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Research Paper

Labour market dynamics and skill development: bibliometric and scientometric analysis

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Abstract: The relationship between labour markets and skill development has become a central area of research, particularly as Industry 4.0 and rapid technological transformation reshape the demand for skills. We use bibliometric and scientometric analysis in this study to investigate the main research trends, key publications, and evolving thematic clusters in this field of inquiry. We review 623 articles published between 1975 and 2024 and analyse the impact of automation on the demand for soft and technical skills, as well as how the skill mismatches between education and the labour market have evolved over time. In addition, the study highlights a skewed global map of research activity, which is concentrated in the United States, Europe and the Asia-Pacific region but has sparse coverage in Africa and parts of South Asia. These results point to the need for stronger collaboration between the university and industry in tailoring skill training to the changing needs of the labour market. Therefore, the findings have significant implications for policy makers, educators, and entrepreneurs interested in promoting the adaptability of the labour force in the digital age.

Keywords: Labour market dynamics; skill development; employability; Bibliometrics; Scientometrics; Industry 4.0; workforce adaptability.

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1. Introduction

1.1 Background and motivation

The relationship between education, skills and labour-market outcomes has long been central to labour economics, higher education research and workforce policy. Human-capital accounts treat education and skill formation as investments that can enhance productive capacity and improve earnings or employment prospects (Becker, 1962; Heckman & Kautz, 2012). Signalling accounts, by contrast, emphasise that employers cannot directly observe applicants' productivity and therefore rely on qualifications, grades, experience and other visible indicators when making recruitment decisions (Piopiunik et al., 2020; Spence, 1973). These perspectives are analytically distinct but not mutually exclusive: education may develop productive capabilities while simultaneously supplying the signals through which those capabilities are recognised and rewarded (Hussey, 2012).

Technological transformation has made this relationship more dynamic and more difficult to interpret. Digitalisation, automation and artificial intelligence alter occupational tasks, reorganise production and create demand for new combinations of technical, cognitive and interpersonal competencies. Evidence of a wage premium for AI-related skills demonstrates that emerging technological capabilities can acquire labour-market value rapidly (Alekseeva et al., 2021), while more recent worker-level research shows that AI exposure is associated with changes in task content, skill use

and wages within occupations rather than only with the disappearance or creation of entire occupations (Engberg et al., 2025). Consequently, the central question is no longer simply whether education increases employability. It is also how educational institutions, employers and workers identify changing skill requirements, how quickly capabilities can be renewed, and how reliably credentials continue to communicate productive capacity.

1.2 Research gap

Research addressing these questions has expanded across several disciplinary traditions, but the resulting knowledge base remains intellectually fragmented. Labour-economics studies commonly examine returns to education, occupational mobility, mismatch and wage effects. Higher education and employability research focuses on graduate preparedness, curriculum design, employer expectations and career transitions. Management and technology scholarship gives greater attention to organisational adaptation, Industry 4.0, digital transformation and the reconfiguration of work. These streams increasingly use a shared vocabulary—skills, employability, mismatch, adaptability, technology and human capital—yet they do not necessarily employ the same theoretical assumptions or units of analysis. A shared term such as "skill gap," for example, may refer to an individual's capability deficit, an employer's recruitment difficulty, a curriculum-workplace misalignment or a structural shortage within an industry. Rikala et al. (2024) show that Industry 4.0 skill-gap research remains heterogeneous in both conceptualisation and measurement, illustrating why the accumulation of publications does not automatically produce conceptual integration (Rikala et al., 2024).

Previous bibliometric studies have mapped valuable parts of this terrain. Dinh et al. (2023) examined employability research, Masduki et al. (2022) mapped graduate employability, Martin Gomez and Bartolome Muñoz de Luna (2023) reviewed skills learning for graduate employability, and Malanski et al. (2022) analysed labour within agrifood value chains (Dinh et al., 2023; Malanski et al., 2022; Martin Gomez & Bartolome Muñoz de Luna, 2023; Masduki et al., 2022). Their contributions establish the growth and thematic diversity of particular research streams. However, their substantive boundaries leave a broader intellectual question unresolved: how have labour-market dynamics, employability, skills mismatch, soft skills, technological change and educational adaptation become connected within the same scholarly conversation over time, and has this convergence produced a coherent explanatory field or only an aggregation of adjacent topics?

This question matters theoretically and practically. Without an integrated account, clusters identified through bibliometric mapping risk being treated as self-explanatory, although their meaning depends on the theories and debates from which their keywords emerged. The same pattern can support different interpretations: a concentration of terms relating to credentials and employer perceptions may indicate the continuing importance of signalling, whereas terms relating to earnings, productivity and performance may reflect a human-capital interpretation. Likewise, growing attention to digital and soft skills may indicate complementarity between technological and interpersonal capabilities, but keyword co-occurrence alone cannot establish that one produces the other. A theoretically grounded map is therefore required to distinguish the intellectual structure of the field from causal claims that the data cannot support.

1.3 Research questions and contribution

The present study addresses this gap through a bibliometric and scientometric analysis of 623 Web of Science Core Collection articles published between 1975 and 2024. It asks four questions: First, what are the most influential articles, journals, authors and countries at the intersection of labour-market dynamics and skill development? (RQ1). Secondly, what keyword co-occurrence clusters characterise the intellectual structure of the field, and how do they relate to human-capital and signalling traditions? (RQ2). The third research question (RQ3) is: How are scientific

production and international collaboration geographically distributed? And finally: How does the integrated map corroborate, extend or complicate prior bibliometric reviews of employability and Industry 4.0 skills? (RQ4).

The study makes four principal contributions. First, it provides a longitudinal account of how research on capability formation, labour-market recognition, mismatch and technological reconfiguration has developed within a shared field. Second, it interprets the resulting thematic structure through human-capital and signalling perspectives, connecting bibliometric patterns to substantive theory without treating co-occurrence as causal evidence. Third, it identifies the geographic and disciplinary asymmetries that shape the knowledge base, including the concentration of research within high-income labour-market contexts. Fourth, it delimits the interpretive scope of bibliometric evidence and translates what would previously have been policy prescriptions into an explicit research agenda. The study's 1975–2024 window and transparent Web of Science design support these intellectual contributions by making long-term thematic change and collaboration patterns visible.

The remainder of the article proceeds as follows. Section 2 reviews the theoretical and substantive literature on human capital, signalling, employability, skills mismatch and technological transformation, and develops the integrative framework used to interpret the bibliometric results. Section 3 explains the data, search strategy and analytical procedures. Section 4 presents publication, citation, geographic, collaboration and cluster findings. Section 5 interprets those findings in relation to the literature and theoretical framework. Section 6 develops the theoretical, research and practical implications, and Section 7 concludes.

2. Literature review and theoretical framework

2.1 Human capital, signalling and the education–employment relationship

Human-capital theory provides one of the most influential explanations of the relationship between education and labour-market outcomes. In this tradition, education, training and experience are investments that can increase productive capability and generate returns through higher earnings, improved employment prospects or greater adaptability (Becker, 1962). The framework has progressively widened beyond formal qualifications and technical knowledge. Research on non-cognitive capabilities demonstrates that motivation, perseverance, self-regulation and other behavioural attributes can also contribute to educational and labour-market outcomes (Heckman & Kautz, 2012). This wider conception is particularly relevant to contemporary employability research, in which communication, collaboration, adaptability and problem-solving are frequently discussed alongside occupation-specific and digital skills.

Signalling theory offers a different account of the same empirical association. Employers make recruitment decisions under uncertainty and cannot observe an applicant's future productivity directly. Educational credentials, grades, work experience and demonstrated skills can therefore function as signals that reduce informational uncertainty (Spence, 1973). Experimental evidence indicates that employers respond to multiple skill signals when assessing entry-level applicants, supporting the view that employability depends partly on how capabilities are communicated and interpreted rather than only on whether they exist (Piopiunik et al., 2020). Research on overeducation and qualifications mismatch further shows that the market value of credentials is conditioned by institutional and occupational context (García-Mainar & Montuenga, 2019).

The two traditions should not be presented as mutually exclusive alternatives. The same educational experience may build productive capability and provide a credible signal of that capability. Hussey's (2012) examination of MBA education illustrates the empirical difficulty of separating human-capital augmentation from signalling value, while the broader literature indicates that the balance between the

two mechanisms may differ by programme, occupation and career stage (Hussey, 2012). For the present study, the theories are therefore used as complementary interpretive lenses. Clusters centred on productivity, earnings, performance and returns are likely to draw more directly on human-capital reasoning; clusters centred on credentials, employer perceptions, requirements and recruitment are more readily interpreted through signalling. Bibliometric co-occurrence cannot determine which mechanism causally dominates, but it can reveal where the field's theoretical vocabularies concentrate and overlap.

2.2 Employability, graduate preparedness and skills mismatch

Employability extends beyond possession of a fixed list of skills. It concerns the capacity to obtain, retain and move within employment, and therefore reflects interactions among individual capabilities, educational opportunities, employer practices and labour-market conditions. A systematic review by Eimer and Bohndick (2023) demonstrates the plurality of employability models used in higher education, underscoring that employability may be conceptualised as an outcome, a developmental process, a set of resources or a relation between individuals and context. This plurality is analytically important: universities can develop capabilities and career-management resources, but they do not control labour demand, recruitment conventions or the structural availability of suitable work (Eimer & Bohndick, 2023).

