ECONOMIC AND BUSINESS REVIEW

Volume 28 | Issue 2 Article 5

June 2026

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Recommended Citation

Erjavec, E. (2026). Towards an Inclusive Labour Market: Skills for the Future. *Economic and Business Review, 28*(2), 155-175. https://doi.org/10.15458/2335-4216.1373

REVIEW ARTICLE

Towards an Inclusive Labour Market: Skills for the Future

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Abstract

In the transition to a knowledge-based society, human capital has become a key driver of economic growth, innovation, and social progress. As industries evolve and new technologies reshape labour markets, the development of future skills plays a crucial role in ensuring workforce adaptability, productivity, and long-term competitiveness. A bibliometric analysis aims to examine the importance of human capital for economic growth and the transition to a knowledge economy, synthesizing existing research and academic discussions. By systematically reviewing the literature, this paper seeks to provide insights into how skills and education contribute to sustainable economic development and social resilience. Furthermore, it identifies key research gaps, emerging trends, and the evolving role of human capital in an era of rapid technological change. Additionally, this paper develops a conceptual framework outlining the essential skills required for the future workforce, integrating insights from technological advancements, economic shifts, and industry transformations. The framework categorizes skills into core areas, including digital literacy, AI proficiency, data analytics, sustainability expertise, and soft skills such as adaptability and critical thinking. Furthermore, this paper explores the necessary transformations within the workforce, highlighting the structural changes needed in education, corporate training, and policy frameworks to align skill development with future market demands. By mapping the transition pathways, this paper provides recommendations for workforce adaptation, ensuring that businesses, governments, and educational institutions are prepared to meet evolving labour-market needs.

Keywords: Future skills, AI, Human capital, Workforce transformation

JEL classification: O30, O35, J00

1 Introduction

In the age of digital transformation, climate urgency, and rapid technological innovation, labour markets are undergoing unprecedented disruption. Automation, artificial intelligence (AI), and sustainability imperatives are reshaping industries and redefining job profiles. Consequently, the development of future-oriented skills has become a cornerstone of economic competitiveness, innovation capacity, and inclusive social progress.

This paper investigates how human capital—particularly future-relevant skills—underpins economic transformation and labour-market resilience. It conducts a comprehensive bibliometric analysis to map the evolution of academic discourse on future skills, while also integrating institutional reports and global policy perspectives. The central objective is to provide an evidence-based framework that guides policymakers, educators, and businesses in aligning workforce development with emerging labour-market demands.

The research adopts a bibliometric methodology using tools such as R (Bibliometrix) and VOSviewer to systematically examine over 17,000 scholarly documents. The analysis identifies influential authors, journals, collaboration networks, and dominant research clusters. This quantitative mapping is complemented by a narrative synthesis of key themes to build a conceptual framework on future skill requirements.

Received 8 April 2025; accepted 21 January 2026.
Available online 1 June 2026

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https://doi.org/10.15458/2335-4216.1373

The study contributes to three critical domains: (a) identifying missing workforce skills in the areas of AI, digital technologies, and sustainability; (b) assessing upskilling and reskilling strategies for workforce adaptability; and (c) analysing the transformation of education and training systems in response to technological and economic shifts. The conceptual framework developed links these three domains, offering a roadmap for managing workforce transitions in a dynamic global economy.

While the paper synthesizes global academic and policy perspectives, it acknowledges limitations related to regional specificity, informal learning pathways, and nonlinear workforce transitions. The framework proposed is not exhaustive but is designed to evolve through empirical testing and contextual adaptation.

The paper is structured as follows: Section 2 outlines the theoretical background and formulates the key research questions. This is followed by subsections that detail the bibliometric methodology, the results and thematic mapping, concluding with research gaps. Section 3 develops the policy and managerial implications framework, with a focus on missing skills, upskilling/reskilling, and education reform; Section 4 focuses on discussion, and Section 5 concludes.

2 Theoretical background

The theoretical foundation of this paper lies at the intersection of human capital theory, innovation systems, and organizational adaptability. Traditional economic models have long recognized the contribution of education and skills to productivity growth (Becker, 1964). However, the contemporary challenge lies not merely in quantifying human capital, but in understanding which new competencies are required to meet the demands of rapidly evolving technologies, green transitions, and changing organizational structures.

The core theoretical research question guiding this paper is: How do future skills, in particular digital, AI, and sustainability-related competencies, function as strategic enablers of economic transformation, and how can education, training, and policy systems evolve to support their development? The literature has increasingly acknowledged that workforce transformation hinges on three interrelated processes: (a) identifying missing skills, including deficits in AI proficiency, data literacy, and sustainability knowledge (Dondi et al., 2021; Frey & Osborne, 2017); (b) addressing upskilling and reskilling needs through lifelong learning, corporate training, and modular credentials (OECD, 2019; SkillsFuture Singapore, 2023); and (c) transforming education and training systems to integrate digital tools, agile curricula, and interdisciplinary learning (Venkatesh, 2000; Verhoef et al., 2021).

Seen through an innovation-systems lens, the same skill set can travel very different paths depending on where it lands. In some places it is taken up and amplified by dense networks of firms, universities, and public agencies; in others it stalls because the complementary pieces (e.g., standards, finance, regulation) are missing (Freeman, 1987; Lundvall, 1992; Malerba, 2002). Zooming in to the organization, the resource-based view and dynamic capabilities perspective show how those skills are actually put to work, bundled with assets and routines, reconfigured as technologies shift, and translated into performance (Barney, 1991; Teece, 2007; Teece et al., 1997). Taken together, these perspectives recast skills not as fixed endowments but as strategic complements. They help firms sense technological change, seize opportunities through job redesign and new processes, and continually transform to sustain advantage.

Despite these insights, the literature remains fragmented across disciplines and lacks a unified conceptual structure. This paper addresses this gap by using bibliometric methods to synthesize the academic landscape, mapping the relationships among key concepts and identifying underexplored thematic clusters. The bibliometric approach supports theory building by visualizing how academic debates have evolved over time and where future research should focus; to ensure methodological rigor and reproducibility, we follow best-practice guidelines and tooling widely adopted in management and information sciences (e.g., Aria & Cuccurullo, 2017; Donthu et al., 2021; van Eck & Waltman, 2010, 2023). In doing so, it strengthens the theoretical understanding of how human capital adapts to technological and environmental disruptions, and how skill systems must coevolve to sustain competitiveness and inclusion (World Economic Forum, 2025).

While traditional economic research often focuses on measurable outputs such as productivity and GDP growth, what remains insufficiently explored is which new skills will be required as businesses adapt to rapid technological advancements and shifts in the economic landscape. As automation, AI, and digitalization reshape industries, evidence shows the coexistence of substitution and complementarity effects on labour, increasing demand for advanced digital literacy, data analytics, AI proficiency, and cybersecurity alongside socioemotional and problem-solving capabilities (Acemoglu & Restrepo, 2019; Autor, 2015; World Economic Forum, 2025). Simultaneously, the evolving business environment requires adaptability, critical thinking, problem solving, and leadership in digital and remote work settings.

Table 1. Step-by-step research approach summary.

Research goals	• Comprehensive analysis of papers on the development of the skills for the future focusing on the identification of the key topics and key gaps • Dynamics of the development of the field • Topic development and main concepts in the topics • Identification of gaps in the literature
Data collection	• Scopus • Boolean keywords: "skills" OR "skills for the future" OR "competencies" OR "upskilling" OR "reskilling" AND "digital" OR "AI" OR "automation" AND "technological change" OR "industry 4.0" OR "sustainability" OR "green skills" AND "productivity" OR "innovation" in abstract, title, or keywords
Data preparation and cleaning	• Period: up to 2024 • Publication stage: final • Language: English • Other types: review, conference review, note, editorial, letter, short survey, retracted, erratum excluded (1001)
Data set characteristics	• 17,629 documents ∘ 12,304 articles ∘ 2745 book chapters ∘ 1491 books ∘ 1080 conference papers • 4320 different sources
Analysis and results	• Bibliometric analysis using R and VOSviewer • Visualization and interpretation, supported by standard literature review of key authors and concepts • Conclusions, limitations, and guidelines for future research

Source: Own representation, but inspired by Roblek et al. (2022).

Additionally, as sustainability and the green transition become central to economic strategies, knowledge of sustainable business practices, circular-economy principles, and environmental, social, and governance (ESG) expertise will be increasingly essential (International Labour Organization, 2019; OECD, 2019). Understanding how these skills must evolve to meet future challenges remains a key research gap. This gap presents an opportunity to better understand the role of human capital in accelerating innovation, supporting industrial transitions, and enhancing labour-market efficiency. To address this, a systematic bibliometric analysis of the literature on human capital and future skills is conducted, identifying key themes, methodological approaches, and ongoing discourse.

2.1 Bibliometric analysis

The application of bibliometric methods is becoming increasingly widespread across various academic disciplines. In the current research environment, where empirical contributions are highly valued, leading to extensive, fragmented, and sometimes debated research streams, bibliometrics has emerged as a valuable tool for science mapping. This analysis follows established bibliometric methodologies (Aria & Cuccurullo, 2017; Aria et al., 2024; De Bellis, 2009; van Raan, 1993; Zupic & Čater, 2015). The statistical computing environment R, along with the Bibliometrix package developed by Aria and Cuccurullo (2017) and its accompanying biblioshiny application, was utilized to carry out the analysis. Additionally, VOSviewer was employed to explore the thematic structure in greater depth.

