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Future Skills, Workforce Agility, and Human Resource Transformation in the AI Era: A Systematic Literature Review

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ABSTRACT

Artificial intelligence (AI) is transforming work and human resource management (HRM), increasing the demand for future skills and workforce agility while raising concerns about employee well-being, autonomy, and the ethical governance of technology. This study aims to integrate the literature on future skills, workforce agility, HR transformation, and human-centered AI to clarify their conceptual relationships and identify key research gaps. Using a systematic thematic and integrative literature synthesis, the review examines contributions from human resource management, strategic management, information systems, and humanistic management. The synthesis indicates that digital and AI-related capabilities must be developed alongside critical thinking, creativity, collaboration, adaptability, and continuous learning. These capabilities can support workforce agility, while HR transformation provides organizational mechanisms for skills development, talent management, and the integration of AI into work processes. However, the literature remains fragmented in its definitions and measurements of future skills and agility, and empirical evidence explaining how agility translates into organizational performance remains limited. Research on human-centered AI in HRM is also insufficient to establish how technological efficiency can be reconciled with employee autonomy, well-being, and ethical accountability. The review highlights the need for an integrative framework connecting skills development, workforce agility, HR transformation, and human-centered governance. Future research should prioritize construct standardization, empirical and longitudinal testing, and examination of the organizational conditions under which AI augments rather than undermines human work.

Keywords: Future Skills, Workforce Agility, Human Resource Transformation, Artificial Intelligence, Human-Centered AI.

I. Introduction

The functions of human resource management have changed radically over the past two decades under market and technological forces, becoming more cross-functional and data-driven, while artificial intelligence increasingly performs advanced data analysis, generates system and process efficiencies, and contributes to organizational value creation (Fenwick, Molnár, & Frangos, Revisiting the role of HR in the age of AI: bringing humans and machines closer together in the workplace, 2024). Yet scholarship on human-AI interaction at work remains limited and fragmented, and a neglect of human considerations in the design and deployment of HR technologies can actively hamper AI-enabled digital transformation (Fenwick, Molnár, & Frangos, Revisiting the role of HR in the age of AI: bringing humans and machines closer together in the

workplace, 2024). This asymmetry rapid technological capability accompanied by comparatively weak human and organizational theory is the starting point for the present review.

The problem is not confined to technology adoption. Talent management has faced sustained criticism for two decades for being overly static and offering little in terms of enabling strategic agility, precisely at a moment when organizations depend on agility to manage dynamic operating conditions (Jooss, Collings, McMackin, & Dickmann, 2023). The literature on AI applications in HRM has expanded sharply, and AI-augmented HRM has assumed strategic importance for achieving HRM domain-level outcomes, organizational outcomes, and sustainable competitive advantage, yet the field lacks a focused synthesis capable of connecting contextual factors to outcomes (Prikshat, et al., 2023). Meanwhile, evidence from studies of the future of work indicates that the technological endowment and readiness of a company directly shapes the skills of its employees, making skills development a structural rather than a discretionary concern (Cramarenco, Burcă-Voicu, & Dabija, 2023, p. 733). Taken together, these observations define the central concern of this review: how organizations are moving unevenly and with unresolved conceptual tensions from skills-based models of organizing work toward human-centered workplaces, and what this movement implies for future skills, workforce agility, and the transformation of HR itself.

II. Literature Review and Hypothesis Development

2.1. Future Skills and Skills-Based Organizations

The human-centered organization has a distinct intellectual lineage. Since McGregor's *The Human Side of Enterprise* was published in 1957, various models, methodologies, and tools have been designed to operationalize Theory Y in the Western workplace, and organizational forms drawing on Theory Y thinking such as sociocracy and B-corps have emerged, while the human-centered organization itself has not yet been codified in the same way (Townsend & Romme, 2024, p. 53). The concept's synthesized definition ties together a purpose extending beyond profit, positive human experiences on the job in terms of ownership, engagement, and participation, team structure, participatory practices and tools, and humanistic values such as dignity and well-being at the center (Townsend & Romme, 2024, p. 65).