Employer expectations nevertheless shape how employability is operationalised. Tushar and Sooraksa's (2023) semi-systematic review identifies recurring demand for communication, teamwork, problem-solving, adaptability and other transferable capabilities, alongside technical competence. Poláková et al. (2023) similarly document the increasing prominence of soft skills in technologically changing workplaces. These findings challenge a simple opposition between "hard" and "soft" skills. As work becomes more data-intensive and technologically mediated, employees may need to combine digital knowledge with judgement, communication and coordination. Employability is therefore better understood as a hybrid capability profile whose value depends on occupational and organisational context (Poláková et al., 2023; Tushar & Sooraksa, 2023).

Skills mismatch describes a related but distinct problem: the capabilities or qualifications supplied by workers do not correspond fully to those required or used in available jobs. Mismatch may be vertical, when education or skill levels exceed or fall below job requirements, or horizontal, when the field or type of capability differs from the work performed. These dimensions should not be collapsed. McGuinness and Sloane (2011), for example, show that education and skill mismatch can have different associations with graduate outcomes, while García-Mainar and Montuenga (2019) connect overeducation and qualifications mismatch to signalling within a segmented labour market (García-Mainar & Montuenga, 2019; McGuinness et al., 2018; McGuinness & Sloane, 2011). More recent evidence shows that mismatch following job displacement can deepen employment and earnings losses when workers move into occupations that do not use their existing skill portfolios effectively (Neffke et al., 2024).

The mismatch literature also complicates claims that universities merely need to "follow employer demand." Employer requirements are heterogeneous, change over time and may reflect short-term recruitment practices as well as durable capability needs. Conversely, curricular change is institutionally slow and cannot anticipate every occupational transition. The central research issue is therefore alignment rather than one-way responsiveness: how educational institutions interpret demand, how employers articulate and signal requirements, how workers translate learning across contexts, and how policy supports retraining and mobility. This relational interpretation provides the bridge between employability scholarship and the labour-market traditions mapped in the present study.

2.3 Industry 4.0, digital transformation and artificial intelligence

Industry 4.0 brought automation, interconnected production, advanced analytics and cyber-physical systems into a common account of industrial transformation. Its significance for labour-market research lies not only in the prospect of job displacement, but also in the reorganisation of tasks and the changing composition of capabilities within jobs. Islam (2022) identifies technological, methodological, social and personal competencies as relevant to employability under Industry 4.0, while Rikala et al. (2024) show that the concept and measurement of Industry 4.0 skill gaps remain inconsistent across studies. The latter finding is especially important for bibliometric interpretation: rapid growth in a topic can coexist with conceptual ambiguity about what is being measured, and at which level the "gap" resides (Islam, 2022; Rikala et al., 2024).

The movement from Industry 4.0 toward more human-centred accounts of Industry 5.0 has reinforced attention to complementarity between technology and human capabilities. Poláková et al. (2023) place soft skills at the centre of this transition, while Kolade and Owoseni's (2022) systematic review connects digital transformation to debates on technological unemployment, wage inequality and job polarisation. Taken together, these studies suggest that workforce transformation is not adequately described as a uniform shift from low skills to high skills. It involves redistribution of tasks, changing combinations of capabilities and unequal adjustment costs across workers, occupations, firms and regions (Kolade & Owoseni, 2022; Poláková et al., 2023).

Artificial intelligence intensifies these dynamics. Vacancy-based evidence shows strong growth and wage premiums for AI-related skills, suggesting that firms value scarce technological capability and that AI demand can spill over into broader organisational hiring patterns (Alekseeva et al., 2021). Worker-level evidence from Germany further indicates that AI exposure is associated with within-occupation changes in tasks, skills and wages (Engberg et al., 2025). These findings support a task- and capability-based interpretation of technological change: occupations are bundles of activities that may be substituted, complemented or reorganised differently. They also reinforce the need for lifelong learning because the relevant unit of adaptation is often the task or skill portfolio rather than the occupational title alone.

The post-2015 and post-2020 growth visible in the present dataset should therefore be interpreted cautiously. The rise coincides with the diffusion of Industry 4.0 discourse, accelerated digital transformation, expanding automation research and more recent attention to AI-enabled work. The bibliometric data can demonstrate temporal association and thematic change, but they cannot by themselves establish that any one technological development caused publication growth. A defensible interpretation should combine the timing of the publication curve with keyword evolution and cluster composition and should acknowledge the normal citation lag affecting recent studies.

2.4 Integrative framework and unresolved intellectual gap

The reviewed literature can be organised as a connected process with four analytically distinct layers. The first is capability formation: education, training and experience develop technical, cognitive, interpersonal and adaptive capacities. The second is labour-market recognition: employers interpret credentials and other signals when making recruitment, allocation and reward decisions. The third is alignment or mismatch: capabilities may correspond imperfectly to job requirements because of curricular delay, information problems, occupational restructuring or restricted mobility. The fourth is technological reconfiguration: digitalisation, automation and AI alter tasks, requirements and the value assigned to particular capability combinations. Human-capital theory is most directly concerned with the formation and productive use of capability, whereas signalling theory illuminates how capability is communicated and recognised under uncertainty. Employability and mismatch connect these mechanisms to transitions and outcomes, and technological transformation changes the conditions under which all four layers operate.

Despite increasing thematic overlap, it remains unclear when these layers became integrated within one research field, which concepts bridge them, and whether newer technology-focused scholarship has displaced or recombined older debates concerning returns, inequality, credentials and mismatch. It is also unclear whether the field's apparent integration extends geographically or is disproportionately structured by research from high-income economies with formal labour markets and degree-based recruitment systems. These are not merely questions about the number of studies, databases or years covered. They concern the intellectual architecture of the literature and the conditions under which its concepts can be generalised.

The present bibliometric study addresses this gap by tracing longitudinal publication and citation patterns, identifying thematic clusters and conceptual bridges, and examining the geography of research production and collaboration. The framework guides interpretation without pre-determining the findings: clusters are examined for their relationship to capability formation, market recognition, mismatch and technological reconfiguration, while human-capital and signalling perspectives are used to interpret, not causally explain, their vocabularies. This approach positions the study as an account of how the field has been assembled over time and where its unresolved theoretical and geographic tensions remain.

Section 3 sets out how the study operationalises this framework through bibliometric and scientometric analysis of 623 Web of Science-indexed articles.

3. Methodology

The scope of the article search was limited to those that dealt with the issue 'Labour Market', and the area of study 'Skill development', as recorded in the Web of Science Core Collection (Turulja et al., 2023).

Review methods answer different kinds of questions. Systematic reviews use explicit inclusion and appraisal procedures to synthesise evidence relating to a bounded question, while scoping reviews are especially useful for clarifying concepts, evidence types and research boundaries across a broad or emerging topic (Snyder, 2019). Meta-analysis is appropriate when sufficiently comparable quantitative studies permit the aggregation of effect sizes. Bibliometric analysis has a different purpose: it examines large-scale publication, citation, co-authorship and keyword relationships to reveal the intellectual, social and conceptual structure of a research field (Donthu et al., 2021). Because the present study asks how a multidisciplinary field developed over five decades, which actors and publications shaped it, how concepts clustered and how collaboration was distributed geographically, bibliometric–scientometric mapping is more suitable than effect aggregation or a narrowly bounded evidence synthesis. Its strength is structural and longitudinal visibility; its limitation is that citation and co-occurrence patterns do not establish causal mechanisms or evaluate the substantive quality of every included study. The interpretation is therefore grounded in a dedicated narrative synthesis of the field's central theories and debates, consistent with guidance that rigorous reviews should connect method, synthesis and contribution (Paul & Criado, 2020).

3.1 Data source and selection criteria

Citation analysis, country and author analysis, journal analysis, network graphs, cluster analysis, and keyword co-occurrence analysis are used in this review to reveal the intellectual structure of a research field, in this case, labour market and skills. These techniques provide a framework (Chen et al., 2024; Clarke & Braun, 2017; Créquit et al., 2018; Gaggero et al., 2020; Luo & Saeheaw, 2024; Malanski et al., 2022) for mapping the thematic evolution, collaboration structure, and structure of the research in this field (based on the selected queries). The citation analysis, specifically highlighting the most highly cited papers, is crucial to identify seminal research that has had a significant influence on the field (Healy et al., 2022; Waugh & Ruppel, 2004). The geographical distribution of publications and citations also reveals

regional contributions to research in this field and disparities in research output and citation impact (Leydesdorff & Persson, 2010; Pan et al., 2012). Through productivity and citation analyses, we can discover the top researchers and the thought leaders in our field. This will allow early-career scholars to find a mentor, and it will allow journals to find reviewers (Dinh et al., 2023).

Journal evaluations, according to the number of articles and citations, help identify core publishing venues (Vinkler, 2010). The data emerging from journals are important for researchers targeting their submissions and for institutions managing library resources or assessing research performance (Bornmann & Leydesdorff, 2014; Tahamtan et al., 2016). Network graphs visualising country collaborations provide insights into international research linkages (Gürsoy, 2023; Santos et al., 2023). Cluster analysis, which organises related keywords into themes, identifies the conceptual structure of the field (Anderson et al., 1987; Muntaner et al., 2012). Finally, keyword co-occurrence networks establish conceptual relations and emphasise emergent themes (Lukac, 2021).

