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From automation to augmentation: Human resource's journey with artificial intelligence

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ABSTRACT

This article examines the strategic integration of artificial intelligence (AI) in human resource management (HRM), highlighting both its opportunities and its challenges. While AI can improve HRM functions such as recruitment, performance evaluation and employee development, it also raises concerns related to algorithmic bias, technostress and resistance to change. To navigate these complexities, we present a structured two-tiered model that balances algorithmic efficiency with human-centred workforce development. Unlike previous studies that explore AI-driven human resource management in isolation, this research provides a comprehensive strategy for AI adoption that improves employee engagement, optimises HR decision-making and fosters organisational resilience.

In addition to outlining the role of AI in human resource management, we explore its practical implications, ethical considerations and associated risks, offering strategies to mitigate bias, promote transparency and foster organisational readiness for AI-driven transformation. We also emphasise the importance of pilot studies and empirical validation to assess the model's effectiveness in diverse organisational contexts. By providing a structured roadmap for AI integration, this study contributes to the ongoing discourse on how human resource management can lead, rather than simply adapt to, AI-driven workforce transformation.

1. Introduction

The contemporary economic landscape has been profoundly reshaped by digitalisation, encapsulated in the concept of Economy 4.0. The rapid expansion of digital technologies — including intelligent robotics, the Internet of Things (IoT), Cloud Computing (CC) and Artificial Intelligence (AI) — has transformed labour dynamics by introducing automation and reshaping traditional work structures [1,2]. These changes are even more deeply rooted in the broader paradigms of Industry 4.0 and the emerging Industry 5.0, which emphasise not only technological optimisation but also human-centricity, sustainability, and resilience in industrial systems [3-5]. These advances aim to improve both organisational performance and human well-being,

particularly through the integration of connected and adaptive technologies such as AI and IoT.

The implications of these changes go beyond mere technological integration, impacting job stability, job design and workforce management. While some scholars predict significant job losses due to automation [6], others argue that innovative technologies will create new job opportunities, transforming roles rather than eliminating them [7, 8]. What all perspectives share is the expectation of a profound and imminent transformation of work [8-10]. Despite this growing academic focus, a significant gap remains: how organisations, and in particular human resource management (HRM), should navigate these disruptions to optimise human and technological potential [2].

In this context, beyond isolated case studies and analyses of the

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automation of work, the role of human resource management (HRM) in actively shaping this transformation remains unexplored. However, HRM professionals play a key role in the allocation of resources, the management of learning processes and the redesign of job functions to help organisations adapt to modern technologies [11,12]. Furthermore, as industrial systems evolve towards interconnected, data-rich environments, the integration of people-centric HRM into digital architectures becomes a fundamental component of industrial information integration (Brunzuni et al., 2023; [13]). Therefore, HRM plays a crucial role in ensuring that technological design serves both organisational efficiency and core human priorities — including inclusion, well-being, and sustainable development.

The integration of AI into the workplace highlights two core HRM responsibilities: developing new skills and redesigning roles. These skills can be developed internally, through retraining and upskilling programmes, or externally, by hiring or outsourcing specialised talent. However, over-reliance on outsourcing can weaken organisational resilience in the long term [14], reinforcing the need for HRM to lead structured workforce adaptation strategies. In this regard, HRM plays a strategic role both in supporting digital transformation and in aligning workforce design with Industry 5.0 objectives, which include mass customisation, agile skills development, and collaboration between people and machines [15,16].

At the same time, the redesign of jobs is essential in this new context. Research highlights that factor such as autonomy, variety of tasks and meaningful work directly influence motivation, well-being, turnover rates, and performance [17-19]. It is therefore crucial that new jobs not only address technological demands but also improve the experience and satisfaction of employees [8,19,20].

HRM itself is being transformed by AI. Digital technologies have already transformed business operations, including people management practices [21,22]. One of the most disruptive developments is algorithmic employee management (AM), where AI-driven systems make HR decisions with minimal human oversight [23]. While existing research often criticises AM for reducing worker autonomy and increasing stress [21,24,25], these discussions tend to focus on-demand work and underestimate AM's impact on traditional employment structures.

Although the literature identifies the risks and opportunities associated with AI, it often lacks structured frameworks to guide HRM in aligning AI implementation with employee engagement and organisational well-being. Furthermore, little research situates HRM within the information integration architectures that underpin industrial digital ecosystems, especially in contexts where interoperability, data transparency and interaction between people and machines are essential [3, 5,26]. This paper addresses that gap by proposing a dynamic model that captures the dual role of AI in HRM: as a process automation tool and as a driver of employee empowerment. Unlike previous research, which focuses on isolated aspects such as automation, skills adaptation or employee supervision, our approach integrates these dimensions into a two-tier strategy that balances algorithm-driven efficiency with people-centred management. This structured perspective provides organisations with a practical roadmap for navigating digital transformation, while ensuring employee satisfaction and long-term sustainability. By introducing this structured approach, our study advances existing research by providing a practical and adaptable framework that has not been previously explored in AI-driven HRM strategies. This novel contribution ensures that organisations can systematically integrate AI into HRM while preserving employee engagement and well-being. In this way, it aligns with the strategic agenda of Industry 5.0, placing HRM at the centre of inclusive and sustainable industrial innovation [4,27]. This strategic redefinition responds to the immediate needs of organisations while aligning with future labour market trends, ensuring that the workforce is prepared for the challenges and opportunities presented by the next generation of digital technologies. In this regard, reskilling and upskilling strategies that go beyond formal technical qualifications are essential — particularly those fostering

transversal competencies, continuous learning and human-centred system interaction — as key levers for aligning HRM with the principles of Industry 5.0.

