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Integrating artificial intelligence and human resource management: a review and future research agenda

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ABSTRACT

The integration of artificial intelligence (AI) into human resource management (HRM) represents a rapidly evolving area of practice and research. This review aims to identify nascent AI research trends within HRM and capture the value potential of technology. We outline the developmental trajectory of AI in HRM research and discuss the implications of management theories on AI in organizations. Based on co-word network analysis, the study identifies four pathways of published articles related to HRM: AI-enhanced collaboration, AI-driven workplace, AI-enabled business models, and AI-powered innovation. Finally, we highlight promising avenues for future research across four intersecting domains to advance understanding in this intelligence era.

KEYWORDS

Artificial Intelligence (AI); human resource management (HRM); Algorithmic human resource management (AHRM); literature review

Introduction

Artificial intelligence (AI) is widely acknowledged for transforming conventional notions of work, workers, and workplaces (Cascio & Montealegre, 2016). In practice, human resource management (HRM) is dedicated to addressing challenges related to attracting, retaining, and developing talent while fostering business growth (Jackson et al., 2014). Recently, scholars have contributed to the literature through thematic reviews addressing various aspects of HRM and technology. These reviews primarily aim to understand the knowledge foundations of HRM and AI across three critical domains: the impact of different technological categories, such as artificial intelligence, robotics, and advanced technologies, on organizational and employee outcomes (Budhwar et al., 2022; Malik et al., 2023; Pereira et al., 2023; Vrontis et al., 2022); the organizational

resources necessary for developing AI capabilities in HRM (Chowdhury et al., 2023); and the application of AI across HRM functions (Qamar et al., 2021; Stone et al., 2024).

Despite recent research focusing on the transformative impact of technologies on management, the rapid pace of technological innovation has introduced complexities to HR's adaptation efforts concerning artificial intelligence. The lack of technological adaptability within HR may trigger upheaval throughout the entire organization, compromising the benefits of AI and increasing governance costs (Basu et al., 2023). The public adoption of large language models such as ChatGPT has intensified discussions about both the potential and risks of AI (Budhwar et al., 2023; Chowdhury et al., 2024). Within the concept of dueling visions of artificial intelligence, AI is envisioned as a transformative tool that could open a new era of prosperity and, even more provocatively, as a potential form of alien intelligence (Roose, 2023). It would be essential for humanity to exercise extreme caution in deploying AI to prevent it from seizing control and posing an existential threat to our survival.

In light of the AI complexity and diversity, along with the growing imperative for ethical considerations, we consider it valuable to undertake an exploration of the underlying knowledge structures (Andrieux et al., 2024). It is time to reflect, redefine, and rebuild HRM to align with the pace of modernization and contribute to achieving a broader spectrum of strategic goals. The development and effectiveness of AI-based HR tools should not be solely contingent on technological advancements (Pan & Froese, 2023). Instead, the outcomes of AI implementation depend on transforming the people-centric HRM deployment (Charlwood & Guenole, 2022). The capacity of current HR tools and processes must continuously evolve to manage the extensive skill shifts brought about by the advent of AI (Gong et al., 2024). In this context, this review analysis is guided by the research question: *How can the integration of artificial intelligence (AI) elevate human resource management (HRM) research and practice?*

Compared to reinventing the wheel, a birds-eye literature review is beneficial as it provides insights into the future by drawing on previous research and enables HR departments to adapt to potential technological challenges (Kim et al., 2021). Therefore, we undertook a comprehensive bibliometric analysis to systematically map the AI-HRM research landscape (Ribeiro-Navarrete et al., 2024). As a powerful research approach, keyword co-occurrence networks allow researchers to identify specific knowledge structures and topics within the universe of knowledge while also aiding in uncovering emerging research trends and domains (Adriaanse & Rensleigh, 2013; Donthu et al., 2021).