The analysis followed a structured five-stage approach (Table 1). In the first stage, the research questions were formulated, and the research design was established. The second stage involved compiling a bibliometric data set, which included data acquisition from Scopus. The third stage focused on preparing the data, followed by conducting the analysis, which encompassed both content analysis and the visualization of findings. Lastly, in the final stage, the results were interpreted, and the paper's limitations were identified, along with recommendations for future research.

The analysis was performed on the period up to December 2024 with search terms: skills, skills for the future, competencies, upskilling, reskilling, digital, AI, automation, technological change, Industry 4.0, sustainability, green skills, productivity, innovation. The search was limited to "Business, Management and Accounting." The sources were limited to articles, early-access articles, book chapters, and proceeding papers. Also, the research was limited to the English language. The decision to limit the paper to English was made with the intention of also analysing the content. Although other languages are important for dissemination in domestic academic and professional

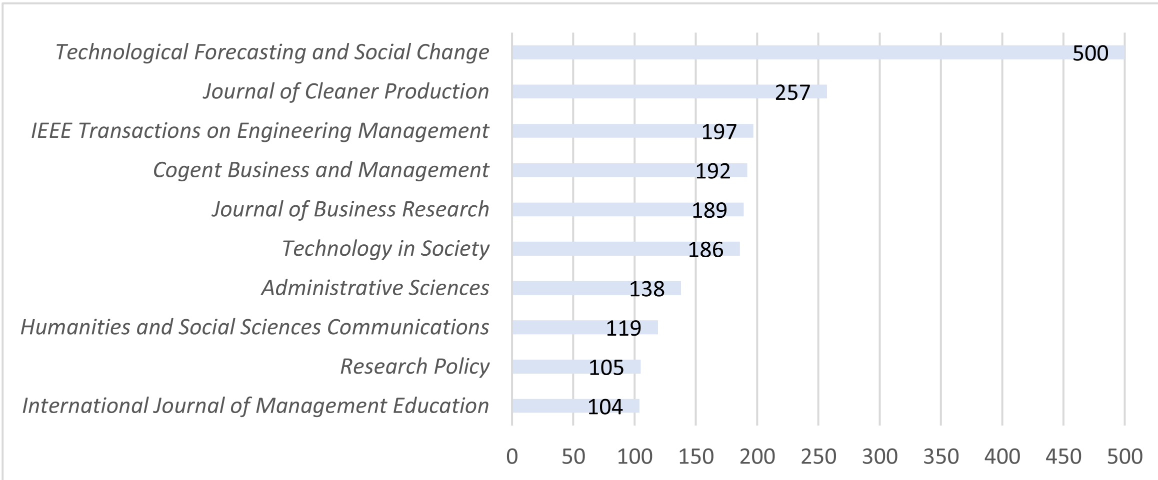

Fig. 1. Most relevant sources.

communities, the number of papers excluded from the analysis worldwide is very small and will not significantly impact the analysis or the outcomes.

2.2 Results

2.2.1 Sample description

17,629 documents (articles, book chapters, books, conference papers) from 4320 different sources were included in the analysis. This research considered 1,304 articles, 2745 book chapters, 1491 books, and 1080 conference papers. The paper was limited to English-language contributions, meaning that a total of 46 contributions (16 Portuguese, 13 Spanish, 4 Serbian, 4 Lithuanian, 3 Chinese, 2 Russian, 2 Italian, 1 French, 1 Croatian) were not included.

The analysis of journal contributions to research on future workforce skills, Industry 4.0, AI, automation, and sustainability (see Fig. 1) reveals significant interdisciplinary engagement across technology, business, policy, and education fields. The most influential journal in this data set is *Technological Forecasting and Social Change*, with 500 published documents, which indicates that long-term technological transformations and their impact on the workforce remain central themes in future skills research (Dwivedi et al., 2023). The *Journal of Cleaner Production* (257 documents) follows, highlighting the growing importance of sustainability and green skills in workforce transitions (Sarkis et al., 2011). The high volume of publications in this journal suggests that sustainable production processes, circular-economy strategies, and climate-conscious competencies are becoming integral to the Industry 4.0 framework. Journals with a strong focus on engineering and industrial management, such as *IEEE Transactions on Engineering Management* (197 documents), emphasize technical workforce skills, automation integration, and digital transformation in manufacturing and operations (Gunasekaran et al., 2020). Business- and management-oriented publications, including *Cogent Business and Management* (192 documents) and the *Journal of Business Research* (189 documents), contribute to understanding how organizational strategies, leadership approaches, and entrepreneurial mindsets influence digital upskilling and reskilling initiatives (Dwivedi et al., 2021).

Emerging research trends are further reflected in *Technology in Society* (186 documents), which explores the broader societal implications of automation, AI-driven decision making, and labour-market shifts. Additionally, *Administrative Sciences* (138 documents) and *Humanities and Social Sciences Communications* (119 documents) signal an increasing engagement with HR strategies, workforce education policies, and social aspects of digital transformation. *Research Policy* (108 documents) contributes to discussions on government interventions, regulatory frameworks, and AI governance, demonstrating that policy considerations play a crucial role in shaping future workforce competencies. The presence of the *International Journal of Management Education* (104 documents) further reinforces the role of education in preparing the workforce for Industry 4.0, emphasizing digital literacy, lifelong learning, and training adaptation (Venkatesh, 2000).

The distribution of research across these journals highlights that the future skills landscape is deeply interconnected with technology, sustainability, business strategy, and policy innovation. The increasing contributions to sustainability-focused journals suggest that green skills and environmental competencies are becoming fundamental workforce requirements,

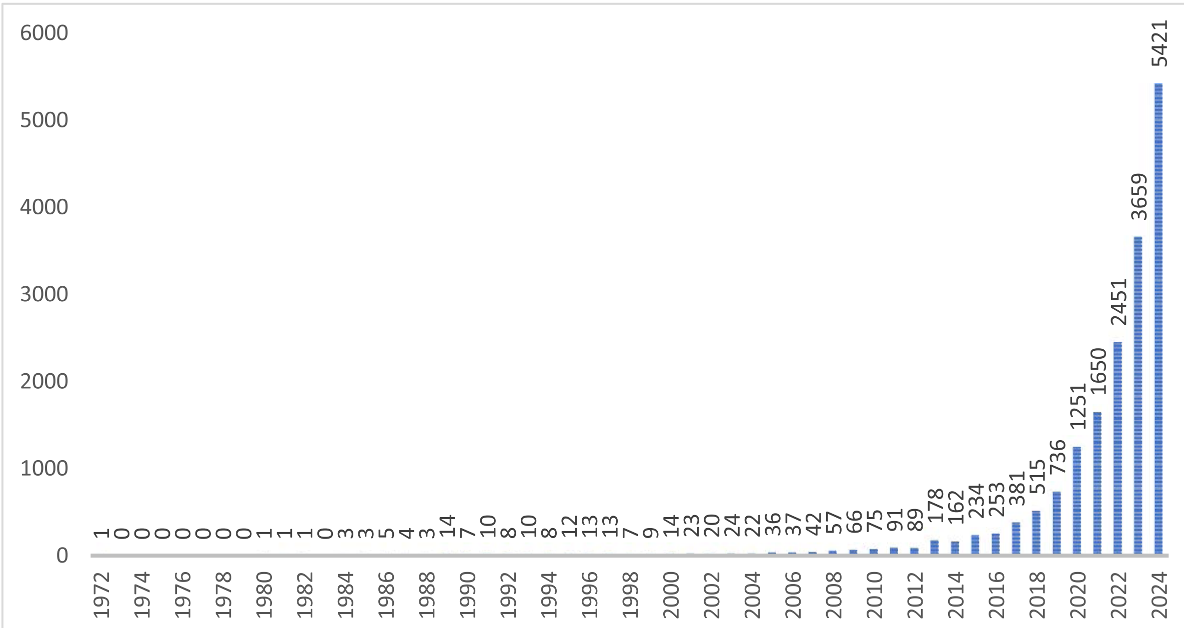

Fig. 2. The number of works published by year: 1972 to end of 2024.

alongside digital and AI-related capabilities. Furthermore, the significant presence of business and management journals underscores that organizational agility, innovation-driven leadership, and workforce adaptability remain critical factors in navigating technological disruptions and future labour-market demands.

The 17,629 documents included in the dataset were written by total of 38,346 authors (some papers were coauthored). 2972 were written by a single author, while the coauthored papers had an average of 3.04 coauthors. The data set was described by 32,034 author keywords and 17,998 additional keywords.[1] The average "age" of the papers (years from publication) was 3.64 years. The average citation frequency per paper was 20.01.

The theme of future workforce skills has evolved significantly over the past four decades (see Fig. 2). Early research (1980s–2000s) primarily focused on the role of technical training and STEM education in labour markets. With the emergence of Industry 4.0 (2010–2024), discussions expanded to include digital transformation, AI governance, and sustainability-driven competencies (Dwivedi et al., 2023). Analysing the annual scientific production reveals a significant rise in publications post-2015, reflecting the growing urgency of addressing skills gaps.

