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# Digital Upskilling and Reskilling for Smart Manufacturing Workforce: A Bibliometric Analysis (2020–2025)

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## Abstract

Industry 4.0 and smart manufacturing paradigms have fundamentally altered the skill profiles required of the industrial workforce. Consequently, digital upskilling and reskilling have become paramount strategies within human resource development (HRD). Despite increasing academic attention, the literature lacks a comprehensive bibliometric evaluation of these digital training initiatives specifically tailored to smart manufacturing environments. To address this void, the present study conducts a bibliometric review of Scopus-indexed literature from 2020 to 2025. Through VOSviewer software, we analyze publication trajectories, influential contributors, primary publication outlets, citation impacts, and thematic networks. The results demonstrate an accelerated publication rate post-2020, converging around four primary clusters: Industry 4.0 competency frameworks, digital training infrastructures, workforce adaptability, and continuous learning. This analysis not only delineates a roadmap for future academic inquiry but also provides strategic guidance for HRD practitioners managing industrial transitions.

**Keywords**: Digital Upskilling, Reskilling, Smart Manufacturing, Industry 4.0, Bibliometric Analysis, Workforce Development, Human Resource Development.

## 1. Introduction

The manufacturing sector is undergoing a profound transformation. The integration of cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and advanced robotics, collectively known as Industry 4.0, is fundamentally reshaping production and organizational structures. More importantly, it is shifting human capital requirements (Li, 2022; Saniuk et al., 2021). As automation takes over routine cognitive and manual tasks, the need for advanced digital competencies among factory workers has surged. This shift has created a widening skills gap that challenges both global firm competitiveness and worker employability.

Consequently, upskilling (enhancing current skills) and reskilling (learning entirely new ones) have become urgent priorities in human resource development (HRD). The World Economic Forum estimates that by 2025, half of all employees will need reskilling to keep pace with technological adoption (Li, 2022). This reality hits the manufacturing workforce especially hard, as their roles face direct disruption from automation. In response, organizations are increasingly turning to digital training programs, blended learning, and tech-driven workplace education to bridge the gap (Baethge-Kinsky, 2020; Rangraz & Pareto, 2021).

While academic interest in this area is growing, the literature on digital upskilling in smart manufacturing remains scattered. Previous studies have explored specific pieces of the puzzle, such as Industry 4.0 competency frameworks (Saniuk et al., 2021), digital learning tools (Giannakos et al., 2021), vocational training hurdles (Spöttl & Windelband, 2021), and barriers for SMEs (Hansen et al., 2025). However, the field still lacks a comprehensive, quantitative synthesis that maps its overall intellectual structure. Without this broader perspective, it is difficult for researchers and HRD practitioners to see where current knowledge clusters, what gaps remain, and which future research avenues are most promising.

To address this, bibliometric analysis offers an objective way to map a research domain's landscape (Bartolacci et al., 2020; Klarin, 2024). Unlike traditional literature reviews, bibliometrics uses quantitative data like citation networks, co-authorship, and keyword clustering to reveal how a field is conceptually evolving (Al-Khoury et al., 2022; Herrera-Franco et al., 2020). Recent studies have successfully applied this method to related HR topics, such as digital HRD in maritime shipping (Autsadee et al., 2023), staff competencies for digital transformation (Gobniece & Titko, 2024), and broader HRM 5.0 practices (Capolupo et al., 2025), proving its effectiveness for synthesizing fast-growing areas of research.

Building on this foundation, this study conducts a bibliometric analysis of Scopus-indexed articles focused on digital upskilling and reskilling within the smart manufacturing workforce. We focus on the 2020–2025 period to capture the most relevant recent developments. This specific timeframe allows us to examine the landscape just before the pandemic, the rapid acceleration of digital learning it triggered, and the stabilized training practices that have emerged in its aftermath.