The remainder of this paper is structured as follows: [Section 2](#) reviews the relevant literature on AI-driven workforce transformation and HRM strategies. [Section 3](#) introduces our dynamic model, detailing its theoretical foundations and practical implications. [Section 4](#) discusses the application of the model in real-world organisational settings, followed by an analysis of its benefits and challenges. Finally, [Section 5](#) presents the conclusions, limitations, and directions for future research.

2. Equilibrium: the double impact of automation and digitisation on employment

Over the last decade, the implications of automation and digitisation for employment have been the subject of intense debate. Scholars such as Acemoglu and Restrepo [28], Arntz et al. [7] and Mokyr et al. [29] have analysed whether these technological advances could lead to widespread job displacement or, on the contrary, usher in a new era of job creation and increased demand through technology integration. While estimates vary—some point to significant cost savings and possible wage pressures due to robotisation [30], and others suggest that improvements in the quality of products and services could boost demand and employment [29]—the consensus is that technology will transform the workforce.

This ongoing transformation is increasingly framed within the paradigm of Industry 5.0, which emphasises a people-centred approach, sustainability and system resilience as key principles guiding the integration of digital technologies into industrial and organisational processes [4,5]. Discussions of the employment effects of automation and digitisation typically present two perspectives: a pessimistic one, predicting insufficient job creation to offset job losses [6,31], and an optimistic one, supported by historical trends, suggesting that technology will create new opportunities by shifting workers into new roles rather than making them obsolete [29,32,33]. While quantitative studies show several potential job shifts [6,34], the European Commission warns that labour market polarisation could exacerbate wage inequality between high-skilled and low-skilled workers. Despite these concerns, some studies indicate minimal or positive effects of AI on employment, highlighting potential benefits such as reduced wage inequality [35-38] and the emergence of new employment opportunities in digitally transforming sectors [33,39,40].

Despite these contradictory predictions, it is widely recognised that digital transformation is reshaping employment at all levels, including work structures, task expectations, and work-life balance [41-43]. Positive aspects of this transformation include increased productivity, greater attractiveness of work tasks and improved work-life balance through better coordination and knowledge sharing [44,45]. In addition, new skills are in demand in sectors such as manufacturing, providing workers with opportunities to adapt. Furthermore, the use of AI can free people from tasks with low motivational potential [46]. However, digitalisation also brings significant challenges. The shift towards digital skills creates income inequality, as high-skilled jobs offer higher wages, while lower-skilled roles are more susceptible to automation [42], and changes in employment relationships, such as the rise of flexible and temporary contracts, impact job security and benefits [47]. Unpredictable schedules in the gig economy require new health and safety measures, and the shift to low-paid work affects financial stability and mental health ([48,49]; Palumbo et al., 2023). As digitalisation continues to reshape the employment landscape, concerns are growing about the erosion of social rights and global operational challenges [50]. Decentralisation and outsourcing complicate labour law enforcement and reduce the influence of trade unions, increasing unemployment risks. In addition, issues such as job security and skills shortages highlight the risks of digital transformations in industrial relations [51,52].

A critical review of this body of research highlights that while discussions on automation and digitisation are often presented from a macroeconomic perspective, it is crucial to understand how these developments also impact at the individual firm level. In this context, the role of HRM professionals is essential, as they oversee managing these transformations within organisations. They must maximise the opportunities and mitigate the associated risks, facilitating an environment in which the business can not only survive, but also thrive in an era defined by digital transformation.

AI can play a pivotal role in several critical aspects of HRM, such as identifying and training new skills, improving job satisfaction and work-life balance, and implementing work structures that promote greater autonomy and flexibility. This approach prepares organisations to adapt to current changes, equipping them to lead innovation and operational efficiency. However, research has largely overlooked the role of HRM professionals as key agents in AI-driven workforce transformation. This study directly addresses that gap by placing HRM at the centre of AI-enabled workforce adaptation, highlighting its strategic role in shaping not only the redesign of work, but also the employee experience and organisational resilience. Unlike previous research that focused mainly on macroeconomic effects or isolated functions of HRM, this paper presents a structured model that establishes these professionals as a key factor for the integration of AI, bridging the gap between strategic decision-making and employee engagement. By adopting an integrative approach, this study advances the discourse on AI in HRM, offering a clear roadmap for organisations to align technological efficiency with workforce empowerment and the sustainable development of human capital.

3. Strategic human resource management in the AI era: enabling growth and navigating challenges

The above discussion on the employment impact of AI incorporation reveals that it is mainly a quantitative forecast that needs to be systematically adjusted in the face of rapid technological progress. However, a common denominator of these debates is the recognition of the potential of AI to transform employment [53,54]. While it is clear that AI can replace elementary tasks, it is also crucial to develop specific skills in areas where human intelligence remains irreplaceable. Moreover, the integration and development of AI-related technologies pose a double challenge for people management in organisations: the need to incorporate specialised staff in AI technologies, as well as to update existing workforce competencies for digitally enhanced environments [10,55].

Studies on the impact of innovative technologies on the labour market highlight that automation can enhance workers' skills [31], since AI eliminates routine tasks and encourages the development of skills for complex jobs that cannot be automated. The increasing deployment of AI also requires new skills and knowledge, such as the ability to work with data and algorithms and adapt to modern technologies, including proficiency in programming languages such as Python, SQL, and JAVA [12,56]. Huang et al. [53] also point out that AI and automation are increasing the importance of social and emotional skills, such as communication, teamwork, and empathy, which are more difficult to automate than technical skills. Arntz et al. (2016) add that AI and automation mainly affect routine and predictable tasks, while tasks requiring prominent levels of creativity, social intelligence and physical dexterity are less likely to be automated, underlining the need to value these skills in the future workforce.