2.2.2 Development of the field

The first papers discussing how future skills need to adapt to economic and technological changes date back several decades. Early research recognized that technical change and automation would significantly impact employment, requiring workers to acquire new competencies. In one of the earliest contributions to this field, Senker (1981) examined the impact of technological change on employment and international competition, particularly in the UK. The paper highlighted that as manufacturing industries struggled with global competitiveness, new skills would be necessary to mitigate job displacement. The paper underscored the role of national policies and workforce adaptation strategies in addressing structural unemployment caused by automation. A key theme emerging from early literature is the challenge of skill obsolescence due to increasing complexity in organizational structures and technological integration. Burack (1972) discussed how technological advancements in computerization and automation posed threats to managerial and professional roles. The paper argued that organizations must develop proactive training programmes to ensure that employees and leaders remain competitive in their roles. This need for continuous learning remains a fundamental aspect of contemporary debates on lifelong

[1] Author keywords are chosen by the author to best reflect the content of the document. Additional keywords are chosen by Scopus and are standardized to vocabularies derived from thesauri that Elsevier owns or licenses. Unlike author keywords, additional keywords take into account synonyms, various spellings, and plural forms.

learning and workforce adaptability in the era of AI and Industry 4.0. As automation and robotics became more integrated into industrial processes, scholars focused on how technology could complement human work rather than replace it. Kamali et al. (1982) proposed a framework for integrated assembly systems, emphasizing the interplay between human labour, automation, and robotics. Their work anticipated modern discussions on human–AI collaboration and the need for workers to develop hybrid skills that combine technical expertise with oversight of automated systems. The notion that machines should enhance human capabilities rather than substitute them is now a critical discussion point in workforce planning for Industry 4.0. A key area of interest in the 1980s was the impact of new production technologies on industrial relations and skill requirements. Warner (1984) examined the role of microprocessor-based systems such as flexible manufacturing systems (FMS), CAD/CAM, and CNC in transforming workplaces. The paper found that such technologies led to skill polarization, where some workers required higher levels of technical proficiency, while others experienced deskilling due to automation. This early insight mirrors modern concerns about workforce polarization, where high-skilled digital jobs grow while routine cognitive and manual jobs decline. The paper also emphasized the role of formal participatory structures in determining how well workers adapted to technological change, a discussion that remains relevant in the implementation of AI-driven workplace transformations today. Beyond the immediate impact of technology on labour markets, early research also explored how organizations learn and adapt to innovation. Ettlie and Rubenstein (1980) applied social learning theory to production innovation, arguing that successful technology adoption depends on an organization's ability to diffuse new knowledge and foster a learning-oriented workforce. Their findings suggested that human resource strategies play a crucial role in determining whether employees embrace or resist technological change. Today, this insight supports the need for workplace learning programmes, reskilling initiatives, and corporate upskilling investments to ensure that employees can effectively transition into digital and AI-enhanced roles.

One of the foundational contributions to the 1990s discussion was made by Sanchez (1995), who examined the role of strategic flexibility in product competition. The paper introduced a framework where flexibility depends on both resource adaptability and a firm's coordination capabilities in dynamic product markets. The paper also identified two key technological innovations—CADD/computer-integrated manufacturing (CIM) systems and modular product design—that had enhanced firms' ability to create new products efficiently and respond to market demands with agility. The implications for future workforce skills are clear: As firms leverage AI-driven product development, automation, and advanced manufacturing, workers must possess technical competencies in digital systems, adaptability to modular and agile work processes, and the ability to integrate new technologies into their workflows (Sanchez, 1995). A complementary perspective is offered by Williams and Edge (1996), who analysed the social shaping of technology (SST) and how it affects technological adoption and workforce skills. Their paper challenged the linear model of innovation, arguing that social, economic, and technical factors jointly influence how technology is designed and implemented. This insight is critical for understanding the human side of digital transformation, as the successful adoption of new technologies is not solely determined by technical feasibility but also by organizational culture, workforce readiness, and skill development programmes. It underscores the importance of digital literacy, adaptability, and change management skills in fostering successful transitions to new technological paradigms (Williams & Edge, 1996). The resource-based view (RBV) of product development, explored by Verona (1999), further extends this discussion by examining how firms leverage their internal capabilities to enhance process efficiency and product innovation. The paper highlights that successful firms not only acquire advanced technologies but also build functional and integrative capabilities that allow them to maximize the impact of these technologies. The creation, utilization, and capitalization of workforce competencies play a critical role in ensuring that businesses can transition to sustainable production models, improve productivity, and remain competitive in global markets (Verona, 1999).

In the early 21st century, scholars began investigating how technological change, automation, and digital transformation impact workplace competencies, highlighting the need for continuous upskilling, reskilling, and adaptability. One of the foundational studies in this domain is Venkatesh (2000), who examined the determinants of perceived ease of use in technology adoption (see Table 2). The paper introduced a theoretical model integrating control, intrinsic motivation, and emotion—the technology acceptance model (TAM)—, highlighting how users develop perceptions of technology usability over time. The paper's findings remain highly relevant in the era of AI and Industry 4.0, as workers must not only acquire digital skills but also overcome psychological and motivational barriers associated

Table 2. Most globally cited papers, Scopus, 1972–2024.

Most globally cited papers	Total citations (TC)	TC per Year	Normalized TC
Venkatesh (2000)	4660	179.23	11.09
Frey and Osborne (2017)	3453	383.67	71.69
Verhoef et al. (2021)	2287	457.40	73.16
Xu et al. (2018)	2242	280.25	43.04
Frank et al. (2019)	1933	276.14	49.36
Dwivedi et al. (2021)	1835	367.00	58.70
Dwivedi et al. (2023)	1750	583.33	170.09
Malerba (2002)	1641	68.38	6.51
Fiss (2007)	1639	86.26	13.87
Danneels (2002)	1591	66.29	6.31

with technological adoption. This suggests that future training programmes should focus not only on technical competencies but also on enhancing employees' confidence, adaptability, and digital playfulness (Venkatesh, 2000). Building on the relationship between technological innovation and workforce skills, Danneels (2002) explored the dynamics of product innovation and firm competencies. The paper applied organizational learning theory to show that companies must balance exploitation (leveraging existing skills) and exploration (developing new competencies). The paper highlights the path-dependent nature of skills development, reinforcing the importance of lifelong learning and continuous professional development in an era of rapid digitalization (Danneels, 2002). A complementary perspective is offered by Garud and Karnøe (2003), who introduced the bricolage-versus-breakthrough framework in technology entrepreneurship. Their paper emphasized distributed and embedded agency, showing that technological change is not a top-down process but an evolving ecosystem where various stakeholders contribute. This insight is crucial for understanding how workers must develop interdisciplinary skills, integrating technical expertise with collaborative problem solving and innovation management (Garud & Karnøe, 2003).

The intersection of IT capabilities and workforce development was further explored by Ray et al. (2005), who investigated the impact of IT on customer service performance. Their paper found that the mere presence of IT resources does not automatically translate to superior firm performance. Instead, the ability of organizations to integrate IT with workforce competencies and process efficiencies determines its success. This finding is highly relevant for future skills development, as workers must not only use IT tools but also understand how to integrate them strategically into their roles. The paper's emphasis on shared knowledge between IT and other business units suggests that future employees must develop cross-functional digital skills (Ray et al., 2005). Further advancing this discussion, Aral and Weill (2007) examined IT investments, organizational capabilities, and firm performance. Their findings confirmed that IT investments alone do not drive business success—instead, the key determinant is how IT assets align with organizational strategy and workforce capabilities. The paper's focus on mutually reinforcing IT capabilities aligns with Industry 4.0 and smart manufacturing, where automation, AI, and big data analytics are transforming job roles. As such, employees must continuously upskill to extract value from IT innovations and ensure that their organizations maintain a competitive edge (Aral & Weill, 2007).

Another study on the future of employment and job automation was conducted by Frey and Osborne (2017). Their research assessed the susceptibility of jobs to computerization, estimating the likelihood of automation for 702 occupations using machine-learning models. The paper found that low-skill, routine-based jobs are at the highest risk, while roles requiring social intelligence, creativity, and complex problem solving are less susceptible to automation. This paper reinforced the importance of upskilling and reskilling to ensure workforce employability in digitally transforming economies. Workers must increasingly develop technological literacy, critical thinking, and adaptability to remain relevant in an AI-dominated labour market (Frey & Osborne, 2017). The rise of Industry 4.0, which integrates cyber–physical systems, IoT, cloud computing, and big data analytics, further complicates the demand for future skills. Xu et al. (2018) reviewed the state-of-the-art technologies driving Industry 4.0 and highlighted their transformative impact on global manufacturing. Their paper indicated that countries with well-structured digital transformation policies, such as Germany's Industry 4.0 initiative and China's Made in China 2025, are better positioned to harness these changes. The paper underscores the need for advanced digital competencies, automation expertise, and interdisciplinary technical skills to successfully integrate Industry 4.0 technologies into business operations (Xu et al., 2018). The adoption patterns of Industry 4.0 technologies in manufacturing firms were further explored by Frank et al. (2019). Their paper classified Industry 4.0 technologies into front-end (smart manufacturing, smart products, smart supply chains, and smart working) and base technologies (IoT, cloud services, big data, and analytics). The findings revealed that many firms struggle to fully integrate big data and analytics, despite their importance in digital transformation. This highlights a crucial skill gap—future workers must develop expertise in data analytics, digital twins, and AI-powered decision making to optimize Industry 4.0 implementation (Frank et al., 2019).

Beyond technical skills, the transition to AI-driven workplaces and Industry 4.0 requires strong managerial and cognitive capabilities to navigate complex strategic transformations. Helfat and Peteraf (2015) introduced the concept of managerial cognitive capability, emphasizing that dynamic capabilities require both physical and mental adaptability. Their research proposed that managers must develop sensing, seizing, and reconfiguring skills to effectively leverage digital transformation and innovation. This perspective aligns with the growing need for leaders who can integrate automation with strategic decision making while fostering continuous workforce learning and adaptation (Helfat & Peteraf, 2015). A crucial intersection between Industry 4.0 and sustainability is explored by de Sousa Jabbour et al. (2018), who examined how Industry 4.0 technologies can drive environmentally sustainable manufacturing. Their paper identified 11 critical success factors for integrating Industry 4.0 and green manufacturing, suggesting that firms must train employees in both technological and environmental competencies. The findings underscore the need for future skills to extend beyond digital expertise and include sustainability knowledge, circular-economy principles, and ESG considerations (de Sousa Jabbour et al., 2018).