## 1.1. Research Objectives

To address the identified gaps, this study seeks to answer the following research questions (RQs):

- RQ1: What are the publication trends and growth trajectories of research on digital upskilling and reskilling in smart manufacturing between 2020 and 2025?
- RQ2: Who are the most prolific authors, and which journals and countries are at the forefront of this research domain?
- RQ3: What are the dominant thematic clusters and keyword co-occurrence networks within the current literature?
- RQ4: What are the critical research gaps, and what future directions should scholars and HRD practitioners pursue?

## 1.2. Significance of the Study

This study contributes to the existing literature in three distinct ways. From a theoretical standpoint, it delivers the first bibliometric synthesis of digital upskilling and reskilling specifically within the smart manufacturing context, thereby establishing a foundational knowledge map for future research. On a practical level, it equips HRD managers and organizational leaders with a structured guide to evidence-based practices and emerging strategies for digital workforce development. Finally, the study expands the methodological toolkit of the HRD field by demonstrating the efficacy of VOSviewer-based bibliometric mapping.

# 2. Literature Review

## 2.1. Smart Manufacturing and the Workforce Transformation Imperative

Smart manufacturing, defined by the integration of digital technologies such as cyber-physical systems, IoT, big data analytics, AI, and additive manufacturing, has become the defining paradigm of modern industrial development (Saniuk et al., 2021). However, this transformation goes far beyond mere technological upgrades; it is fundamentally an organizational and human challenge. For instance, Hansen et al. (2025) observed 30 manufacturing SMEs and found that the pace of digital transformation relies heavily on worker competencies, with most firms citing skill shortages as a major hurdle to Industry 4.0 adoption. Similarly, Spöttl & Windelband (2021) emphasize that evolving work structures and human-machine interactions are generating entirely new qualification demands across both shop-floor and middle-management roles.

Consequently, the skills required in these advanced environments now span technical, cognitive, and social domains. Saniuk et al. (2021) point to critical competencies like IoT operation, data analytics, cybersecurity, programming, and cross-functional collaboration. Furthermore, Baethge-Kinsky's (2020) study of German industrial firms reveals that digitalization does not necessarily replace traditional manufacturing skills; rather, it complements them. Workers are now expected to develop higher-order analytical and problem-solving abilities alongside their existing technical foundation. This reality highlights a dual imperative for the current workforce: upskilling to enhance current expertise and reskilling to acquire entirely new capabilities.

Expanding on this, Juasiripukdee et al. (2025) examined developing economies and uncovered a significant divide between industry expectations and workers' actual competencies, particularly in advanced areas like robotics and IoT. This finding underscores the urgent, global need for structured digital learning interventions within the manufacturing sector.

## 2.2. Digital Upskilling and Reskilling: Conceptual Foundations

Conceptually, upskilling entails the refinement of existing skill sets to align with shifting job requirements, whereas reskilling necessitates the acquisition of novel competencies for role adaptation (Li, 2022). Embedded within the theoretical frameworks of HRD and organizational learning, these strategies are vital for modern workforce agility. Li (2022) compellingly argues that to build a resilient Industry 4.0 workforce, organizations must institutionalize lifelong learning as a continuous strategic imperative rather than treating it as a series of isolated training events.

Digital iterations of these processes diverge from conventional training via their utilization of advanced, technology-mediated modalities ranging from AI-driven personalized learning and LMS to immersive VR/AR environments (Autsadee et al., 2023; Giannakos et al., 2021). Highlighting the strategic impact of these technologies, Giannakos et al. (2021) demonstrated how learning analytics and customized educational pathways elevate organizational performance. Grounding these concepts empirically, Rangraz & Pareto (2021) explored work-integrated learning during an SME's Industry 4.0 transition, confirming that successful digital transformation hinges profoundly on the robust architectural design and institutional backing of learning initiatives.

## 2.3. E-Learning and Digital Training in Organizational Contexts

The wider organizational discourse on e-learning supplies an essential foundation for digital upskilling mechanisms. Empirically, Zhang et al. (2023) demonstrated that technology-mediated training substantially elevates employees' professional acumen and positively influences organizational expansion, establishing a robust performance rationale for digital learning investments. Corroborating this, Syed et al. (2023) investigated employee perceptions, concluding that e-learning platforms markedly augment competency and productivity when designed with optimal interactivity, personalization, and content relevance.