3.2 Search query on Web of Science

Combining these approaches produces actionable insights on labour markets, facilitating informed policy decisions, encouraging academic–industry partnerships, and allowing the identification of trends over time. Ultimately, this integration can help stakeholders connect education to labour demand and support labour force adaptability. The methods were selected in line with the bibliometric guidelines of Donthu et al. (2021) and the interdisciplinary research mapping principles of Huutoniemi and Rafols (2017). The exact query was:

TS = ("labor market " OR "employment market" OR "job market" OR "workforce market" OR “occupational market" OR "human capital market" OR "employment sector")

AND

TS = ("skill gap*" OR "reskilling" OR "upskilling" OR "in-demand skill*" OR "workforce skill*" OR "soft skill*" OR "technical skill*" OR "future skill*" OR "industry 4.0 skill*" OR "industry 4.0 competencies" OR "workplace skill*" OR "emerging skill*")

Timespan: 1975-01-01 to 2024-04-12

Document types: Article, Review, Proceedings Paper

Language: All

Date of extraction: 2024-04-12

The query requires the intersection of a labour-market expression and one of the listed skill-related expressions. It therefore defines a bounded corpus rather than a comprehensive sample of all research on employability, digital skills or the future of work. Relevant publications that do not use both sets of expressions may be missed. A complementary search using these broader terms would be needed to assess the sensitivity of the findings to the search design.

The resulting sample comprised 623 articles: 214 in Education and Educational Research, 175 in Business Economics, 79 in Computer Science, and 155 distributed across 64 other subject areas (e.g., engineering and psychology). Thus, our final sample consisted of 623 articles for 1975–2024.

3.3 VOSviewer settings and clustering parameters

Normalisation was performed using association strength; clustering used VOSviewer's smart-local-moving algorithm (modularity-based) with the default resolution parameter of 1.00 and a minimum cluster size of five keywords. The procedure initially returned six clusters; the smallest, containing fewer than five keywords, fell below the minimum-cluster-size threshold and was absorbed into its nearest neighbour by cosine similarity, yielding the final five clusters. To provide a graphic description of the bibliographic results, the visualisation software VOSviewer 1.6.20 (van Eck & Waltman, 2016; Waltman et al., 2010) was used. This software compiles bibliographical data and displays the results in various maps and tables.

The dataset was analysed in VOSviewer using the frequency and co-occurrence of keywords. Initially, a total of 712 'Keywords Plus' terms were retrieved. 72 out of 712 keywords appeared at least five times. One of these was a direct search-string anchor and was removed to prevent circularity, yielding the final 71 keywords used in the co-occurrence analysis. To ensure consistency, singular/plural variants and synonyms were combined with the word that occurred the most times (e.g. competence 8 times, competences 12 times; both were combined to 'competences' 12). To prevent a circular argument, the main domain and subdomain's search-string keywords were not included in the final list of the 71 keywords. The five-occurrence threshold for keyword inclusion follows the recommendation in the VOSviewer manual (van Eck & Waltman, 2016) to exclude idiosyncratic terms while retaining thematically representative ones; sensitivity checks at thresholds of 3 and 7 produced substantively similar cluster structures (Waltman et al., 2010).

3.4 Author and country attribution

Country attribution follows first-author affiliation, in line with standard bibliometric practice (Leydesdorff & Persson, 2010). Where the first author reported multiple affiliations, the primary affiliation was defined as the one listed first in the byline of the Web of Science record, which follows the author's own ordering. This convention is transparent and replicable, but it underweights the contribution of secondary institutions, as further described in the following section.

3.5 Methodological limitations and bias-mitigation strategies

A number of limitations are noted, together with the mitigation adopted in each case. Firstly, there is database bias. The Web of Science under-represents non-English venues, applied-training journals and Global-South publishers relative to Scopus, Dimensions or Google Scholar (Mongeon & Paul-Hus, 2016). As a partial mitigation we ran a sensitivity check on the top 30 article and country lists using author-supplied keywords only, with substantively unchanged results, and treated the sparse participation of African and South-Asian venues as a finding to be interpreted, rather than an anomaly to be suppressed. Secondly, English-language publications dominate the WoS Core Collection. This inflates the visible contribution of Anglophone countries and depresses that of Francophone Africa, Lusophone Latin America and East-Asian domestic-language journals. We flag this when discussing geographic distribution.

With regard to journal-coverage bias, the 2015 expansion of the ESCI index alters the temporal comparability of the annual counting series. We report both the raw annual publication series and note this discontinuity in Figure 1. First-author-affiliation bias was mitigated as multi-affiliated authors are attributed only to their first-listed affiliation, underweighting secondary institutions. Finally, with regard to citation-lag bias, papers published after 2020 have had less time to accumulate citations; this well-documented effect (Wang, 2013) partly accounts for the under-representation of recent work in the top-30 cited list.

More generally, bibliometric evidence can identify which concepts co-occur, how the collaboration network is shaped, and when thematic emphases shift. It cannot identify institutional motivation, curriculum-design decisions, employer behaviour or policy causation. Where the Discussion and Implications draw such inferences, they are framed as research agendas or testable hypotheses, not as conclusions from the bibliometric evidence.

4. Findings

4.1 Publication and citation trends

Annual publications for the 623 WoS-indexed articles on labour-market dynamics and skill development rise sharply from 2010 onwards, accelerating after 2016 and peaking at 90 articles in 2024 (Figure 1). Citation growth does not track the publication trend proportionally: citations peak earlier and decline after 2021, consistent with a citation-lag effect and shifting research interests.

Historical drivers of the trend. Three inflection points visible in Figure 1 warrant interpretation rather than description alone. Publication volume accelerates from 2015 onwards, expands sharply after 2020, and shows citation growth flattening even as publications rise. Each of these movements has plausible historical drivers that align with well-documented shifts in the wider research and policy environment.

The post-2015 acceleration coincides with the international consolidation of the industry 4.0 discourse. The term was first coined in Germany in 2011 (Rikala et al., 2024), but its diffusion into English-language labour-market and higher education scholarship intensified after 2015, as European industrial policy, World Economic Forum reports and OECD skills-outlook publications reframed workforce adaptation in the language of technological transformation. The same period saw the expansion of the Web of Science ESCI index in 2015, which broadened journal coverage and mechanically raised annual publication counts. The observed acceleration is therefore compatible with both a substantive shift in research attention and a change in database coverage; the two effects are analytically inseparable in the current data.

The post-2020 explosion is more sharply concentrated. Three overlapping developments plausibly account for it. First, the COVID-19 pandemic disrupted labour markets, accelerated remote-work adoption and made workforce-skill mismatch an urgent policy problem in most OECD economies, generating a surge of research attention. Second, the rapid diffusion of generative artificial intelligence from late 2022 onwards reframed skill obsolescence and reskilling debates around a new set of technological capabilities (Alekseeva et al., 2021; Engberg et al., 2025). Third, employability concerns intensified as graduate cohorts entering the post-pandemic labour market faced uncertain occupational trajectories, prompting expanded research on graduate preparedness and curriculum adaptation. The 2024 peak of 90 articles reflects the compound effect of these three shocks in a research field that was already growing.

The apparent flattening, and after 2021 decline, of citation growth alongside rising publication counts is not a paradox. It is the well-documented citation-lag effect (Wang, 2013): recently published articles have not yet accumulated the citation stock that older canonical works have built over one or two decades. Post-2020 work is over-represented in publication counts but under-represented in citation counts, and citation-based measures of the field's post-2020 activity should therefore be revisited at the five-year mark. A secondary factor is that recent Industry 4.0 and generative-AI scholarship is dispersed across many emerging venues (proceedings, technology-in-society journals, applied ICT outlets) rather than concentrated in the classical labour-economics journals that dominated pre-2020 citation counts; consolidation of this literature into a shared canon has not yet occurred.

Read together, these three interpretations qualify the descriptive trend in an important way. The publication surge is neither a straightforward indicator of scholarly maturation nor an artefact of database expansion alone; it is a compound outcome of policy discourse, technological shock, pandemic disruption and indexing change. The temporal shape of Figure 1 should therefore be read as evidence of the field's responsiveness to external drivers, not as a natural growth curve.

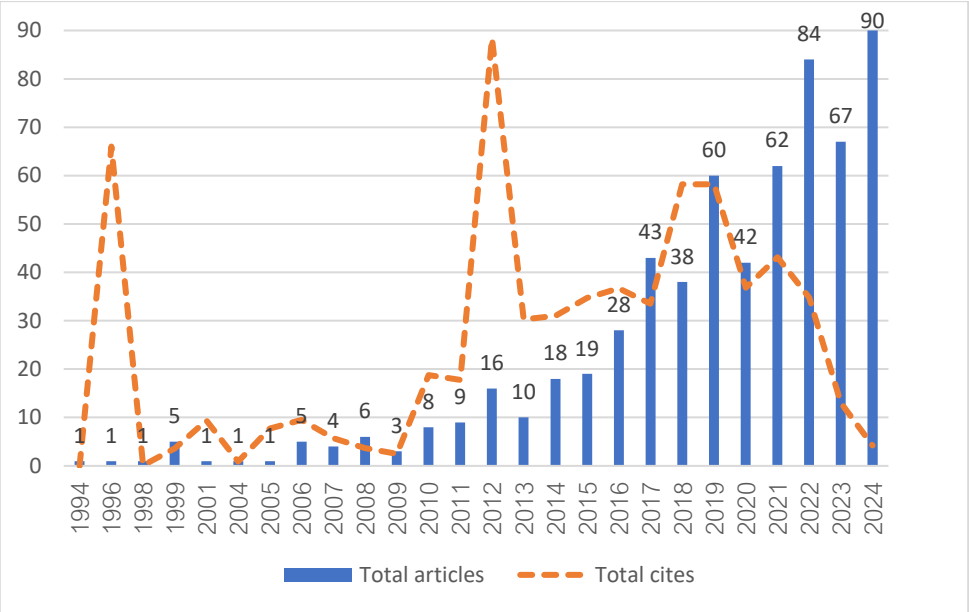


Figure 1. Annual publication counts (bars, left axis) and cumulative citations (line, right axis), 1975–2024. Source: *authors' own*

For the selected keyword queries, the ten most cited articles (Table 1) were published between 1996 and 2020 and received a total of 2,453 citations. The full list of ranked cited articles can be found in Appendix A.

