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Human Capital in AI-Enabled Digital Transformation: A Systematic Review of Workforce Competencies and HRM Mechanisms

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ABSTRACT

This article presents a systematic literature review of the role of human capital in digital transformation and artificial intelligence (AI), focusing on how these developments reshape workforce competencies and human resource management (HRM) during the transition from Industry 4.0 to Industry 5.0. Following the PRISMA guidelines, the study combines thematic coding with comparative analysis. From an initial pool of 216 publications, 46 studies were selected for in-depth analysis. The review examines how AI and digitalisation change workforce skill requirements and how HRM mechanisms can help organisations develop and sustain the necessary competencies. The findings indicate a shift from routine and manual tasks toward hybrid competency profiles that integrate data analytics skills, AI literacy, human-machine interaction skills, and higher-order socio-cognitive capabilities, including adaptive reasoning, collaboration, and ethical judgement. HRM emerges as a strategic integrator that supports continuous reskilling, predictive skills-gap analysis, and the development of effective human-AI teams. Based on these findings, the study proposes a multilevel framework explaining how institutional mechanisms, organisational strategy, HRM practices, and human-AI complementarity jointly shape workforce competitiveness in AI-enabled digital transformation. The framework contributes to human-centric digitalisation by linking workforce competitiveness to capability velocity and human-AI complementarity. It also provides managerial implications for designing learning, governance, and decision-making structures that enable organisations to respond to evolving competency requirements and translate technological potential into sustainable operational advantages.

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1. Introduction

Contemporary organizations increasingly confront the need to reconfigure business processes under the influence of artificial intelligence and broader digital technologies. This transition extends well beyond conventional automation and necessitates a fundamental reconsideration of the human role within work systems. Technological innovations including artificial intelligence, robotics and collaborative robots, and advanced logistics tools embedded in value chains are expected to reshape human–machine interaction profoundly. These developments simultaneously expand the scope for enhanced decision-making and introduce emergent, and often unpredictable, implications for the quality and nature of work. [1–3].

Over the past decade, the trajectory of Industry 4.0 has been dominated by efficiency gains derived from data-driven automation, interconnected production systems, and smart manufacturing architectures, frequently overshadowing its early commitments to social sustainability. The emergent paradigm of Industry 5.0, by contrast, introduces a deliberate human-centric realignment. It prioritises inclusive innovation, environmental responsibility, and systemic resilience, thereby seeking to harmonise technological progress with societal welfare and ecological limits [4].

Within this shift, high-resolution data on human factors become integral to optimising human-machine interfaces (HMI) and enhancing operator-system collaboration. Effective operationalisation of Industry 5.0 further presupposes an expanded skill base among employees, particularly in data analytics, artificial intelligence (AI), and advanced digital technologies, including HMI configuration and data-supported decision processes [5]. In this paradigm, human intelligence, creativity and adaptability are of key importance [6].

For the effective implementation of digitalization technologies, it is necessary to consider not only the technological innovations themselves, but also the socio-organizational context of their application, including the specifics of human interaction with digital systems [6, 7]. The future of work, as increasingly noted in contemporary scholarship, is likely to be shaped not by competition between humans and AI, but by the efficacy of their complementary integration. Within this landscape, the central challenge becomes the cultivation of skills and competencies that enable employees not merely to adjust to technological change, but to participate actively in innovation processes and sustainable value creation. The accelerating diffusion of artificial intelligence, big-data analytics, and cloud-based architectures has triggered a sharp rise in demand for digital competencies across sectors. These capabilities extend beyond basic data handling to include an understanding of digital system architectures, automation principles, and cybersecurity foundations. Such competencies constitute the core enablers of workforce participation within digital ecosystems and are increasingly required not only among technical experts, but also among managers, analysts, and training professionals across organizational hierarchies.

In this literature review, the authors examine the scholarly literature on the role of human capital in the process of digitalization of production in the context of the transition from Industry 4.0 to Industry 5.0, as well as in the widespread introduction of AI.

The research questions are as follows:

RQ1: How are AI and digital transformation changing the skill requirements for employees?

RQ2: Through which HRM mechanisms and capability-building practices can organizations most effectively develop, sustain, and integrate these competencies to strengthen long-term competitiveness?

To answer these questions, we applied thematic coding and comparative analysis, blending content analysis with expert interpretation. In total, the review identified 216 publications, from which 46 highly relevant sources were selected for in-depth analysis in line with the PRISMA

guidelines. Based on these sources, we developed a conceptual framework aligning institutional mechanisms, organizational capabilities, competency evolution, and the strategic role of HRM in industrial and logistics sectors. The novelty of this study lies in the development of a multilevel conceptual framework that integrates institutional governance mechanisms, organisational capabilities, HRM systems, and human-AI complementarity into a unified explanation of workforce competitiveness in Industry 5.0.

2. Methodology

The review is based on thematic coding and comparative analysis. A systematic analytical approach, with elements of content analysis and expert interpretation was used.

The research design follows established standards of transparency, reliability, and methodological rigour and is structured in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. PRISMA is an evidence-based minimum reporting guideline for the preparation and presentation of systematic reviews and meta-analyses [8]. Recent systematic reviews across related domains have successfully applied this framework, including studies on AI in education [9], multicriteria decision-making in manufacturing [10].

The review procedure comprised several sequential and interconnected stages (Figure 1):

- formulation of research questions consistent with the overarching research objective;
- specification of inclusion and exclusion criteria for literature selection;
- systematic retrieval of sources from Scopus, Web of Science, and ScienceDirect;
- multi-level screening of titles, abstracts, and full texts;
- qualitative synthesis through thematic organization and conceptual coding.

The study adopts a qualitative synthesis strategy that combines structured content analysis and theoretical integration – an approach particularly suitable for complex and context-dependent research domains such as digital transformation and human capital development.

To ensure a systematic and comprehensive representation of the scholarly landscape, the literature search employed a set of core conceptual terms, including organization, automation, Industry 4.0, Industry 5.0, human capital, digital competencies, human resource management, and artificial intelligence. Searches were executed across titles, abstracts, and keywords, drawing on peer-reviewed journal articles, conference proceedings, and academic monographs published in English between 2016 and 2025. To extend the coverage and reduce the likelihood of omission, a snowball sampling technique was applied by screening the reference lists of initially retrieved publications and integrating additional relevant sources.

A multi-stage selection protocol guided the construction of the final corpus. The initial database search (Scopus, Web of Science, ScienceDirect) was followed between January and November 2025 by screening against predefined inclusion and exclusion criteria. Chronological, geographical and typological diversity was monitored to ensure representativeness. The resulting literature set predominantly covers the period 2016-2025, corresponding to the diffusion of Industry 4.0 and the conceptual emergence of Industry 5.0, and thereby incorporates the most current theoretical and empirical developments.

The final dataset comprises peer-reviewed journal articles and scholarly book chapters as core academic material, complemented by policy documents from the European Commission that articulate strategic priorities for the Industry 5.0 transition. The integration of academic and applied sources facilitated a synthesis of conceptual development with operational insight and policy relevance, thereby enhancing the analytical depth and practical utility of the review.

Clear and consistently applied criteria determined the final literature set. First, thematic completeness was ensured: selected publications had to cover the core dimensions of the research

topic. Second, only sources directly addressing human capital within digital transformation were retained to maintain relevance and analytical focus. Third, methodological rigour was prioritised, favouring studies with transparent research design, robust evidence, and clearly described analytical procedures. Publications lacking methodological clarity or discussing relevant concepts only superficially were excluded. This approach ensured a reliable and scientifically valid evidence base.

The initial search yielded 216 publications meeting the basic inclusion parameters (year, language, subject focus). After removing duplicates ($n = 17$) and irrelevant works ($n = 46$), and excluding sources with a purely technological orientation, approximately 120 publications remained. A subsequent detailed review resulted in a final corpus of 46 studies, combining empirical research with conceptual and methodological contributions to provide a multidimensional view of the topic (see Figure 1).

Citavi software supported document organization, tagging, annotation, and bibliographic management, enabling a structured and efficient synthesis of the literature.