Furthermore, Giannakos et al. (2021) established that the rich behavioral data generated by e-learning systems, when leveraged through learning analytics, can profoundly optimize training efficacy and organizational learning trajectories. This capability holds particular significance for smart manufacturing environments, where digital training data can be seamlessly integrated with production analytics to refine targeted HR interventions.

Providing a structural overview of this domain, Gobniece & Titko (2024) mapped the literature on staff competency development for digital transformation. Their bibliometric analysis delineated five primary thematic clusters ranging from digital technologies and HR innovation to IT competencies. Notably, their findings underscored a chronic misalignment between theoretical frameworks and practical implementation systemic gap that closely mirrors the challenges reported in the manufacturing sector.

## 2.4. Bibliometric Analysis in HRD Research

Bibliometric analysis is increasingly recognized as a rigorous, transparent methodology for systematically synthesizing voluminous academic literature (Klarin, 2024). Utilizing quantitative indicators to assess bibliographic data allows scholars to delineate intellectual networks, chart conceptual trajectories, and expose structural research gaps with a precision that enriches traditional qualitative reviews (Bartolacci et al., 2020; Herrera-Franco et al., 2020).

In the context of HRD, this methodology has been successfully deployed across multiple specialized domains. Autsadee et al. (2023), for example, mapped the adoption of digital HRD tools in the maritime sector, identifying key learning technologies alongside implementation barriers. Concurrently, Capolupo et al. (2025) leveraged bibliometrics to investigate HRM 5.0, concluding that Industry 5.0 necessitates a paradigm shift toward human-centric, digitally competent continuous learning frameworks. Additionally, Al-Khoury et al. (2022) validated the efficacy of VOSviewer for mapping decades of research, providing a methodological precedent that directly informs the current investigation.

Crucially, however, while bibliometric analyses have proliferated in parallel disciplines, the literature lacks an equivalent mapping dedicated exclusively to digital upskilling and reskilling within the smart manufacturing sector. Fulfilling this significant empirical and methodological void is the central focus of this paper.

## 2.5. Research Gap and Theoretical Framework

Ultimately, the preceding review reveals a distinct gap: while substantial research exists regarding Industry 4.0 skill requirements, digital learning technologies, and manufacturing workforce transformation, these three streams have evolved largely in isolation. As recent bibliometric studies in adjacent HRD fields suggest, there is a pressing need to systematically synthesize these fragmented domains. To interpret the bibliometric landscape mapped in this study, we adopt an integrated theoretical framework. By converging Human Resource Development theory (focusing on capability building), Organizational Learning theory (addressing systemic knowledge acquisition), and Technology Acceptance models (explaining digital tool adoption), this tripartite framework provides a comprehensive lens for contextualizing our findings.

# 3. Methods

To systematically map the intellectual landscape of this field, this study employs a bibliometric analysis design. As a quantitative approach, bibliometrics applies statistical and mathematical tools to evaluate bibliographic data, making it highly effective for identifying key contributors, tracing structural evolution, and revealing thematic clusters within a specific body of literature (Bartolacci et al., 2020; Klarin, 2024). In executing this design, the study strictly adheres to established bibliometric protocols. This entails a systematic database search, rigorous data cleaning and deduplication, and subsequent network visualization using VOSviewer software, aligning with validated methodologies in recent peer-reviewed literature (Al-Khoury et al., 2022; Herrera-Franco et al., 2020; Salgado Moreno et al., 2024).

## 3.1. Data Source and Search Strategy

The Scopus database (Elsevier) was selected as the primary data source for this research. As the world's largest abstract and citation database of peer-reviewed literature, Scopus offers comprehensive coverage across engineering, business, management, accounting, and the social sciences fields that are all highly relevant to this interdisciplinary topic (Al-Khoury et al., 2022). Furthermore, its advanced search interface accommodates complex Boolean queries and facilitates the seamless export of rich bibliographic metadata, including titles, abstracts, author affiliations, publication outlets, citation metrics, and author keywords.