Table 1. Top ten most cited articles. Source: *authors' own*

	Article	Author(s)	Journal	Year	Total citations	Average per year
1	Hard evidence on soft skills	Heckman, J. J.; Kautz, T.	Labour Economics	2012	734	56.46
2	The role of premarket factors in black-white wage differences	Neal, D. A.; Johnson, W. R.	Journal of Political Economy	1996	660	22.76
3	Big Data Investment, Skills, and Firm Value	Tambe, P.	Management Science	2014	204	18.55
4	An exploratory study of factors affecting undergraduate employability	Finch, D. J.; Hamilton, L. K.; Baldwin, R.; Zehner, M.	Education And Training	2013	186	15.5
5	Skill gaps, skill shortages, and skill mismatches: evidence and arguments for the United States	Cappelli, P. H.	Ilr Review	2015	154	15.4
6	Estimating Industry 4.0 impact on job profiles and skills using text mining	Fareri, S.; Fantoni, G.; Chiarello, F.; Coli, E.; Binda, A.	Computers in Industry	2020	118	23.6
7	Active learning in engineering education. A review of fundamentals, best practices and experiences	Hernandez-de-Menendez, M.; Vallejo Guevara, A.; Tudon Martinez, J. C.; Hernandez Alcantara, D.; Morales-Menendez, R.	International Journal of Interactive Design and Manufacturing - Ijidem	2019	107	17.83
8	Skills mismatch concepts, measurement and policy approaches	McGuinness, S.; Pouliakas, K.; Redmond, P.	Journal of Economic Surveys	2018	105	15
9	Four field-related educational resources and their impact on labor, consumption, and sociopolitical orientation	van de Werfhorst, H. G.; Kraaykamp, G.	Sociology of Education	2001	94	3.92
10	Employability: a contemporary review for higher education stakeholders	Small, L.; Shacklock, K.; Marchant, T.	Journal of Vocational Education and Training	2018	91	13

Across the 623-article sample, the aggregate citation count on the extraction date was 6,485. All citation percentages reported below use this figure as the denominator. Appendix A shows the thirty most cited articles, including their authors, journal, year of publication, total number of citations, and average citations per year. The most-cited article is Heckman and Kautz's (2012) "Hard evidence on soft skills", published in Labour Economics, which alone accounts for 11.32% of the sample's citations (734 of 6,485). Its dominance is analytically informative rather than merely descriptive: it signals that the field's citation gravity has settled on the argument that non-cognitive traits, communication, perseverance, teamwork, are consequential for employability and earnings, and that this argument has proved more citable than any other in the sample (Heckman & Kautz, 2012; Vadie & Lipták, 2023). Earlier influential studies, such as Neal and Johnson (1996), focus on structural inequalities and pre-market factors that make for unequal wages (Livingstone et al., 2023; Neal & Johnson, 1996), while more recent contributions mark the pivot towards technology-driven skill demand (Tambe, 2014).

Two temporal patterns in the top thirty are worth noting because they qualify how the citation record should be read. Twenty-two of the thirty most cited articles were written between 2010 and 2024, and eleven within the last decade, noting that there are 551 publications of the 623 articles in the full sample, between 2014 and 2024. The five most cited papers represent 29.88% of all citations, while the ten most cited show 37.83%, indicating a highly concentrated citation structure typical of fields organised around a small number of canonical statements rather than a diffuse research front. Those numbers suggest that the field's intellectual centre of gravity is organised around three closely connected concerns: human capital and soft skills; structural inequalities in the labour market; and the reshaping of skill demand by technological change.

4.2 Countries with the highest number of articles and citations

Table 2 reports on the thirty most productive countries, ordered by article count (Panel A) and by citations (Panel B). Country of origin follows the first-affiliation rule set out in Section 3.4.

Table 2. Countries with the most publications and citations. Source: *authors' own*

Panel A: Ordered by number of papers				Panel B: Ordered by number of citations			
ID	Countries/Regions	No. Papers	Citations	ID	Countries/Regions	No. Papers	Citations
1	USA	126	3248	1	USA	126	3248
2	Italy	41	366	21	Ireland	10	1000
3	Russia	38	0	9	Canada	26	389
4	Spain	38	319	7	Germany	28	378
5	Malaysia	33	185	10	England	26	367
6	Brazil	28	84	2	Italy	41	366
7	Germany	28	378	14	Peoples R China	18	334
8	Portugal	27	79	4	Spain	38	319
9	Canada	26	389	12	Australia	20	293
10	England	26	367	5	Malaysia	33	185
11	Romania	22	18	17	Netherlands	13	168
12	Australia	20	293	15	Poland	16	121
13	India	19	27	22	France	9	114
14	Peoples R China	18	334	16	Mexico	13	113
15	Poland	16	121	20	Czech Republic	10	92
16	Mexico	13	113	6	Brazil	28	84
17	Netherlands	13	168	8	Portugal	27	79

18	Ukraine	13	0	19	Indonesia	11	64
19	Indonesia	11	64	30	Belgium	6	49
20	Czech Republic	10	92	27	South Africa	8	47
21	Ireland	10	1000	33	Bangladesh	5	43
22	France	9	114	25	Slovakia	9	41
23	Hungary	9	28	24	Saudi Arabia	9	39
24	Saudi Arabia	9	39	28	Switzerland	7	36
25	Slovakia	9	41	23	Hungary	9	28
26	Greece	8	28	26	Greece	8	28
27	South Africa	8	47	13	India	19	27
28	Switzerland	7	36	32	Morocco	6	24
29	Austria	6	5	38	Sweden	5	23
30	Belgium	6	49	31	Finland	6	22

The concentration is noticeable. The United States alone contributes 20.2% of articles and 50.1% of citations. Read by publication volume, the United States is followed by Italy, Russia and Spain; read by citation impact, the picture reorders sharply: Ireland (from 10 articles) and Canada eclipse most higher-producing countries. This asymmetry between publication volume and citation impact is itself informative, and points to a persistent structural inequality in whose research reaches the indexed literature. Africa and much of South Asia are almost entirely absent from Table 2, which is a finding to be taken seriously rather than an artefact to be smoothed over: it reflects a combination of Web of Science coverage patterns and real inequities in global research capacity. This limits the geographical generalisability of any claim built on the current sample and is one of the reasons the study's contribution is framed as a research agenda rather than a policy prescription (see Section 5.4).

Table 3 presents publication sources ordered by number of publications in Panel A and by total citations in Panel B. Each panel reports the source identifier, source name, publication count and total citations. Panel B includes sources with a single publication. Both panels are ordered by number of papers.

Table 3. Journals with the highest number of articles and citations. Source: *authors' own*

Panel A:				Panel B:			
ID	Journals	No. papers	Citation	ID	Journals	No. papers	Citation
1	Sustainability	11	45	5	Labour Economics	6	755
2	Education and Training	10	362	27	Journal of Political Economy	2	667
3	Education Sciences	8	99	2	Education and Training	10	362
4	Higher Education Skills and Work-Based Learning	8	52	10	Management Science	4	240
5	Labour Economics	6	755	16	Ilr Review	3	168
6	Journal of Technical Education and Training	6	18	32	Work and Occupations	2	119
7	2024 Ieee Global Engineering Education Conference, Educon 2024	6	2	76	Computers in Industry	1	118
8	12th International Conference of Education, Research and Innovation (Iceri2019)	6	1	28	International Journal of Interactive Design and Manufacturing - Ijidem	2	109
9	Industry and Higher Education	5	56	77	Journal of Economic Surveys	1	105
10	Management Science	4	240	3	Education Sciences	8	99
11	International Journal of Engineering Education	4	45	78	Sociology of Education	1	94
12	Journal of Information Technology Education-Research	4	18	31	Conservation Biology	2	93
13	Pertanika Journal of Social Science and Humanities	4	9	29	Journal of Vocational Education and Training	2	91

14	Ieee Access	4	8	79	Journal of Medical Internet Research	1	87
15	9th International Conference on Education and New Learning Technologies (Edulearn17)	4	4	80	Economic and Labour Relations Review	1	87
16	Ilr Review	3	168	81	Proceedings of the National Academy of Sciences of the United States of America	1	83
17	Journal Of Education for Business	3	51	82	Social Forces	1	83
18	Sage Open	3	25	83	Journal of Law & Economics	1	77
19	Journal of International Migration and Integration	3	13	30	Economics of Education Review	2	76
20	International Journal of Manpower	3	9	84	Information Economics and Policy	1	61

The two panels, A and B, only partially overlap, and the mismatch itself is the analytically interesting result. Sustainability leads the productivity ranking with eleven articles (1.7% of the sample), a position consistent with its open-access model and broad thematic remit, which invites contributions at the intersection of education, economic transformation and labour-market reform. Citation impact, however, is concentrated elsewhere. Labour Economics alone attracts 755 citations from six articles, and together with Journal of Political Economy, Education and Training, Management Science and ILR Review accounts for roughly 33.8% of all citations in the sample. In other words, a small number of specialised, long-established journals in labour economics and management continue to set the citation agenda even as newer open-access venues drive publication volume. This divergence between where the field publishes and where it accumulates influence has implications for how the intellectual structure of the field should be read: productivity rankings capture activity, while citation rankings capture consolidation, and the two answer different questions.