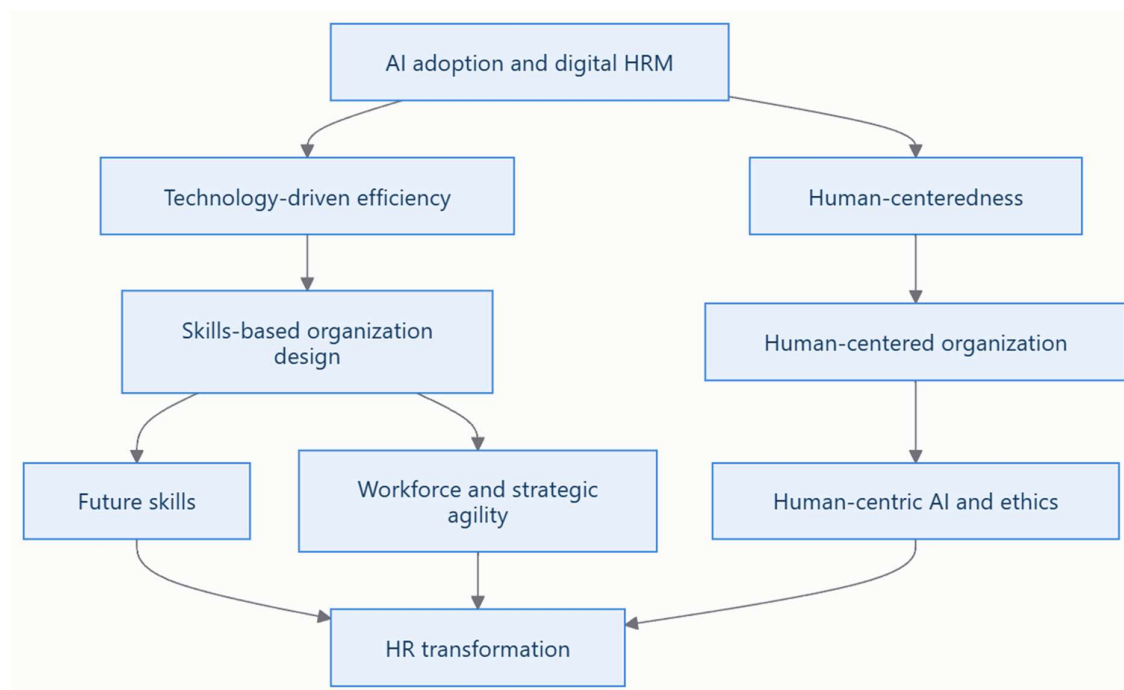


Figure 1. Conceptual Framework of AI-Driven HR Transformation: Linking Future Skills, Workforce Agility, and Human-Centeredness

a. From Job-Based Roles to Skills- and Competency-Based Work

The literature reviewed here converges on a reframing of work itself: rather than treating the job as the stable unit of analysis, contemporary research foregrounds discrete skillsets and competencies that must be continuously reconfigured as technologies change. Bouwmans and colleagues describe digital transformation as a transformative shift driven by the innovative use of digital technology and strategic resource optimization, one in which employees are a strategic pillar and their ability to adapt is a critical determinant of success; when some tasks become obsolete and others emerge, it becomes crucial that employees adopt essential skillsets for DT (Bouwmans, Lub, Orlowski, & Nguyen, 2024, p. 3). This reframing has conceptual roots in competency theory. Chouhan and Srivastava note that the resultant of a critical behaviour is higher performance, and that the level of performance low, moderate or high is always determined by the level of knowledge, skill and attitude (Chouhan & Srivastava, 2014, p. 17). Competency, on this account, is not a job title but a bundle of underlying attributes that can be described, classified, and deliberately developed.

b. Frameworks and Taxonomies of Digital and AI-Related Skills

The most comprehensive consolidation of DT skills to date is the Digital Transformation Skills Framework developed by Bouwmans and colleagues through a PRISMA-based systematic review. Thirty-six articles were selected and examined using thematic analysis, yielding a framework containing six overarching skillsets and 44 underlying skills, covering digital work, entrepreneurship, evidence-based work, collaboration, communication, and adaptation; three of the six skillsets are further delineated into subgroups, and definitions were developed for each skillset, subgroup, and skill based on definitions, descriptions, and indicators provided in the 36 articles, with the three co-authors reaching absolute interrater agreement on the definitions (Bouwmans, Lub, Orlowski, & Nguyen, 2024; Bouwmans, Lub, Orlowski, & Nguyen, 2024, p. 1). A notable methodological finding is the terminological fragmentation of the field: the included articles employed diverse labels for essential DT skills, some focusing on digital technology-related hard skills such as digital or data literacy, others on transformation-oriented soft skills such as entrepreneurial and open innovation competences, and still others on combinations labelled 21st century skills, transprofessional competencies, near-future key skills, and future skills (Bouwmans, Lub, Orlowski, & Nguyen, 2024, p. 7). The DTSF positions itself explicitly as a foundation for re- and upskilling initiatives (Bouwmans, Lub, Orlowski, & Nguyen, 2024, p. 1).

Table 1. Frameworks and Taxonomies of Digital and AI-Related Skills

Framework	Empirical basis	Structure	Level of application
Digital Transformation Skills Framework (Bouwmans, Lub, Orlowski, & Nguyen, 2024; Bouwmans, Lub, Orlowski, & Nguyen, 2024, p. 1)	Systematic review of 36 articles	6 skillsets, 44 skills; 3 skillsets subdivided	Organization-wide DT capability
Critical skills for the digital workplace (Weritz, 2022)	Cross-case analysis of 9 multinationals	9 named skills (entrepreneurial mindset, digital responsible thinking, digital literacy, transformative skills, personal development, communication, community management, data analytics, web development)	Leadership and workforce training
Digital skills at work (Audrin, Audrin, & Salamin, 2024)	Literature review, 5 expert interviews, 2 pilots (n = 22; n = 106), validation survey (n = 923)	8 dimensions, 52 items	Individual-level measurement in workplaces

21st-century digital skills (Laar, Deursen, Dijk, & Haan, 2019, p. 93)	Systematic literature review plus large-scale survey of professionals	6 generic skills: information, communication, collaboration, critical-thinking, creativity, problem-solving	Knowledge work
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Two observations follow from placing these side by side. First, there is substantial convergence on a hybrid composition: digital literacy and data analytics appear alongside collaboration, communication, and adaptation, which supports the claim that DT contexts demand not only job-specific and ever-changing technological skills but also soft skills such as collaboration, problem solving, and project management (Bouwman, Lub, Orłowski, & Nguyen, 2024, p. 3). Second, the frameworks differ in whether they treat digital skills as a generic competence or as a domain-specific one; van Laar and colleagues observe that although ICTs are pervasive at work, not all employees have the skills to take advantage of the richness of activities and the variety of learning opportunities they offer, and that people vary greatly with regard to their digital skill levels (Laar, Deursen, Dijk, & Haan, 2019, p. 93).