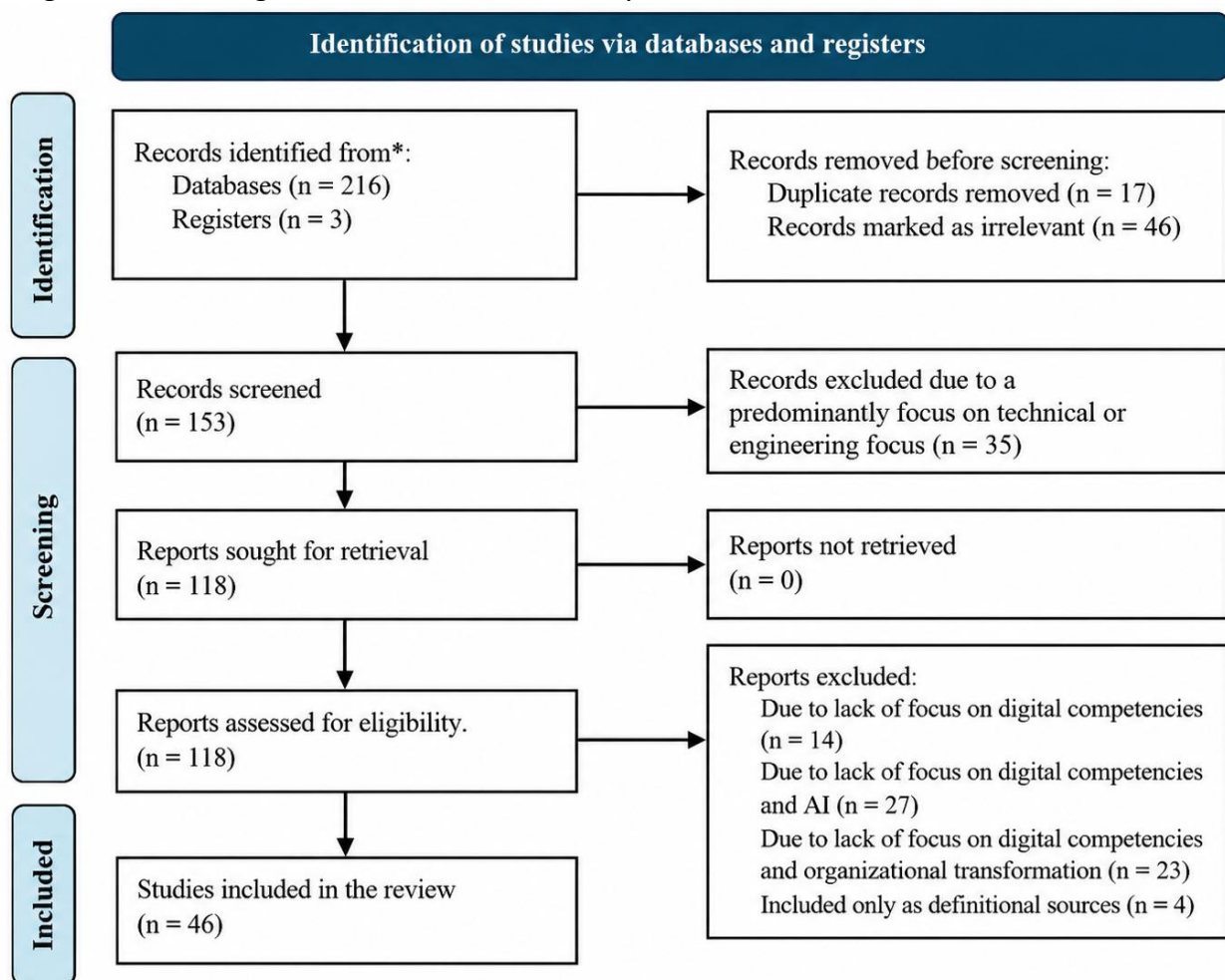


Fig. 1. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only

Digital skills and innovation in the era of digital transformation

Digital transformation within Industry 4.0 and 5.0, reshapes organisational structures, innovation mechanisms, and approaches to human capital development. The expansion of intelligent technologies, automation and data-driven decision-making elevates the strategic relevance of analytical reasoning, data literacy, and digital competence among employees.

While digital literacy involves the confident and critical use of a full range of digital technologies for information, communication and basic problem-solving in all aspects of life [11], digital competence goes far beyond this. It is defined as the knowledge, skills and attitudes required for the confident, critical, and responsible use of and engagement with digital technologies for learning, at work, and in participation in society [12].

Empirical evidence confirms that digital maturity correlates strongly with workforce digital competence [7,13], positioning human capital development as a necessary driver of technological transformation [14, 15]. One comprehensive analysis [16], further demonstrates that organisations proficient in digital analytics achieve significantly higher innovation outcomes than those with limited adoption, reinforcing the notion that technological tools alone do not generate innovation without skilled human engagement. Its findings underscore employee participation as a critical mechanism that enhances both organisational innovation capabilities and process efficiency.

In the context of manufacturing sectors in emerging economies, Horvat and co-authors [7], identify personnel and communication as one of five core dimensions of organisational development. This dimension encompasses task coordination, competence-building practices, and training structures. Skill development systems evolve progressively with organisational maturity, shifting from an absence of formal training to the implementation of advanced e-learning environments [17]. Such evolution [7], contributes to the formation of internal innovation ecosystems. At a broader societal level, knowledge transformation processes including upskilling, reskilling, and deskilling reshape labour structures, professional identities, and socio-cultural norms. In logistics and supply-chain contexts, the systematic diffusion of digital solutions improves operational efficiency, reduces congestion, and strengthens environmental responsibility. Evidence from [18, 19] shows that digital skill formation is interlinked with workplace innovation, participatory communication, and managerial support rather than occurring as an isolated technical intervention. Digitalisation is increasingly recognized as a precondition for the sustainable and carbon-neutral redesign of logistics systems [20]. Complementary findings indicate that AI-, IoT- and big-data-driven port infrastructures facilitate emissions monitoring, risk management, and safety enhancement, expanding organisations' capacity to experiment with new business models and digital service offerings [21]. Such cross-functional integration accelerates innovation cycles and enables firms to generate competitive digital value.

As AI gains momentum across industries, the skills employees need are rapidly evolving. AI technologies are permeating workplaces worldwide from healthcare to manufacturing fundamentally altering job roles and competencies. As AI systems grow more capable, humans are increasingly required not only to use these technologies as tools but to collaborate with them as partners in accomplishing complex goals [22]. For example, in supply-chain environments, integration of IoT, advanced analytics and cyber-physical systems provides real-time visibility across distributed nodes, improving responsiveness and organizational resilience. This marks a shift from siloed process optimization to network-based decision-making grounded in predictive data capabilities.

Taken collectively, these developments demonstrate that data-analytic and digital competencies represent a strategic foundation for long-term innovation rather than a purely operational skill set. Digital proficiency emerges through collaborative problem-solving, knowledge exchange, and co-creation rather than through isolated training practices [18,19]. Organizations that fail to embed digital literacy broadly across the workforce constrain the transformative impact of technological investments, irrespective of their scale.

A broad scholarly consensus reinforces the notion that digital transformation is restructuring occupational profiles and skill requirements across sectors. Researchers [23] argue that technological

and institutional change forces workers and organisations to reinterpret qualifications, redefine occupational roles, and confront persistent gendered divisions of labour. Fareri and co-authors [24] show that job design is shifting from routine physical tasks toward digital, cognitive and relational skills. Sima and colleagues [25] highlight continuous learning, adaptability and digital training ecosystems as fundamental to workforce development in Industry 4.0. The emergence of Industry 5.0 extends this logic from automation-led efficiency toward human-machine complementarity. Alongside technical literacy, competencies such as resilience, adaptability, and ethical awareness are becoming critical to employability and performance [26]. Kraus and co-authors [27] add that hybrid and digitally mediated workplaces reconfigure labour relations and institutional expectations while simultaneously creating risks of technological exclusion and stratified access to digital opportunity.

These insights from the literature underscore that technology adoption alone is insufficient, human capital readiness and organisational context critically determine the success of Industry 4.0/5.0 initiatives.

3. Main Findings: Thematic Dimensions of Human-Centric Digitalization

The results of the systematic review results converge around five thematic dimensions that characterize the transition towards Industry 5.0. These dimensions reflect a multilevel evolution from the nature of work at the individual level to organizational capabilities and broader institutional frameworks. Below we discuss each theme and its implications supported by insights from the reviewed literature (see Figures 2 and 3).