4.3 Authors and international collaboration

Overall, the sample contained 1,818 authors, with a mean of 2.9 authors per article. Twenty-one authors contributed more than two papers, and seven contributed at least four: Patricia Caratozzolo (Mexico) (5), Jose Daniel Azofeifa (Mexico) (4), Sara Bonesso (Italy) (4), Fabrizio Gerli (Italy) (4), Faizan Javed (USA) (4) and Matt McNair (USA) (4). The absence of any single dominant author group indicates that the field is not organised around a small number of canonical research programmes but is distributed across many small clusters, a structural feature consistent with the multidisciplinary character of the topic.

The country co-authorship network shown in Figure 2 was constructed in VOSviewer with a minimum of five documents per country, which reduces the 87-country sample to the 38 countries with substantive publication activity. The United States sits at the centre of the largest hub, with dense links to European and Asia-Pacific partners. Italy, Germany and Spain form a coherent European sub-cluster, while China and Malaysia anchor Asia-Pacific collaboration. Brazil and South Africa appear as emerging integrated nodes. The network is strongly inter-regional across North America, Europe and Asia, but the sparse participation of countries such as Bangladesh and Colombia reinforces the geographical asymmetry already visible in Table 2 and points to where structural inclusion in the field's collaborative infrastructure remains limited.

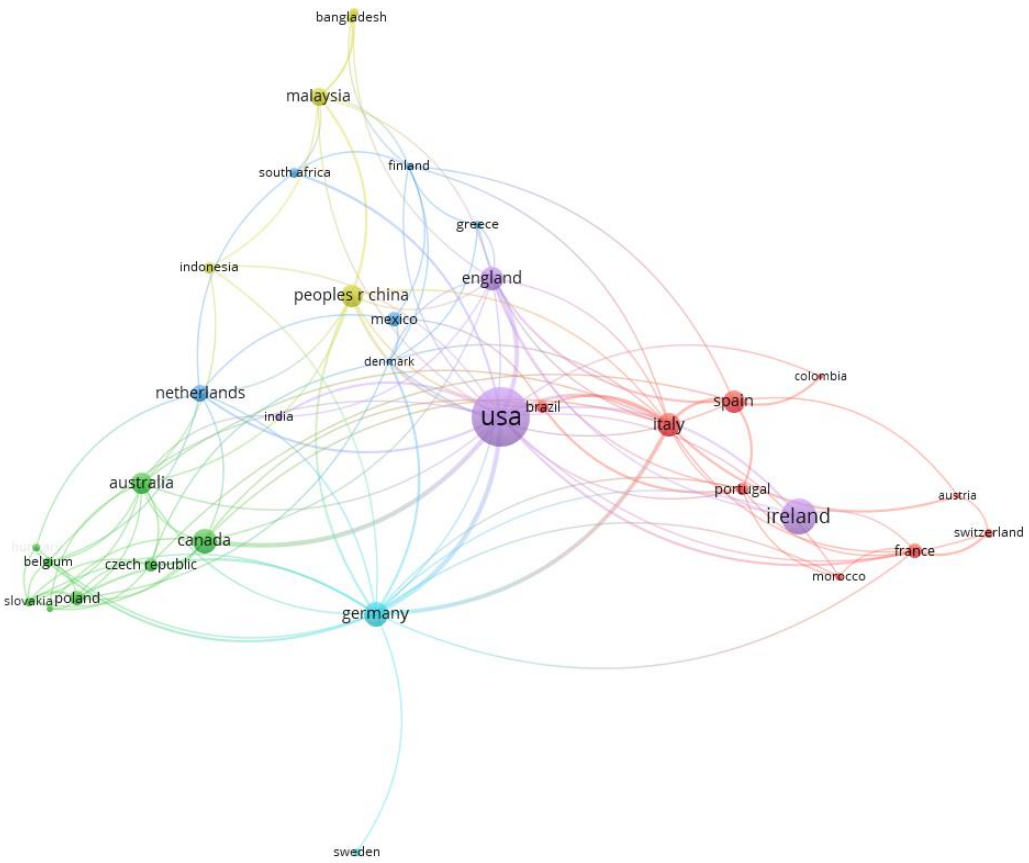


Figure 2. International collaboration among countries, 1975–2024. Source: *authors' own*

4.4 Cluster analysis

Applying the VOSviewer settings reported in Section 3.3 to the co-occurrence matrix of the 71 retained keywords yielded five thematic clusters, shown in Table 4 and visualised in Appendix C. Rather than re-describing each cluster's keyword membership, which the table already reports, we read the clusters here for what their composition and adjacencies imply about the field's intellectual structure. Table 4 presents the keyword grouped with the VOSviewer analysis, along with the corresponding articles, (n) represents the number of articles.

Table 4. Thematic clusters. Source: *authors' own*

Num	Cluster 1 Labour Market Dynamics and Social Issues	(n)	Cluster 2 Employment and Economic Factors	(n)	Cluster 3 Organisational Design and Skills	(n)	Cluster 4 Higher Education and Employability	(n)	Cluster 5 Employability, Soft Skills, and Student Engagement	(n)
1	attitudes	5	behaviour	5	big data	8	attributes	7	construction	7
2	discrimination	8	education	53	design	5	business	13	employability	23
3	earnings	14	employment	24	engagement	5	competences	12	future	17
4	gender	12	firms	5	experience	5	curriculum	8	graduate employability	6
5	health	9	growth	7	framework	6	employability skills	5	leadership	5
6	job	12	impact	30	knowledge	14	employers	12	performance	20
7	labor-market	48	inequality	10	management	21	hard	6	personality	8
8	labor-market outcomes	12	information	7	model	8	higher-education	32	perspectives	5
9	metaanalysis	6	investment	8	satisfaction	5	market	9	school	6
10	migration	7	jobs	9	science	7	needs	5	soft skills	40
11	mobility	6	labor	13	skills	36	perceptions	25	students	31

12	outcomes	9	polarization	7	teachers	5	requirements	5	workplace	5
13	overeducation	6	productivity	6	technology	10	university	6		
14	race	8	technological-change	6						
15	returns	11	unemployment	7						
16	trends	5								
17	wages	8								
18	work	34								

The five clusters are not independent research programmes but interconnected thematic zones, and the boundaries between them are analytically informative. Cluster 4 (Higher Education and Employability) sits adjacent to Cluster 3 (Organisational Design and Skills), reflecting a live conceptual traffic between how universities cultivate skills and how organisations absorb them; the recurring vocabulary of curricula, training programmes and competency frameworks indexes an ongoing accommodation to data-driven management and to changing forms of work. Cluster 5 (Employability, Soft Skills and Student Engagement) complements Cluster 4 by foregrounding non-cognitive traits, leadership, personality, communication, as mediators between education and workplace performance, a pattern that reproduces at the field level the citation dominance of Heckman and Kautz (2012) noted in Section 4.1.

Clusters 1 and 2 together supply the macro-structural framing within which the education-to-work clusters operate. Cluster 1 (Labour Market Dynamics and Social Issues) is dominated by the vocabulary of inequality, discrimination, wages and labour-market outcomes; Cluster 2 (Employment and Economic Factors) foregrounds employment, education, growth and technological change. Read against theory, Cluster 1 is human-capital-native (Section 6.1), while Cluster 2 is where the skills-polarisation and technology-driven demand literatures do their work. The absence of a single cluster explicitly organised around labour-market segmentation, despite the presence of its core vocabulary in Cluster 1, is one of the more diagnostic patterns in the network graph (Appendix C) and is discussed further in Section 5.3.

5. Discussion

5.1 Seminal contributions and emerging trends

The distribution of citations across the field indicates where consensus has crystallised and where new evidence has not yet been metabolised by the citing community. The top position of Heckman & Kautz's paper on soft skills (Heckman & Kautz, 2012), with 11.32% of total citations (734 of the 6,485 total citations), reflects its role in connecting the education and labour-market outcomes literatures. Together with Neal and Johnson (1996) and Tambe (2014), the top three articles account for approximately 24% of total citations. This concentration is consistent with the highly skewed citation distribution documented in comparable bibliometric fields (Bornmann & Leydesdorff, 2014; Neal & Johnson, 1996; Tambe, 2014).

Sixteen of the top 30 cited articles were published in the last decade (2014–2024), but only three after 2020. This is consistent with the well-established citation-lag effect (Wang, 2013): recent work has not yet had time to accumulate the citation stock that would place it among the top-cited. Annual publication counts, which continue to rise sharply through 2024 (Figure 1), are a more informative signal of post-2020 activity than citation counts.

A second factor is that recent Industry 4.0 and AI-related work is dispersed across multiple emerging venues rather than concentrated in the classical labour-economics journals that dominated pre-2020 citation counts; consolidation of this literature into a shared canon has not yet occurred (Vásquez et al., 2026).

5.2 Geographical imbalances and collaboration networks

With 50.1% of the total citations, the United States is the most dominant in driving global research agendas, coupled with 20.2% of the publications. Other developed nations like Canada and Germany also show a good standing, while regions of Africa and South Asia are under-represented (Pan et al., 2012). An intensive network of cooperation connecting America, Europe and the Asia-Pacific region - as illustrated in Figure 2 - reveals how research is now an international enterprise.