We connected key search terms using two sets of keywords: HRM-related words and AI-related technologies. Guided by the logical sequence outlined by Zupic and Čater (2015), we conducted a bibliometric analysis in four steps (see the analytical details in Appendix A): (1) We retrieved articles from the Web of Science (WOS) covering the period from 1956 (the year from which the Social Sciences Citation Index was first introduced) to 2024 (Mongeon & Paul-Hus, 2016). The articles were selected using two identified categories of keywords: HRM-related terms and AI-related technologies. To ensure the relevance of our sample, we reviewed the abstracts of all articles and excluded articles that focused exclusively on the optimization of algorithmic models or the refinement of AI techniques. In total, 406 articles were included in the analysis; (2) we summarized the most influential articles (Appendix B), traced the knowledge trajectory, and mapped the theoretical development of AI in research; (3) we performed a keyword co-occurrence analysis on articles. Using the VOS (Visualization of Similarities) methodology, we then derived four distinct research clusters, each defined by a set of closely interconnected terms; (4) finally, we proposed future research directions based on the intersectional topics found within these clusters.

The study makes three contributions. First, this review offers a structured and dynamic overview of the HRM research domain and establishes new trajectories for future inquiry across various delineated AI subfields (Grote et al., 2024; Raisch & Fomina, 2024). Second, we systematically examined the application of existing theories in research to uncover opportunities for advancing theoretical development (Pan & Froese, 2023). Third, compared to other literature review methodologies, bibliometric analysis demonstrates distinct methodological strengths by significantly reducing biases in the processes of literature retrieval and synthesis (van Eck & Waltman, 2010; Zupic & Čater, 2015).

The evolving process of AI & HRM research

Through the analysis, this review gained a comprehensive overview of the AI-HRM literature. Figure 1 illustrates the publication trend of research in AI and HRM. We further examined the publication volume in several top-tier journals. Based on the key milestones, we propose that the field has undergone three primary developmental stages: pre-development and information introduction, volatile climb and data transformation, thriving growth and intelligent advancement. Figure 2 illustrates the timeline of knowledge development.

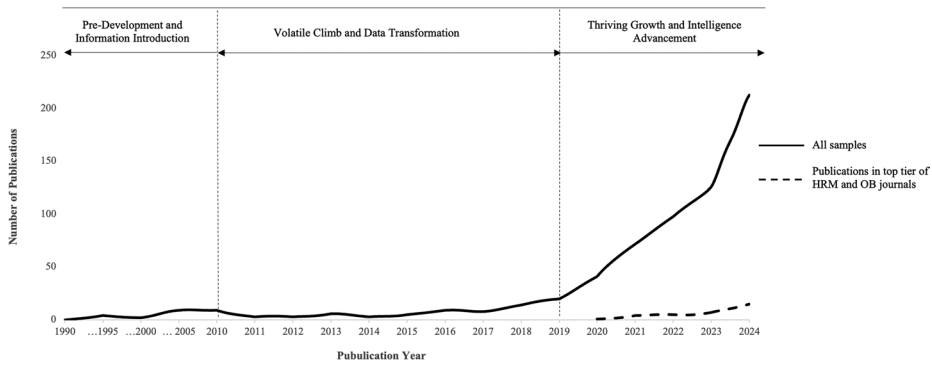


Figure 1. The development trend of AI research in HRM. *Note:* Due to the word limit, we only provide the complete reference information for the papers we cited in the text; the remaining ones are available upon request. Top tier journals: Human Resource Management Journal (UK); British Journal of Industrial Relations; Human Resource Management (USA); Industrial Relations; Work, Employment and Society; Organization Science; Human Relations; Leadership Quarterly; Organization Studies; Organizational Research Methods.