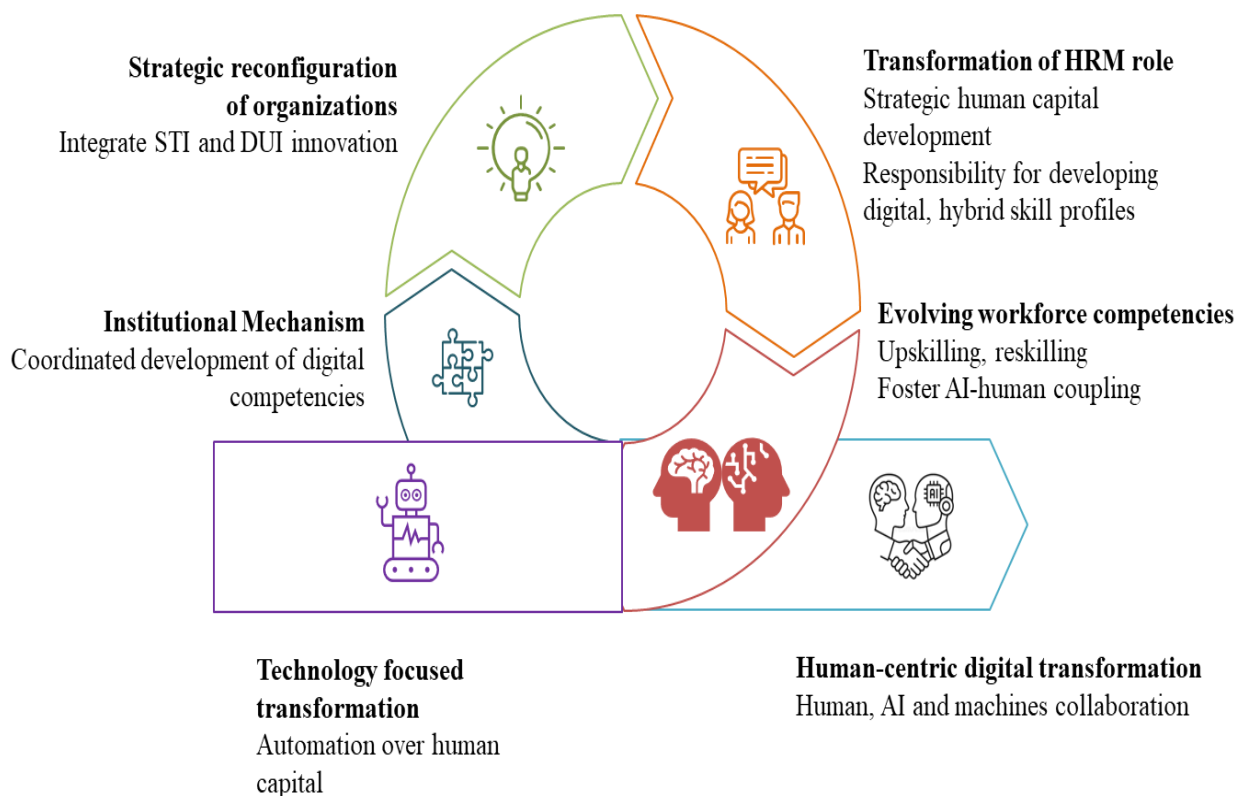


Fig. 2. From technology-oriented digitalization to human-centric digital transformation

(a) AI transforming workforce requirements

AI-driven transformation is reshaping workforce skill requirements at a fundamental level. The most pronounced shift concerns the reallocation of human effort away from routine, repetitive, and

data-intensive activities toward tasks that complement rather than mirror machine capabilities. Previously, employees were occupied with manual data processing and procedural work; now, such functions can be automated, enabling labour to be redirected toward analytical, creative, and collaborative problem-solving tasks [28]. This transition expands the value of distinctly human strengths such as critical thinking, emotional intelligence, and strategic judgement while AI manages operational volume, pattern detection, and high-risk or monotonous work. Early evidence suggests that this complementary task division not only enhances productivity but may also increase job satisfaction by allowing workers to engage more frequently in cognitively meaningful tasks [22, 28].

However, productivity gains are not guaranteed. Introducing AI into workplaces without equipping employees to cooperate with it can generate inefficiencies, frustration, or over-reliance. As Beretta and co-authors [22] emphasize, high performance in AI-human coupling requires several preconditions: first, employees must be capable of interpreting and anticipating the behavior of AI agents; second, they need a well-calibrated level of trust to ensure appropriate use; third, they should be able to rely on AI outputs to make informed decisions; and fourth, they must retain sufficient control over the system to operate and intervene effectively. These requirements illustrate that future workforces need hybrid competence profiles that blend technical literacy with domain expertise and adaptive soft skills. Workers must not only know how to operate AI systems, but also when to question them, how to contextualize algorithmic suggestions, and how to intervene in novel or ambiguous situations. AI is no longer merely a tool it is an operational collaborator, and employees must be trained to function in mixed teams that include non-human intelligent agents.

The increasing integration of AI in industrial environments has important productivity implications, particularly in the emerging Industry 5.0 paradigm. While Industry 4.0 focused predominantly on automation and cyber-physical efficiency, Industry 5.0 prioritizes human-machine synergy, combining AI's analytical speed with human creativity, ethical reasoning, and situational adaptability. Evidence from China illustrates that firms with stronger human–AI collaboration models achieve superior input–output efficiency, especially when complemented by R&D investments in innovation capacity, digital infrastructure, and workforce development [28].

The impact of AI is further magnified by the emergence of edge AI, where computational intelligence moves closer to physical environments in factories, offices, and urban infrastructure. Wen and co-authors [29] describe task-oriented AI architectures that distribute computation across devices and cloud resources, integrating sensing, communication, and machine learning in real time. Such systems demand multidisciplinary expertise: engineers fluent in both deep learning and network optimization, technicians able to interpret on-device AI decisions, and interface designers trained in human-factor psychology. These emerging roles are replacing traditional siloed IT positions and elevating lifelong learning as a core workforce expectation.

Furthermore, AI-enabled decision-support systems are also reshaping professional practice in complex fields such as logistics and urban planning. For example, Tupayachi and co-authors [30] demonstrate how AI can construct scenario-based ontologies and knowledge graphs to support freight-transport decision-making. Yet instead of eliminating human involvement, these technologies intensify the need for domain-specific judgement. Expert practitioners remain responsible for validating model assumptions, assessing contextual relevance, and aligning recommendations with strategic or ethical priorities [30].

These findings reinforce a strategic lesson for industry: AI delivers returns only when embedded in environments that simultaneously cultivate human skills. Regions or industries slow to develop complementary workforce capabilities risk widening productivity gaps, reinforcing inequalities in technological benefit distribution.

(b) Evolving workforce competencies

Digital transformation is driving a profound shift in the competency profile required of the workforce. Our review reveals a clear trend: the demand for traditional manual or routine skills is declining, while demand for a hybrid skill set that combines digital literacy, cognitive agility and socio-emotional intelligence is raising. According to [15], the introduction of Industry 4.0 technologies and tools is significantly transforming the production environment and placing new professional demands on employees. In the human-centric digital economy, employees are expected to be not only technically proficient (e.g., comfortable with data analytics, HMI operation, and the use of AI tools) but also adaptable learners and effective communicators.

Horváth and Szabó [31] emphasize that one of the main barriers to the implementation of Industry 4.0 principles and the transition to Industry 5.0 remains the shortage of qualified specialists and the lack of skills required to work with new technologies. Adaptation requires lengthy training, retraining and upskilling of personnel, which makes the development of digital skills in human capital a strategic priority for accelerating the sustainable transition of industry. Companies that are able to respond flexibly to these challenges and invest in innovation and systematic training gain long-term competitive advantages. Meanwhile, organizations that ignore this vector risk losing skilled personnel, suffering declining productivity and losing market position. Additionally, several authors [25-27] agree that the future of organizations lies in hybrid systems that combine human creativity with technological precision.

Adaptive and continuous learning skills are frequently highlighted because workers must regularly upskill or reskill to keep pace with technological change. Johansson and Abrahamsson [23] highlight that on the one hand, there are growing demands for skills and qualifications (upskilling), and on the other hand, there is fragmentation and loss of holistic knowledge (deskilling). In this context, training factories and so-called 'learning islands' are becoming particularly important, as they need to be adapted to the formation of new digital and cognitive competencies necessary for the successful integration of Industry 4.0/5.0 principles. The literature also points to the importance of creative and critical thinking skills which allow human workers to do what AI cannot: pose new questions craft novel solutions, and exercise judgement in complex unstructured situations [24, 25].

However, the transition to Industry 5.0 demands significant investment in human capital. Educational institutions and organizations need to collaborate on training programs, continuous professional development, and credentialing systems that foster these digital-cognitive and socio-emotional competencies. Moreover, equitable access to such learning platforms is a key policy concern, as skill gaps risk widening digital divides. The broad diffusion of competencies supported through by higher education–industry collaboration is essential for realising the productivity and innovation benefits of advanced technologies.

(c) The role of HRM in sustaining workforce competitiveness

In a global and unstable economy, a number of traditional professions will cease to exist, while new jobs will emerge, especially in developing market segments of the economy, leading to the transformation and renewal of the labour market [1, 32, 33]. The rollout of Industry 4.0 has changed the working environment in manufacturing, transforming traditional skills and making it critical for employees to adapt to new requirements (e.g., non-technical competencies and data analysis) in order to remain professionally relevant. Moreover, AI fundamentally transforms human resource management (HRM) by enabling data-driven recruitment, competency mapping, performance evaluation and training. The digital transformation of personnel selection, for example, shows that AI-enhanced tools improve efficiency, reduce bias, and optimize candidate-job matching, ultimately strengthening the organization's human capital [34]. Additionally, AI enhances HRM functions

through predictive analytics that identify skill gaps, forecast future workforce needs, and personalize learning trajectories [35]. In this context, HR departments are increasingly responsible for cultivating the human capital needed for digital innovation. This involves implementing continuous learning ecosystems (e.g. upskilling/reskilling programs, e-learning platforms), fostering employee well-being and engagement, and nurturing an organizational culture that embraces change. Training factories and learning environments must be redesigned to reflect the competencies demanded by Industry 5.0, which establishes new norms for decentralized, digitized production with high autonomy of technological systems. This shift deepens the interconnection between people, machines, and digital infrastructure, enabling fully integrated production environments and supply chains [15].