To sustain workforce competitiveness in an era of rapid technological change, firms must invest in organizational learning and knowledge transfer. Argote (2013) explored how organizations create, retain, and transfer knowledge, highlighting that firms with strong learning cultures adapt faster to innovation. The paper revealed that productivity gains are directly linked to an organization's ability to systematically capture, share, and apply new knowledge. This insight reinforces the importance of lifelong learning, digital upskilling, and structured corporate training programmes in ensuring that employees can keep pace with evolving technological demands (Argote, 2013).

A key contribution to this field in the 2020s was made by Verhoef et al. (2021), who examined digital transformation as a process encompassing digitization, digitalization, and full-scale transformation. Their paper highlights that successful digital transformation requires new business models, growth strategies, and digital competencies. This aligns with the increasing need for digital literacy, data analytics skills, and AI proficiency to adapt to technology-driven workplaces (Verhoef et al., 2021).

The role of AI in transforming job markets and organizational processes has been widely studied. Dwivedi et al. (2021) explored the multidisciplinary impact of AI across industries, finding that AI-driven automation will reshape sectors such as finance, healthcare, logistics, and retail. As AI increasingly augments or replaces human tasks, employees must develop AI integration skills, problem-solving abilities, and adaptability to remain relevant in their fields (Dwivedi et al., 2021). A more recent paper by Dwivedi et al. (2023) analysed the implications of generative AI models, such as ChatGPT, for business, research, and education. The findings suggest that AI-driven automation will enhance productivity but may also create ethical and job displacement challenges. The paper underscores the importance of critical thinking, AI oversight skills, and digital ethics to ensure that workers can leverage AI responsibly while mitigating risks related to misinformation and algorithmic bias (Dwivedi et al., 2023). Beyond AI, the metaverse has emerged as a potential game changer in digital interaction and business operations. Dwivedi et al. (2022) examined the metaverse's impact on marketing, education, and healthcare, arguing that extended reality (XR) and virtual collaboration tools will require workers to develop new digital-communication and immersive-technology skills. This suggests that future employees must be proficient in virtual collaboration platforms, digital marketing in the metaverse, and cybersecurity in virtual environments (Dwivedi et al., 2022). The role of algorithms in reshaping work processes is further explored by Kellogg et al. (2020), who introduced the six Rs of algorithmic control: restricting, recommending, recording, rating, replacing, and rewarding. Their paper highlights how AI-powered algorithms influence hiring, performance evaluation, and workplace management, suggesting that employees must develop algorithmic literacy, adaptability to digital work environments, and awareness of AI-driven decision-making processes (Kellogg et al., 2020). Another perspective on AI and business transformation is provided by Di Vaio et al. (2020), who examined the relationship between AI and sustainable business models (SBMs). Their findings suggest that AI can drive sustainability by optimizing resource management, reducing waste, and supporting circular-economy initiatives. However, they also emphasize the need for green skills, ethical AI governance, and sustainability knowledge to align AI with the United Nations' Sustainable Development Goals

Table 3. Summarization of key thematic clusters in future skills research.

Key authors	Thematic focus	Main implication
Senker (1981), Burack (1972)	Impact of early automation on employment and managerial roles	Need for proactive national policies and continuous learning to combat obsolescence
Kamali et al. (1982), Warner (1984)	Technology integration and skill polarization	Hybrid skills and participatory structures essential for adaptation
Ettlie and Rubenstein (1980), Argote (2013)	Organizational learning and innovation adoption	Learning cultures and knowledge sharing drive successful transitions
Sanchez (1995), Verona (1999)	Strategic flexibility and internal capabilities	Adaptable digital skills and integrative competencies support innovation
Williams and Edge (1996), Garud and Karnøe (2003)	Sociotechnical shaping and distributed innovation	Change management and interdisciplinary skills are vital
Venkatesh (2000), Danneels (2002)	Technology acceptance and skills evolution	Training must address motivation and support lifelong learning
Ray et al. (2005), Aral and Weill (2007)	IT capabilities and performance	Strategic IT use requires digitally competent and aligned workforce
Frey and Osborne (2017), Xu et al. (2018), Frank et al. (2019)	Job automation and Industry 4.0	Workforce needs tech-savviness, adaptability, and decision-making skills
Helfat and Peteraf (2015), de Sousa Jabbour et al. (2018)	Leadership and sustainability	Digital, managerial, and environmental competencies are increasingly critical
Dwivedi et al. (2021, 2022, 2023), Di Vaio et al. (2020), Kellogg et al. (2020)	AI, ethics, and workforce transformation	AI literacy, ethical awareness, and algorithmic skills shape future readiness
Mikalef et al. (2020), Vrontis et al. (2022)	Big data and HR transformation	Data literacy and human–machine collaboration redefine digital roles

(SDGs; Di Vaio et al., 2020). The increasing reliance on big data analytics has transformed decision making in businesses. Mikalef et al. (2020) explored how big data analytics capabilities (BDACs) enhance competitive performance by enabling firms to generate insights and strengthen dynamic capabilities. Their paper underscores the importance of data literacy, analytical thinking, and business intelligence skills for future employees, as organizations increasingly rely on data-driven strategies (Mikalef et al., 2020). The impact of AI and robotics on human resource management (HRM) has also been a growing area of research. Vrontis et al. (2022) conducted a systematic review of how intelligent automation is transforming HR functions, including recruitment, training, performance management, and decision making. The paper found that HR professionals must develop AI-related skills to manage human–machine collaboration effectively, as well as address ethical concerns, algorithmic bias, and digital employee experience (Vrontis et al., 2022).

Table 3 synthesizes foundational contributions to the literature on future workforce skills by clustering key authors according to their thematic focus and core insights. The table illustrates how the evolution of the field has been shaped by diverse yet interconnected streams of research. Early studies, such as those by Senker (1981) and Burack (1972), emphasized the disruptive effects of automation on employment and managerial roles, underscoring the importance of proactive workforce policies and continuous learning systems. As technological systems became more integrated, scholars such as Kamali et al. (1982) and Warner (1984) introduced the notion of skill polarization and the growing need for hybrid human–machine competencies. Parallel contributions by Ettlie and Rubenstein (1980) and Argote (2013) positioned organizational learning as a critical enabler of innovation adoption. From a strategic perspective, Sanchez (1995) and Verona (1999) highlighted the relevance of internal capabilities and adaptability, while Williams and Edge (1996) and Garud and Karnøe (2003) emphasized sociotechnical coevolution and the distributed nature of innovation processes. The psychological and behavioural aspects of technology use were addressed by Venkatesh (2000) and Danneels (2002), who underscored the need for training programmes that foster both skill acquisition and learner motivation. As digital infrastructure became central to firm performance, studies by Ray et al. (2005) and Aral and Weill (2007) pointed to the alignment of IT capabilities with workforce strategies. More recent literature, including that of Frey and Osborne (2017), Xu et al. (2018), and Frank et al. (2019), has responded to the challenges of automation and Industry 4.0, advocating for adaptable and tech-savvy workforces. Emerging

Table 4. Most relevant authors in the field (until the end of 2024).

Author	H index [a]	G index [b]	M index [c]	Total citations	No. of papers	Production year started
Dwivedi, Y. K.	20	25	2.5	9056	25	2018
Venkatesh, V.	4	4	0.154	6879	4	2000
Raman, R.	7	12	1.4	6087	12	2021
Dubey, R.	11	12	1.1	6009	12	2016
Hughes, L.	4	4	0.8	4972	4	2021
Janssen, M.	3	3	0.6	4955	3	2021
Rana, N. P.	11	16	2.2	4451	16	2021
Kar, A. K.	9	10	1.125	4308	10	2018
Gunasekaran, A.	16	20	1.6	4042	20	2016

[a]The H index of a journal's or author's paper is equal to, for example, 5, if five publications have at least five citations each, and the other (five) papers have no more than five citations each. [b] The G index is a variant of the H index that, in its calculation, gives credit for the most highly cited papers in a data set. [c] The M index is another variant of the H index that displays the H index per year since first publication (Egghe, 2006; Hirsch, 2005).

concerns around leadership, sustainability, and AI ethics are addressed by Helfat and Peteraf (2015), de Sousa Jabbour et al. (2018), Dwivedi et al. (2021, 2022, 2023), and Di Vaio et al. (2020), all of whom converge on the critical role of new competencies ranging from environmental literacy to algorithmic accountability. Finally, the integration of big data and AI into HRM and decision-making processes, as discussed by Mikalef et al. (2020) and Vrontis et al. (2022), underscores a broader shift towards data-driven and human-centric organizational models. Collectively, these thematic clusters provide a comprehensive understanding of the multidimensional skill transformations required in an era marked by rapid technological, organizational, and societal change.

2.2.3 Most influential authors

The bibliometric analysis of leading authors in the field of future skills, Industry 4.0, AI, and digital transformation (see Table 4) reveals the significant contributions of scholars shaping discussions on workforce adaptation, digital competencies, automation, and sustainability.