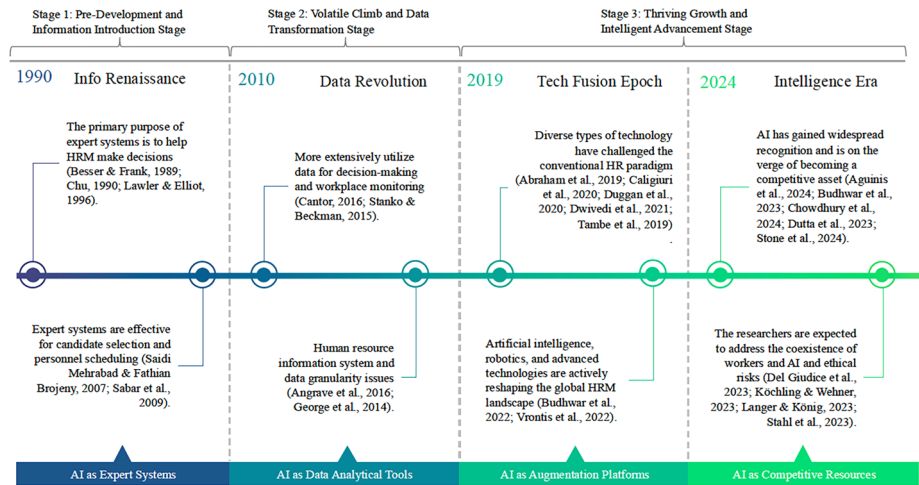


Figure 2. Evolution of knowledge developments in the field of AI & HRM. *Note:* Due to the word limit, we only provide the complete reference for the papers we cited in the text. The remaining ones are available upon request.

Pre-development and information introduction stage (1990s to 2010)

The first stage, from 1990 to 2010, marked the onset of early research endeavors that introduced AI technology into management. This stage marks the end of the AI winter and the onset of a period of significant harvest (Haenlein & Kaplan, 2019). Scholars began to conceptualize AI as an information-rich expert system (Gupta, 2000; Yoon & Guimaraes, 1995). IBM's Deep Blue chess program is a prominent example of an expert system, notably defeating the world human champion in 1997, symbolizing a significant milestone in the development of AI. In HRM,

the primary objective of these expert systems was to assist HRM in making more precise and efficient decisions (Besser & Frank, 1989; Lawler & Elliot, 1996). Furthermore, well-developed systems could effectively support HRM in talent selection, job scheduling, and other decision-making processes (Saidi Mehrabad & Fathian Brojeny, 2007).

Volatile climb and data transformation stage (2010–2019)

The second phase can be described as the period from 2010 to 2018. The breakthrough of artificial general intelligence has ushered in an era where widely adopted AI technologies, including virtual assistants and search engines, have become integral tools accessible to the masses (Russell, 2021; Siau & Wang, 2019). A key driving force in this stage was the rise of data analysis and big data, leading organizations to utilize data more extensively for decision-making. Additionally, a new direction began to develop during this phase, with data collection and analysis techniques increasingly used to monitor worker behavior in various workplaces (Curchod et al., 2020; Stanko & Beckman, 2015). Drawing upon this dataset, the scholarly field of HR analytics gained prominence as a highly influential discipline. As Angrave et al. (2016) stated, HRM is encountering the challenges posed by big data. The research in this field's emphasis transitioned from the quantity of accessible data to the data's quality, that is, the capacity to supply resources for in-depth analysis that effectively anticipates behaviors (Angrave et al., 2016; George et al., 2014).

Thriving growth and intelligent advancement stage (2019 to present)

Since 2019, AI has transitioned into the popularization phase, with increased accessibility and widespread applications across a broader range of work. The substantial surge in remote work prompted by the global pandemic served as a driving force that ignited scholarly interest in investigating how technology is reshaping the landscape of contemporary remote workplaces (Caligiuri et al., 2020; Newlands, 2021). Some extensively cited studies are Tambe et al. (2019) for delineating the specific challenges posed to HR by different stages within the AI lifecycle, Faraj et al. (2018) for providing how algorithms reshape the organizational knowledge system, Kellogg et al. (2020) and for restricting the domains and orientations of algorithmic control over workers. In summary, during this period, AI technology began to be extensively employed across diverse domains of HR, hence characterizing it as the era of technology fusion epoch.