c. AI Literacy, AI Competency, and the Data-Analytics Layer

AI-specific skills have been theorized separately from general digital skills, and the literature distinguishes between literacy and competency. Ng and colleagues conceptualized AI literacy across four aspects know and understand, use and apply, evaluate and create, and ethical issues grounded in a review of 30 existing peer-reviewed articles and adapted from classic literacies, with the explicit aim of establishing a consolidated definition, teaching approach, and set of ethical concerns as groundwork for later competency development and assessment criteria (Ng, Leung, Chu, & Qiao, 2021). In a later study of teachers' AI digital competencies, the same research group situates this within two foundational competency sets: the Five Big Ideas in AI as a K–12 education framework articulating four foundational concepts (perceptions, representations, reasoning, learning, natural interaction and societal impact), and Long and Magerko's proposal of 16 competencies spanning recognition and understanding of AI, interdisciplinary skills, distinguishing general from narrow AI, identifying strengths and weaknesses, imagining future applications and societal impacts, knowledge representations, decision making, machine learning, the roles of humans in AI, data competency, learning from data, critically interpreting data, higher-level reasoning, sensors, and ethical concerns (Ng, Leung, Su, Ng, & Chu, 2023, p. 143). The necessary AI competencies were subsequently categorized into four cognition domains know and understand; use and apply; evaluate and create; and ethical issues designed to foster AI knowledge from low to high thinking skills, inspired by Bloom's Taxonomy (Ng, Leung, Su, Ng, & Chu, 2023, p. 143).

d. Technical, Human, and Conceptual Skills for Worker–AI Coexistence

Zirar and colleagues provide the most explicit tripartite architecture for skills in AI-enabled workplaces. This tripartite grouping echoes earlier competency classification. As reviewed by Chouhan and Srivastava, Katz and Kahn grouped competency into three areas that later expanded into four: technical or functional (knowledge, attitudes, skills associated with the technology or functional expertise required to perform the role); managerial (required to plan, organize, mobilize and utilize various resources); human (required to motivate, utilize and develop human resources); and conceptual (the ability to visualize the invisible, think at abstract levels, and use that thinking to plan future business) (Chouhan & Srivastava, 2014, p. 17). The convergence is significant: the human and conceptual categories that competency theory has long treated as managerial attributes reappear in the AI literature as the skills that determine whether workers and intelligent systems can coexist productively rather than competitively.

e. Job-Proof Skills: Critical Thinking, Creativity, and Empathy

The notion of skills that resist automation is developed most directly by Dumitru and Halpern, who introduce the concept of "job-proof skills" and highlight critical thinking, problem-solving, empathy, ethics, and other human attributes that machines cannot replicate with the same standards and agility (Dumitru & Halpern, 2023). Their argument rests on a dual premise: advancements in AI have the potential to disrupt various professions including programming, legal work, and radiology, yet solely relying on AI systems can lead to errors and misjudgments, emphasizing the need for human oversight (Dumitru & Halpern, 2023). They further maintain that critical thinking can be taught and learned through appropriate classroom instruction and transfer-focused approaches, that the need for it is reinforced by the influx of information and the spread of misinformation in the age of social media, and that there is a correlation between jobs requiring critical thinking skills and their resistance to automation (Dumitru & Halpern, 2023).

f. Lifelong Learning, Upskilling, Reskilling, and Employability

Across the AI and Industry 4.0 literatures, the response to skills obsolescence is framed as continuous rather than episodic. Cramarenco and colleagues find that the large-scale adoption of AI-related technologies has led to a clear need to upskill the professional profile of employees toward so-called human-machine competencies and/or to reskill employees to adopt new job requirements, with an evident need for continuous learning focused on digital skills; critically, they also find that the mismatch between an employee's skills and job-related skills may affect well-being, acting as a stressor and leading to increased levels of dissatisfaction (Cramarenco, Burcă-Voicu, & Dabija, 2023, p. 737). This links skills policy directly to employee outcomes rather than treating reskilling as a purely technical exercise.

2.2. Workforce Agility and Dynamic Capabilities.

a. Distinguishing Organizational, Workforce, and Strategic Agility

Agility is generally described as the ability to gain effective advantage, exploit opportunities and withstand threats derived from frequent and sometimes unexpected changes, responding quickly by reconfiguring resources, strategies, and people in an efficient and effective manner (Tessarini & Saltorato, 2021, p. 156). Workforce agility is the construct that redirected attention from the enterprise to the people within it. Breu and colleagues conducted what they describe as the first empirical study to examine how the pressures of organizational agility impact upon the workforce, using survey evidence from 515 UK organizations, and found that agile workforces acquire the five capabilities of intelligence, competencies, collaboration, culture and information systems (Breu, Hemingway, Strathern, & Bridger, 2002). Strategic agility operates at a different level again and carries a distinctive conceptual lineage. Doz and Kosonen analyse the meta-capabilities underlying strategic agility, clustered around strategic sensitivity (both the sharpness of perception and the intensity of awareness and attention), resource fluidity (the internal capability to reconfigure business systems and redeploy resources rapidly), and leadership unity (the ability of the top team to make bold decisions fast, without getting bogged down in win-lose politics at the top) (Doz & Kosonen, 2008).