Among the most influential contributors, Yogesh K. Dwivedi stands out as a key figure, with extensive research on AI-driven business models, digital transformation, and workforce reskilling. His work highlights the increasing importance of AI literacy, digital governance, and automation adaptation in contemporary organizations (Dwivedi et al., 2023). Similarly, Viswanath Venkatesh has provided foundational research on technology acceptance and digital learning behaviours, offering critical insights into how workers adapt to new technologies, digital platforms, and automation systems (Venkatesh, 2000). In addition to AI and digital transformation, scholars such as Raman and Dubey have contributed significantly to Industry 4.0 adoption, automation, and smart manufacturing. Their research focuses on supply-chain AI integration, predictive analytics, and cyber–physical systems, underlining the need for technical expertise in IoT, robotics, and AI-powered decision making (Sharma et al., 2022). Gunasekaran has also been instrumental in advancing research on digital supply chains and manufacturing automation, emphasizing the shift towards smart factories and real-time data-driven operations (Gunasekaran et al., 2020).

Sustainability in the context of digital transformation is another emerging research theme. Joseph Sarkis has contributed extensively to studies on green manufacturing, circular-economy principles, and sustainable supply chains, reinforcing the growing demand for eco-innovation skills and environmental governance knowledge (Sarkis et al., 2011). Additionally, Rana and Hughes focus on the intersection of digital transformation and business resilience, shedding light on how organizations can integrate sustainability and digital skills into their workforce strategies (Dwivedi et al., 2021).

Fig. 3 points out three major collaboration clusters. The red cluster (Kumar, Singh, Sharma, Gupta, etc.) consists of researchers actively contributing to Industry 4.0 and workforce skills development. The central author, Kumar, A., has the highest connectivity with multiple coauthors. This group of authors primarily focuses on automation, digital transformation, and employability skills in the era of AI-driven industries. The green cluster (Vrontis, Chatterjee, Chaudhuri, etc.) is less interconnected but features strong ties among a few core authors. Their research focuses on digital skills, knowledge management, and the intersection of business strategy with workforce competencies. The blue cluster (Wang, Liu, Zhang, etc.) appears to be more isolated, meaning the authors collaborate within their own network but have fewer interconnections with the red and green clusters. Their research emphasis might be regional or institution-based, potentially focusing on technical skills in AI and advanced manufacturing.

The collaboration network shows that Kumar, A., and Wang, Y., are the most prominent nodes, indicating highly influential researchers with

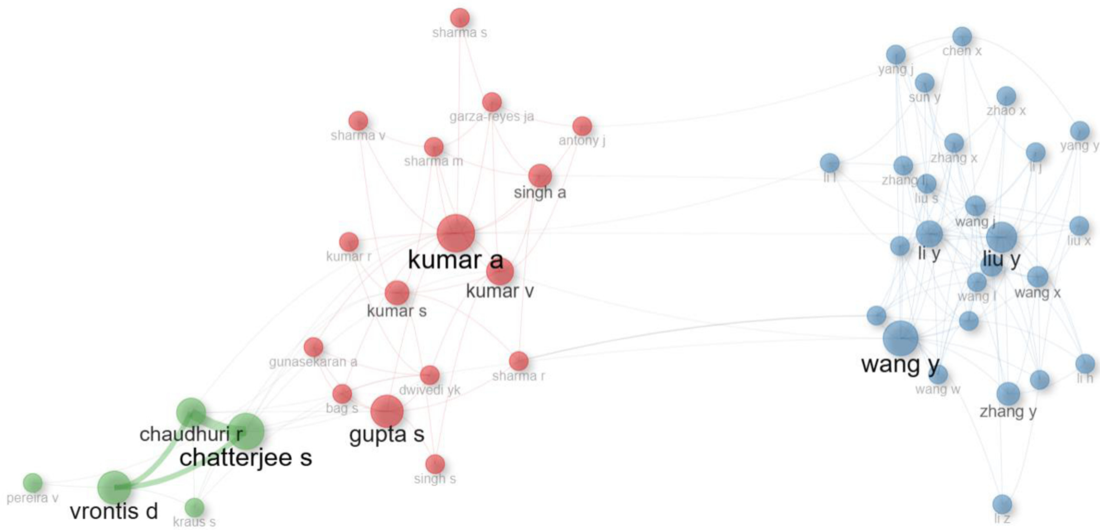

Fig. 3. Collaboration network in the analysed literature set, Scopus, 1972–2024.
Source: Scopus, analysis in R.

extensive collaborative networks. Liu, Y., and Chatterjee, S., are also central figures within their respective clusters, while Vrontis, D., appears to be a key connector between business-related research and digital transformation.

The low degree of interconnectivity between these clusters suggests that research on future skills is still highly specialized, with minimal interdisciplinary collaboration between scholars in business strategy, AI-driven workforce skills, and manufacturing. Future research could benefit from greater cross-disciplinary engagement to bridge these domains and provide a more integrated perspective on digital workforce transformation.

2.2.4 *Citation network analysis*

The evolution of research on future skills, Industry 4.0, digital transformation, and sustainability is evident in the citation network analysis of Scopus-indexed literature from 1972 to 2024 (see Fig. 4). The network illustrates key research clusters, highlighting prominent authors and thematic interconnections. The network comprises several key clusters, each representing distinct research trajectories within the domain of digital competencies, AI, automation, sustainable workforce transformation, and organizational adaptation.

One of the most influential clusters in the citation network is centred around Yogesh K. Dwivedi, whose research explores AI-driven workforce transformation, digital adoption, and emerging technologies in business and management. His work, frequently cited in discussions on AI literacy, automation strategies, and future workforce adaptability, aligns with the increasing necessity for AI-related upskilling and digital decision-making competencies (Dwivedi et al., 2023). Another key researcher, Demetris Vrontis, has contributed extensively to business strategy and digital skills development, with a focus on competency-based learning models and strategic reskilling approaches in an Industry-4.0-driven economy (Vrontis et al., 2022). Similarly, Sascha Kraus is well-represented in the network, with his research delving into entrepreneurship, digitalization, and business sustainability, highlighting the intersection between technological disruption and skills transformation (Bouncken et al., 2021; Kraus et al., 2021).

In the realm of Industry 4.0 technologies and smart manufacturing, Morteza Ghobakhloo emerges as a key figure, with significant contributions exploring the technological evolution of Industry 4.0, digital factory automation, and cyber–physical systems. His work emphasizes the need for technical training in IoT, AI-integrated manufacturing, and advanced robotics to sustain future workforce readiness (Ghobakhloo, 2018, 2020). Likewise, Joseph Sarkis, another highly cited researcher in this domain, focuses on sustainability and green transitions within Industry 4.0, particularly the integration of circular-economy principles and digital sustainability frameworks (Sarkis et al., 2011). His research reinforces the growing demand for green skills, eco-innovation, and regulatory compliance awareness among employees adapting to sustainable industry transformations.

The network also reveals distinct thematic clusters, with red clusters focusing on business strategy, digital skills, and innovation-driven reskilling efforts (e.g., Vrontis, Christofi, Calandra). The yellow clusters, on

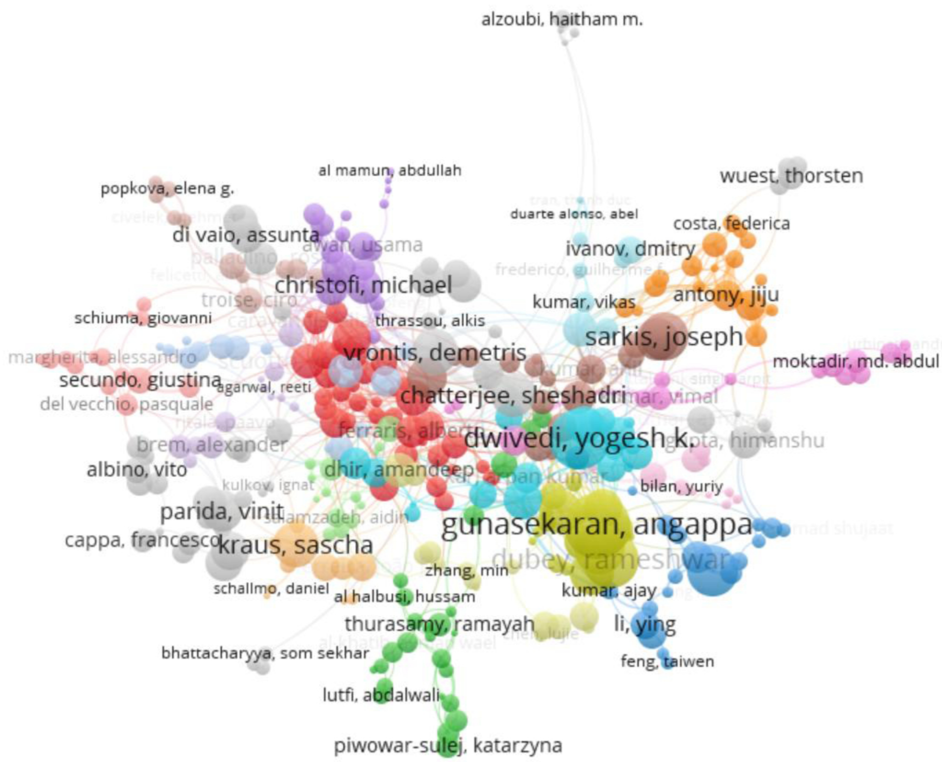

Fig. 4. Citation network in the analysed literature set, Scopus, 1972–2024.
Data: Scopus. VOSviewer analysis.

the other hand, are dominated by Industry 4.0 and sustainability research, reflecting the growing integration of digitalization and environmental responsibility (e.g., Gunasekaran, Ghobakhloo, Li Ying). Cyan clusters emphasize AI adoption, automation strategies, and human–machine collaboration, with key contributors including Dwivedi, Skare, and Chatterjee. Meanwhile, green clusters focus on sustainable business models, circular economy, and digital workforce transformation, highlighting scholars such as Piwowar-Sulej, Feng, and Lutfi.