Entering the intelligence era, AI is akin to an intelligent companion seamlessly integrating into human life (De Vaujany et al., 2021). Advanced generative AI tools like ChatGPT not only unlock new possibilities for

HR but also introduce continuous uncertainty (Budhwar et al., 2023). Such AI technologies are no longer mere auxiliary tools. They are now considered invaluable resources capable of providing organizations with a sustained competitive advantage (Chowdhury et al., 2023). Future research is expected to delve into the coexistence of workers and workplace AI (Zirar et al., 2023), the ethical risks posed by technology (Stahl et al., 2023), and how AI can genuinely achieve sustainable HRM (Budhwar et al., 2023).

Most cited theories adopted in AI and HRM research

This review synthesized the primary theories currently adopted. Table 1 presents the AI-related problems these theories address. For the firm-level research, theoretical analysis reveals the motivation that prompts firms to adopt AI. One of the most cited theories is the labor process theory (Braverman, 1975; Thompson, 1989). Labor process theory serves as a framework to dissect the configuration of production relations in the AI-enabled platform economy, facilitating an assessment of issues encompassing platform control, resistance, and exploitation (Gandini, 2019; Heiland, 2022). The experiences of workers and their responses to control systems vary significantly during the labor process, and these differences, in turn, influence organizational outcomes, determining whether organizations choose to adopt algorithmic management (Kellogg et al., 2020; Veen et al., 2020). The second most influential theory is the well-established socio-technical systems perspective (Leavitt, 1964; Manz & Stewart, 1997). The collaboration between AI and employees fosters the creation of social-technical capital and competitive advantages for firms (Makarius et al., 2020; Shin & Park, 2019). Also, the ambidexterity view is impactful (March, 1991; Tushman & O'Reilly, 1996). To maximize the benefits of AI adoption, firms navigate and reconcile specific conflicting dimensions between AI and human capabilities—such as authentic human emotional expression versus AI's high productivity—to achieve ambidexterity (Del Giudice et al., 2022; Wirtz, 2020).

For the employee-level research, contrasting with the previous perspective, scholars analyzed the elements that promote or hinder individuals from adopting AI. Technology affordance theory suggests that the interaction between individuals and robots depends on their intentions and purposes in achieving goals (Leonardi, 2011; Leung et al., 2023; Norman, 1988; Shin & Park, 2019). Current research substantiates the notion that AI exerts varying effects on distinct groups. For example, one key aspect of cognitive appraisal theory is its assertion that employees' cognitive perceptions of intelligent technologies, artificial intelligence, robots, and algorithms (STARA) can influence their appraisal of threats posed by

Table 1. Major theories adopted in AI and HRM research.