As several studies [33, 36, 37] noted HRM is becoming one of the decisive factors in the success of digital transformation. The transition from Industry 4.0 to Industry 5.0 is accompanied not only by a transformation in the qualification requirements for employees, but also by a profound restructuring of HRM and organizational strategies [33].

In the context of the interaction of AI and humans, HRM is acquiring a strategically expanded role as both an enabler and a facilitator of workforce transformation. Rather than simply coordinating personnel, HRM is becoming responsible for developing hybrid skill profiles that combine digital literacy, algorithmic awareness, and advanced social-cognitive abilities. The key challenge now lies not only in hiring or training technical specialists, but also in creating environments in which AI systems and human expertise complement rather than supplant one another. This requires competency frameworks that emphasize collaboration with AI agents, continuous retraining pathways, and mechanisms for fostering measured trust in algorithmic decision-making. HRM must also ensure that performance assessments, reward structures, and job design consider the distinctive contributions of human intelligence (creativity, intuition, and ethical principles), while simultaneously leveraging AI for accuracy and data processing. HRM thus becomes the architecture through which organizations realize the complementarity of humans and AI, align skills development with technological development, and ensure human agency in increasingly automated work systems.

(d) Strategic reconfiguration of organizations

Digitalisation has become a central driver of organisational transformation, reshaping business processes across sectors at uneven but accelerating rates. Firms leading this transition tend to demonstrate higher innovation capacity, particularly in developing new products and services. Consequently, digital transformation is redefining the role of employees in organisational innovation processes [16]. With the rapid development of technology, especially AI, intelligent manufacturing systems integrate human-cyber-physical systems in which people, cybernetic and physical systems interact to achieve jointly optimised goals. Within such systems, human labour shifts toward creative, cognitive and decision-intensive tasks [6].

Although there is no universally accepted definition of digital transformation, academic consensus views it as a deep structural reconfiguration of organisational strategy, architecture, and operations [3, 38]. The primary objective is performance improvement through technological integration. However, transformation outcomes depend critically on digital competence within management, scalable and flexible business processes, customer-centric digital experience, and organisational capacity for continuous innovation [13, 31, 39]. Sustainable development, as Mahmood and Mubarik [39] emphasize, requires balancing exploration (innovation and the creation of new opportunities) and exploitation (incremental efficiency gains). In this dynamic, intellectual capital and learning capacity emerge as core determinants of long-term competitiveness.

Digital transformation thus demands not only new technological infrastructures, but also organisational cultures capable of learning, adaptation, and collaborative knowledge use. Maturity

models have become widely used tools for assessing such readiness. Hein-Pensel and co-authors [40] argue that competitiveness increasingly depends on the degree to which digital capabilities are integrated with human-centric priorities, a view reinforced by Tyagi and colleagues [41]. Accordingly, investment in digital tools must be complemented by trust-based work structures and organisational learning environments.

Alasoini and Selander [16] further distinguish two complementary modes of innovation: the STI (science-technology-innovation) mode and the DUI (doing-using-interacting) mode. The STI mode relies on formal research and scientific knowledge, supporting innovation through codified evidence and technology-driven development. The DUI mode, by contrast, is grounded in experiential learning, user engagement, and tacit knowledge exchange within networks of practice. The DUI mode assigns a central role to employees, whose expertise, judgement, and informal knowledge generation underpin incremental innovation and continuous improvement. While the STI pathway generates transferable scientific outcomes, the DUI pathway enables adaptive, context-sensitive learning embedded in everyday work.

Several scholars also highlight barriers to the adoption of transformation. Schumacher and co-authors [14] note that firms frequently struggle to interpret Industry 4.0 concepts, align them with strategy, or assess their readiness, which hinders implementation. This uncertainty underscores the need for decision support frameworks and methods capable of linking strategic priorities to operational execution. Reviewing the determinants of digital maturity in small and medium-sized enterprises (SMEs), van Tonder *et al.*, [13] find that human capital remains as critical as strategy, leadership, culture, processes, products, and technology. Similar research suggests that firms lacking clear Industry 4.0 objectives should prioritise lean-oriented process redesign, enterprise-wide digitalisation, and workforce development to build motivation and capability [15, 42].

Reconfiguration as an element of an organisation's dynamic capabilities is a key mechanism for adapting to a changing external and internal environment. Dynamic capabilities refer to a firm's ability to integrate, rebuild, and reconfigure internal and external competencies in response to change [43]. In this context, reconfiguration functions as a mechanism for aligning existing resources and capabilities with strategic intent. Corporate development typically unfolds through three trajectories: expansion, downsizing, and innovation-driven renewal; each requiring distinct patterns of resource reallocation, process adaptation, and competency development. Expansion entails the mobilisation of additional assets and infrastructural capacity; downsizing emphasises efficiency, consolidation, and the sharpening of core competencies; innovation involves generating novel combinations of capabilities, technologies, and knowledge. Accordingly, reconfiguration is not a discrete intervention but a continuous, systemic capability that underpins strategic agility. It enables organisations to sustain competitive advantage under conditions of uncertainty and environmental turbulence [43-45].

Within this broader transformation landscape, AI-human coupling is becoming a decisive strategic factor shaping how organisations compete, innovate, and allocate talent. Rather than replacing workers, firms increasingly deploy AI as a complementary cognitive agent, automating repetitive decision processes while enabling humans to focus on judgement-intensive, creative and collaborative tasks [28]. This complementarity, however, materialises only when companies develop the human capabilities required to interpret, supervise and co-create value with AI systems. Berretta and co-authors [22] argue that high-performance human-AI teams depend on calibrated trust, transparency of system behaviour and the preservation of human oversight, conditions that require deliberate strategic investment in training, workflow design and governance. Emerging architectures such as edge-AI amplify this requirement, as distributed intelligence embedded in factories, devices

and logistics systems demands multidisciplinary professionals capable of navigating sensing, communication and real-time decision layers [29]. Likewise, AI-supported planning frameworks in transport and freight management highlight that strategic value arises not from automation alone, but from human experts who validate AI-generated insights and contextualise them within complex decision environments [30]. Across sectors, evidence therefore indicates that the strategic advantage of AI does not lie in displacement, but in the coupling the alignment of intelligent systems with human judgement, learning capacity and ethical discretion. In this regard, organisations that invest in nurturing human-AI symbiosis are better positioned to convert technological capability into sustainable competitive performance.

into sustainable competitive performance.

(e) Institutional coordination mechanisms

At the broader ecosystem level, institutional mechanisms play a pivotal role in enabling human centric digital transformation. Here institutional mechanisms are understood as a set of formal and informal rules, procedures, actors, and coordination tools [46, 47]. At the macro level, this implies that coherent macro-level frameworks, including government policies, educational programs, industry standards, and public-private partnerships, are critical for scaling up digital innovations beyond isolated experiments. For example, policies that promote digital skills training across society, standards that ensure interoperability of new technologies, and incentives for ethical AI adoption all create an environment where businesses and workers can thrive in Industry 5.0. At the micro level, this requires strategic reconfiguration, ongoing investment in R&D and human resources, sustainable HRM practices, and an organisational culture that encourages adaptation and experimentation. The effectiveness of the institutional mechanism will determine whether digital transformation is sustainable and inclusive or remains a fragmented initiative limited to individual organisations or sectors.

Research shows that digitalization does not succeed on technology alone, rather it depends on coordinated governance structures, regulatory frameworks, and collective action among government, academia, business and civil society [47]. When institutional arrangements lack coherence, digital initiatives tend to emerge in isolated pockets, resulting in duplication, limited interoperability, and widening digital divides [48]. Conversely, well-designed institutional ecosystems enable knowledge flows, investment in skills, and scaling of innovation beyond individual organizations or sectors [49].

Empirical evidence shows that the economic and social benefits of digitalisation in transport and logistics materialise only when institutional frameworks ensure accountability, stakeholder participation, and policy continuity over time [49, 50]. Doherty and colleagues [50] observe that smart mobility systems such as automated platforms, real-time data environments, and integrated mobility services advance more rapidly than the regulatory systems intended to govern them. This misalignment results in fragmented deployment, duplicated investments, and insufficient interoperability. Their concept of purposive governance underscores the need for institutional capacities to articulate public value, coordinate multi-actor ecosystems, and regulate private technology providers whose systems increasingly shape mobility outcomes.