The analysis highlights several emerging research trends and skill requirements critical for future workforce development. First, the prominence of AI-related research underscores the necessity for AI literacy, machine-learning expertise, and digital governance competencies in contemporary workplaces (Dwivedi et al., 2023). Second, the widespread adoption of Industry 4.0 technologies indicates the demand for smart manufacturing expertise, automation management, and cyber–physical-systems proficiency (Ghobakhloo, 2020). Third, sustainability-focused research suggests that future employees must develop eco-innovation capabilities, circular-economy knowledge, and sustainable production skills to support digital sustainability transitions (Sarkis et al., 2011). Lastly, behavioural and strategic adaptability remains essential, as organizations navigate digital transformation, skills obsolescence, and continuous-learning challenges (Bouncken et al., 2021; Kraus et al., 2021).

2.2.5 Keywords

The keyword analysis of the data set (see Fig. 5) highlights the dominant research themes shaping discussions on future workforce skills, Industry 4.0, digital transformation, and sustainability. The visualization of keyword co-occurrences reveals several interconnected clusters, emphasizing the core areas of technological adaptation, employment shifts, sustainability-driven innovation, and organizational agility. The largest clusters centre around “digital transformation” and “Industry 4.0,” which underscores the increasing focus on how businesses and labour markets integrate AI, automation, and data-driven decision making (Dwivedi et al., 2023). This aligns with ongoing research emphasizing the necessity of technical competencies in machine learning, big data analytics, and AI governance (Venkatesh, 2000). Furthermore, the strong link between “innovation” and “knowledge management” suggests that continuous learning, upskilling, and knowledge-sharing strategies play a crucial role in ensuring workforce adaptability (Dwivedi et al., 2021).

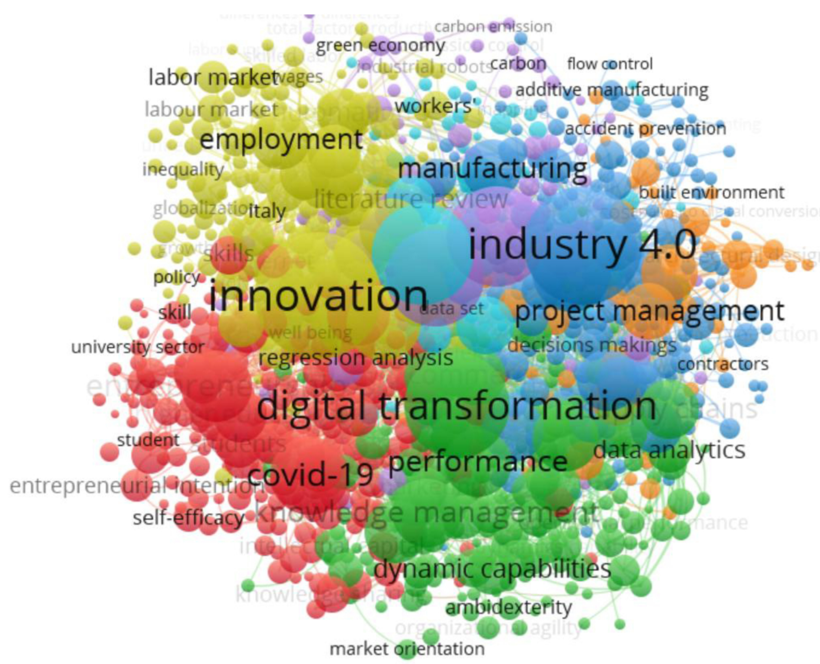

Fig. 5. Keywords in the analysed database, Scopus, 1972–2024.
Data: Scopus. VOSviewer analysis.

Fig. 5 shows strong sustainability salience with keywords "green economy," "sustainability," "carbon emissions" signalling a broad pivot toward environmental themes consistent with emerging green-skills and circular-economy agendas (Sarkis et al., 2011). In the Industry 4.0 context, the map also surfaces terms linked to energy efficiency, carbon-neutral strategies, and regulatory compliance, pointing to these capabilities as sources of competitive advantage. Prominent labour-market terms "labour market," "employment," "workers" coappear with digitalization topics, highlighting active inquiry into how automation reshapes job structures and elevates the need for reskilling and interdisciplinary training programmes (Gunasekaran et al., 2020).

The figure further shows postpandemic themes through the proximity of COVID-19 to performance-related terms, reflecting sustained attention to remote work, digital workplaces, and employee well-being (Sharma et al., 2022). Frequent co-occurrence of project management, dynamic capabilities, and decision making underscores managerial focus on agile leadership, organizational adaptability, and strategic resilience in the digital economy, including the integration of AI-enabled decision tools across functions (Kraus et al., 2021).

2.3 Research gaps and future directions

Despite substantial progress in understanding future skills development, several gaps remain that warrant further investigation. One of the key limitations in current research is the lack of interdisciplinary approaches (Ejsmont et al., 2020; Montanari et al., 2023). While many studies focus either on technological advancements or business strategies, few integrate perspectives from economics, education, and psychology. A more holistic approach that considers the intersection of these fields would provide deeper insights into how workforce skills can be developed in alignment with broader economic and social changes. Another critical gap is the lack of longitudinal studies. Most existing research assesses the short-term impacts of training programmes, neglecting to track long-term career progression and workforce mobility (Rikala et al., 2024; Shiri et al., 2023). Understanding how workers adapt and transition throughout their careers is essential for designing effective lifelong-learning programmes and reskilling initiatives that maintain their relevance over time (Peck et al., 2022).

Policy interventions in skills development remain underexplored. While various government-led digital training programmes and public–private partnerships have been implemented, there is a lack of empirical studies evaluating their effectiveness (Dwivedi et al., 2021). Future research should examine which policies yield the most positive outcomes and how they can be scaled to support broader workforce transformation.

The emergence of AI-driven job transformation presents another critical area for research. Much of the current literature focuses on automation's role in displacing jobs, but there is limited understanding of how AI is shaping the evolution of work beyond mere automation. Research is needed on the rise of hybrid human–AI work environments, where AI complements human capabilities rather than replacing them. Investigating how businesses and employees can successfully navigate these new work dynamics will be crucial for developing forward-looking workforce strategies. Furthermore, regional disparities in digital-skills adoption remain a pressing concern. Skill gaps vary widely between developed and developing economies, influenced by factors such as access to education, technological infrastructure, and government policies. Future studies should explore how different economic contexts affect the adoption of digital skills and what strategies can be employed to bridge these gaps, ensuring that all regions benefit from technological advancements.

Lastly, there is an urgent need to examine the ethical and psychological implications of workforce automation. The social consequences of automation extend beyond job displacement to issues such as worker well-being, job satisfaction, and mental health. Ethical AI governance frameworks must be developed to ensure that automation enhances rather than disrupts workforce stability. Future research should explore how businesses and policymakers can mitigate these challenges, fostering an environment where technology and human labour coexist productively.

Building on the bibliometric findings and the synthesis of key literature, Table 5 identifies the main research gaps that currently hinder the development of a future-ready workforce. These gaps span several interconnected domains, including the lack of interdisciplinary research in AI workforce transformation, limited longitudinal evaluation of reskilling outcomes, insufficient policy interventions, regional inequalities in digital skill adoption, and the underexplored psychological and ethical dimensions of automation. Each of these gaps corresponds to a distinct thematic cluster ranging from employment equity to technological disruption, highlighting the multifaceted nature of workforce transformation in the digital age. These gaps are not isolated issues; rather, they represent systemic deficiencies across knowledge production, policy design, and implementation mechanisms.

Critically, the policy implications that are later on derived from these gaps point to the necessity of systemic, layered interventions. These gaps highlight persistent challenges that hinder the effective development and implementation of future skills strategies. They are not only empirical voids but also strategic blind spots that affect the alignment of skill supply with evolving labour-market demands. The firm level translates each gap into concrete actions that organizations can implement in parallel with public interventions, ensuring that strategic intent is matched by operational execution.

The lack of interdisciplinary approaches, especially in the context of AI and workforce transformation, reveals a fragmentation in the academic and policy literature. Although technological innovation increasingly intersects with societal, economic, and psychological dimensions, research efforts remain siloed within individual disciplines. This prevents a holistic understanding of how future skills evolve and how they should be integrated into broader sociotechnical systems. Bridging this gap requires stronger cross-sectoral and interdisciplinary collaboration, particularly in designing responsive education and training systems that reflect the complexity of AI-driven transitions. At the firm level, this means establishing cross-functional teams and communities of practice that bring together operations, HR/learning and development, data/AI, and sustainability, anchored by shared objectives and key results and common problem statements; partnerships with universities and vendors for challenge-based projects help embed interdisciplinary learning into day-to-day work.

The limited presence of longitudinal studies points to an overreliance on short-term metrics and outcomes when evaluating training or upskilling initiatives. This restricts the ability of policymakers and educators to assess whether such programmes lead to lasting changes in employability, career progression, or labour mobility. Longitudinal data is critical for understanding how individuals navigate transformations over time and for building dynamic skill systems that adapt as workers move between sectors or as technologies evolve. Within companies, the parallel remedy is to institute a “skills observatory” tagging roles and skills in the HR information system, running cohort skill assessments and A/B pilots (e.g., human–AI workflows versus baseline), and reviewing quarterly key performance indicator dashboards that link learning inputs to operational outcomes (productivity, quality, time to proficiency, mobility).