Table 2. Distinguishing Organizational, Workforce, and Strategic Agility

Construct	Principal level	Defining emphasis
Organizational agility	Firm / enterprise	Four categories drivers, enablers, capabilities, dimensions connected from a dynamic capability perspective; drivers necessitate capabilities realized through interdependent enablers (Walter, 2020, p. 343)
Workforce agility	Workforce / employee	Five capabilities: intelligence, competencies, collaboration, culture and information systems (Breu, Hemingway, Strathern, & Bridger, 2002); four dimensions: proactivity, flexibility and adaptability, resilience, competence (Tessarini & Saltorato, 2021, p. 155)
Strategic agility	Top management / firm strategy	Strategic sensitivity, resource fluidity, and leadership unity, all three required (Doz & Kosonen, 2008)

b. The Dynamic-Capabilities Lens and Its Micro-Foundations

Teece's account of dynamic capabilities summarizes them as three clusters of entrepreneurial activities that take place concurrently throughout the organization: sensing, seizing and transforming (Teece, 2018, p. 364). The activities for sensing include environmental scanning, which brings disorganized information and unstructured data from the external environment into the organizational system; managers at various levels must generate and test hypotheses about latent consumer demand, technological possibilities, and other forces that affect the firm's future, and an effective intra-organizational network requires decentralizing authority, creating a collaborative organizational culture, and propagating a shared vision (Teece, 2018, p. 364). Seizing capabilities determine how quickly the system can respond to opportunities and threats once they have been identified and deemed important, through activities such as investing to commercialize new technologies and designing or updating and implementing business models (Teece, 2018, p. 364). Dynamic capabilities are undergirded by "microfoundations," that is, "distinct skills, processes, and organizational activities": sensing consists of scanning, learning, and interpreting data; seizing is captured by utilizing existing and newly acquired assets and skills; and when a firm recognizes an

opportunity that could lead to a competitive advantage, it needs reconfiguring capabilities to reorganize its resources to take advantage of it (Quayson, Bai, Sun, & Sarkis, 2023, p. 4824).

c. Drivers and Antecedents of Workforce Agility

The empirical base for claims about what produces workforce agility remains qualitatively oriented. Ajgaonkar and colleagues build their framework from in-depth qualitative interviews with senior information technology professionals, managers, directors and leadership, coding and analysing data through the Gioia methodology (Ajgaonkar, Neelam, & Wiemann, 2021).

d. Measuring Workforce Agility

Measurement has lagged conceptual development. Petermann and Zacher observe that several different workforce agility measures are used in the literature, which complicates the comparison of findings, and that relations between agility and positive work outcomes such as higher performance or increased well-being have often been suggested but rarely empirically tested (Petermann & Zacher, Workforce Agility: Development and Validation of a Multidimensional Measure, 2022). To address these gaps they developed a new workforce agility measure, compared it to established measures, and tested its relations with work outcomes across two samples ($N_1 = 218$, $N_2 = 533$); Sample 1 was used to examine factor structure for item selection and Sample 2 to confirm the 10-factor structure and compare predictive validity across three agility scales (Petermann & Zacher, Workforce Agility: Development and Validation of a Multidimensional Measure, 2022).

e. Talent Management, Skills-Matching, and Strategic Agility

Talent management has faced ongoing criticism for being overly static in its approach, offering little in terms of enabling strategic agility a problem given that organizations increasingly rely on strategic agility to manage dynamic business operations (Jooss, Collings, McMackin, & Dickmann, 2023). Drawing on matching theory and adopting an agility lens, Jooss and colleagues explicate a skills-matching perspective on talent management, including initial and dynamic skills-matching in external and internal labor markets, through which organizations can build dynamic capabilities underlying strategic sensitivity and resource fluidity; their qualitative design encompassed 34 interviews in 15 organizations (Jooss, Collings, McMackin, & Dickmann, 2023). This portrays skills-matching as an illustration of a processual view on talent management and yields a model of developing strategic agility through skills-matching that is responsive to external and internal demands (Jooss, Collings, McMackin, & Dickmann, 2023). Harsch and

2.3. Human Resource Transformation and AI-Augmented HRM

a. Agile HR: 'Agile for HR' and 'HR for Agile'

Agile HR is well-established in practice and has emerged as a research area in the last four years, yet no comprehensive review of the literature existed until Moh'd and colleagues conducted a systematic mapping study that identified 86 relevant primary studies (Moh'd, Gregory, Barroca, & Sharp, 2024). Their findings organize the field into seven research topics falling under two major themes: *Agile for HR*, concerning how the HR function adopts agile practices, and *HR for Agile*, concerning how the HR function supports an agile organisation (Moh'd, Gregory, Barroca, & Sharp, 2024). The HR for Agile theme is more mature, with more research papers, proposed models, and frameworks, while the body of publications overall is fragmented and diverse, with most articles published after 2019, primarily in multidisciplinary journals, incorporating a mix of theoretical and empirical approaches (Moh'd, Gregory, Barroca, & Sharp, 2024). Their contributions to practice include findings that agile HR practices benefit organisations, that agile talent acquisition facilitates organisational agility, and that HR can transition to agility by making small changes to their practices rather than undergoing radical change (Moh'd, Gregory, Barroca, & Sharp, 2024).