Three factors plausibly explain this concentration. First, Web of Science historically prioritises English-language and Global-North publishers, systematically under-sampling Francophone Africa, Lusophone Latin America and East-Asian domestic-language venues. Second, research capacity and funding for bibliometric or labour-market work are unevenly distributed globally, with high-income economies benefiting from established doctoral pipelines and international networks. Third, the concepts through which the field organises itself, formal wage employment, degree-based signalling, standardised skill taxonomies, presuppose institutional conditions that hold unevenly across labour markets. The concentration is therefore best read not as a natural pattern but as a co-produced outcome of database coverage, funding geography and conceptual portability.

Two implications follow. First, the theoretical vocabulary of the field is disproportionately shaped by high-income OECD labour markets, in which formal wage employment, degree-based signalling and codified skill taxonomies dominate. The applicability of this vocabulary to informal, agrarian or developmental labour markets is under-tested, a gap that a bibliometric map can identify but not close. Second, initiatives such as the EU's Horizon Europe missions on skills, UNESCO's Global Skills Academy and the ILO's Skills for Employment programme are candidates for redressing this asymmetry; whether they in fact do so is an empirical question beyond the scope of this study.

5.3 Journals and thematic clusters

The five-cluster structure locates our contribution with respect to prior bibliometric reviews and identifies specific unresolved debates. Cluster 1 is themed around Labour Market Dynamics and Social Issues (keywords: earnings, returns, discrimination, overeducation, wages, race, gender, mobility). This cluster corresponds to the returns-to-education and labour-market-discrimination traditions in labour economics. It is largely absent from the Scopus-based windows of Dinh et al. (2023) and Masduki et al. (2022), whose focus on employability under-samples this literature. Its co-presence with the employability clusters (4 and 5) is a distinctive feature of the WoS-based 50-year map. Read through human-capital and inequality research, this juxtaposition places individual capability development alongside the conditions under which capabilities are rewarded (Becker, 1962; Neal & Johnson, 1996). It suggests a basis for studying employability and structural disadvantage together, without establishing a causal link between them.

Cluster 2 encompasses Employment and Economic Factors (education, employment, growth, impact, productivity, unemployment, technological-change, polarization). This cluster maps onto the skill-biased-technical-change and skills-polarisation debates (Autor et al., 2006). Malanski et al. (2022) touch on the productivity side within agrifood value chains but do not surface the polarisation debate directly. The co-occurrence of polarization (n = 7) with technological change (n = 6) in this cluster is direct bibliometric evidence that the debate is active in our sample, but not evidence about its resolution. In the context of research on labour-market polarisation, this cluster connects skill demand with changes in employment and productivity rather than treating higher skill requirements as a uniform process (Autor et al., 2006; Kolade & Owoseni, 2022). The network cannot establish which occupations gained or lost employment.

Cluster 3 centres upon Organisational Design and Skills (big data, design, engagement, framework, knowledge, management, skills, technology). This cluster overlaps thematically with the work of Škare et al. (2022) on entrepreneurial skills and

extends to organisational-level design and knowledge management. The combination of knowledge, management and technology provides an organisational lens on skill development: the value of individual capabilities can be examined alongside the practices through which firms deploy them. This reading connects the cluster to research on data-related capabilities and entrepreneurial skills, while leaving the direction of these relationships to further empirical study (Tambe, 2014; Škare et al., 2022).

Cluster 4's themes revolve around Higher Education and Employability (attributes, business, competences, curriculum, employability skills, employers, higher-education, market, needs, perceptions, requirements, university). This is the closest analogue to Dinh et al. and Martin Gomez & Bartolome Muñoz de Luna (Dinh et al., 2023; Martin Gomez & Bartolome Muñoz de Luna, 2023). Its prominent nodes, requirements, employers, perceptions, foreground the signalling-theoretic reading of higher education (Spence, 1973).

Finally, Cluster 5 is themed around Employability, Soft Skills and Student Engagement (construction, employability, future, graduate employability, leadership, performance, personality, soft skills, students, workplace). Its convergence on soft skills (n = 40) and employability (n = 23) is consistent with Masduki et al. (2022) and with Heckman and Kautz's (2012) framing of non-cognitive skills as productive traits.

All prior reviews confirm employability as an integrative node; our map suggests it plays a bridging role. We are not aware of an existing bibliometric review that brings labour-market segmentation (Cluster 1) into the same map as employability (Clusters 4–5). Reading these clusters alongside one another appears to be where a bibliometric mapping can most productively be brought into dialogue with theory.

The distinction between Clusters 4 and 5 can be read as a difference in emphasis. Cluster 4 foregrounds the institutional and employer vocabulary through which higher education is linked to employability, whereas Cluster 5 foregrounds graduate attributes such as soft skills, leadership, personality and performance. This distinction is compatible with the signalling and human-capital perspectives in Section 2.1, but the combined network does not establish whether the boundary between the clusters has narrowed over time.

5.4 Interpretive scope of bibliometric evidence

Bibliometric methods identify concept co-occurrence, citation impact, collaboration structure and thematic drift. They do not identify institutional motives, curriculum decisions, employer choices or policy causation. In the sections that follow, wherever we discuss implications for education systems, employers or policy, these are stated as research questions that qualitative case-study, employer-side survey or task-level administrative-data analysis could answer, not as findings of this study.

6. Implications

By visualising the intellectual structure of the research field and its international collaboration patterns, this study contributes both theoretically, by providing a foundation for refining accounts of the education–employment relationship, and practically, by offering a point of orientation for researchers and industry actors navigating that relationship.

6.1 Theoretical implications

Two theoretical traditions organise most of the field. The human-capital tradition (Heckman et al., 2006; Becker, 1962) reads skills, including non-cognitive skills, as productive investments that raise wages. The signalling tradition (Spence, 1973) reads credentials as low-cost observables that firms use to sort workers whose true productivity is unobservable. The two are not mutually exclusive (Lange & Topel, 2006), and our co-occurrence map is compatible with both readings.

The human-capital reading is most clearly anchored in Cluster 1 (Labour Market Dynamics and Social Issues), whose high-frequency terms, earnings (n = 14), returns (n = 11) and wages (n = 8), constitute the core vocabulary of the returns-to-education literature. Cluster 5 extends this tradition into non-cognitive productive capital: its convergence on soft skills (n = 40) and performance (n = 20) reflects the broader move, most influentially articulated by Heckman and Kautz (2012), to treat behavioural and interpersonal attributes as productive investments that generate labour-market returns in the same theoretical register as formal qualifications.

The signalling reading is most clearly anchored in Cluster 4 (Higher Education and Employability), whose high-frequency terms, requirements (n = 5), employers (n = 12) and perceptions (n = 25), name the mechanism by which credentials operate as observables that employers interpret under uncertainty. The persistence of skills mismatch as a research theme, documented by Cappelli (2015) and McGuinness et al. (2018), is consistent with this account: as credentials proliferate and their informational content becomes noisier, the sorting function of the signal becomes more difficult to sustain. The bibliometric map cannot adjudicate between these traditions—no keyword co-occurrence pattern can—but it identifies with precision the terms and clusters at which such adjudication would have to occur.

6.2 Research implications

After 2020, annual publication counts rise sharply (peak at 90 in 2024) while citations to the same recent papers remain low. This is not a paradox: it is the well-documented citation-lag effect (Wang, 2013), amplified by the pandemic-era disruption to review cycles. For interpretation, this means the top 30 cited list under-samples post-2020 work and should not be read as evidence that the field is failing to respond to Industry 4.0 or generative-AI shocks. Publication counts are the more informative signal for recent activity; citation-based measures should be revisited at the five-year mark.

The co-presence of education-focused journals (Sustainability, Education and Training, Higher Education Skills and Work-Based Learning) with labour-economics journals (Labour Economics, ILR Review) and management journals (Management Science) demonstrates that the field, though intellectually coherent, remains structurally fragmented across publishing venues. Two research directions follow. Cross-disciplinary triangulation: administrative-data studies that follow curriculum reforms through to labour-market outcomes are needed to test whether the human-capital or the signalling reading better explains post-2020 outcomes. Global South integration: case-study work on skill-formation systems in under-represented regions is needed to test the transportability of concepts developed in OECD labour markets.

6.3 Practical implications

The bibliometric map does not itself establish causal claims about how education, work or policy should be arranged (Section 5.4). It does, however, reveal where the field has invested its collective analytical attention, and this pattern of attention offers a defensible basis for concrete recommendations to the three principal constituencies the literature addresses: universities, employers and policymakers. The recommendations below are grounded in the density and persistence of specific keyword clusters and citation patterns rather than derived from any single study within the sample.

For universities, the co-occurrence of curriculum (n = 8), requirements (n = 5), perceptions (n = 25) and employers (n = 12) in Cluster 4, together with the sustained citation dominance of skills-mismatch scholarship (Cappelli, 2015; McGuinness et al., 2018), points to curriculum–employer alignment as the single most consistently articulated concern in the field. Concretely, universities should institutionalise mechanisms that translate employer skill-demand signals into curriculum design on a rolling basis rather than through periodic programme reviews: employer advisory panels with genuine curricular authority, work-integrated learning components embedded across programmes rather than concentrated in final-year internships, and periodic labour-market audits of programme content against occupational-forecasting

data. The proximity between Clusters 4 and 5 further indicates that the historical separation between "hard" (technical) and "soft" (interpersonal) skills is no longer analytically tenable; contemporary curriculum design needs to integrate digital, technical and interpersonal capabilities within the same learning experiences rather than treating them as separate curricular tracks.