Theories	Application level*	AI related topics	Theoretical explanation	Examples	Type
Labor Process Theory	Macro	Focus on the dynamic relationship of control and power in algorithm-supported labor processes.	• By focusing on production and labor relations, LPT can reveal the unique control characteristics of work organization supported by algorithms. • As algorithm-supported platform work emerges as a new stage in the ongoing restructuring of capital production processes, workers' experiences and their responses to control systems vary significantly during the labor process.	Heiland (2022); Kellogg et al. (2020); Veen et al. (2020).	C/E
Sociotechnical Systems Theory	Macro	Algorithms is regarded as socio-technical systems for managing interactions between humans and technology.	• The collaboration between artificial intelligence and employees can create social-technical capital and generate competitive advantages. • The advancement of artificial intelligence technology demands coordinated evolution between technical systems and social systems.	Makarius et al. (2020); Parent-Rocheleau and Parker (2022); Shin and Park (2019).	C/E
Ambidexterity View	Macro	Organizations simultaneously pursues conflicting dimensions of AI and human capabilities to achieve performance.	• Service delivery mode ambidexterity enables the simultaneous pursuit of genuine emotional expression by employees and the high productivity and scalability provided by artificial intelligence during service delivery. • The ambidextrous organization uses humanoid robots to support daily activities for employees or in product generation.	Del Giudice et al. (2022); Wirtz (2020).	C/E
Transaction Cost Theory	Macro	The transaction costs of using AI alter attitude towards technology.	• The firm is considering the cost of adopting AI for making decisions regarding AI implementation.	Arias-Pérez and Vélez-Iramillo (2022); Pan et al. (2022)	E
Algorithmic Control	Macro	Employers use algorithms to direct, evaluate and discipline workers.	• Algorithmic control in the workplace operates through various mechanisms including restricting, recommending, recording, rating, replacing, and rewarding. • Algorithms are employed to direct and allocate tasks, manage performance and rewards, and align the actions of workers with the interests of the organization. • Algorithmic control within gig economy platforms exerts influence over the well-being and behavior of workers.	Duggan et al. (2023); Kellogg et al. (2020); Lefcoë et al. (2024); McDaid et al. (2023); Norlander et al. (2021); Waldkirch et al. (2021); Wiener et al. (2023); Wood et al. (2019).	C/E
AI Lifecycle	Macro	Operations, data generation, machine learning, and decision making.	• Focusing on each stage of the AI lifecycle can help pinpoint solutions to the general challenges that HR poses for AI. • Human resources leaders need to understand and promote the different stages of the artificial intelligence lifecycle, while developing new capabilities to achieve their goals.	Chiodo et al. (2024); Tambe et al. (2019).	C

(Continued)

Table 1. Continued.

Theories	Application level*	AI related topics	Theoretical explanation	Examples	Type
Competitive Psychological Climate	Micro	AI create a foster competition among employees.	• The application of AI has led to an increase in turnover intention among employees who feel they are working in a highly competitive environment. • In a competitive climate, anthropomorphic robots exacerbated employees' STARA awareness. • Artificial intelligence increases employees' autonomy in human-machine collaboration, enabling them to better control their resources to cope with work pressures and challenges.	Li et al. (2019); Yang et al. (2024)	E
Conservation of Resources theory	Micro	AI technology provide personal resource utility for employees.	• For certain employees, the deployment of AI also represents a loss of resources, as it poses a threat to their roles and responsibilities. Employees formulate different coping strategies based on their smart technology, artificial intelligence, robotics, and algorithms (STARA) awareness. • STARA awareness is a key source of work-related stress that influences employees' cognitive appraisal of threats to their job conditions.	Qiu et al. (2022); Zhang et al. (2023).	E
Cognitive Appraisal Theory	Micro	Interactions with AI can influence individual appraisal processes	• Employees who trust AI are better able to engage in positive interactions with their environment and effectively collaborate with AI. • Algorithmic affordance provides users with opportunities for action, allowing individuals to perceive these actions based on characteristics present in the environment. • The way individuals interact with affordance of service robots depends on their intentions and purposes for achieving goals. • When augmented AI enhances rather than replaces workers, the relationship between consumers and workers will be strengthened.	Ding (2021); Hur and Shin (2024); Yam et al. (2023).	E
Person–Environment Fit Theory	Micro	Current employee skills do not align well with AI-driven work environment.		Ding (2021); Kong et al. (2023) .	E
Technology Affordance Theory	Macro	AI affordance is a part of the relationship between actors and their environment.		Leung et al. (2023); Shin and Park (2019).	E
Consumer–Autonomous Technology–Worker Framework	Micro	Autonomous technology alters the relationship between workers and consumers.		Van Doorn et al. (2023)	C
Social Exchange Theory	Micro	AI interactions influence the dynamics of relationships	• AI mediated social exchanges enhance employees' personalized experiences, thereby prompting reciprocal behaviors and improving overall HR efficiency.	Dutta et al. (2023); Malik et al. (2022)	E