b. Agile Work Cultures and HR's Enabling Role

Reviews of the IT sector highlight the dynamic interplay between HR practices and agile methodologies, illustrating the critical role of HR in enabling agile transformations (Ajayi & Udeh, 2024, p. 1153). The agenda this literature sets out is explicitly forward-looking, calling for research on the impact of emerging technologies on agile work cultures, the role of HR in fostering inclusivity and diversity within agile teams, and the long-term effects of agile practices on employee well-being and organizational performance, alongside case studies of successful agile transformations facilitated by HR (Ajayi & Udeh, 2024, p. 1153). As agile methodologies continue to evolve, the role of HR in supporting and shaping these transformations

becomes increasingly crucial, and by adopting strategic HR practices and fostering a culture of agility organizations can navigate the complexities of the digital era more effectively (Ajayi & Udeh, 2024, p. 1153).

c. Tensions and Paradoxes

Agility is not achieved without contradiction. Ambituuni and colleagues investigate what HRM operational models and practices are developed in response to paradoxical tensions associated with striving for strategic agility in project-based organizations, and name the paradox of agile HRM as improvising within purposeful boundaries: as the complexity of the environment grows, project teams' responses must be requisitely creative, yet teams must also operate in ways that converge on client goals, such that improvisation and innovative action need to be guided and disciplined (Ambituuni, Azizsafaei, & Keegan, 2021, p. 180). Strode and colleagues provide complementary empirical evidence from three case studies of diverse organizations transforming to agility, each choosing a different focus culture change, strategic change, and operational change and present 13 tensions analysed through the lens of paradox theory, showing that tensions occur *during* transformations to agility and not just in fully agile organizations (Strode, Sharp, Barroca, Gregory, & Taylor, 2022). At the level of the HR function itself, McMackin and Heffernan's diagnosis of the neglect of HR operating models in SHRM research points to a structural tension between practitioner-led experimentation and academic theory building (McMackin & Heffernan, 2020), while Moh'd and colleagues conclude that more academic work is needed on agile HR to improve conceptual clarity, theory building and development, understanding of benefits and value for the business, identification of challenges, understanding of contextual factors, and critical exploration of outcomes (Moh'd, Gregory, Barroca, & Sharp, 2024). Taken together, the tensions documented in this literature are less incidental frictions than constitutive features of the transition from agility as an aspiration to agility as an operating reality (Ambituuni, Azizsafaei, & Keegan, 2021; Strode, Sharp, Barroca, Gregory, & Taylor, 2022, p. 180).

2.4. The Transformation of the HR Function: From Administrative Roles to AI-Assisted HR

a. From Administrative Function to Business Partner

The normative redefinition of the HR function began with a decisive break from its administrative self-image. Storey's typology explicitly warned against any evolutionary teleology implying uniform "progress" towards HRM or the "changemaker" type, a danger implicit in all developmental typologies; Ulrich's model, by contrast, was founded on translating the ascendant HRM paradigm into a new set of roles for HR professionals as champions of competitiveness (Caldwell, 2003, p. 1003). To achieve this transformation, the function had to confront the myths and negative counter-images of its past by founding professional identity on value creation a shift from "what is done to what is delivered" which allowed Ulrich to present the multiple and often conflicting roles of HR professionals as proactive "business partners" who finally dispense with their reactive, inflexible and inward-looking past (Caldwell, 2003, p. 1003). Crucially, this role architecture was never conceived as a universal template. The twenty-first-century HR organization is grounded in a contingency logic: corporate strategy focuses on the portfolio or mix of businesses while business-unit strategy focuses on how a unit anticipates and services customers, and each view of strategy leads to business organization choices that then lead HR organization choices (Ulrich, Younger, & Brockbank, 2008, p. 849). HR structure, in other words, is derived from business strategy rather than designed in isolation from it.

b. Critiques and Paradoxes of the Business Partner Model

The business partner model's diffusion has been accompanied by a sustained critical literature that questions both its durability and its professional consequences. Gerpott argues that the approach gained widespread acceptance in organizational practice because of its functionality in addressing tensions inherent in HRM, categorizing contradictory HRM demands into tensions of (1) identity, (2) learning, (3) performing and (4) organizing; the implementation of the business partner model resolves these tensions in the short term by addressing the opposing forces separately, yet these resolution strategies are not sustainable and threaten the long-term impact of HRM (Gerpott, 2015). Wright's analysis of the "internal consultant" reinvention sharpens the professional-identity critique. While many HR managers gain greater self-esteem and organizational status from the identity and role of business partner/internal consultant, this does not equate to a broader identity as a member of an HR "profession" (Wright, 2008). Two developments are central: first, the focus on the business partner/internal consultancy role has undermined any pretence to a unitary and cohesive occupational identity, as the bifurcation between routine transactional and strategic transformational activities encourages competition within the HR profession between different sub-

groupings; second, this strategy of redefinition has reduced the entry barriers demarcating HR activities and facilitated the entry of new occupational groups and rival managerial specialisms (Wright, 2008).