Institutional mechanisms encompassing public policy, regulatory instruments, and industry standards therefore operate as active drivers rather than passive background conditions in digital transformation processes. Bag and co-authors [51] show that manufacturing firms in an emerging economy respond strongly to such institutional pressures: regulatory requirements, competitive market pressures, and normative expectations embedded in certification systems collectively accelerate the adoption of digital tools, often triggering the initial phase of transformation. In this

sense, institutional systems act as enabling infrastructure, shaping incentives, expanding digital capability formation, and facilitating inclusive innovation trajectories. Strengthening institutional capacity is thus central to ensuring that digital transformation evolves as a coherent, socially embedded process rather than as fragmented, isolated technological experimentation.

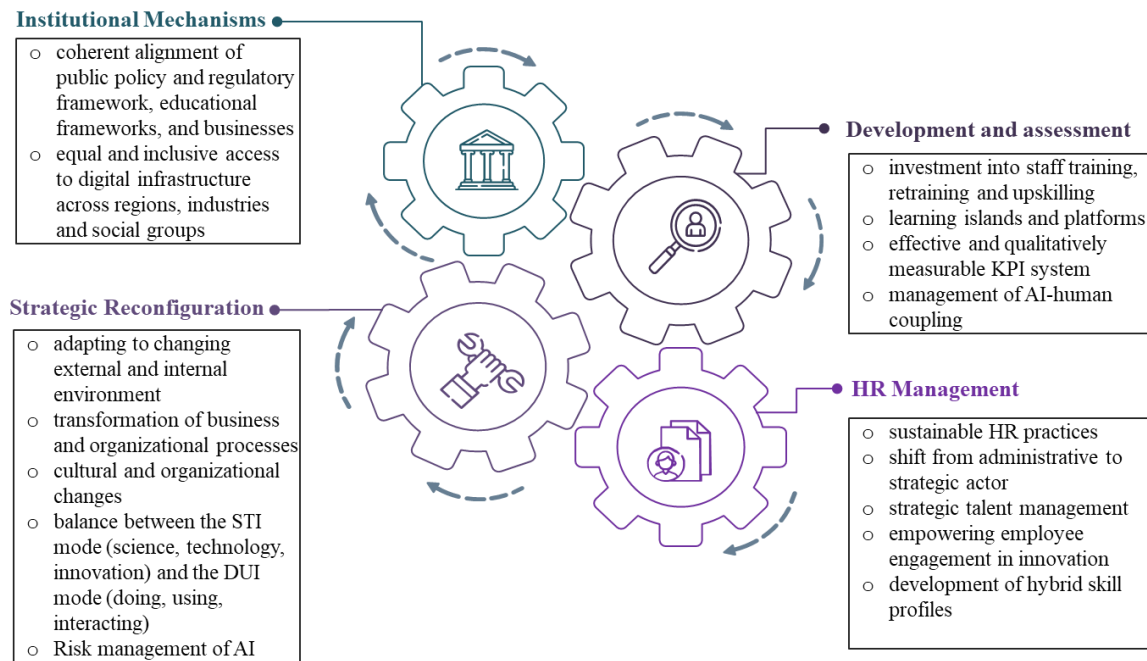


Fig 3. Key drivers of digital skills development

4. Challenges and risks of AI-human collaboration

The accelerating integration of AI into operational systems has brought productivity gains, decision-making precision, and novel forms of value creation. However, beneath these advantages lies a structural vulnerability that has received comparatively less analytical attention: the gradual erosion of the human comparative advantage.

One concern is the risk of over-reliance on AI systems without adequate human oversight. Berretta and colleagues [22] emphasize the danger of “automation bias,” where humans trust AI decisions too readily, even in situations where the system may be flawed or ill-suited. Without calibrated trust and adequate understanding of AI behaviour, teams risk poor decision outcomes, especially in safety-critical environments. Another challenge is the asymmetry in system complexity and human comprehension. Complex edge AI systems, such as those described by Wen and co-authors [29], involve highly specialized coordination of sensing, communication, and learning components. This complexity can make it difficult for non-expert users to understand or control system behaviour, leading to potential breakdowns in human-AI teaming when unexpected scenarios arise. Additionally, Tupayachi and colleagues [30] similarly highlight the dependency of AI-powered systems on high-quality, structured data, which is often lacking in under-resourced regions. Inconsistent or biased data inputs could compromise AI-supported decision-making and reinforce existing inequalities.

From a broader ethical and societal standpoint, a critical challenge in human-AI integration lies in maintaining complementarity rather than drifting toward substitutability. While current scholarship broadly converges on the view that AI does not eliminate labour universally, this consensus does not rule out the probability of a delayed yet substantial displacement effect. Substitution may occur

incrementally rather than abruptly, rendering segments of the workforce economically peripheral over time.

Should AI continue to advance exponentially, the cognitive gap between humans and machines will not merely narrow but may invert. This trajectory is underpinned by three observable technological dynamics. First, self-learning architectures increasingly update autonomously, reducing dependence on human programming. Second, reinforcement-driven optimisation enables systems to enhance performance without external intervention. Third, cognitive technologies exhibit scaling economics in which intelligence can expand while marginal costs decline.

If the pace of AI development outstrips the rate at which workers acquire new competencies, the human role shifts from central node to bottleneck within value-creation chains. Employability becomes contingent upon augmentation literacy, that is, the ability to collaborate with systems that already surpass human analytical capacity. Labour remains relevant only where it amplifies algorithmic capability rather than replicates it.

As AI approaches generalised competency, tasks involving modelling, optimisation, and forecasting may be executed autonomously. Historically, economic systems reorganise around the most efficient actor; accordingly, the principal risk is not competition, but the gradual depreciation of human default agency. With analytical and routine functions increasingly automated, human value concentrates in domains characterized by high uncertainty (creativity, ethics, and contextual interpretation), that will persist only if deliberately sustained.

Safeguarding a meaningful role for human labour requires anticipatory design rather than reactive adaptation. Industry 5.0 must institutionalise:

- human-in-the-loop governance mechanisms,
- ethical co-decision frameworks,
- competency-building trajectories that precede automation,
- education oriented toward reasoning rather than information retention.

This approach is not a defensive posture against AI, but an optimisation of the human + algorithm configuration. A resilient labour market is driven not by substitution, but by complementarity with positive synergistic returns.

Digital transformation has redefined competitiveness: knowledge alone is insufficient. Advantage derives from capability velocity, that is, the rate at which individuals can learn, integrate AI, and co-create innovation. Human labour does not disappear; it is re-ranked, prioritising those who adapt more rapidly than automation advances. In this emerging landscape, the future of work is shaped less by replacement than by differentiation. Artificial intelligence can amplify human potential but only where human capabilities evolve at a pace commensurate with machine intelligence.

Given the assessment of the risks associated with increasingly super-intelligent AI systems and the observable trajectory of digitalisation, the central task is not only technological restraint, but also the construction of institutional and organisational architectures in which the expansion of AI capability is matched by and contingent upon the strengthening of human potential rather than its depreciation. In this framing, technological progress and human development are not opposing vectors but interdependent assets: AI scales computational intelligence, while governance systems must scale human relevance.

Figure 4 illustrates the hierarchical functional significance of three interdependent control layers. The foundational layer is the technical governance contour, encompassing explainable AI (XAI), algorithmic auditing, transparency protocols, and model-verification mechanisms. Its primacy lies in the fact that, without monitoring and interpretability at the architectural level, higher-order regulatory or managerial interventions are structurally weakened. In other words, technical

governance is not a supplementary safeguard but the precondition for every subsequent form of oversight.

The second tier - the organisational control layer - operationalises governance in practice. It defines the allocation of responsibility between actors, embeds risk-management routines, and formalises human-in-command decision authority and AI interruption/override procedures. At this level, governance becomes actionable rather than declarative: the system's autonomy remains bounded because the organisation retains the ability to pause, redirect, or revoke algorithmic decisions. This stratum therefore determines the real managerial capacity to constrain or guide AI behaviour.

At the apex lies the institutional governance contour, comprising sectoral standards, regulatory frameworks, compliance systems, and supervisory instruments of state and cross-sector policy. Its function is to secure fairness, macro-stability, and long-horizon accountability across digital ecosystems. Yet its efficacy is conditional: without transparency in the technical layer and operational control within organisations, institutional regulation becomes symbolic rather than substantive.