For employers, the convergence of Cluster 3 (big data, technology, knowledge, management) with Cluster 5 (soft skills, leadership, performance, personality) indicates that the 'technologically-adapting workplace' requires an integrated technical-plus-interpersonal skill profile rather than a stratified division between "technical" and "human" roles. Two operational implications follow. First, employers should invest in structured skills-forecasting practices, task-level analysis of how automation, digitalisation and AI are reshaping specific roles within the firm, rather than relying on generic future-of-work reports. The evidence base on within-occupation task change (Alekseeva et al., 2021; Engberg et al., 2025) is now sufficiently developed to support firm-level application. Second, employers should treat lifelong learning not as an individual employee responsibility but as an organisational capability, embedding structured reskilling and upskilling pathways within employment relationships rather than delegating them to external providers.

For policymakers, the pronounced geographic concentration documented in Section 5.2, together with the persistent salience of labour-market inequality vocabulary in Cluster 1 (discrimination, gender, race, wages, mobility), points to two priority areas of intervention. First, workforce reskilling policy should be designed to reach populations who face the highest adjustment costs, not those who are already best positioned to adapt; the evidence on skill mismatch following job displacement (Neffke et al., 2024) indicates that generic reskilling programmes without targeted support for displaced workers risk widening rather than closing capability gaps. Second, regional research and skills capacity development requires attention to the geographic asymmetries in the visible research base itself: the near-absence of African, South Asian and much of Latin American scholarship from indexed labour-market research is a structural feature of the global skills-knowledge system, and initiatives such as the EU's Horizon Europe missions on skills, UNESCO's Global Skills Academy and the ILO's Skills for Employment programme should be evaluated not only on their direct workforce impact but on whether they succeed in shifting the geography of research capacity itself.

These recommendations are grounded in the density and persistence of the field's collective analytical attention as revealed by the map, not in causal evidence from any single study. Their empirical validation in specific institutional, sectoral or regional contexts requires complementary evidence from employer-side surveys, longitudinal graduate-outcome studies, task-level administrative-data analysis and qualitative case-study work, directions developed in Section 7.

7. Conclusion

This study examines 623 Web of Science-indexed articles published from 1975 to 2024 at the intersection of labour-market dynamics and skill development. It offers four contributions. First, to our knowledge it offers one of the longest-window integrated bibliometric maps of the field currently available, drawing together literatures on employability, Industry 4.0 skills and labour-market outcomes that have largely been examined in isolation. Second, it identifies five keyword co-occurrence clusters and reads them through the human-capital and signalling traditions developed in Section 2.1, locating with precision the vocabulary at which these traditions engage without adjudicating between them. Cluster 1 and Cluster 5 anchor the human-capital reading through the earnings, returns and non-cognitive-productivity vocabularies; Cluster 4 anchors the signalling reading through the credentials, employer-perceptions and requirements vocabularies. Read together, the clusters support a view of the field as a connected process spanning capability formation, market recognition, alignment and technological reconfiguration. Third, it documents a geography of research production concentrated in the United States,

Europe and the Asia-Pacific region, with pronounced under-representation of Africa and much of South Asia. As Section 5.2 develops, this concentration is best interpreted not as a natural pattern but as a co-produced outcome of database coverage, funding geography and the institutional portability of the field's core concepts. Fourth, and consistent with the interpretive scope delimited in Section 5.4, it translates what would previously have been policy recommendations into a research agenda. Bibliometric evidence identifies where the field's theoretical vocabularies concentrate and overlap, but it cannot establish institutional motive, curriculum decisions, employer behaviour or policy causation; these questions require complementary evidence.

Three lines of future work follow. (a) The next generation of maps should triangulate WoS with Scopus, Dimensions and Global-South-inclusive sources to test the robustness of the geographic pattern. (b) Task-level administrative-data studies are needed to test whether the human-capital or the signalling reading better explains post-2020 labour-market outcomes under generative-AI adoption. (c) Qualitative case-study work on curriculum reform, employer skill-demand articulation and Global-South skill-formation systems can address the questions that bibliometric evidence poses but cannot answer.

Methodologically, we acknowledge that reliance on Web of Science introduces coverage and language biases (Section 3.5). Future iterations that integrate multiple databases and qualitative evidence will be better positioned to test the questions that this map has made visible. The broader significance of this map extends beyond its methodological contribution. Over the fifty years covered by this study, employability, technological change, skill formation and labour-market adaptation have converged from separate scholarly conversations into a single, if still theoretically uneven, interdisciplinary field. The pace of that convergence has accelerated markedly since 2015, and the emergence of generative artificial intelligence as a general-purpose technology is already beginning to reshape the questions the field asks about how skills are formed, how quickly they depreciate, how credentials communicate capability under conditions of rapid technological change, and how labour markets absorb workers whose task portfolios are being redefined within occupations rather than across them. The map presented here is therefore not only a retrospective account of what the field has been, but a diagnostic starting point for what it must become. For researchers, educators, employers and policymakers navigating an AI-enabled workforce transformation whose full effects have yet to materialise, the intellectual coherence of this field, and the willingness of scholars across labour economics, higher education, management and computer science to work across its internal boundaries, will determine whether the next fifty years of research produce evidence adequate to the scale of the transformation the world of work is now undergoing.

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Author Contributions Statement (CRediT)

Conceptualization: KB, AD, MK, and IC; Methodology: MK, IC, AD; Validation of the methods and results: KB, AD, MK, and IC; Investigation: KB; Formal Analysis: KB, MK; Writing – Original Draft Preparation: KB, IC, MK; Writing – Review & Editing: KB, AD, MK, and IC. Project Management & Oversight: AD, MK, and IC;

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are publicly available in a GitHub repository. Through the following repository link: https://github.com/bourgoukalil-cloud/Labour-Market-Dynamics-and-Skill-Development-Bibliometric-Dataset-WoS-623-

Declaration of Generative AI Use

During this research, the authors used ChatGPT (OpenAI) for limited assistance with coding and debugging. The authors carried out the data preparation, developed the majority of the code, and wrote the main manuscript themselves. The authors take full responsibility for the code, analyses, and content of the publication.

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Appendices

Appendix A. Thirty most cited publications

	Article	Author	Journal	Year	Total citations	Average per year
1	Hard evidence on soft skills	Heckman, J. J.; Kautz, T.	Labour Economics	2012	734	56.46
2	The role of premarket factors in black-white wage differences	Neal, D. A.; Johnson, W. R.	Journal of Political Economy	1996	660	22.76
3	Big data investment, skills, and firm value	Tambe, P.	Management Science	2014	204	18.55
4	An exploratory study of factors affecting undergraduate employability	Finch, D. J.; Hamilton, L. K.; Baldwin, R.; Zehner, M.	Education and Training	2013	186	15.5
5	Skill gaps, skill shortages, and skill mismatches: Evidence and arguments for the United States	Cappelli, P. H.	ILR Review	2015	154	15.4
6	Estimating Industry 4.0 impact on job profiles and skills using text mining	Fareri, S.; Fantoni, G.; Chiarello, F.; Coli, E.; Binda, A.	Computers in Industry	2020	118	23.6
7	Active learning in engineering education. A review of fundamentals, best practices and experiences	Hernandez-de-Menendez, M.; Vallejo Guevara, A.; Tudon Martinez, J. C.; Hernandez Alcantara, D.; Morales-Menendez, R.	International Journal of Interactive Design and Manufacturing – IJIDEM	2019	107	17.83
8	Skills mismatch: Concepts, measurement and policy approaches	McGuinness, S.; Pouliakas, K.; Redmond, P.	Journal of Economic Surveys	2018	105	15
9	Four field-related educational resources and their impact on labor, consumption, and sociopolitical orientation	van de Werfhorst, H. G.; Kraaykamp, G.	Sociology of Education	2001	94	3.92
10	Employability: A contemporary review for higher education stakeholders	Small, L.; Shacklock, K.; Marchant, T.	Journal of Vocational Education and Training	2018	91	13
11	Mapping of crowdsourcing in health: Systematic review	Créquit, P.; Mansouri, G.; Benchoufi, M.; Vivot, A.; Ravaud, P.	Journal of Medical Internet Research	2018	87	12.43
12	Is it better to invest in hard or soft skills?	Balcar, J.	Economic and Labour Relations Review	2016	87	9.67
13	Graduate readiness for the employment market of the 4th industrial revolution The development of soft employability skills	Teng, W.; Ma, C.; Pahlevansharif, S.; Turner, J. J.	Education and Training	2019	86	14.33
14	Skill discrepancies between research, education, and jobs reveal the critical	Börner, K.; Scrivner, O.; Gallant, M.; Ma, S.; Liu, X.; Chewning, K.; Wu, L.; Evans, J. A.	Proceedings of the National Academy of Sciences of the United States of America	2018	83	11.86