This transformation aligns with the evolution of industrial systems towards Industry 5.0, where human-centricity, adaptability, and seamless human-machine integration define the next phase of technological and organisational development [5,13]. The adoption of AI and automation is therefore shaping a shift in the skills and capabilities needed in the workforce, with an increasing focus on non-routine tasks and the development of new technical skills and soft skills. It is essential to recognise that the impact of each technology varies by occupation,

which may lead to improved performance with AI support or place workers in direct competition with these technologies. It is also crucial to consider how jobs evolve with technological development [32,57], which calls for a continuous review of job competencies to identify the skills essential for effective AI adoption and maximise its benefits. This includes AI literacy training to understand its capabilities and limitations [58,59], technical skills to handle AI-based decision support tools (Choudhury et al., 2022; [59]) and general cross-training that prepares all employees for digital transformation, minimising resistance, and barriers to technology implementation [60].

This broad debate elucidates the transformative potential of AI in reshaping employment and highlights the challenges and opportunities it introduces to the workplace. AI applications in HRM cover multiple functions, each of which contributes to improving efficiency and employee engagement. In recruitment, AI automates resume screening and improves interview processes through AI-based assessments. In talent management, predictive analytics enable personalised career development and training recommendations. AI-powered feedback mechanisms and sentiment analysis can improve employee engagement and workplace well-being, while algorithmic decision-making in performance evaluation facilitates more objective assessments. In addition, AI-driven compensation systems ensure fairer salary structures by analysing internal and market data. These advances allow human resources management to adopt a data-based approach while maintaining a people-centred organisational culture.

As AI redefines the employment landscape by automating routine tasks and accentuating the need for sophisticated technical and soft skills, HRM professionals are central to navigating these changes. They are tasked with the dual tasks of promoting employee empowerment and addressing the complexities introduced by technological advancement, ensuring that the workforce is not only prepared but also thrives in this unique environment, as well as mitigating resistance to technological change and the potential ramifications of work automation [10]. Despite the challenges, AI offers significant organisational benefits [55,59], so the imperative for firms to embrace AI is clear, as failure to do so could negatively affect competitiveness and long-term viability [61,62]. However, organisations also need to be aware of the potential adverse effects on their workforce, including technostress, especially among less tech-savvy employees [63]. In short, HRM professionals are at a crossroads, tasked with redesigning workplaces to harness the potential of AI while addressing employee concerns about psychological well-being, motivation, and performance [1,10]. There is compelling evidence to support the creation of enriched job roles that offer diversity, autonomy, and development opportunities, resulting in higher employee satisfaction [64]. AI contributes significantly to this process by personalising job roles, reducing absenteeism and decreasing turnover [60].

In conclusion, the successful integration of AI into organisations, making it a catalyst for growth rather than a risk, depends critically on strategic HRM. Key challenges identified include the need to continuously upgrade workers' skills and competencies to manage and adapt to modern technologies; mitigate adverse effects such as technostress and reduced employee autonomy; and redesign job roles to be more enriching and aligned with both human and technological capabilities. The role of HRM is critical in this process for several reasons. First, HRM professionals are in a unique position to identify skills gaps and develop training programmes that not only equip employees with technical skills, but also reinforce social and emotional skills, which are less susceptible to automation. Second, HRM can lead the creation of enriched work roles that integrate technology appropriately to improve employee satisfaction and performance, which is essential for talent retention and organisational innovation. In addition, HRM plays a crucial role in implementing strategies to ensure that AI adoption is perceived as an improvement rather than a threat by fostering an organisational culture that values both technological innovation and human development. This includes involving employees in the design and implementation of technology solutions, ensuring transparency and fairness in the use of

AI, and actively managing change to alleviate fears and resistance. Finally, by elevating HRM's role in organisational strategy, companies can ensure that the use of AI contributes optimally to business goals without sacrificing employee well-being. In short, effective, and initiative-taking HRM is indispensable to navigate the challenges of the digital age and transform AI into a true catalyst for growth rather than a vector of disruption.

4. The role of human resources management in managing artificial intelligence integration and employee engagements

As we have outlined, in today's business environment, organisations are faced with the pressing need to adapt to digitised environments to remain competitive. Failure to adapt threatens operational efficiency and adaptability, compromising long-term sustainability in a fiercely competitive market [61,62]. The adoption of AI in business processes offers benefits such as automation of complex tasks to increase efficiency, real-time analytics for accurate decision-making, and personalisation of offerings to improve customer satisfaction [55,59]. In complex industrial environments, these transformations are increasingly integrated into integrated information architectures, where AI-based HRM systems must interact seamlessly with broader organisational data ecosystems, including production, logistics, and performance management systems [3,5]. In this sense, aligning AI-based HRM systems with the principles of Industry 5.0 requires a dual focus: enhancing operational efficiency while ensuring that technological systems remain adaptable, inclusive, and supportive of human capabilities.

However, this transformation also generates considerable challenges, such as employee resistance, insecurity, and diminished motivation, especially among those less familiar with innovative technologies [1,10,63].

In this context, HR professionals must not only function as managers of employee retraining, but also as key mediators to manage resistance to technological change and, at the same time, address the potential impact on their psychological well-being, motivation, and performance [1,10]. Algorithmic Human Resource Management (AHRM) emerges as a strategic tool in this transformation process. AHRM uses algorithms and Large Language Models (LLMs) to enhance traditional HR functions such as goal setting, tracking, and compensation management. It also supports personalised training and recruitment strategies, as well as AI-based decision-making through workforce analytics [22,65,66]. In addition, AHRM plays a crucial role in personalising continuous training and employee development, tailoring processes to individual needs and fostering digital competencies [67].