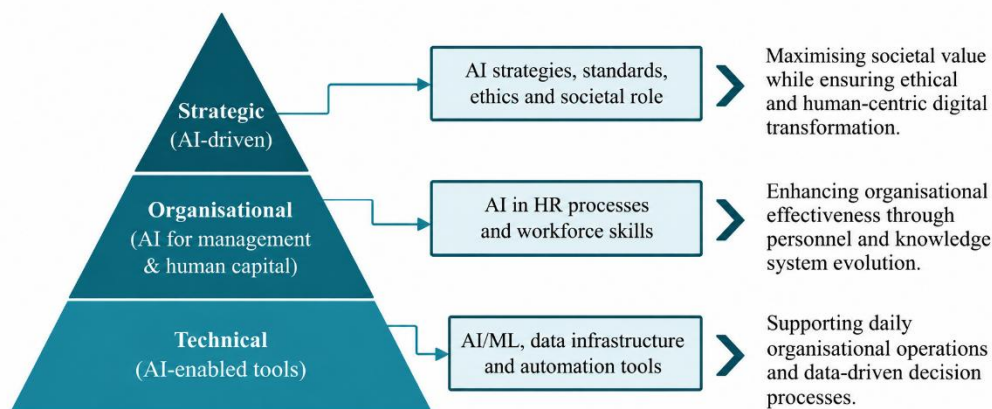


Fig 4. Prioritised governance model for high-autonomy AI systems

Accordingly, the model visualised in Figure 4 articulates a sequential logic of implementation:

(1) establish transparency and controllability at the technical layer → (2) embed organisational authority and risk-management → (3) scale institutional regulation.

Such a layered approach minimises technological and social risk during AI expansion, ensuring that autonomy is not merely permitted but governed, interpretable, and ultimately aligned with human-centred objectives.

In sum, the successful integration of AI into the labour market will depend not only on technical capability and education but also on establishing safeguards (ethical, legal, and operational) that ensure inclusive, reliable, and human-centric outcomes.

5. Conceptual Evidence Mapping: Citation-Concept Matrix

To move beyond narrative accumulation of knowledge and toward an analytically structured evaluation of the research domain, a conceptual coverage matrix (Table 1) was developed to systematically compare the thematic density of all 46 reviewed sources. The objective of this synthesis mechanism is not merely the descriptive sorting of the literature, but an operational mapping of how scholarly attention is distributed across the core dimensions of AI-enabled transformation, workforce capability formation, and governance within the transition from Industry 4.0 to Industry 5.0.

Each publication was assessed against nine conceptual categories derived inductively from the review corpus: (1) digital transformation and Industry 4.0, (2) Industry 5.0/human-centric paradigms, (3) workforce skills and competence development, (4) human–AI collaboration, (5) HRM mechanisms, (6) dynamic learning and absorptive capacity, (7) governance and institutional frameworks, (8) sectoral embedding in logistics/manufacturing/transport, and (9) sustainability and just-transition relevance. For every paper, the strength of conceptual presence was evaluated on a four-point scale (0 = absent, 1 = marginal reference, 2 = secondary but relevant, 3 = central thematic focus). This allowed the transformation of qualitative literature into a structured evidence grid (Table 1) capable of showing intensity patterns, gaps, and thematic convergence.

By compressing 46 research contributions into a single analytical representation, the matrix enables a transition from fragmented scholarly signals toward an integrated domain architecture. It thus provides a transparent foundation for subsequent interpretation and theory development: instead of inferring thematic emphasis intuitively, conceptual weight becomes empirically visible. This evidence synthesis offers not only a cartographic overview of the field but also a diagnostic tool for identifying research asymmetries, blind spots, and directions for future research. The discussion that follows builds directly upon these mapped patterns to extract conceptual pathways explaining how human capital, HRM structures, and technological architectures co-evolve within the logic of Industry 5.0.

Table 1
Citation-Concept Matrix

#	Source (first author, year)	DT4.0	IND5	SKILLS	AI	HRM	LEARN	GOV	SECTOR	SUST
1.	Abourokbah <i>et al.</i> , [52]	2	0	1	1	0	3	0	2	1
2.	Abrahamsson <i>et al.</i> , [1]	1	1	3	0	2	1	2	0	3
3.	Abril-Jiménez <i>et al.</i> , [6]	3	2	2	1	1	1	0	1	1
4.	Alasoini & Selander, [16]	2	1	2	0	2	3	1	0	1
5.	Atay <i>et al.</i> , [53]	2	3	3	2	3	2	1	0	1
6.	Bag <i>et al.</i> , [51]	3	1	1	3	1	2	3	1	3
7.	Baranyi, [34]	2	1	2	2	3	1	0	0	0
8.	Berretta <i>et al.</i> , [22]	2	2	2	3	2	2	0	0	0
9.	Caiado <i>et al.</i> , [15]	3	1	1	1	1	2	0	2	1
10.	Docherty <i>et al.</i> , [50]	2	1	1	2	0	1	3	3	2
11.	European Commission, [4]	2	3	3	2	2	2	3	1	3
12.	Fareri <i>et al.</i> , [24]	3	1	3	2	1	1	0	0	0
13.	Frank <i>et al.</i> , [38]	3	0	1	2	0	1	0	2	1
14.	Hanisch <i>et al.</i> , [49]	2	1	1	2	0	1	3	0	1
15.	Hein-Pensel <i>et al.</i> , [40]	2	3	2	1	1	2	1	1	2
16.	Helfat & Peteraf, [44]	0	0	1	0	0	3	0	0	0
17.	Horvat <i>et al.</i> , [7]	3	1	2	1	1	2	1	2	1
18.	Horváth & Szabó, [31]	3	1	2	1	1	1	2	1	1
19.	Johansson & Abrahamsson, [23]	2	1	2	1	1	1	1	0	2
20.	Karim & Capron, [45]	0	0	1	0	0	3	0	0	0
21.	Kraus <i>et al.</i> , [27]	2	1	3	2	2	2	1	0	1
22.	Kryukov <i>et al.</i> , [18]	3	1	2	1	1	1	1	3	1
23.	Lu, [2]	3	0	1	2	0	1	0	1	0
24.	Maasouman & Demirli, [42]	1	0	1	0	0	2	0	1	0
25.	Maden Eyiusta & Esen, [35]	1	1	2	1	3	2	0	0	1
26.	Mahmood & Mubarik, [39]	2	0	2	1	1	3	0	0	1
27.	Martini <i>et al.</i> , [36]	2	3	2	3	1	2	2	0	3
28.	Neugebauer <i>et al.</i> , [37]	3	0	1	2	0	1	0	2	0
29.	Ning & Yao, [20]	3	1	2	1	0	2	0	3	2

Table 1

Continued

#	Source (first author, year)	DT4.0	IND5	SKILLS	AI	HRM	LEARN	GOV	SECTOR	SUST
30.	OECD, [48]	2	1	3	2	1	2	3	1	3
31.	Putnik <i>et al.</i> , [19]	2	1	3	1	2	2	0	3	1
32.	Raina <i>et al.</i> , [54]	2	2	2	3	2	3	1	0	3
33.	Saniuk & Grabowska, [32]	2	3	3	2	2	2	1	2	2
34.	Sardi <i>et al.</i> , [33]	1	1	2	1	3	2	0	0	1
35.	Schumacher <i>et al.</i> , [14]	3	1	1	1	1	2	0	2	0
36.	Schumacher <i>et al.</i> , [3]	3	1	1	1	1	2	0	2	1
37.	Sima <i>et al.</i> , [25]	3	1	3	2	2	2	0	0	1
38.	Sun & Song, [28]	2	3	2	3	1	2	0	2	1
39.	Trenerry <i>et al.</i> , [26]	3	1	3	2	2	2	1	0	1
40.	Tupayachi <i>et al.</i> , [30]	2	1	1	3	0	2	1	3	2
41.	Tyagi <i>et al.</i> , [41]	2	3	3	2	3	2	1	0	2
42.	UNDP CDO, [47]	2	1	3	2	1	2	3	1	3
43.	van Tonder <i>et al.</i> , [13]	3	1	2	1	1	2	1	1	1
44.	Wen <i>et al.</i> , [29]	2	1	1	3	0	1	0	1	0
45.	Yang J. <i>et al.</i> , [5]	2	3	3	2	1	2	0	3	1
46.	Yang & Hsieh, [21]	3	1	2	2	1	1	1	3	2

0 – not present / irrelevant; 1 – minor / background mention; 2 – secondary but visible theme; 3 – core concept of the paper; DT4.0 – Digital transformation / Industry 4.0 / industrial digitalization; IND5 – Industry 5.0 / Society 5.0 / explicitly human-centric paradigm; SKILLS – Workforce skills, competencies, human capital, green skills; AI – Artificial intelligence in work systems, human–AI interaction, AI governance; HRM – HRM / talent management / employee-driven innovation; LEARN – Absorptive capacity, learning, dynamic capabilities, knowledge creation; GOV – Governance, institutions, policy, institutional pressures; SECTOR – Strong sectoral focus on transport / logistics / ports / supply chain / manufacturing; SUST – Sustainability, green transition, circular economy, just transition; Note: numbers in square brackets in the “Source” column refer to the numbered reference list.