c. Digital Competencies and the Reshaping of HR Work

Digitalization has altered not only HR structures but the competency base on which they rest. Competencies cannot be observed directly but can only be measured by action aimed at achieving specific objectives, and the ongoing development of HR technologies creates new tasks and roles for HR professionals, motivating them to develop strong HR technology competencies (Mazurchenko & Maršíková, 2019, p. 76). The documented evolution shifts HR from traditional to digital competencies and technical skills: relationship management (consultation) gives way to digital literacy; ethical practice to digital communication (social media); business acumen to data analytics and cloud technologies; HR expert knowledge to dealing with complexity (multitasking); workforce planning and change management to working in an agile way and creativity; diversity management and cultural awareness to lifelong learning and skills development; and critical thinking to problem-solving through digital solutions (Mazurchenko & Maršíková, 2019, p. 76). A related distinction separates strategic HR competencies business knowledge and active involvement in strategic decision-making from functional HR competencies tied to the delivery of HR operations, personal credibility and active use of HR technologies (Mazurchenko & Maršíková, 2019, p. 76).

d. HR Digitalization and HR Analytics: Enablers, Barriers and Adoption

The optimistic account of HR analytics as a "must have" capability has been directly contested. Angrave and colleagues take issue with claims that analytics will ensure HR's future as a strategic management function while transforming organizational performance for the better, arguing that unless the HR profession engages operationally and strategically to develop better methods and approaches, existing practices of HR analytics are unlikely to deliver transformational change; indeed, current trends may seal the exclusion of HR from strategic, board-level influence while doing little to benefit organizations and actively damaging the interests of employees (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016). The adoption record bears out the scepticism about pace. Human resource analytics is attracting increasing interest as an innovative practice, and the emergence of disruptive technologies such as artificial intelligence, computational intelligence techniques, data mining, machine learning and the Internet of Things has speeded up data-driven decision-making in HRM in domains such as candidate selection, employee mood and sentiment analysis, and attrition prediction prompting organizations to invest in analytics infrastructure including tools, capabilities and other resources; yet the pace of adoption of HR analytics has not been as expected (Shet, Poddar, Samuel, & Dwivedi, 2021, p. 312). The scientific evidence base for adoption decisions is itself thin: while there is a positive relationship between HR analytics and organizational effectiveness, there is limited scientific evidence to aid decision-making in the adoption of HR analytics (Trenerry, et al., 2021, p. 620777).

Table 4. HR Digitalization and HR Analytics

Category	Factor	Source
Enabler	Change management (identified as the key enabler)	(Verma, Rana, & Meher, 2023)
	Learning culture; training and development; e-learning management; HR transformation	(Verma, Rana, & Meher, 2023)
Barrier	Data & models	(Fernández & Gallardo-Gallardo, 2020, p. 163)
	Software & technology	(Fernández & Gallardo-Gallardo, 2020, p. 163)
	People	(Fernández & Gallardo-Gallardo, 2020, p. 163)
	Management	(Fernández & Gallardo-Gallardo, 2020, p. 163)
Moderator	HR professional analytics skills	(Trenerry, et al., 2021, p. 620777)
	Managerial buy-in	(Trenerry, et al., 2021, p. 620777)
	Integration of HR information technology	(Trenerry, et al., 2021, p. 620777)

e. AI-Assisted HRM Ecosystems

The shift from analytics to AI-assisted HRM reframes the unit of analysis from isolated tools to an ecosystem. Analyzing multiple data sources from a global information technology consulting multinational

enterprise, Malik and colleagues unpack the configuration of a digitalized HR ecosystem of artificial intelligence-assisted HRM applications and HR platforms, developing a framework that maps the nature and purpose of such an ecosystem for delivering exceptional employee experience as an antecedent to employee engagement; employing the lenses of EX, EE, AI-mediated social exchange and engagement platforms, the study establishes how AI-assisted HRM fits into an organization's ecosystem and how it impacts EX and EE, finding that AI-assisted applications for HRM enhance EX and, thus, EE, with increases in employee productivity and HR function's effectiveness (Malik, Budhwar, Mohan, & Srikanth, 2022, p. 97).

Table 5. AI-Assisted HRM Ecosystems

HR domain	AI/AI-assisted application	Source
Recruitment and selection; training and development; performance management; talent management; employee turnover; reward management; job design; employee satisfaction; employee engagement	AI-enabled HRM applications entering strategic HRM discussions across sub-functional domains	(Prikshat, Malik, & Budhwar, AI-augmented HRM: Antecedents, assimilation and multilevel consequences, 2021, p. 100862)
Global recruitment, mobility and labour-market forecasting	Randstad Big Data: locates job requirements and skills satisfiable across regions and countries, promotes geographic mobility, offers "business gateways" and vocational retraining, informs site location by skills accessibility, and predicts recruitment trends	(Allal-Chérif, Aránega, & Sánchez, 2021, p. 120829)
Staffing and internal mobility	P-MART: skill ontology of 8000+ skills, matching algorithm, "nearby" skill-based staffing, gamified demand creation, embedded interactive query assistant chatbot	(Malik, Budhwar, Mohan, & Srikanth, 2022, p. 109)
Employee service and career guidance	liPA chatbot: over 1 million queries answered with >80% accuracy; proactive recommendations from compensation break-up and vacation planning to career guidance and wellness	(Malik, Budhwar, Mohan, & Srikanth, 2022, p. 109)
Attrition and retention	Deep Neural Networks for churn prediction	(Srivastava & Eachempati, 2021)
Talent career management	Intelligent HRM automation solution based on a talent intelligent module	(Faqihi & Miah, 2023)

f. AI-Driven Talent Management and the Redesign of Talent Practices

AI-driven talent management has been approached both as a design problem and as a strategic reorientation. Faqihi and Miah set out to discover the new requirements for generating an AI-oriented artefact so that issues pertaining to talent management are effectively addressed; the design artefact is an intelligent HRM automation solution for talent career management based primarily on a talent intelligent module, with improving connections between professional assessment and planning features as the key goal (Faqihi & Miah, 2023). Utilising a design science methodology, they investigate organised machine learning approaches as the key component of a complete AI solution framework, informed by a suggested moderation of technology–organization–environment theory with the theory of diffusion of innovation, and offer recommendations for practical approaches researchers may follow to fulfil a company's specific requirements for talent growth (Faqihi & Miah, 2023).