AHRM contributes to the development of more efficient job designs by automating repetitive tasks and enabling personalised work experiences, which together increase motivation, job satisfaction and reduce absenteeism and turnover [60]. In addition, by analysing data on tasks and responsibilities, AI can identify job characteristics that drive motivation and engagement. It can also streamline recruitment processes by refining resume screening and reducing bias [68]. In the area of compensation and benefits management, it facilitates the tailoring of compensation packages [69]. It also improves performance management by dissecting heterogeneous data and complementary metrics, facilitating goal setting and monitoring employee progress [65,66].

The advantages of AHRM need to be weighed against the disadvantages that may limit its effectiveness. Employee autonomy may be compromised by algorithms that dictate task selection based on external metrics such as customer satisfaction, which may reduce their freedom of choice [70,71]. In addition, AI may increase job complexity and require new skills, intensifying information processing demands that may overwhelm employees [72]. Increased performance standards can lead to a perception of increased workload and stress. Constant supervision may also cause employees to focus on specific tasks, neglecting less supervised tasks and decreasing task variety [73,74].

Therefore, the integration of AHRM into HR functions has the

potential to both enhance and hinder work design and business productivity, depending on how the technology is managed and employees are engaged. Workers may resist change by rejecting it outright or, more subtly, through acts of disobedience. Resistance tends to be strongest when employees perceive that the introduction of AI threatens their autonomy, job security or working conditions, leading to perceptions of unfairness [24]. Ghislieri et al. [2] highlight the importance of early and active employee involvement in the design and implementation of digital technologies to minimise these risks. In this task, HRM must also take an initiative-taking and collaborative approach to managing workplace and organisational change.

Previous research highlights that to minimise risks and maximise synergies, AI and HRM implementation must be transparent, equitable and involve active employee participation [21]. Transparency, defined as the degree of justification for the implementation of algorithms and how they work [75], is crucial for employee understanding and acceptance of these systems [76]. This includes clarifying monitoring and control systems to avoid negative impacts [77] and ensuring that employees understand the performance criteria, which facilitates valuable feedback and increases the clarity of their roles. In terms of fairness, it is vital to minimise bias and discrimination in algorithm programming, ensure fair decisions and protect data privacy [60,68]. Monitoring systems must be perceived by employees as adequate, which improves their acceptance and reduces resistance to these systems [78]. Involving employees in the adaptation of these systems can help to prevent them from feeling like mere data subjects and increase the perceived importance of their tasks [79]. Furthermore, minimising the number of aspects monitored by AI can increase the perceived complexity and importance of the task [76].

It is also essential that employees have mechanisms for influence and control over AI systems. Allowing them to review collected data and reject tasks without penalty can improve their acceptance and job satisfaction [70,77]. Introducing the role of 'algorithmic auditor' empowers workers to contest biased outcomes, enhancing fairness [75]. Furthermore, giving employees the option to temporarily disengage from the system and prioritise their judgement can be beneficial [80,81]. It is crucial that employees participate in the development of the system, providing their data and insights to better inform the algorithms [80,82]. This collaborative and transparent approach is essential to ensure that the integration of AI into HRM is fair and effective.

Beyond these considerations, the rise of large language models (LLMs), such as ChatGPT, introduces both significant opportunities and critical challenges for HR management. LLM can improve HR functions by automating recruitment processes (reducing time and costs), generating personalised development plans for employees tailored to individual skills and training needs, and assisting in workforce analysis. However, its applicability also raises concerns regarding potential biases, ethical transparency and an overreliance on AI-driven decision-making. Because LLM are trained on large-scale data sets, their results depend heavily on the quality and integrity of the underlying data. If datasets are biased or incomplete, AI-based hiring, promotions and performance evaluations risk being suboptimal and inequitable. To mitigate these risks, HR professionals must ensure that AI-based HR strategies incorporate algorithmic auditing, ongoing validation and human oversight. Therefore, although LLMs can significantly improve HR efficiency, the strategic role of HR professionals remains indispensable to ensure fairness, accountability and ethical governance in AI-based HR management.

5. Integrating artificial intelligence and human resources management: A dynamic model for digital transformation

In the changing landscape of digital transformation, organisations face the dual challenge of harnessing advanced technologies such as AI while ensuring the engagement and adaptability of their workforce. Our discussion has highlighted the profound impact of digitalisation on

employment dynamics, highlighting both the opportunities for enhancing job roles and the potential pitfalls, such as increased job complexity and the risk of technostress. The role of HRM is critical in navigating these changes, not only adapting to them, but actively leading the transformation. HRM professionals face a complex task: redesigning workplaces to adapt to technological advances, while fostering an organisational culture that values both human and technological capabilities. To address these challenges, we propose a dynamic model that integrates AHRM with traditional HR practices to optimise the digital transformation process. As illustrated in Fig. 1, our model emphasises the cyclical interaction between ‘hard’ management tactics, such as strategic job design, and ‘soft’ management elements, which include fostering transparency, participation, and fairness in the workplace. Our model proposes a dynamic two-tiered approach to integrating AI into human resources management, combining algorithmic optimisation of basic functions with strategies that guarantee employee engagement and cultural adaptation. This two-tier logic reflects the growing demand in industrial settings for integrated systems that can align algorithmic processes with human capital strategies, ensuring interoperability between AI-based management tools and broader organisational information systems [3,5].

Hard level: empowering management with AI. This layer focuses on improving the efficiency of human resources management through process automation and data-driven decision making. AI optimises key functions such as recruitment, training, performance evaluation and compensation, enabling HR professionals to move from administrative functions to strategic workforce planning. In manufacturing industries undergoing digital transformation, this automation plays a key role in harmonising HR operations with production systems and the supply chain, contributing to seamless data integration and operational responsiveness [4]. It also favours personalisation and fairness in development and remuneration, while improving objectivity by reducing human bias. In addition, predictive analytics enables HR managers to anticipate workforce trends, address retention risks and make more accurate and timely decisions.