6. Discussion: Conceptual Multilevel Framework

The purpose of this systematic review was to examine the evolving landscape of digital competencies required for the transition from Industry 4.0 to Industry 5.0 and to identify the HRM mechanisms that enable organisations to cultivate and sustain such capabilities. Across 46 carefully selected publications, a consistent empirical and conceptual pattern emerged: workforce competitiveness in AI-enabled industrial and logistics systems is no longer depends on technological adoption alone, but rather on the depth, adaptability, and integration of human capital capabilities. This review thus provides a structured answer to the research questions by synthesising the competencies most critical for the new production paradigm and the organisational mechanisms through which they are effectively developed.

The central challenge becomes the cultivation of skills and competencies that enable employees not merely to adjust to technological change, but to participate actively in innovation processes and sustainable value creation. The accelerating diffusion of artificial intelligence, big-data analytics, and cloud-based architectures has triggered a sharp rise in demand for digital competencies across sectors. These capabilities extend beyond basic data handling to include an understanding of digital system architectures, automation principles, and cybersecurity foundations. Such competencies constitute the core enablers of workforce participation within digital ecosystems and are increasingly required not only among technical experts, but also among managers, analysts, and training professionals across organisational hierarchies.

Critical Workforce Competencies for Industry 5.0 (RQ1)

Findings demonstrate a clear reconfiguration of skill demand, shifting from routine operational functions toward hybrid profiles that combine digital literacy, analytical cognition, and socio-

emotional capabilities. The most widely recognised competency clusters include: (i) data-analytic proficiency and AI literacy [21, 24], (ii) technological interaction skills including HMI configuration and cyber-physical interface handling [15], and (iii) higher-order human abilities creativity, adaptive reasoning, collaborative intelligence, and ethical judgement [25, 55]. These capabilities enable workers to interpret algorithmic outputs, supervise automated systems, and intervene in ambiguous scenarios roles that machines are not yet structurally equipped to fulfil.

This review confirms that Industry 5.0 does not replace human labour; rather, it elevates the value of human-machine complementarity. Productive AI implementation depends on human oversight, calibrated trust, and contextual interpretive capacity [22]. Workers become strategic decision-makers rather than executors of predefined tasks, and labour value shifts from operational throughput to innovation velocity and learning capacity. Consequently, workforce competitiveness in Industry 5.0 is determined not only by what employees know, but by how rapidly they acquire, integrate, and recombine knowledge in dynamic environments.

Additionally, the emergence of hybrid human-machine teams enhances organizational resilience by enabling adaptive reconfiguration under uncertainty. Workers equipped with advanced digital skills (e.g., data literacy, interaction with smart systems) are better able to exploit AI-generated insights, accelerate learning cycles, and contribute to sustainability-oriented innovation [53]. Conversely, a lack of digital skills or organizational support structures can decelerate innovation adoption or generate resistance to technological change. This transformation is accompanied by the need for continuous learning and the development of upskilling and reskilling practices.

HRM Mechanisms for Competency Development and Workforce Sustainability (RQ2)

Evidence across reviewed sources indicates that the most effective organisational pathway to sustaining these competencies lies in robust HRM systems that institutionalise continuous learning and capability renewal. Several mechanisms emerged as foundational. First, reskilling and upskilling ecosystems including modular training, micro-credentialing, and e-learning facilitate iterative skill adaptation aligned with rapid technological change [31, 33]. Second, predictive talent analytics and skills-gap diagnostics are increasingly deployed to anticipate workforce needs, optimise training investments, and personalise development trajectories [35]. Third, the redesign of training factories and learning environments supports immersion-based acquisition of digital-cognitive skills essential for operating autonomous production systems. These mechanisms ensure that capability formation is continuous, data-supported, and strategically aligned with organisational transformation.

A further insight from this review is the role of HRM as an integration function linking technology adoption with human development. HRM systems that reward adaptive behaviour, encourage collaborative experimentation, and embed trust-building in AI-supported workflows enable firms to move from automation-centric Industry 4.0 operations toward human-centric Industry 5.0 logic [37, 41]. Conversely, organisations lacking structured HRM capability-building practices risk labour stratification, technological exclusion, and operational underutilisation of intelligent systems. Sustainable competitiveness therefore depends not solely on digital infrastructure, but on institutionalised mechanisms for learning acceleration and capability retention.

Complementarily, organisational strategies for digital transformation are determined not only by the level of technological equipment, but also by the degree of digital maturity and the company's ability to absorb and use knowledge (absorptive capacity). According to Cohen and Levinthal [56] Место для ввода текста., absorptive capacity can be formed as a by-product of investments in R&D, production processes, or targeted technical training of personnel. Absorptive capacity is understood as the dynamic ability of an organisation to identify, interpret and apply external knowledge to develop new competencies and innovations [56], which is critically important in the transition to

Industry 5.0. Abourokbah and co-authors [52] claim that absorptive capacity significantly moderates the relationship between digital capability and innovation performance [51]. Thus, organizations with strong absorptive capacity translate digital insights into innovation, resilience and sustainability-oriented outcomes. This involves the integration of two innovation modes: STI-mode (science, technology, innovation), based on formalised knowledge, and DUI-mode (doing, using, interacting), based on practice and interaction. Their combination allows for a balance between theoretical and contextual knowledge, with human capital serving as the key carrier and integrator of this knowledge. Additionally, recent literature emphasises that organizations able to embed AI insights into decision structures through formal and informal learning routines show significantly higher innovation and sustainability outcomes [54]. Therefore, the STI and DUI learning modes [16], provide a useful conceptual framework: AI contributes to STI by generating codified analytical knowledge, while employee experience, experimentation, and collaborative problem-solving strengthen DUI learning. High-performing organizations integrate both modes, allowing human and machine intelligence to co-evolve.

6.1 Synthesis and Theoretical Contribution

This work contributes to emerging scholarship by defining competency structures relevant to post-automation production systems and by clarifying the organisational mechanisms through which such competencies materialise. It also positions HRM as a strategic conduit through which firms convert technological potential into operational advantage. The evidence reviewed suggests that capability development is not peripheral to transformation it is its determining condition.

The transition from Industry 4.0 to Industry 5.0 thus represents not merely a technological shift but a paradigm of human-machine symbiosis. Organisations that institutionalise continuous learning, predictive talent analytics, and integrated HR-driven skill ecosystems will be better positioned to generate innovation, resilience, and sustainable competitive performance in AI-mediated production networks. Integrating the above dimensions, we propose a conceptual multilevel framework for human-centric digital transformation (see Figure 5).

The scheme illustrates a three-tier governance framework linking institutional structures, organisational capabilities, and human-level competencies to a unified outcome. Conceptually, the model is structured hierarchically: the outcome occupies the highest position, representing the desired performance state of a digitally transformed system (e.g., sustainable competitiveness, innovation capacity, resilience, productivity, or socio-technical balance). Unlike prior studies that focus separately on digital skills, AI adoption, or HRM practices, this review integrates these dimensions into a single explanatory framework.

Macro-level. Institutional Mechanism: This layer reflects regulatory, policy, and ecosystem-level conditions enabling digital transformation. It includes national strategies, standards, incentives, multi-actor coordination systems, and public-sector governance of AI adoption. The institutional domain shapes long-term structural direction and provides conditions for fairness, diffusion of competencies, and system-wide scalability.

Meso-level. Organizational Strategy: Positioned centrally, this layer translates macro-level regulations into internal architectures. It encompasses digital maturity, leadership, resource allocation, absorptive capacity, and hybrid human–AI workflow design. Organisational strategy mediates between external institutional forces and internal human-capital conditions, determining whether transformation produces efficiency, resilience, or fragmentation.

Micro-level. Two Human-Centric Dimensions: HRM as a strategic actor managing reskilling, upskilling, workforce planning, learning design, and cultural acceptance of AI; and evolving skills and

competencies - reflecting the adaptability, digital literacy, creativity, and augmentation capacity of employees. These two nodes represent the human substrate of transformation and jointly determine how effectively AI can complement rather than substitute human value.