The search strategy was developed iteratively and validated through pilot searches. The final search string applied to TITLE-ABS-KEY fields was constructed as follows:

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TITLE-ABS-KEY ( ( "upskilling" OR "reskilling" OR "digital training" OR "workforce
development" ) AND ( "manufacturing" OR "industry 4.0" OR "smart manufacturing"
)) AND PUBYEAR > 2018 AND PUBYEAR < 2026 AND ( LIMIT-TO ( DOCTYPE,"ar"
) ) AND ( LIMIT-TO ( SUBJAREA,"SOCI" ) OR LIMIT-TO ( SUBJAREA,"BUSI" ) OR
LIMIT-TO ( SUBJAREA,"ENGI" ) ) AND ( LIMIT-TO ( LANGUAGE,"English" ) )
```

This string targets the title, abstract, and keywords fields to maximize recall while maintaining relevance. The publication year filter (PUBYEAR > 2018 AND < 2026) restricts results to 2020–2025. Additional filters specify article document type (DOCTYPE = ar) and English language, consistent with standard bibliometric practice (Gobniece & Titko, 2024; Klarin, 2024).

## 3.2. Inclusion and Exclusion Criteria

Following the initial retrieval, a rigorous screening process was conducted based on predefined eligibility parameters. Articles were included if they met all the following criteria: (1) published in peer-reviewed journals indexed in Scopus; (2) explicitly addressed digital training, upskilling, or reskilling within a manufacturing or Industry 4.0 context; (3) published between January 1, 2020, and December 31, 2025; and (4) written in English.

Conversely, records were excluded if they: (1) were conference papers, book chapters, editorials, or review articles that did not meet rigorous peer-review standards; (2) focused on upskilling or digital learning exclusively in non-manufacturing sectors (e.g., healthcare or education); or (3) lacked sufficient bibliographic metadata required for bibliometric visualization.

## 3.3. Data Collection and Processing

Upon executing the query within the Scopus Advanced Search interface, the resulting records were exported as a CSV file. This dataset captured all essential bibliographic metadata, including author details, affiliations, article and source titles, publication years, abstracts, keywords (both author and index), and citation counts. To ensure data integrity, the records were first screened using Scopus's built-in deduplication tool, followed by rigorous manual verification.

The refined dataset was subsequently imported into VOSviewer (version 1.6.20, Leiden University) widely recognized as the premier software for bibliometric mapping (Klarin, 2024; Salgado Moreno et al., 2024). This tool enabled the construction and visualization of complex intellectual structures, such as co-authorship networks, co-citation networks, bibliographic coupling, and keyword co-occurrence maps. Furthermore, to complement VOSviewer's spatial mapping, the R-based Bibliometrix package (accessed via the Biblioshiny interface) was utilized for deeper performance analysis and longitudinal trend identification. This dual-software approach firmly aligns with the methodological best practices recommended by Klarin (2024).

## 3.4. Analytical Framework

The analytical framework for this study was structured into two primary layers: performance analysis and science mapping. The first layer, performance analysis, evaluates the descriptive statistics of the dataset. This includes tracking annual publication trajectories, identifying the most prolific authors and institutions, and highlighting highly cited articles and leading journals. Essentially, this phase addresses the fundamental "who" and "how much" questions of the research landscape (Bartolacci et al., 2020). The second layer, science mapping, utilizes network visualization to decode the field's intellectual structure. Here, keyword co-occurrence analysis was deployed to uncover dominant research themes and their interconnections, mapping how frequently terms appear together to reveal distinct conceptual sub-themes (Klarin, 2024). Additionally, bibliographic coupling was utilized to group articles with shared reference lists, thereby exposing common theoretical foundations.