Soft level: driving commitment and change management. The soft dimension supports the human side of digital transformation through participatory and trust-based strategies. These include structured training in digital skills, transparent communication and employee feedback mechanisms on AI-driven processes. Pilot programmes and iterative adjustments help align AI implementation with employee expectations, promoting acceptance and collaboration.

Feedback loop and continuous improvement. A central feature of our

model is the positive feedback loop it generates. As employees interact with and benefit from AI-enhanced processes, their confidence, skills and willingness to engage with these systems increase. This virtuous cycle reinforces both the technical and cultural dimensions of AI integration, ensuring continuous adaptation and strategic alignment over time.

By combining these interdependent levels, the model offers a comprehensive roadmap for the sustainable and ethical adoption of AI in human resources management.

These transformations fall into two distinct categories, each of which makes a unique contribution. The first category involves continuously updating knowledge about future HR technology trends, human-robot collaboration, and emerging work paradigms. This includes the deployment of digital technologies that are central to organisational transformation, particularly within core HR functions such as training, recruitment, rewards, and talent management. The second category focuses on redefining HR leadership, equipping professionals with the strategic skills necessary to integrate AI seamlessly into workforce management and decision-making. The integration of these two categories results in improved job roles that are readily accepted by job holders, not only increasing their satisfaction and motivation, but also deepening their commitment to the organisation, as they see their active role in management and decision-making.

The relationship model outlined acts as a foundational phase to drive the transformation process (Transformation Loop 1). The benefits derived from leveraging digital transitions subsequently drive the adoption of innovative algorithmic HRM processes, synchronised with technological advances. The continuous and deeper integration of these interpersonal changes facilitates new job redesigns, unlocking additional potential benefits. In this way, the transformation process is cyclically restarted at a more advanced stage (Disruption Loop 2). This method promotes a revolutionary approach to people management, tailored to and in support of the individuals in the organisation, thus accelerating the company’s digitalisation efforts and securing a competitive advantage.

Accordingly, we propose a model of interaction between AI integration and people-centred development, aimed at identifying the essential factors for an end-to-end digital transformation. This model is depicted in Fig. 2, which encapsulates this transition model.

The scenarios described in Fig. 2 effectively illustrate the potential paths and their implications in transformation management:

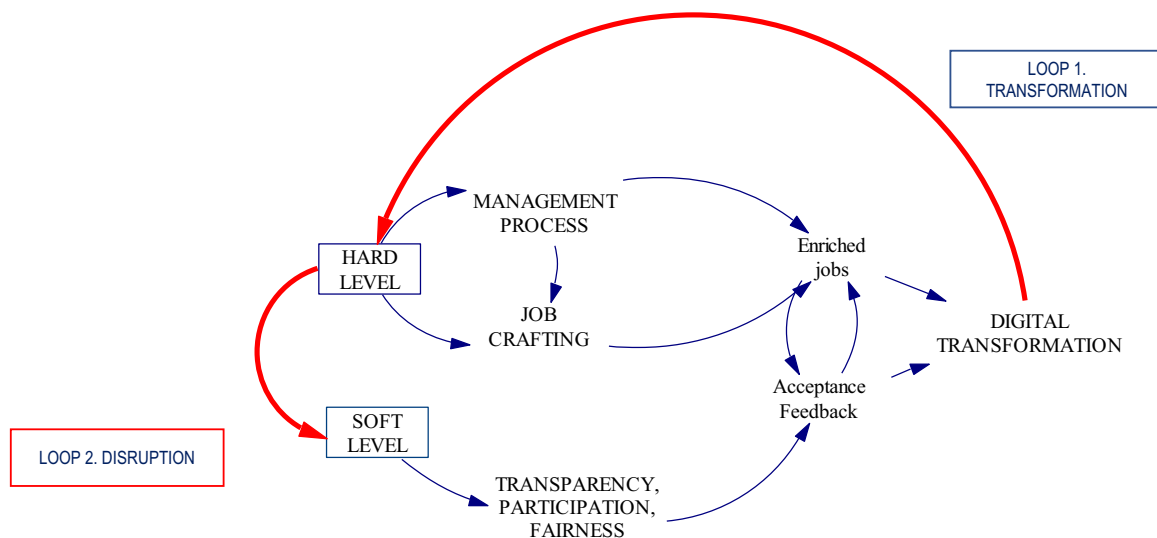


Fig. 1. A synergistic HRM model: integrating AI for enhanced organizational dynamics. Source: own elaboration