Another major gap concerns the underexplored nature of policy interventions aimed at fostering digital inclusion. While many national and international strategies acknowledge the importance of digital and green skills, there is a lack of robust empirical evaluation regarding which interventions are most effective, scalable, and equitable. This limits the ability to translate insights into concrete action, particularly for vulnerable or digitally excluded populations. More evidence is needed on how digital literacy can be meaningfully developed through formal education, workplace learning, and community-based programmes. At the enterprise level, firms can

Table 5. Identified research gaps and their policy and firm implications.

Research gaps	Thematic cluster	Policy implications	Firm implications
Lack of interdisciplinary approaches	AI in workforce transformation	Encourage cross-sector collaboration in AI research	Cross-functional teams; AI community of practice; challenge projects with universities; staff rotations; shared objectives and key results.
Limited longitudinal studies	Reskilling strategies	Fund long-term workforce tracking initiatives	Skills observatory (HR information system tags); cohort skill tracking; A/B pilots (human–AI vs. baseline); quarterly outcome dashboards
Underexplored policy interventions	Digital skills & inclusion	Develop digital literacy programmes	Tiered digital literacy baseline; paid learning time; microcredentials; mentors; accessibility-by-design content
Emerging AI-driven job transformation	Automation & employment trends	Implement regulatory frameworks for AI ethics	Responsible-AI governance; role/SOP redesign for human–AI teaming; incident/feedback channels
Regional disparities in digital skills adoption	Workforce equity & accessibility	Invest in infrastructure for underserved regions	Remote-first learning; loaner devices/data stipends; local partnerships; flexible scheduling; site-level uptake monitoring
Ethical & psychological impacts of automation	Worker well-being	Introduce policies to support displaced workers	Redeployment & reskilling guarantees; internal talent marketplace; change-management coaching; support through employee assistance programme; participatory redesign workshops

deploy tiered digital-literacy baselines (foundational → advanced), offer paid learning time and portable microcredentials, provide mentors and accessibility-by-design content, and track uptake and completion by site, role, and demographic segment to ensure equitable access.

Table 5 also highlights the emerging transformation of work driven by AI, which has not been fully captured by existing research frameworks. The discussion has often centred on automation and job displacement, with less attention paid to how AI reshapes job content, decision-making structures, and skill profiles in nuanced ways. In particular, the shift toward hybrid human–AI collaboration raises new demands for cognitive, emotional, and ethical competencies that go beyond technical training. This evolving landscape calls for the establishment of regulatory frameworks and ethical standards that guide AI adoption in labour markets. Complementing this, firms should implement responsible-AI governance (use policies, risk/impact checks, human-in-the-loop criteria), redesign roles and SOPs for human–AI teaming, and provide sandbox training and incident/feedback channels so that capability building, risk management, and job redesign move together.

A persistent concern is the regional disparity in digital-skill adoption, particularly between developed and developing economies or between urban and rural areas. Unequal access to infrastructure, training opportunities, and institutional support systems leads to uneven capacity for digital transformation. This undermines inclusive economic development and creates fragmented labour markets. Addressing this issue requires targeted investment in digital infrastructure, locally adapted training programmes, and inclusive public–private partnerships that ensure equal participation in the digital economy. For firms operating across multiple sites, this means instituting remote-first learning options, providing loaner devices and data stipends where needed, partnering with local training providers, enabling flexible schedules for shift workers, and monitoring site-level participation to detect and close access gaps.

Finally, the ethical and psychological consequences of automation remain undertheorized in current policy discourse. Beyond the economic impact of job loss, automation can induce stress, reduce job satisfaction, and erode worker autonomy. Addressing these challenges requires not only technological safeguards but also support systems that prioritize worker well-being. This includes career counselling, mental health resources, and social protection mechanisms that help individuals navigate uncertainty and change. In firms, effective complements include redeployment and reskilling guarantees, internal talent marketplaces tied to skill badges and mobility offers, change-management coaching for managers and teams, access to employee assistance programme services, and participatory redesign workshops that give employees a voice in how tasks and tools evolve.

Table 5 illustrates how the transformation of work involves more than just technical reskilling; it demands a strategic, inclusive, and human-centred approach. These gaps underscore the need for further empirical research, policy innovation, and collaborative design across the education, policy, and business sectors, with firm-level practices providing the connective tissue that links high-level strategy to measurable improvements in jobs, performance, and inclusion.

3 Policy and managerial implications: Pathway to the future

Based on the insights of the thorough bibliometric analysis providing the fundamentals for the future skills development and revealing the mismatch in business needs with the current state of workforce skills, the policy and managerial implications for the future skills were modelled. This chapter provides a structured approach to identifying essential competencies, workforce transformation pathways, and policy interventions needed to prepare for an AI-driven and sustainable economy. It outlines four key layers:

- identifying missing skills,
- upskilling and reskilling needs,
- transformation of education and training, and
- policy and managerial implications.

The policy and managerial implications provide a structured roadmap for addressing the evolving needs of the labour market in response to digitalization, automation, and the global sustainability agenda. Drawing on the findings of the bibliometric analysis as well as leading international reports and national policy documents, including those from the OECD (2019), World Economic Forum (2025), Dondi et al. (2021), SkillsFuture Singapore (2023), and Bakhshi et al. (2017), the framework illustrates how the workforce can transition from its current state of skill deficits toward a future-ready configuration through targeted education, public intervention, and business integration.

3.1 Development of the policy and managerial implications framework

The starting point of the framework is a recognition of the widespread gaps in current workforce capabilities. These gaps are not isolated but systemic, affecting key domains such as digital literacy, artificial intelligence fluency, green and sustainability knowledge, cognitive flexibility, and leadership skills. Studies by Dondi et al. (2021) and the World Economic Forum (2025) have emphasized that while demand for digital and AI-related skills is growing rapidly, the supply of qualified professionals remains limited, with significant disparities across sectors and regions. Similarly, OECD (2019) and SkillsFuture Singapore (2023) have identified critical deficiencies in sustainability-oriented skills, including those related to circular-economy practices, climate change adaptation, and ESG compliance. Beyond technical abilities, the framework also highlights the importance of cognitive and social-emotional skills. Bakhshi et al. (2017) report that adaptability, critical thinking, and emotional intelligence are among the most in-demand competencies, particularly in environments where human–AI collaboration is becoming the norm. These soft skills are foundational for navigating uncertainty, collaborating in diverse teams, and leading innovation in rapidly evolving contexts. Deficiencies in business and strategic management capabilities are also becoming more visible as firms adapt to hybrid work models and global digital markets.

Table 6 organizes the framework into three outer layers: (a) “Policy & regulation (macro),” (b) “Education & training (meso),” and (c) “Business implementation (micro),” linked by two inner mechanisms, “Skills gap discovery” and “Experimentation & learning,” with “Data & infrastructure” and “Inclusion & equity safeguards” as cross-cutting enablers, and “System outcomes & targets” closing the feedback loop. The table starts from a recognition of persistent capability gaps in digital literacy, AI fluency, sustainability knowledge, and sociocognitive skills such as adaptability and leadership. Recent evidence documents rapid growth in demand for digital and/or AI capabilities alongside uneven supply across sectors and regions (Dondi et al., 2021; World Economic Forum, 2025) and parallel shortfalls in sustainability-oriented competences spanning circular-economy practices, climate adaptation, and ESG (OECD, 2019; SkillsFuture Singapore, 2023). Beyond technical proficiencies, the table foregrounds transferable skills (e.g., adaptability, critical thinking, and emotional intelligence) as essential complements in human–AI collaboration and innovation contexts (Bakhshi et al., 2017).

Within this structure, the “Policy & regulation” column specifies system levers (funding, standards, accreditation, responsible-AI guidance) that set direction and incentives; “Education & training” translates these priorities into programmes and credentials (modular/stackable pathways, work-based learning, recognition of prior learning); and “Business implementation” details how firms operationalize capability building (job redesign, learning-and-development portfolio, tech/tooling, change management). The “Skills gap discovery” and “Experimentation & learning” columns form an inner loop: organizations identify priority skills and roles, test solutions via pilots and sandboxes, and scale what works. The “Data & infrastructure” and “Inclusion & equity” columns ensure evidence portability (common taxonomies, privacy-preserving analytics) and fair access (paid learning time, accessibility, bias audits) across sites

Table 6. Policy and managerial implications framework.