To ensure analytical robustness, the threshold for keyword co-occurrence was set at a minimum of five appearances per term, aligning with established bibliometric norms (Al-Khoury et al., 2022; Herrera-Franco et al., 2020). Finally, the thematic clusters generated by VOSviewer’s modularity-based algorithm were qualitatively reviewed, interpreted, and labeled by the research team based on the predominant content of each group.

## 3.5. Quality and Validity Considerations

Because the validity of any bibliometric study relies heavily on the quality of its underlying dataset, several measures were implemented to ensure methodological rigor. Initially, the search string underwent pilot testing and was peer-reviewed by two independent researchers before final execution. During the screening phase, inclusion and exclusion criteria were applied independently by two reviewers, with any discrepancies strategically resolved through consensus discussions. Furthermore, Scopus was deliberately chosen over alternatives like Web of Science due to its superior coverage of the interdisciplinary management and engineering literature crucial to this topic; however, the inherent limitation of relying on a single database is duly acknowledged (Gobniece & Titko, 2024). Finally, to prevent the analytical fragmentation of related concepts, manual keyword normalization was conducted, standardizing synonymous terms such as 'Industry 4.0' and 'Fourth Industrial Revolution' before the network visualization.

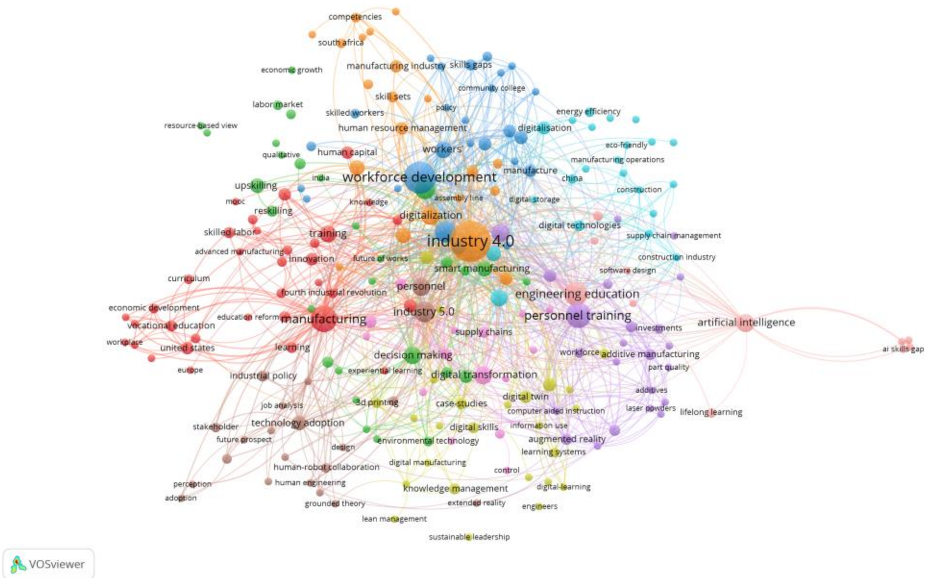
### 3.6. Ethical Considerations

Because this bibliometric analysis relies entirely on secondary, publicly accessible bibliographic data extracted from academic databases, it does not involve human subjects or primary data collection. Consequently, institutional ethical approval was not required. Furthermore, all analyzed literature has been meticulously cited and appropriately attributed to ensure strict adherence to academic integrity throughout the study.

## 4. Results and Discussion

The keyword co-occurrence network generated via VOSviewer presents an intellectual map of digital upskilling and reskilling research within the smart manufacturing context for the 2020–2025 period. In this visualization, node size represents the frequency of a keyword's occurrence, edge thickness reflects the strength of co-occurrence links between keywords, and colors denote membership in distinct thematic clusters (Kuzior et al., 2023). The analysis yielded eight primary clusters, reflecting interconnected yet thematically distinct research streams.

The largest nodes dominating the center of the network are "industry 4.0," followed by "workforce development," "manufacturing," "engineering education," "personnel training," and "digital transformation." The central positioning of these nodes indicates that they serve as critical thematic bridges across the various clusters, while simultaneously establishing them as the most productive themes within the analyzed literature (Rosak-Szyrocka & Knop, 2024). This finding aligns closely with the argument that Industry 4.0 functions as a unifying conceptual framework, synthesizing diverse discourses on labor, technology, and learning within the manufacturing sector (Li, 2022).