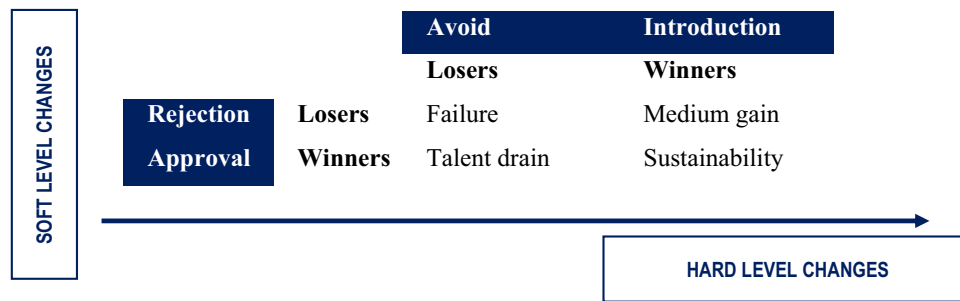


Fig. 2. Transition model.
Source: own elaboration

- **Avoiding technological changes:** Organisations that choose to avoid embracing technological change risk losing their competitive advantage as competitors advance through AI deployment. In this scenario, managing employee attitudes may seem less critical, but the organisation could face long-term survival challenges (Failure).
- **Positive employee attitudes:** Conversely, if employees view the incorporation of AI positively, they are more likely to proactively enhance their technological skills and explore new job opportunities that utilise these advancements. However, this enthusiasm could lead to talent attrition, potentially diminishing the company’s competitiveness and long-term viability (Talent drain).
- **Technological implementation without HR Strategy:** Initiating technological change without a comprehensive HR strategy to ensure employee buy-in may produce some immediate improvements. However, this approach is likely to fail to realise the full potential benefits due to employee resistance. Ignoring change management in the workforce can lead to increased perceptions of loss of autonomy, distrust, increased workloads and technostress, undermining employee satisfaction, motivation, and performance (Medium gain).
- **Coordinated AI implementation with HR Strategy:** The most effective approach is to synchronise the implementation of AI with a sound HR strategy. This ensures that employees take full advantage of and embrace the technological benefits. The focus is then on designing and developing enriched roles that improve job satisfaction and performance, leading to sustainable success (Sustainability). This integration is particularly valuable in cyber-physical and hybrid systems, where aligning technological adoption with human adaptation is essential for maintaining industrial agility and performance continuity (Brunzuni et al., 2023; [13]).

This synthesis underscores the existence of a single win-win position where companies thrive in the digital transformation process. It relies on two key pillars: reinforcing the strategic role of HR within organisations and recognizing employees as crucial strategic assets even in the era of Industry 4.0. By effectively and sustainably managing digital transformation, these critical stakeholders jointly contribute to the organisation’s success.

Although this model is conceptual in nature, its structure allows for practical validation and adaptation in diverse organisational contexts. The framework provides a well-defined strategy for integrating AI into HRM through a balance between algorithmic efficiency and human-centred management, making it suitable for empirical testing. The practical application of this model is expected to produce significant improvements in HRM practices. Thus, it is expected that organisations that implement this structured approach can improve workforce adaptability through AI-driven reskilling programmes, leading to increased employee satisfaction and engagement. In addition, the model promotes talent retention and reduces staff turnover by aligning AI with personalised career development opportunities. By integrating AI into HR decision-making processes, companies can improve the accuracy of

performance evaluation, reduce bias, and foster a more resilient workforce. These advantages position HR management as a strategic enabler of AI-driven transformation within integrated organisational systems, reinforcing its role in both the human and technical subsystems of digital industrial ecosystems.

6. Implications, limitations, and future research

This article presents important theoretical and practical contributions, while acknowledging certain limitations. Theoretically, it introduces a dynamic model for integrating AI into human resource management, emphasising the interaction between the introduction of AI and people-centred development. This model innovates by providing a structured framework that highlights the dual influence of AI on both human capital enhancement and job role transformation, adding depth to the existing discourse on digital transformation in the workplace. It also expands theoretical understanding of how technology reshapes job characteristics and work experiences, offering nuanced insights into the current debate on the dual impact of digitisation and automation on employment.

Beyond these contributions, the proposed framework is designed to generate measurable improvements in HRM practices. By applying this approach, organisations can enhance workforce adaptability through structured AI-based retraining programmes, leading to higher job satisfaction and engagement by integrating AI in a way that empowers employees rather than merely automating tasks. Furthermore, the model promotes talent retention and reduces staff turnover by aligning AI with both personalised career development pathways and financial and non-financial incentives. Additionally, HR decision-making is optimised through more accurate performance evaluations and equitable compensation structures. Finally, this approach fosters a more resilient workforce by mitigating technostress and ensuring that AI adoption aligns with employee skill sets and organisational culture, ultimately reinforcing HRM’s role as a strategic enabler in AI-driven transformations. In data-intensive industrial settings, this role goes beyond administrative efficiency to include strategic integration with digital infrastructures such as enterprise resource planning (ERP), cyber-physical systems (CPS) and real-time performance monitoring platforms, positioning HRM as a link between human capital and industrial information systems.

In addition to these AI-driven advances, the rise of large LLMs, presents new opportunities for HRM. LLMs can improve HR functions by automating recruitment processes, assisting with performance evaluations, and supporting employee development through AI-based personalised learning tools. They can also improve HR decision-making by analysing staff sentiment and predicting attrition risks. However, their implementation also poses significant challenges, such as bias in language models, ethical concerns regarding data privacy, and the need for human oversight to prevent AI-driven decision-making from undermining fairness and transparency. To fully leverage the benefits of LLMs in HRM while mitigating these risks, organisations must develop

governance frameworks that ensure transparency, fairness, and compliance with ethical and legal standards.

While this model is conceptual, it provides a structured basis that can be empirically evaluated in different organisational contexts. Future research could focus on validating its effectiveness in improving workforce adaptability, job satisfaction and decision-making efficiency, ensuring that AI integration strategies are aligned with both business objectives and employee well-being. In practice, this paper serves as a guide for HR professionals to adapt to AI and leverage it effectively in their organisations. It outlines detailed strategies for leading the transformation to a digitally competent workforce, while ensuring that employee well-being and motivation remain a priority. In particular, it provides practical information on the skills and competencies needed for an AI-enhanced work environment, including specific AI skills training, experience enhancement and critical cross-training. In addition, it explores the implementation of AM in HR, offering strategies to address the challenges it presents, such as potential loss of autonomy and resistance to change. Future research should focus on assessing the model empirically, evaluating its effectiveness in improving workforce adaptability, job satisfaction, and HR decision-making efficiency across various industries. As an initial step towards empirical validation, pilot studies in selected organisations could provide valuable insights into the practical challenges and benefits of implementing the model. These studies would allow HR professionals to experiment with AI-based HRM strategies on a smaller scale, measuring their impact on employee engagement, performance evaluation and organisational decision-making. The results of these pilot implementations could serve as the basis for larger-scale empirical research, ensuring that the adoption of AI is aligned with the needs of the workforce and the objectives of the organisation, while mitigating potential risks. Based on this conceptual foundation, future research could also consider the feasibility of applying the proposed model in real-world settings through exploratory pilot studies. These applications, even on a limited scale, could provide valuable insights into the practical usefulness of the model, its adaptability to specific organisational contexts and its potential for refinement. By combining theoretical coherence with applied evidence, the model can serve both as a framework for research and as a practical tool for human resources professionals facing AI-driven transformation.