	Policy & regulation (macro)	Education & training (meso)	Business implementation (micro)
Purpose	Set direction, incentives, safeguards	Convert priorities into programmes & credentials	Deploy skills in work and realize value
Key levers	•Funding •Standards •Tax/levy design •Accreditation •Data access •Responsible AI	•Curriculum design •Qualification frameworks •Work-based learning •Recognition of prior learning	•Job redesign •L&D portfolio •Tech/tooling •Change mgmt
Example actions	•Skills tax credits •Green/AI standards •Portable microcredentials •Open skills/data APIs •Responsible-AI guidance	•Modular credentials •Apprenticeship/dual models •Stackable microcerts •Provider–employer consortia	•Human–AI teaming SOPs •Skills-based hiring •Internal talent marketplace •Manager academy
Metrics/signals	•Participation by segment •Credential uptake •Regional coverage •Compliance/adoption rates	•Completion •Time to credential •Job placement •Employer satisfaction	•Time to proficiency •Cycle time & quality •Mobility/promotion velocity •Retention
	Skills gap discovery (inner loop)	Experimentation & learning (inner loop)	
Purpose	Identify priority skills & roles	Test and scale what works	
Key levers	•Skills taxonomy •Role/task analysis •Demand sensing	•Pilots •A/B tests •Sandboxing •Playbooks	
Example actions	•HR information system skills tagging •Role-gap heatmaps •Task decomposition for AI/green	•A/B pilots (human–AI vs. baseline) •Sandbox training •Playbook creation •Scale-up plan	
Metrics/signals	•Vacancy fill time •Skill gap indices •Task automation risk	•Pilot effect sizes •Adoption/usage •Incident logs •ROI	
	Data & infrastructure (cross-cutting)	Inclusion & equity safeguards (cross-cutting)	System outcomes & targets
Purpose	Make evidence portable & trustworthy	Ensure fair access & outcomes	Productivity, innovation, job quality, inclusion, resilience
Key levers	•Interoperable ontologies •Privacy-preserving analytics •Data contracts	•Paid learning time •Accessibility •Bias checks •Regional access	•Performance & equity targets
Example actions	•European Skills, Competences, Qualifications and Occupations /ontology in HR information system/learning management system •Differential privacy/role-level aggregation •Open dashboards	•Loaner devices/data •Responsible-AI bias audits •Site-level equity goals	•Quarterly skills P&L •Green/AI key performance indicators in objectives and key results •Postimplementation reviews
Metrics/signals	•Data quality •Coverage •Refresh cadence •Reproducibility	•Uptake by segment •Fairness metrics •Grievance resolution	•Output per FTE •Cycle/defect time •Wage & progression •Internal mobility •Emissions/energy

and segments. Finally, the "System outcomes & targets" column specifies what success means (e.g., productivity, innovation, job quality, inclusion, and resilience) and routes evidence back to the policy and education layers.

Read as a whole, Table 6 provides a practical roadmap: macro levers enable mesolevel programme design, which in turn supports microlevel adoption; the inner loop and cross-cutting enablers create rapid feedback cycles so that skill strategies remain adaptive as technologies and markets shift. This table thus connects documented gaps (digital/AI supply constraints; sustainability competencies; sociocognitive capabilities) to coordinated responses across policy, education, and firms, guiding the transformation of workforce skills in line with emerging economic models (Bakhshi et al., 2017; Dondi et al., 2021; OECD, 2019; SkillsFuture Singapore, 2023; World Economic Forum, 2025).

The policy and managerial implications framework (Table 6) of the future skills bridges the gap between the current workforce and future market needs by integrating education, corporate reskilling, policy, and business interventions. By implementing these structured layers, businesses, governments, and academic institutions can ensure a resilient, adaptable, and innovation-driven workforce in an evolving economic landscape. This framework serves as a roadmap for transforming skill development approaches, aligning workforce capabilities with future technological shifts, and fostering a sustainable economic transition.

3.2 Limitations and future directions

The policy and managerial implications framework developed in this paper is both a synthesis of the current literature and a practical tool for navigating the multidimensional process of workforce transformation. It was designed to integrate insights from policy documents, labour-market forecasts, and academic research in order to address the complexity of skill development in a rapidly changing world. One of its main contributions is its structured, layered format, which links missing skills to specific training responses, embeds these within institutional frameworks, and follows through to organizational implementation. This coherence allows the framework to be used as a guide for policymaking, curriculum reform, and business strategy.

Despite its comprehensiveness, the policy and managerial implications framework has several limitations. First, it is built on an abstraction of global trends and may not fully capture the contextual variations in skill needs across regions, sectors, or demographic groups. While the framework includes sustainability and digitalization as global megatrends, the specifics of implementation will vary substantially depending on local infrastructure, policy capacity, and cultural norms. Second, it primarily emphasizes formal learning pathways and institutional interventions, which may overlook the importance of informal learning, experiential learning, and self-directed upskilling that increasingly characterize modern career development. Moreover, the framework assumes a relatively linear and cyclical progression—from skills identification to implementation—whereas real-world transformations are often nonlinear and influenced by disruptions, emergent technologies, and feedback loops that cannot be entirely predicted. For example, sudden advances in generative AI may drastically reshape the skill landscape in ways not yet accounted for. Additionally, the framework does not yet fully incorporate social equity considerations such as gender disparities, access to training for vulnerable populations, or the implications of skill shifts for low-income workers.

Future research should explore how this policy and managerial implications framework can be adapted and tested in empirical contexts. This could include case studies of national skill strategies, sector-specific analyses, or organizational audits that apply the model in practice. Comparative studies across countries and industries could reveal how effectively the framework supports policy coherence and institutional alignment. Further, research should investigate how digital platforms, AI-based adaptive learning, and decentralized education models can be integrated into this framework to enhance flexibility and scalability.

Ultimately, while the policy and managerial implications framework offers a promising approach to structuring the discourse on future skills, it should be seen as an evolving tool, open to iteration and refinement as new data, technologies, and policy challenges emerge. Its continued development will require interdisciplinary collaboration, empirical validation, and sensitivity to the diverse realities of the global workforce.

4 Discussion

The findings of the bibliometric analysis confirm that future skills research is inherently interdisciplinary, drawing from fields such as management, education, economics, information systems, and sustainability studies. This breadth reflects the complex and interconnected challenges that digitalization, automation, and climate change pose to the labour market. Through an analysis of over 17,000 academic publications, this paper reveals how the discourse on skill development has evolved over time and identifies key clusters of research, thematic shifts, and citation patterns. Notably, the most active research areas include digital transformation in education, the implications of AI for employment, and sustainable workforce strategies. A central insight from the bibliometric mapping is the rise of digital and AI competencies as dominant topics in the literature illustrate the widespread scholarly concern with how digital technologies are reshaping job roles. Reports by Dondi et al. (2021) and the World Economic Forum (2025) echo this trend, highlighting the growing demand for data-driven decision making, cybersecurity expertise, and AI literacy in both public and private sectors. However, the bibliometric clusters also reveal that these technical topics are frequently studied alongside nontechnical dimensions such as adaptability, lifelong learning, and organizational change.

Terms such as "green economy," "sustainability," and "carbon emissions" appear frequently in the literature, suggesting a growing convergence between environmental policy and workforce planning. These findings are consistent with the insights from the OECD (2019) and SkillsFuture Singapore (2023), which underscore the need to prepare workers for climate transitions and green growth strategies. The analysis also highlights that research on sustainability skills is increasingly embedded within broader discussions on innovation ecosystems and circular economies.

The bibliometric analysis also reveals a knowledge gap in longitudinal and impact-oriented studies. Most of the literature tends to focus on conceptual explorations or short-term case studies, with limited attention given to long-term outcomes of reskilling programmes or the structural transformation of labour markets. Furthermore, the network analysis of citations shows fragmentation in the field, with limited cross-disciplinary integration between technical disciplines (e.g., computer science) and human-centred domains (e.g., psychology and pedagogy). This aligns with Dwivedi's et al. (2021) observation of insufficient interdisciplinary frameworks for understanding the sociotechnical dimensions of future skills.

The policy and managerial implications framework proposed in this paper addresses these gaps by offering a structured and integrative framework. It comprises four interrelated layers: identifying missing skills, defining upskilling and reskilling pathways, designing public interventions, and implementing business-level transformations. Moreover, it links the most prominent themes in the literature with actionable mechanisms. For example, the gap in AI and digital skills is mapped onto training programmes in data science and cybersecurity; sustainability skill gaps are aligned with ESG-oriented curricula and policy instruments; and soft-skill gaps are addressed through leadership development and emotional intelligence programmes. The third layer emphasizes the critical role of governments, as reflected in both the policy literature and bibliometric data. Research on national digital strategies, public–private partnerships, and lifelong learning appears prominently in both highly cited publications and cluster analyses. These institutional interventions are essential for democratizing access to skills and reducing socioeconomic disparities in training uptake. Finally, the policy and managerial implications framework considers how businesses translate skill strategies into operational changes. Themes such as "corporate learning," "workforce planning," and "AI integration" emerge in the bibliometric analysis as important but underdeveloped areas of research. This suggests a need for greater scholarly attention to implementation dynamics and organizational adaptation. Reports by the World Economic Forum (2025) and Dondi et al. (2021) reinforce this perspective, calling for deeper integration of learning platforms, internal training systems, and leadership frameworks within corporate environments.

By connecting empirical insights from bibliometric mapping with strategic guidance from global reports, this framework provides a comprehensive roadmap for navigating the future of work. It demonstrates that the future skills agenda must be informed by both academic knowledge production and real-world labour market demands, reinforcing the value of continuous dialogue between research, policy, and practice.

5 Conclusion

This paper has shown that skill development is central to the transition toward a more innovative, inclusive, and sustainable economy. Through a bibliometric review of global literature, the research maps the evolution of future skills discourse, identifies major research streams, and uncovers critical gaps in current knowledge. Key findings suggest that while technical competencies in AI and sustainability are indispensable, cognitive and human-centric skills are equally vital for thriving in digital and green transitions.

The policy and managerial implications framework developed in this paper offers a structured framework for skill development that begins with identifying workforce gaps and culminates in business integration. It demonstrates the interconnectedness of education, policy, and business practice in shaping labour-market readiness. This framework provides not only theoretical insight but also practical guidance for designing interventions that prepare the workforce for tomorrow's challenges.

As technology continues to evolve and global sustainability pressures intensify, the need for adaptive, interdisciplinary, and inclusive skill development strategies will grow. Future research should build on this policy and managerial implications framework by exploring longitudinal outcomes of upskilling initiatives, assessing the equity of training access, and evaluating the effectiveness of emerging policies. Ultimately, equipping the workforce with future-ready skills is not just an economic necessity, it is a societal imperative for ensuring shared prosperity and resilience in an era of transformation.

Funding

The work on this paper was partially financed by P5-0128, J5-4540 (Slovenian Research and Innovation Agency).

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