The keyword co-occurrence analysis reveals eight interconnected thematic clusters, with the literature's center of gravity resting on Cluster 1 (Orange), which represents the core of manufacturing digital transformation. This central cluster indicates a paradigm shift from a purely technological focus (e.g., Industry 4.0) to a more human-centric approach, as evidenced by the emergence of Industry 5.0 (Buri & T. Kiss, 2025; Capolupo et al., 2025). This technological foundation is strategically supported by Cluster 2 (Blue), which highlights the Human Resource Management (HRM) dimension in addressing skills gaps. The presence of keywords such as *policy* and *community college* reflects the urgency of aligning competencies through public policy interventions and vocational education institutions (Laundon et al., 2023; Li, 2022). Furthermore, this strategic discourse intersects closely with Cluster 8 (Teal), which contextualizes this transformation within global industrialization and environmental sustainability. The appearance of *energy efficiency* and *China* represents the twin transition agenda, where manufacturing digitalization across various regions proceeds in tandem with eco-friendly operational demands (Hofmann Trevisan et al., 2024)

At the operational and pedagogical levels, the implementation of competency development is comprehensively mapped across three complementary clusters**.** Cluster 3 (Red) serves as the substantive core of educational redesign, encompassing comparative reskilling and upskilling initiatives across diverse geographical regions (e.g., the United States, Europe, and India) and exploring massive digital instruments like MOOCs (Baethge-Kinsky, 2020; Li, 2022). These training initiatives are further enriched by advanced technological tools depicted in Cluster 4 (Purple), where the utilization of immersive technologies such as augmented reality and digital twins dominates the engineering education literature to create efficient, low-risk simulated work environments. (Buri & T. Kiss, 2025; Kaasinen et al., 2020). Beyond formal education and simulation, Cluster 5 (Green) underscores the importance of knowledge management and experiential learning in actual workplace settings. This suggests that current literature views digital skill acquisition not merely as classroom-based but as deeply integrated with daily work practices and sustainable leadership within the manufacturing ecosystem. (Rangraz & Pareto, 2021)

Completing this intellectual map, the literature also highlights crucial dynamics at the sociotechnical interface and the constellation of future challenges. Cluster 7 (Brown) specifically explores the behavioral factors of technology adoption, with a primary focus on human-robot collaboration dynamics and the understanding of worker perceptions through qualitative approaches such as grounded theory (Kaasinen et al., 2020). Finally, Cluster 6 (Pink), centered on artificial intelligence (AI) and lifelong learning, occupies an isolated position on the network's periphery. This structural isolation is a critical finding; it indicates that AI remains an emerging topic that has not yet been fully integrated into the mainstream discourse of manufacturing HRD. This peripheral position reveals a distinct research gap, providing a strong signal that prioritizing the lifelong learning philosophy to bridge the AI skills gap is an absolute imperative for future research agendas and industrial practices (Bukartaite & Hooper, 2023; Jaiswal et al., 2022).

## 5. Conclusion

This study mapped the intellectual landscape of digital upskilling and reskilling within the smart manufacturing context through a comprehensive bibliometric analysis of Scopus-indexed literature from 2020 to 2025. The findings reveal a rapidly expanding, interdisciplinary field that is conceptually anchored by core nodes such as Industry 4.0, workforce development, and digital transformation. By delineating eight interconnected thematic clusters, this research provides the first dedicated bibliometric synthesis of this domain, structurally validating the integration of Human Resource Development (HRD), Organizational Learning, and Technology Acceptance theories to understand industrial workforce transitions.