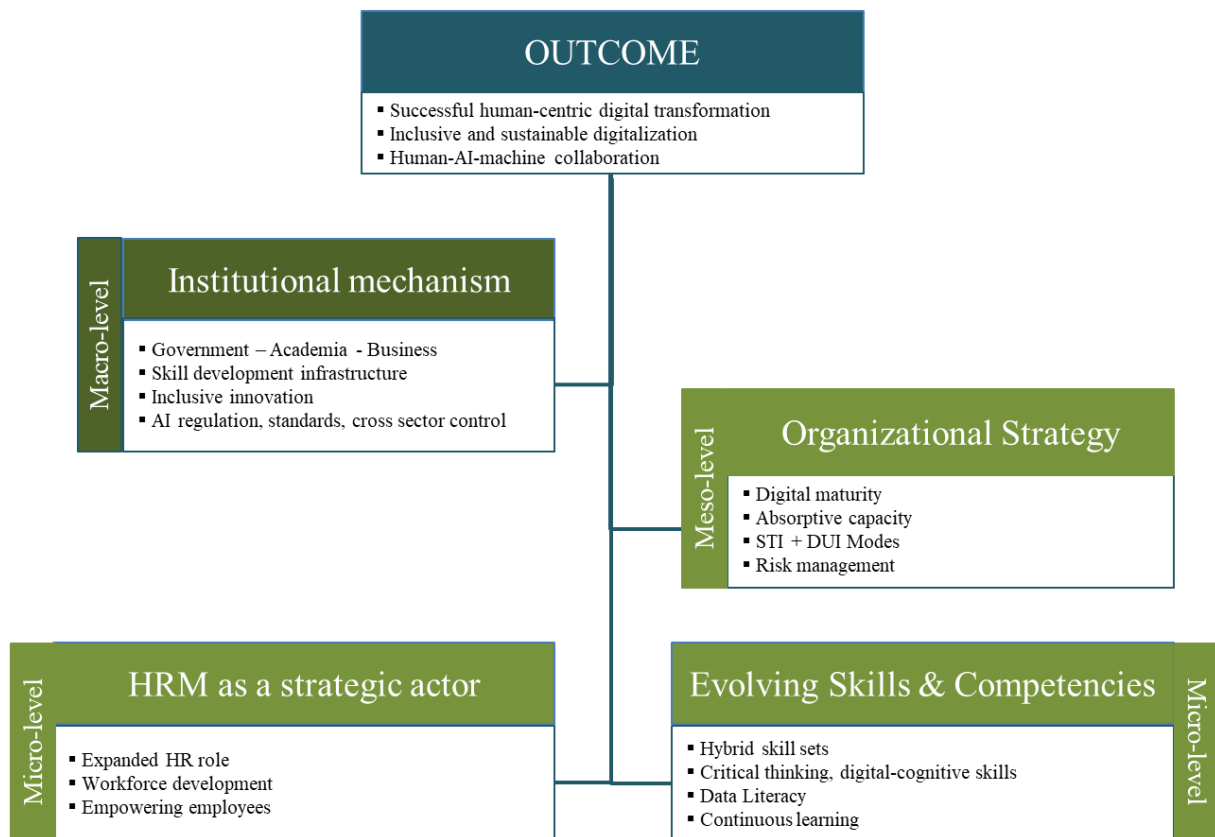


Fig 5. Conceptual multi-level framework diagram

In summary, the scheme demonstrates that successful digital transformation is systemic rather than technological: outcomes are a function of aligned governance, internal strategy, and human capability development across interlocking levels. The existing potential for strengthening cooperation between government institutions, the research community, the education system and business points to a key condition for a successful transition to Industry 5.0: an effectively structured institutional mechanism. It is this mechanism that sets the architecture for the coordinated development of digital competencies, continuous learning, and the transfer of knowledge into practice. The institutional mechanism not only ensures the coordination of actors and the alignment of incentives, but also creates the conditions for the systematic introduction of innovations, the sustainable scaling of digital solutions and the minimisation of the social and technological divide. Its maturity will determine whether the digital transformation is inclusive, reproducible and sustainable over time.

Thus, the central conclusion is the recognition of human capital not as a supporting element, but as a system-forming element of digital transformation. The technologies used only acquire value only in the presence of developed competencies, an adaptive organisational culture, and coordinated institutional mechanisms that ensure the continuity of learning and the fairness of transformation processes. The transition to Industry 5.0 is fully achievable once we realise that the future of the digital industry is determined not by the power of algorithms, but by the quality of interaction between people and machines.

7. Conclusion

This systematic review demonstrates that the transition from Industry 4.0 to Industry 5.0 fundamentally reshapes the role of the workforce, positioning human capital as the principal determinant of organisational resilience and innovation capacity. Digital competencies emerge as the critical lever through which firms convert technological infrastructure into performance gains. The evidence consistently shows that employee value no longer resides in routine operational efficiency, but in adaptive intelligence, creativity, analytical acuity, and the ability to collaborate symbiotically with AI systems. Accordingly, organisations that succeed in fostering these hybrid skill sets are more likely to achieve competitive advantage in AI-enabled production landscapes.

At the same time, the review highlights a structural vulnerability: while AI can amplify human capability, it also has the potential to erode the comparative advantage of labour if competency development lags behind technological progression. Risks such as automation bias, declining human oversight, and progressive substitution are not speculative they are already observable in environments where workers are insufficiently equipped to understand, supervise, or challenge algorithmic outputs. The literature therefore underscores a critical duality: AI is both a catalyst for workforce augmentation and a potential accelerator of skill obsolescence. The direction of impact depends on the strength of organisational and institutional capability-building systems.

For organisations, this creates a strategic imperative. AI-driven transformation does not reward technology acquisition alone; it rewards the velocity of human learning. Firms must cultivate capability development as an ongoing process rather than a discrete training intervention. HRM emerges as the operational core of this transition, responsible for structuring reskilling ecosystems, predictive competence mapping, human AI team design, and continuous learning infrastructures. Competencies must be developed proactively rather than reactively before technological displacement materialises.

In addition, digital transformation within Industry 5.0 is increasingly associated with energy transition and the introduction of green technologies. The dual challenge of green transformation and digitalisation, exacerbated by the impact of artificial intelligence, implies a massive transformation of society and business, of the organisation of labour and the quality of jobs, and of interactions between the private and public sectors in various industries [1]. Employees are required not only to have digital skills, but also to understand the principles of sustainable development, a requirement that is shaping new competency profiles and transforming HR strategies. At the same time, the boundaries between formal knowledge and creative thinking are blurring: successful work in a hybrid environment requires not so much diplomas and certificates as the ability to adapt, ethical judgement and interdisciplinary interaction [36, 41] .

Theoretical and managerial implications

This study contributes to the emerging theory of human-centric digitalisation by demonstrating that workforce competitiveness under Industry 5.0 is determined by the co-evolution of technology and human capability rather than by technological maturity alone. The findings reinforce the view that operational advantage arises from complementarity not substitution between AI and human cognition. Future research should therefore prioritise conceptual models of hybrid intelligence, capability velocity, and human-in-the-loop innovation systems.

Managers should adopt capability-focused transformation strategies that prioritise:

- continuous reskilling and micro-credentialing pathways,
- diagnostic HR analytics to anticipate future skill gaps,
- simulation-based learning environments for AI collaboration,
- trust-building and oversight mechanisms in human-AI decision systems.

Organisations that neglect these mechanisms risk productivity stagnation and labour displacement. Those that embed them systematically are better positioned for durable competitiveness.

Policymakers and educational institutions must expand access to digital competency development to prevent widening inequality and skill-based exclusion. Investments in university–industry partnerships, lifelong learning infrastructures, and digital inclusion programs will be essential to preserve the relevance of human labour in AI-intensive economies. Regulatory frameworks should also reinforce transparency, accountability and safety in algorithmic systems to ensure that AI supplements rather than supersedes human agency.

In summary, Industry 5.0 represents a decisive inflection point in the evolution of production systems: one that will be defined not by the intelligence of machines, but by the intelligence of societies in cultivating human capability. AI offers unprecedented leverage for value creation; yet without strategic investment in human capital, it risks accelerating fragmentation rather than prosperity. The future of work will be neither algorithmic nor human it will be hybrid, and its outcome will depend on whether learning evolves as quickly as technology.

Limitations and future research directions

This study has several limitations that should be considered when interpreting the findings.

As part of a qualitative synthesis, this review gives priority mainly to academic and policy-analytical sources, which may lead to a ‘publication bias effect’: studies with positive results are more likely to be published, while data on unsuccessful or ambiguous digital transformation practices may remain unreported.

Most empirical work originates from digitally advanced regions and high-tech industries, with comparatively less attention to emerging economies, public-sector environments, and labour-intensive manufacturing. Broader geographical comparison and studies in logistics, textile production, healthcare, and public administration would improve generalisability and nuance.

Although the literature on Industry 5.0 and AI-enabled transformation is growing rapidly, many studies remain conceptual or cross-sectional. Evidence on long-term competency evolution, sustained organisational outcomes, or productivity effects over time is still developing. Future research would benefit from longitudinal case studies and panel-based data tracking skill development, innovation performance, and job transformation across multiple years.

Additionally, although competency frameworks are well defined, however, the behavioural dynamics that determine effective collaboration with AI such as trust calibration, decision-delegation thresholds, cognitive load, and adaptive learning processes remain insufficiently examined. Future research would benefit from integrating experimental methods, human-factor modelling, and in-situ workplace observation to capture real patterns of interaction rather than relying on idealised or assumed behavioural responses.

Nevertheless, the results of the study should be interpreted as an analytical basis and a guideline for further research aimed at an in-depth study of the factors of digital competence development, institutional coordination, and practical models for implementing human-centred transformation within the logic of Industry 5.0.

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Conflicts of Interest

The authors declare no conflicts of interest.

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