	need to supply soft skills for the data economy					
15	Labor market flexibility and inequality: The changing skill-based temporary employment and unemployment risks in Europe	Gebel, M.; Giesecke, J.	Social Forces	2011	83	5.93
16	Labor market discrimination and racial differences in premarket factors	Carneiro, P.; Heckman, J. J.; Masterov, D. V.	Journal of Law & Economics	2005	77	3.85
17	The economic returns to field of study and competencies among higher education graduates in Ireland	Kelly, E.; O'Connell, P. J.; Smyth, E.	Economics of Education Review	2010	72	4.8
18	Graduate student's guide to necessary skills for nonacademic conservation careers	Blickley, J. L.; Deiner, K.; Garbach, K.; Lacher, I.; Meek, M. H.; Porensky, L. M.; Wilkerson, M. L.; Winford, E. M.; Schwartz, M. W.	Conservation Biology	2013	70	5.83
19	Skills on the move: Rethinking the relationship between human capital and immigrant economic mobility	Hagan, J.; Lowe, N.; Quingla, C.	Work and Occupations	2011	69	4.93
20	AI meets labor market: Exploring the link between automation and skills	Colombo, E.; Mercorio, F.; Mezzanzanica, M.	Information Economics and Policy	2019	61	10.17
21	Immigrants and the labor market	Smith, J. P.	Journal of Labor Economics	2006	58	3.05
22	Discrimination, complexity, and the public/private sector question	Byron, R. A.	Work and Occupations	2010	50	3.33
23	African American men and the experience of employment discrimination	Mong, S. N.; Roscigno, V. J.	Qualitative Sociology	2010	50	3.33
24	Educational upgrading, structural change and the task composition of jobs in Europe	Hardy, W.; Keister, R.; Lewandowski, P.	Economics of Transition	2018	48	6.86
25	Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies	Iglesias-Pradas, S.; Ruiz-de-Azcárate, C.; Agudo-Peregrina, Á. F.	Computers in Human Behavior	2015	47	4.7
26	Balancing skills in the digital transformation era: The future of jobs and the role of higher education	Goulart, V. G.; Liboni, L. B.; Cezarino, L. O.	Industry and Higher Education	2022	45	11.25
27	More than just good grades: Candidates' perceptions about the skills and attributes employers seek in new graduates	Salas Velasco, M.	Journal of Business Economics and Management	2012	43	3.31
28	Development and initial validation of a perceived future employability scale for young adults	Gunawan, W.; Creed, P. A.; Glendon, A. I.	Journal of Career Assessment	2019	42	7

29	A dynamic capabilities view of employability Exploring the drivers of competitive advantage for university graduates	Finch, D. J.; Peacock, M.; Levallet, N.; Foster, W.	Education and Training	2016	42	4.67
30	Skill: A system for skill identification and normalization	Zhao, M.; Javed, F.; Jacob, F.; McNair, M.	Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence	2015	42	4.2

Appendix B. Full list of 71 keywords with cluster assignments and occurrence counts

id	label	x	y	cluster	Weight <Links>	weight<Total link strength>	Weight <Occurrences>	Score <Avg. pub. year>	Score <Avg. citations>	Score <Avg. norm. citations>	Cluster	No. of Occurrences
47	attitudes	0.8128	0.2659	1	9	10	5	2019	11.8	0.8675	1	220
48	attributes	-0.8456	-0.6215	4	16	26	7	2019.571	11.2857	1.7581	2	197
56	behavior	0.0373	-0.414	2	13	16	5	2019.6	37.4	2.7463	3	135
60	big data	-0.6312	-0.2017	3	15	17	8	2021.125	31.375	3.483	4	145
71	business	-0.5127	-0.3571	4	30	48	13	2019.923	11	1.4689	5	173
111	competences	-0.3265	-0.5118	4	27	46	12	2022.333	6.0833	2.1459		
121	construction	0.1181	0.8798	5	17	23	7	2021	19.5714	2.351		
143	curriculum	-0.6772	-0.5949	4	22	24	8	2016.625	9	1.2763		
156	design	-1.1002	0.3692	3	14	16	5	2021.6	5.6	1.1394		
167	discrimination	0.6331	0.4172	1	17	25	8	2015.375	99	1.6384		
181	earnings	0.8218	-0.3509	1	16	27	14	2015	37.3571	1.9477		
186	education	0.1039	0.0919	2	53	114	53	2019.717	21.8868	1.2487		
194	employability	-0.0953	0.2459	5	34	63	23	2021.435	2.913	1.4779		
195	employability skills	-0.6122	-0.8047	4	13	17	5	2019.6	3.6	0.5116		
202	employers	-0.36	-0.1866	4	27	46	12	2020.167	10.0833	1.6448		
203	employment	0.3112	-0.1072	2	38	63	24	2020.5	22.625	2.1946		
205	engagement	-0.8888	0.6857	3	12	13	5	2021.4	12.8	1.0038		
227	experience	-0.4507	0.5409	3	16	20	5	2020	30	2.7167		
241	firms	0.7864	-0.5324	2	15	20	5	2019	33.4	2.4591		
248	framework	-1.0411	-0.0361	3	17	22	6	2022.833	8.6667	2.2073		
249	future	-0.0089	0.4127	5	26	34	17	2021.529	3.3529	1.1149		
254	gender	0.3696	0.5978	1	25	34	12	2017.667	12.9167	0.8627		
268	graduate employability	-0.0595	0.5646	5	19	22	6	2021.333	12.5	2.5559		
275	growth	0.9407	-0.1349	2	19	25	7	2019.429	5.5714	0.6673		
281	hard	-0.3911	-0.0274	4	11	14	6	2020.833	8.8333	1.5865		
282	health	0.6911	0.2494	1	8	10	9	2019.333	7.5556	0.8686		

288	higher-education	-0.8065	-0.0253	4	36	97	32	2020.281	14.2188	1.9256
310	impact	0.2744	-0.4132	2	39	70	30	2019.867	20.1	2.191
323	inequality	0.7498	0.0196	2	23	30	10	2013.6	33.9	2.2644
325	information	0.5714	-0.4252	2	20	24	7	2019.571	8.8571	1.7638
347	investment	0.6797	-0.3525	2	22	26	8	2022.5	6.5	1.5527
349	job	0.504	0.5378	1	23	35	12	2017.083	11.5833	1.1833
354	jobs	0.4931	-0.0957	2	20	23	9	2019.444	13.2222	1.4466
357	knowledge	-0.7282	-0.3153	3	30	44	14	2022.429	3.4286	1.8274
358	labor	0.5778	-0.2247	2	23	30	13	2020.539	26.1538	3.494
359	labor-market	0.3457	0.1155	1	57	166	48	2018.542	22.3125	2.2598
361	labor-market outcomes	0.2328	-0.2421	1	17	20	12	2019.667	13.3333	1.2897
369	leadership	-0.1911	1.0429	5	10	11	5	2020	22.8	1.725
394	management	-0.1517	-0.1968	3	36	58	21	2021.381	6.381	1.4169
399	market	-0.3341	-0.6958	4	23	31	9	2020.889	16.7778	2.2707
409	metaanalysis	0.3496	1.0111	1	9	10	6	2019.333	132	3.4455
413	migration	1.0233	0.4189	1	10	13	7	2020	13.8571	1.1227
415	mobility	0.8575	0.5177	1	16	22	6	2019.833	12.1667	2.2981
417	model	-0.9687	0.2359	3	20	29	8	2020.375	13.25	1.2281
427	needs	-0.2331	-0.8183	4	11	12	5	2022	3.8	0.7481
453	outcomes	0.0931	-0.1334	1	19	24	9	2020.222	18.2222	1.5231
455	overeducation	0.7755	-0.7015	1	11	15	6	2017	35.5	2.0983
470	perceptions	-0.4976	0.0967	4	41	92	25	2020.84	8	1.4405
471	performance	-0.2674	0.6635	5	30	44	20	2018.8	57.1	2.6497
476	personality	-0.3418	0.8353	5	16	21	8	2021	12.875	1.3536
482	perspectives	0.1481	0.5545	5	16	20	5	2021.8	9	1.9103
484	polarization	0.7876	-0.1533	2	17	22	7	2020.857	12.7143	1.897
497	productivity	1.041	-0.3381	2	13	18	6	2015.667	48.8333	4.1918
521	race	0.4683	0.7157	1	19	26	8	2015.625	22.875	2.323
536	requirements	-0.0346	-0.8437	4	12	14	5	2023	2.4	1.8298
544	returns	0.4288	-0.5782	1	20	30	11	2020.455	5.9091	0.7796
551	satisfaction	-0.9195	-0.1717	3	18	22	5	2020.8	10.6	1.5394

553	school	-0.0585	0.0149	5	15	17	6	2022.833	4.3333	1.9771
556	science	-0.9735	0.497	3	11	14	7	2018.429	5.8571	0.7047
584	skills	-0.2849	-0.365	3	46	104	36	2020.611	11.3333	1.3539
600	soft skills	-0.3241	0.3793	5	46	114	40	2020.65	13.975	1.676
623	students	-0.6306	0.2092	5	45	98	31	2020.677	14.9677	1.9199
635	teachers	-1.241	-0.2188	3	9	12	5	2021.8	2.8	0.3196
641	technological-change	1.0895	0.0451	2	12	15	6	2018.833	21.5	2.0011
643	technology	-0.4771	0.3272	3	20	30	10	2020.6	3.7	1.3539
661	trends	0.2574	-0.6545	1	16	19	5	2022	1.8	1.9331
670	unemployment	0.5228	0.0785	2	19	25	7	2019	9.8571	1.2169
675	university	-0.9283	-0.4629	4	17	27	6	2018.5	42.6667	2.6092
687	wages	0.5566	-0.8341	1	8	10	8	2015.625	13.375	1.1469
699	work	0.1564	0.3487	1	46	105	34	2019	26.5	2.582
706	workplace	-0.2169	0.1555	5	14	20	5	2022.8	3.6	1.143

Appendix C. Co-occurrence of Web of Science Keywords on Skill Development and Labour Market Dynamics using VOSviewer - for the 623 WoS-indexed articles on labour-market dynamics and skill development, 1975–2024.