Practically, this mapping equips HRD managers and organizational leaders with an evidence-based inventory of emerging workforce development strategies. The literature strongly advocates for moving beyond traditional platforms to embrace immersive technologies such as augmented reality and digital twins, coupled with embedded experiential learning mechanisms. Furthermore, the findings emphasize that closing the manufacturing skills gap requires systemic collaboration among enterprises, public policymakers, and vocational education institutions. Looking forward, the structural isolation of the artificial intelligence and lifelong learning cluster on the network's periphery exposes a critical empirical void. Future scholarship must urgently prioritize AI-specific competency frameworks, while also addressing the dual demands of the twin transition (digitalization and environmental sustainability) across both developed and emerging economies.

Finally, while this study strictly adhered to established bibliometric protocols, certain limitations must be acknowledged. The exclusive reliance on English-language publications indexed within the Scopus database may systematically underrepresent scholarly contributions from non-Anglophone regions or alternative repositories. Consequently, future research should complement these quantitative structural findings with in-depth qualitative investigations to further decode the sociotechnical complexities of the future manufacturing workforce.

## 6. References

Al-Khoury, A., Hussein, S. A., Abdulwhab, M., Aljuboori, Z. M., Haddad, H., Ali, M. A., Abed, I. A., & Flayyih, H. H. (2022). Intellectual Capital History and Trends: A Bibliometric Analysis Using Scopus Database. *Sustainability 2022, Vol. 14, 14*(18). https://doi.org/10.3390/su141811615

Autsadee, Y., Jeevan, J., Mohd Salleh, N. H. Bin, & Othman, M. R. Bin. (2023). Digital tools and challenges in human resource development and their potential within the maritime sector through bibliometric analysis. *Journal of International Maritime Safety, Environmental Affairs, and Shipping*, *7*(4). https://doi.org/10.1080/25725084.2023.2286409

Baethge-Kinsky, V. (2020). Digitized Industrial Work: Requirements, Opportunities, and Problems of Competence Development. *Frontiers in Sociology*, *5*, 508518. https://doi.org/10.3389/fsoc.2020.00033

Bartolacci, F., Caputo, A., & Soverchia, M. (2020). Sustainability and financial performance of small and medium-sized enterprises: A bibliometric and systematic literature review. *Business Strategy and the Environment*, *29*(3), 1297–1309. https://doi.org/10.1002/bse.2434

Bukartaite, R., & Hooper, D. (2023). Automation, artificial intelligence, and future skills needs: an Irish perspective. *European Journal of Training and Development*, *47*(10), 163–185. https://doi.org/10.1108/EJTD-03-2023-0045

Buri, Z., & T. Kiss, J. (2025). Digitalisation in the Context of Industry 4.0 and Industry 5.0: A Bibliometric Literature Review and Visualisation. *Applied System Innovation 2025, Vol. 8, 8*(5). https://doi.org/10.3390/asi8050137

Capolupo, N., Maione, G., & Supino, S. (2025). The anatomy of human resource management (HRM) 5.0. A bibliometric review of practices and workforce skills. *TQM Journal*, 1–23. https://doi.org/10.1108/TQM-07-2025-0402

Giannakos, M. N., Mikalef, P., & Pappas, I. O. (2021). Systematic Literature Review of E-Learning Capabilities to Enhance Organizational Learning. *Information Systems Frontiers 2021 24:2*, *24*(2), 619–635. https://doi.org/10.1007/s10796-020-10097-2

Gobniece, Z., & Titko, J. (2024). Staff Competencies for Digital Transformation: Results of Bibliometric Analysis. *Virtual Economics*, *7*(1), 25-46–25–46. https://doi.org/10.34021/ve.2024.7.01(2)

Hansen, A. K., Christiansen, L., & Lassen, A. H. (2025). Technology isn't enough for Industry 4.0: on SMEs and hindrances to digital transformation. *International Journal of Production Research*, *63*(18), 6585–6605. https://doi.org/10.1080/00207543.2024.2305800

Herrera-Franco, G., Montalván-Burbano, N., Carrión-Mero, P., Apolo-Masache, B., & Jaya-Montalvo, M. (2020). Research Trends in Geotourism: A Bibliometric Analysis Using the