Compared to traditional HRM frameworks, which focus primarily on static workforce planning and human-driven decision-making, our model introduces a dynamic, AI-enhanced approach that continuously adapts to technological advances and human capital needs. Unlike algorithmic HR management models that prioritise automation and efficiency, this framework ensures a balanced integration of AI-based decision-making with people-centred workforce engagement. The model is specifically designed to address contemporary HR challenges, including the need for agile workforce reorientation, retention of digitally skilled talent and strengthening employee engagement in AI-driven environments. Through structured feedback loops and change management strategies, it enables organisations not only to implement AI tools, but to do so in a way that aligns with their human development objectives and ethical commitments. This integrative dual-layer model stands out for offering a strategic, ethically grounded and operationally viable roadmap for digital transformation, an approach that, to our knowledge, is not offered by existing conceptual frameworks for human resources management. It positions HR managers not as passive implementers but as active architects of AI-enabled workforce transformation.

However, the article has limitations. The applicability of its ideas and models may not be universally extensive to all industries and organisation sizes. Moreover, due to the rapid pace of technological advances, some debates may quickly become obsolete. Although this paper provides a comprehensive theoretical framework, it would benefit from empirical studies to support its claims, particularly regarding the long-term impact of integrating AI into HRM on employee motivation, job satisfaction and organisational performance.

Consequently, future research should focus on empirically validating

the proposed model in different organisational contexts and industries. It would also be advisable to explore how organisations can adapt AI-driven HRM strategies as the technology evolves. In addition, studying the long-term effects of integrating AI on job satisfaction, performance and team dynamics would provide deeper insight into how AI can be used more effectively in HRM. Such research would not only mitigate the current limitations of the article but also contribute to the broader field of AI in HRM.

Additionally, certain validity challenges should be considered. As a conceptual model, its effectiveness will depend on contextual factors such as industry-specific AI adoption rates, organisational culture, and regulatory frameworks. Furthermore, the use of AM in HRM presents inherent risks, particularly regarding biases in AI-driven decision-making. If AI systems are based on historical data that reflects past inequalities, they can unintentionally reinforce discrimination in hiring, promotion, and remuneration structures. Future empirical validation should assess the adaptability of the model in diverse work environments and develop mechanisms to mitigate biases, ensuring fair and inclusive AI-driven HRM strategies.

Furthermore, ethical concerns must be considered when implementing AI in HRM. Issues such as surveillance of employees, loss of autonomy and data privacy can generate resistance and negatively affect staff morale. Transparency in AI-based decision-making and the inclusion of employees in AI governance processes are essential to maintain trust and acceptance. Furthermore, managers and HR professionals should receive training not only in the adoption of AI, but also in its ethical and social implications, ensuring that AI supports human decision-making rather than replacing it.

Finally, although our model emphasises the balance between AI-driven efficiency and human-centred HRM strategies, its successful implementation will depend on the readiness of the organisation, the commitment of leadership and the acceptance of employees. Future research should examine the barriers to the adoption of AI in HRM and explore strategies to foster a culture of digital trust and responsible integration of AI.

Beyond technical feasibility and strategic alignment, the successful integration of AI into human resource management also requires a firm ethical foundation. Our model explicitly incorporates this dimension by advocating for fairness, transparency and employee empowerment in algorithmic decision-making processes. Instead of treating ethical issues as external constraints, we position them as essential design principles that determine how AI technologies should be adopted, supervised and governed. In this way, the model promotes not only operational efficiency and employee engagement, but also organisational legitimacy and long-term sustainability in the digital age.

Despite these challenges, the structured nature of the proposed model offers a solid foundation for addressing such limitations through iterative development and contextual adaptation. By systematically combining theoretical knowledge with future empirical evidence and ethical safeguards, the model has the potential to become a practical guide for human resource management professionals managing AI-driven transitions in diverse organisational settings.

7. Conclusion

The rise of Industry 4.0 and AI has generated intense debate about the future of employment, from concerns about job losses to the emergence of new opportunities in both established and emerging industries. Although it is unlikely that AI will replace human intelligence at the rate predicted by the most pessimistic forecasts, its integration is already transforming organisational structures, workforce dynamics and the skills required.

This transformation presents both opportunities and challenges. AI improves efficiency, decision-making and cost reduction, but it also demands a rapid adaptation of the workforce and a structured approach to organisational change management. The real challenge is not only to

identify what needs to be done, but to ensure that human resources management leads this transition to align human and technological capabilities in a balanced and sustainable way.

HR managers cannot afford to be passive observers in this process. Instead of merely adapting to technological changes, they must take on an active strategic role in shaping the future of work. AI should not be implemented in isolation; it should be integrated into HR management in a way that strengthens business competitiveness while protecting the well-being of employees. To achieve this, a structured and proactive approach is needed that balances automation with human empowerment, ensuring that AI-driven transformation fosters innovation rather than diminishing job quality. The goal is clear: AI should not be a tool for disruption, but a catalyst for an equitable, efficient and human-centred HR management framework that aligns technological advancement with workforce sustainability.