Note: (1) Macro-level refers to the theory that is mainly applied to the AI impact at the firm level, while the micro-level represents studies using the theory focus on the AI impact at the employee or team levels in the literature. It is worth noting that the theory applications collected are based on the literature, which does not mean the focal theory cannot be applied at a different level.
(2) Type: C = Conceptual research, E = Empirical studies.

work conditions (Ding, 2021; Yam et al., 2023). In conservation resource theory, it is argued that AI can provide frontline workers with personal resource benefits, such as increased autonomy in human-machine collaboration to manage work pressures and challenges better (Hobfoll, 1989; Qiu et al., 2022). However, for certain groups, AI represents resource loss, posing threats to their roles and risks of occupational displacement (Zhang et al., 2023). Research further elucidated how these individual differences lead to varying firm outcomes. A key finding from person-environment fit is that employees who trust AI can better engage positively with their environment and collaborate effectively with technology (Kong et al., 2023; Kristof, 1996). The potential competitive psychological climate created by AI among employees increases intentions to leave the organization (Li et al., 2019).

In addition, scholars studying the impact of AI at the individual level integrate AI elements into existing theories, aiming to identify viable pathways to address obstacles in human-machine collaboration. The consumer-autonomous technology-worker framework is a notable example demonstrating how the triadic relationship is strengthened when AI is used to enhance rather than replace workers (Van Doorn et al., 2023). Another relevant theory is social exchange theory, which is grounded in the concept of reciprocity (Cropanzano & Mitchell, 2005). Scholars have demonstrated that AI, by offering personalized experiences to employees and facilitating direct communication with leaders anytime and anywhere, is viewed as a form of personalized commitment from the organization (Dutta et al., 2023; Malik et al., 2022). Employees exhibit increased trust and enhanced engagement in return due to positive experiences with AI.

Clustering extant knowledge

Based on co-word analysis, we identified four pathways in the current research. Figure 3 highlights the main keywords associated with these four clusters. The first cluster (red, $N=17$ terms) focuses on *AI-enhanced collaboration*, including studies on employee performance, job satisfaction, and a wide range of employee behaviors. The second cluster (blue, $N=12$ terms), theoretical as the *AI-driven workplace*, encompasses research on the adoption and impact of AI technology in human resource management functions. The third group (green, $N=5$ terms), theoretical as the *AI-enabled business models*, includes research on gig economy platform workers who extensively use algorithms and AI technology. The fourth group (purple, $N=8$ terms), theoretic as *AI-powered innovation*, covers research on innovation and digital transformation. Table 2 depicts the four clusters and their focus.

Table 2. Structure of clusters.

Clusters	AI-enhanced collaboration	AI-driven workplace	AI-enabled business models	AI-powered innovation
Color	Red	Blue	Green	Purple
Keywords	Perceptions, engagement, satisfaction, commitment, trust, motivation	HR analytics, justice, selection, turnover, ethics, data bias	Gig economy, algorithmic management, platform work	Future of work, innovation, knowledge, creativity
Subtopic and their foci	<i>Employees and Managers</i> AI shapes employees' positive work experiences and exacerbates psychological fears of technology.	<i>Efficiency</i> AI assists in accessing information and streamlining management processes.	<i>Algorithmic controls</i> It guides workers' behaviors using recommendation-based algorithms and constraints workers' behaviors using monitoring algorithms.	<i>Exploitation</i> AI fosters interactive integrated knowledge systems. AI allows flexible and efficient configuration of existing resources.
	<i>Decision-makers</i> Proactively and flexibly leveraging AI to foster collaboration between technology and humans.	<i>Effectiveness</i> AI assists in achieving accuracy and objectivity in decision making and predicting the future behaviors.	<i>Workforce adaptability</i> The tense relationship between platforms and workers. Workers employ various strategies in response to algorithms.	<i>Exploration</i> AI presents significant opportunities for business and service innovation.
Examples	Dutta et al. (2023); Liang et al. (2022); Malik et al. (2022); Pei et al., 2024; Tong et al. (2021).	Acikgoz et al. (2020); Bondarouk et al. (2017); Keding and Meissner (2021); Metcalf et al. (2019); Mori et al. (2024).	Dagnino and Armaroli (2019); Duggan et al. (2020); Möhlmann et al. (2023); Veen et al. (2020); Wood et al. (2019).	Ameen et al. (2024); Botega and da Silva (2020); Faraj et al. (2018); Mikalef and Gupta (2021); Philippart (2022).