g. Internal Talent Markets, Mobility and Retention

Internal mobility has become a central mechanism through which organizations attempt to realize the value of their human capital and a source of measurable risk. Internal talent markets, created when firms post open jobs and invite current employees to apply, enhance the value of an organization's human capital by generating complementary person–job matches, yet these markets generate more internal rejections than matches, as not all internal applicants are hired (Dlugos & Keller, 2020). Analyzing 9,355 rejections in a single firm over a five-year period, Dlugos and Keller find that rejected employees are significantly less likely to exit when they are interviewed by the hiring manager (compared to being rejected earlier) and when they are rejected in favor of another internal candidate (compared to an external candidate) (Dlugos & Keller, 2020). The theoretical explanation is informational: variations in post-rejection turnover are shaped by the information that the market provides employees about their likelihood of future internal advancement despite being rejected in the present, with hiring manager decisions about whom to interview and hire signalling to rejected candidates their ability to meet the criteria for similar jobs in the future and the likelihood that those jobs will be filled internally (Dlugos & Keller, 2020).

h. Fairness, Justice and the Human-Centered Constraint

The expansion of algorithmic and AI-assisted decision-making into HR raises questions that go beyond predictive accuracy. Algorithmic decision-making is becoming increasingly common as a new source of advice in HR recruitment and HR development, and while firms implement it to save costs as well as increase efficiency and objectivity, it might also lead to the unfair treatment of certain groups of people, implicit discrimination, and perceived unfairness; current knowledge about these threats is mostly unexplored in the human resource management context, prompting a systematic review of 36 journal articles from 2014 to 2020 covering applications and possible pitfalls in recruitment and development (Köchling & Wehner, 2020, p. 795). Experimental evidence on employee reactions specifies where the human-centered constraint bites. In a study examining decision making in six HRM functions and manipulating the decision maker and decision valence (positive or negative), the use of human decision makers over AIs generally resulted in better perceptions of respectful treatment, and people experiencing positive over negative decisions generally reported better perceptions of respectful treatment; in instances where these cases conflict, on some indicators people preferred positive AI decisions over negative human decisions, and qualitative responses show how people identify justice concerns with both AI and human decision making (Bankins, Formosa, Griep, & Richards, 2022). The implication for redesign is that legitimacy is not conferred by the sophistication of the system but is negotiated through interactional justice, trust, dehumanization and perceptions of decision-maker role appropriateness (Bankins, Formosa, Griep, & Richards, 2022).

2.5. Human-Centered AI, Workforce Transformation, and Future Skills

a. Human-Centered AI, Employee Well-Being, and Responsible HRM

The integration of artificial intelligence (AI) into human resource management (HRM) creates opportunities to improve efficiency, decision-making, and workforce development. However, technological performance alone is insufficient to determine the success of AI adoption. Human-centered organizations emphasize dignity, employee growth, participation, meaningful work, and well-being as essential organizational values (Townsend & Romme, 2024). Similarly, human-centric AI prioritizes human needs, ethical considerations, transparency, explainability, and meaningful human control rather than focusing exclusively on technical capabilities (Fenwick et al., 2024; Xu et al., 2022). This perspective challenges traditional HRM approaches that prioritize organizational performance while treating employee well-being as a secondary concern. Guest (2017) argues that employee well-being and positive employment relationships should be central to HRM because they can contribute to both individual and organizational performance. Cooke et al. (2022) further emphasize that human-centered HRM can support sustainable workforces and organizations, although digital technologies may affect workers differently according to their socioeconomic circumstances.

Evidence regarding AI and employee well-being remains mixed. AI may improve productivity and task optimization, but it can also increase technostress, job insecurity, and exhaustion. Valtonen et al. (2025) found that AI adoption influenced employee well-being indirectly through task optimization and safety rather than through a direct relationship. Chuang et al. (2025) similarly reported that AI efficacy and generative AI could improve productivity, engagement, and job satisfaction, whereas AI-related technostress increased exhaustion and work–family conflict. These findings indicate that the consequences of AI depend on how technologies are implemented and integrated into work processes. AI may also affect professional identity and the meaningfulness of work. Strich et al. (2021) demonstrated that employees can experience identity

threats when AI replaces important tasks and limits their influence over decisions. Bankins and Formosa (2023) distinguish three pathways through which AI shapes work: replacing tasks, creating new responsibilities associated with managing AI systems, and augmenting human capabilities. These pathways can produce different outcomes depending on job design, employee autonomy, and opportunities to use skills. Parker and Grote (2019) therefore emphasize proactive work design, human-centered technology development, organizational support, and training that enables employees to participate in shaping technological change.