This article contributes to this debate by offering a structured framework that enables HR management to effectively drive the integration of AI. Unlike previous research that examines isolated aspects of AI in HR management, the proposed model offers a comprehensive two-tier strategy that balances efficiency with employee engagement. By adopting this approach, organisations can turn AI from a disruptive force into a strategic enabler of sustainable workforce development.

HRM professionals are not just witnesses, but key architects of the AI-driven workplace. The decisions made today will define the future of work, determining whether AI becomes a force for human progress or a mechanism of displacement. Success lies in understanding what needs to change, but also in leading this change decisively. The future of HRM will not be determined solely by AI, but by those who actively integrate AI into a vision of work that is both innovative and human-centred.

Ethical rules

The manuscript has not been published previously and is not

Appendix. Methodological roadmap for empirical validation

This appendix describes a practical framework for empirically validating the conceptual model proposed in this article. It is intended as a complementary tool for future research and implementation in organisations. Its inclusion responds to the need to provide an empirical basis without compromising the theoretical nature and structural balance of the manuscript.

Research design and strategy

A mixed-methods design is recommended to evaluate both the organisational outcomes of AI integration in human resource management and the employee experience associated with the two-level structure of the model (algorithmic and people-centred).

- Quantitative component: to test the relationship between AI integration, performance indicators and workforce adaptability.
- Qualitative component: to explore employee perceptions, organisational dynamics and barriers to implementation.

This combination allows for triangulation and a more comprehensive validation of the model’s assumptions.

Context and scope

The model is particularly suitable for organisations undergoing digital transformation, especially in sectors such as:

- Manufacturing and logistics: where integration with industrial information systems (e.g., Cyber Physical Systems (CPS); Enterprise Resource Planning (ERP)) is already well advanced.
- Technology-intensive services: where algorithmic decision-making and remote/hybrid work dynamics are common.

A pilot implementation in one or two organisations of this type, possibly through action research or an integrated case study, would provide solid initial evidence.

Key constructs and proposed variables

Model level	Construct	Example variables / Indicators
Hard level (Algorithmic HRM)	AI-based HR efficiency	Time to hire, training Return of Investment (ROI), automation coverage
	Decision support quality	Perceived fairness, accuracy, transparency of AI tools
	Data-driven strategic planning	Predictive HR analytics usage, retention forecasts
Soft level (Human-centred strategies)	Employee engagement	Utrecht Work Engagement Scales (UWES), Net Promoter Score (eNPS)

(continued on next page)

currently under consideration for publication elsewhere.

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Maria Bastida: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alberto Vaquero García:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Miguel Ángel Vazquez Taín:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marisa Del Río Araujo:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(continued)

Model level	Construct	Example variables / Indicators
	Technostress / overload Perceived AI autonomy Role enrichment	STAI scale, Technostress creators scale Technology Acceptance Model (TAM-3) subscales (perceived ease/usefulness, voluntariness) Task variety, perceived purpose, participation in AI design

Instruments and data sources

- Surveys: standardised scales (e.g. Utrecht Work Engagement Scale (UWES); State-Trait Anxiety Inventory (STAI); Technology Acceptance Models (TAM)).
- HRIS and operational metrics: Key Performance Indicators (KPIs) obtained from company systems (e.g. hiring time, performance indicators).
- Interviews/focus groups: with HR managers, team leaders and employees to understand lived experience and resistance.
- Observation/record analysis: optional for organisations with digital data on work activity.

Sampling strategy

- Organisation level: 1–3 companies undergoing AI transformation.
- Respondents: HR professionals, middle managers and employees (minimum 100 respondents for quantitative analysis; 10–20 for qualitative analysis).
- Timing: before/after implementation (or comparison between units with and without integrated AI).

Analytical techniques

- Quantitative: structural equation modelling (SEM), Partial Least Squares (PLS) or regression to test relationships between constructs.
- Qualitative: thematic analysis of interview transcripts and focus groups; triangulation with quantitative results.

Threats to validity and mitigation

Threat	Mitigation
Algorithmic bias	Cross-validation of results and auditing AI decision outputs
Common method variance	Use of multiple data sources (surveys, system data, interviews)
Organisational resistance	Participatory design and change management documentation
Sample generalisability	Replication across sectors or through comparative case studies

Ethical safeguards in empirical testing

In line with the model’s conceptual emphasis on fairness, transparency, and employee empowerment, any empirical implementation should incorporate safeguards aligned with the responsible use of AI. These include:

- Informed consent protocols when collecting employee data related to engagement, autonomy, or algorithmic oversight.
- Fairness audits of AI-based decision-making support tools used during pilot testing.
- Inclusion of feedback loops that allow participants to question, interpret or contextualise the results generated by AI.
- Monitoring of technological stress indicators (e.g. through STAI or UWES) to identify unwanted cognitive or emotional strain.
- Clear governance mechanisms for data privacy, algorithmic transparency, and communication of evaluation criteria.

These elements should be integrated into the research protocol to ensure that empirical testing is not only methodologically sound but also ethically aligned with the human-centred vision of the model.

Research roadmap and contribution

This empirical roadmap enables researchers and practitioners to:

- Validate the dual structure of the model under real-world conditions.
- Test both technical (efficiency, interoperability) and human (engagement, well-being) outcomes.
- Create a cumulative research programme on the responsible integration of AI and human resource management.

Although this appendix is not intended to be a prescriptive methodology, it offers a replicable and adaptable framework that can serve as a guide for future empirical studies aimed at assessing the feasibility, impact and strategic value of the proposed model.

Data availability

No data was used for the research described in the article.

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