Scopus Database. *Geosciences 2020, Vol. 10, 10*(10), 1–29. https://doi.org/10.3390/geosciences10100379
Hofmann Trevisan, A., Acerbi, F., Dukovska-Popovska, I., Terzi, S., & Sassanelli, C. (2024). Skills for the twin transition in manufacturing: A systematic literature review. *Journal of Cleaner Production*, *474*, 143603. https://doi.org/10.1016/j.jclepro.2024.143603
Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: upskilling for artificial intelligence in multinational corporations. *International Journal of Human Resource Management*, *33*(6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114
Juasiripukdee, P., Srisuksai, P., & Nadprasert, P. (2025). Assessment of essential competencies of open university students in Thailand for the sustainable smart manufacturing industry. *Asian Association of Open Universities Journal*, *20*(2), 137–153. https://doi.org/10.1108/AAOUJ-12-2024-0160
Kaasinen, E., Schmalfuß, F., Öztürk, C., Aromaa, S., Boubekeur, M., Heilala, J., Heikkilä, P., Kuula, T., Liinasuo, M., Mach, S., Mehta, R., Petäjä, E., & Walter, T. (2020). Empowering and engaging industrial workers with Operator 4.0 solutions. *Computers & Industrial Engineering*, *139*, 105678. https://doi.org/10.1016/j.cie.2019.01.052
Klarin, A. (2024). How to conduct a bibliometric content analysis: Guidelines and contributions of content co-occurrence or co-word literature reviews. *International Journal of Consumer Studies*, *48*(2), e13031. https://doi.org/10.1111/ijcs.13031
Kuzior, A., Sira, M., & Brożek, P. (2023). Use of Artificial Intelligence in Terms of Open Innovation Process and Management. *Sustainability 2023, Vol. 15, 15*(9). https://doi.org/10.3390/su15097205
Laundon, M., McDonald, P., & Greentree, J. (2023). How education and training systems can support a digitally-enabled workforce for the manufacturing industry of the future: an exploratory study. *Education + Training*, *65*(6–7), 909–922. https://doi.org/10.1108/ET-04-2023-0158
Li, L. (2022). Reskilling and Upskilling the Future-ready Workforce for Industry 4.0 and Beyond. *Information Systems Frontiers*, *26*(5), 1. https://doi.org/10.1007/s10796-022-10308-y
Rangraz, M., & Pareto, L. (2021). Workplace work-integrated learning: supporting industry 4.0 transformation for small manufacturing plants by reskilling staff. *International Journal of Lifelong Education*, *40*(1), 5–22. https://doi.org/10.1080/02601370.2020.1867249
Rosak-Szyrocka, J., & Knop, K. (2024). Navigating the Fourth Industrial Revolution: insights from a comprehensive bibliometric study on Industry 4.0. *Production Engineering Archives*, *30*(4), 501–519. https://doi.org/10.30657/pea.2024.30.47
Salgado Moreno, A. L., Forero, J. A. M., Revilla, R. G., & Moure, O. M. (2024). Research Trends in Communication and Tourism: A Systematic Review and a Bibliometric Analysis. *Administrative Sciences 2024, Vol. 14, 14*(9). https://doi.org/10.3390/admsci14090208
Saniuk, S., Caganova, D., & Saniuk, A. (2021). Knowledge and Skills of Industrial Employees and Managerial Staff for the Industry 4.0 Implementation. *Mobile Networks and Applications 2021 28:1*, *28*(1), 220–230. https://doi.org/10.1007/s11036-021-01788-4
Spöttl, G., & Windelband, L. (2021). The 4th industrial revolution–its impact on vocational skills. *Journal of Education and Work*, *34*(1), 29–52. https://doi.org/10.1080/13639080.2020.1858230
Syed, F. U., Abdul, S. M., Mohd, S., & Are, A. (2023). Employees' perception towards e-learning: an exploratory study in the information technology sector in India. *Industrial and Commercial Training*, *55*(3), 355–363. https://doi.org/10.1108/ICT-11-2022-0082
Zhang, X., Wu, H., Huang, X., Wu, Q., & Wu, Y. (2023). How does online employee training enhance organizational growth? The benefits of integrating educational technology into workplace learning. *Industrial and Commercial Training*, *55*(4), 568–579. https://doi.org/10.1108/ICT-02-2023-0006