI, future of work, decision making, occupational exposure, and adaptive capability.

Social Structure of the Field

The collaboration network reveals that the social structure of the field is characterised by multiple relatively small but visible author clusters rather than a single dense global core. One important cluster is built around Sarah Bankins, Simon Lloyd D. Restubog, and Mauricio Marrone, indicating an active collaboration stream at the intersection of organisational behaviour, work transformation, and employee adaptation. Another cluster forms around Yogesh K. Dwivedi and associated collaborators, reflecting the influence of digital transformation and AI-related management scholarship. A separate collaboration group centres on Arup Varma, Greg J. Bamber, and Herman Aguinis, which suggests the importance of HRM-oriented collaboration in shaping the field. Smaller but visible clusters also emerge around Kim Byung-Jik and Lee Julak, as well as Acemoglu and Restrepo. The presence of these distinct clusters indicates that the field is still somewhat fragmented, with collaboration occurring within thematic or disciplinary sub-communities rather than through a highly integrated network. This fragmented-but-growing collaboration pattern is consistent with the broader profile of an emerging interdisciplinary field. Scholars from economics, HRM, management, information systems, and sociotechnical studies are all participating, but they have not yet converged into a single, strongly interconnected collaboration structure. As the field matures, stronger inter-cluster collaboration may become an important indicator of theoretical integration and cumulative knowledge development.

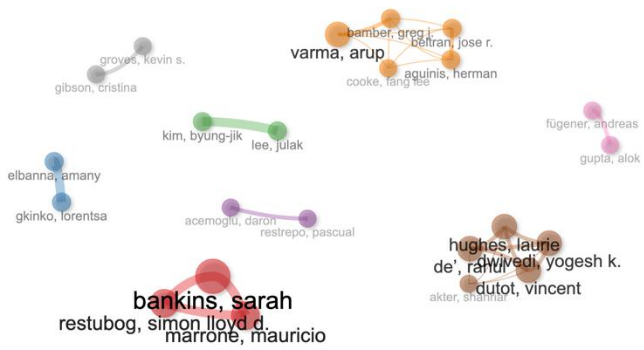

Figure 14. Social Structure of the Field
Source: Biblioshiny

Discussion

The findings of this bibliometric review show that research on technological unemployment in the age of generative AI is no longer organised around a narrow fear of job loss alone. Instead, the field increasingly frames technological change as a broader process of labour market disruption, occupational exposure, decision transformation, and workforce adaptation. This is one of the most important conceptual shifts visible across the results. In earlier automation literature, the dominant question was whether technology would replace workers. In the current literature, the more relevant question is how work is being reconfigured and what kinds of capabilities are required to remain employable within AI-mediated environments.

The results also indicate that generative AI has changed the occupational geography of risk. Concerns are no longer limited to routine manual or clerical labour. The conceptual and intellectual maps show that scholars are increasingly focused on decision-making, future of work, human-centred exposure, and the transformation of knowledge-intensive roles. This suggests that technological

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unemployment in the GenAI era should be understood as a layered phenomenon that includes full displacement, partial substitution, augmentation, role redesign, and shifting skill requirements. Another significant insight is the centrality of reskilling, even when the term itself is not always dominant in the most basic keyword clusters. The field's movement toward human-centred, skill-oriented, and future-of-work themes indicates that reskilling has become an implicit strategic response to disruption. This matters because it shifts the discussion from technological determinism toward adaptive capacity. In other words, the literature increasingly suggests that the future of work will not be shaped solely by what AI can do, but by how workers, firms, education systems, and governments respond to AI-enabled change.

The social and institutional structure of the field further shows that this debate is global but unevenly distributed. Leading countries and affiliations are concentrated in digitally advanced or research-intensive contexts, while collaboration remains partly nationally anchored. This raises an important issue for future scholarship: the current literature may underrepresent low- and middle-income economies, informal labour markets, and contexts with weaker reskilling infrastructures. As a result, global conclusions about technological unemployment may risk being overly shaped by the experience of high-capacity research ecosystems. Overall, the bibliometric evidence suggests that the field is moving from a phase of conceptual alarm toward a phase of analytical differentiation. The future-of-work debate is becoming more precise, more interdisciplinary, and more institutionally grounded. That is a healthy development. Panic is cheap; analytical clarity is rarer and much more useful (Zhou and Hou 2024).