Responsible AI governance is necessary to translate these principles into practice. Papagiannidis et al. (2025) identify structural, relational, and procedural practices as important components of responsible AI governance. Siebert et al. (2022) further emphasize that human responsibility must correspond to actual authority and control over AI-supported decisions. Employee experience provides another link between organizational practices and employee outcomes. It encompasses employees' perceptions of workplace culture, technology, physical environments, relationships, and opportunities for growth (Malik et al., 2022; Plaskoff, 2017). Nevertheless, integrated longitudinal evidence connecting human-centered AI governance with employee experience, dignity, and well-being remains limited.

b. Artificial Intelligence, Skills Demand, and Labor Market Dynamics

A central debate concerns whether AI primarily replaces human labor or enhances human capabilities. Raisch and Krakowski (2021) conceptualize automation and augmentation as interconnected rather than mutually exclusive processes. Automation transfers selected tasks to machines, whereas augmentation combines machine capabilities with human judgment, creativity, and contextual understanding. The outcomes depend on whether employees retain meaningful responsibilities, opportunities for development, and authority over their work. Research on occupational exposure suggests that generative AI differs from earlier automation technologies because it increasingly affects cognitive and language-intensive occupations. Eisfeldt et al. (2023) and Eloundou et al. (2023) found that many higher-wage occupations are exposed to generative AI, particularly those involving analytical, writing, and programming tasks. However, occupational exposure does not necessarily mean job elimination. Cazzaniga (2024) explains that exposure measures indicate the potential integration of AI into work activities but do not independently establish whether AI will complement or substitute for workers.

Labor-market outcomes therefore remain uncertain. Acemoglu and Restrepo (2018) distinguish the displacement of existing tasks from the creation of new tasks that generate additional labor demand. Although AI may eliminate or reduce demand for certain activities, it can also create new occupations and transform existing roles (Goos & Savona, 2024; Kanbach et al., 2023). Empirical findings nevertheless reveal risks. Hui et al. (2024) found reductions in employment and earnings among freelancers in occupations highly exposed to generative AI. Conversely, Brynjolfsson et al. (2025) reported that AI assistance increased productivity among customer-support agents by 15% on average, with particularly strong gains among less experienced workers. These contrasting findings suggest that AI does not produce uniform labor-market outcomes. Benefits depend on task characteristics, employee competencies, organizational practices, and access to training. Jarrahi et al. (2022) argue that effective human-AI collaboration requires mutual understanding between human reasoning and machine decision-making. Accordingly, workforce transformation must address not only technological adoption but also the development of skills that enable employees to work effectively alongside AI.

c. Reskilling, Digital Divides, and Workforce Development

Upskilling and reskilling are essential for helping employees respond to changing skill requirements. Morandini et al. (2023) recommend identifying emerging skill gaps, developing transversal competencies, and providing targeted training opportunities. However, access to training is uneven. Heß et al. (2023) found that workers in occupations more exposed to automation were 15 percentage points less likely to participate in training than less-exposed workers. This disparity may intensify existing inequalities because employees facing greater displacement risks may have fewer opportunities to acquire new competencies. The distribution of AI benefits also depends on digital literacy, socioeconomic conditions, and organizational investment. Carter et al. (2020) warn that AI may reinforce existing digital divides, while Capraro et al. (2024) argue that generative AI can either reduce or exacerbate socioeconomic inequalities. Consequently, workforce development requires coordinated organizational and policy responses that ensure vulnerable workers can access relevant training and participate in the benefits of technological transformation.

d. Synthesis, Research Gaps, and Future Research

The literature reveals three interconnected themes: future skills, workforce agility, and HR transformation. First, organizations need to develop digital, cognitive, interpersonal, and adaptive competencies. Second, workforce agility enables employees to apply and reconfigure these competencies as work requirements change. Third, HR transformation provides organizational mechanisms for workforce planning, learning, talent development, and responsible AI implementation. Despite these connections, important research gaps remain. Conceptual fragmentation persists in the definitions and measurement of future skills and workforce agility. Kotsiou et al. (2022), for example, identified 341 terms across 99 future-skills frameworks, illustrating the lack of consistent terminology. Research on workforce agility similarly lacks sufficiently consolidated theoretical foundations and standardized measurement approaches (Tessarini & Saltorato, 2021; Walter, 2020). Moreover, the mechanisms connecting agility with organizational performance are not always empirically established (Franco & Landini, 2021). A second gap concerns the relationship between AI-enabled HRM and human-centered outcomes. Existing research identifies potential benefits and risks, but longitudinal evidence remains limited regarding how AI governance, employee participation, and work design influence dignity, meaningful work, and well-being. A third gap involves the relationship between labor-market changes and organizational HR practices, particularly how reskilling policies reach workers most vulnerable to technological displacement.

Future research should therefore develop an integrated framework linking future skills, workforce agility, HR transformation, and human-centered governance. Empirical studies should test the mechanisms through which skills development and agility influence work outcomes, improve measurement consistency, and examine AI adoption longitudinally across different organizational and occupational contexts. Research should also investigate how HR functions develop the capabilities required to guide AI implementation responsibly. Overall, the literature suggests that successful workforce transformation cannot be evaluated solely through efficiency or productivity. It also depends on whether organizations develop employee capabilities, preserve meaningful participation, distribute training opportunities fairly, and maintain appropriate human control over AI-supported work. The central challenge is to determine how organizations can combine technological efficiency with workforce adaptability and human-centered principles to support sustainable organizational and employment outcomes.

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