Future Research Agenda

Future research should move in several directions. At the micro level, more work is needed on how workers experience AI exposure in daily practice. This includes job insecurity, deskilling, work intensification, AI reliance, identity shifts, and human–AI collaboration. Studies that examine how workers interpret and adapt to GenAI tools can deepen understanding of the lived experience of labour market disruption. At the meso level, organisational responses deserve greater attention. Research should investigate how firms redesign jobs, distribute tasks between humans and AI systems, reshape recruitment criteria, and build internal reskilling ecosystems. This is especially important in sectors where AI is likely to alter not only tasks but also evaluation systems, communication patterns, and managerial expectations. At the macro level, comparative research across national contexts is urgently needed. Labour regulation, welfare systems, digital infrastructure, educational capacity, and workforce policy differ widely across countries. These institutional differences are likely to shape the real consequences of technological disruption and the effectiveness of reskilling responses. More studies from developing economies, emerging markets, and informal labour settings are particularly necessary. Methodologically, future studies should complement bibliometric analysis with systematic reviews, longitudinal occupational data, sector-based studies, and mixed-method research. Bibliometric mapping is powerful for revealing structure, but it does not by itself explain causal processes or lived experience. A stronger integration of mapping and empirical analysis would make the field far more mature.

Theoretical Implications

This study has several theoretical implications. First, it suggests that technological unemployment should no longer be treated as a simple linear process of machine-for-human replacement. In the GenAI era, a more appropriate theoretical lens is task transformation, where different parts of a job may be substituted, augmented, or revalued in different ways. Second, the results reinforce the usefulness of exposure-based approaches. Occupations should not be analysed as indivisible units (Giordano et al. 2024). Their internal task composition matters, and this is particularly important for cognitive and communication-heavy roles now affected by generative systems. Exposure theory therefore offers a more nuanced way to connect technological capability with labour market outcome. Third, the study points toward the need for theoretical integration across economics, HRM, organisational behaviour, and sociotechnical studies. The field's co-citation and thematic structures show that no single tradition is sufficient on its own. A robust theory of work in the GenAI era must account for productivity, institutional adaptation, skill formation, digital mediation, and inequality simultaneously (Giordano et al. 2024).

Practical Implications

For policymakers, the findings underline the urgency of anticipating labour market change before unemployment effects become fully visible in aggregate statistics. Governments need investment in labour market intelligence, occupational exposure mapping, active labour market policies, and reskilling infrastructure. Waiting until displacement is obvious is a fine way to build policy regret. For universities and training providers, the findings suggest that curricula and lifelong learning systems must evolve rapidly. AI literacy, critical thinking, ethical reasoning, communication, creativity, and adaptive problem-solving are becoming increasingly central. Education systems that remain static while work becomes dynamic will produce skill mismatch at industrial scale. (Bankins et al. 2024) For

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firms and HR leaders, the literature suggests that AI adoption should not be treated merely as a technology project. It is also a workforce design project. Organisations need to identify which tasks can be automated, which require human judgement, and which demand new forms of collaboration between people and intelligent systems. Transparent communication, strategic reskilling, and human-centred implementation will be critical for preventing resistance, distrust, and dysfunctional adoption (Baek et al. 2024).

Conclusion

This study provides a bibliometric map of research on technological unemployment in the age of generative AI by integrating the themes of labour market disruption, job exposure, and reskilling. The findings show that the field is recent, fast-growing, interdisciplinary, and increasingly influential. More importantly, the literature is evolving conceptually. The dominant conversation is no longer limited to automation as a threat to employment quantity; it increasingly addresses how work is reorganised, how occupations are exposed, and how adaptive capacities can be built. The intellectual structure of the field demonstrates that the debate is rooted in labour economics, digital transformation, HRM, and sociotechnical scholarship. Its conceptual structure shows a thematic shift from broad ideas such as automation and technological change toward more precise concerns involving generative AI, future of work, decision making, occupational exposure, and human-centred adaptation. Its social structure reveals growing but still fragmented collaboration among scholars across different disciplinary traditions. Taken together, these findings suggest that technological unemployment in the GenAI era should be understood as a dynamic process of labour transformation rather than a single end-state of job loss. The future of work is not simply being erased by AI, nor is it being magically upgraded by techno-hype. It is being reassembled—unevenly, quickly, and with serious consequences for workers, firms, and institutions.

Limitations

This study has several limitations. First, as a bibliometric review, it relies on publication metadata, citation structures, and keyword relationships rather than full-text interpretation of every document. This means that the analysis is well suited to identifying patterns at scale but less able to capture conceptual nuance in individual studies. Second, the dataset is shaped by explicit screening decisions concerning language, document type, time span, and subject area. These criteria improve analytical focus, but they may exclude relevant work published in other languages, other document types, or adjacent disciplinary domains. Third, the field itself is highly dynamic. Because generative AI is developing rapidly, citation structures and thematic patterns may change quickly, meaning that the present map captures a moving frontier rather than a fully stabilised canon.

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