structured tasks yields a more favorable impact on employee productivity than feedback provided by human managers (Tong et al., 2021).

More specifically, such experiences are associated with personalized and individualized HRM practices. Unlike one-size-fits-all HRM approaches, personalized HRM emphasizes providing tailored HR practices to specific employee groups to align with the diverse values and unique attributes of the human capital employed (Bal & Dorenbosch, 2015; Taskin & Devos, 2005). The advent of AI has enabled the implementation of personalized, hyper-personalized, and individualized HRM approaches—practices once reserved for talented employee groups (Malik et al., 2022). AI allows managers to offer personalized considerations and experiences through AI-mediated social interactions, which may be challenging to achieve in purely human-to-human interactions. For instance, robots and intelligent assistants can provide employees with positive human-machine interactions, fostering positive employee outcomes (Dutta et al., 2023). For employees who fear losing face, using AI to partially substitute leadership intelligence in giving negative performance feedback

encourages them to focus on task-related shortcomings while reducing interpersonal rumination, thereby enhancing job performance (Pei et al., 2024). These outcomes extend to talent attraction and retention and foster positive employee experiences that elicit reciprocal behaviors, evidenced by heightened job satisfaction, enhanced organizational commitment, and diminished turnover intentions (Malik et al., 2022).

In addition, AI systems benefit HR managers and line managers by improving their decision-making efficiency and quality. Some AI-supported practices—most notably, using algorithms to manage platform workers—are assumed to be powerful tools for aligning the interests of managers and employees (Möhlmann et al., 2023). These algorithms play a significant role in improving coordination between management and employees. AI technology can contribute to developing organizational knowledge-sharing capabilities, thereby enhancing productivity, as it can efficiently generate knowledge from various databases. For example, the interaction between individuals and AI-based management practices enhances knowledge-sharing social interactions between talent and multinational corporations, leading to personalized experiences and reducing turnover rates (Malik et al., 2021). Through AI, high-level knowledge sharing in the healthcare sector aids in acquiring new knowledge, skills, and capabilities, guiding employees toward improved productivity. AI systems may also contribute to the development of employee task enjoyment (Norlander et al., 2021) and work goal progress (Tang et al., 2023), which in turn contributes to organizational productivity.

Impact on strategic decision-makers

The decision-makers of AI technology refer to organizational deployers or human resource experts who determine when or how to adopt AI technology to augment existing processes (Langer & König, 2023). The role of decision-makers in AI systems is crucial, as individual differences among leaders significantly influence their attitudes toward technology adoption (Bhatt, 2022). Related research also calls for deployers to recognize the unique, irreplaceable capabilities of human workers, including empathy, reliability, and friendliness (Belanche et al., 2021).

Within organizations, decision-makers may intentionally maintain system opacity to control employees (Kellogg et al., 2020; Rahman, 2021), ultimately resulting in the absence of organizational justice (Ötting & Maier, 2018). Additionally, recent research indicates that top-level deployers, much like most employees, are experiencing the pressure of potential AI replacements. As advanced solutions have surpassed standardized managerial functions, they are gradually encroaching upon what has traditionally been considered the prerogative of human leadership. Therefore, the integration of AI systems necessitates managers to develop technical

and managerial skills to define the capabilities of AI, along with non-technical managerial skills, such as vigilance against AI biases and abuse and ensuring ethical decision-making.

Cluster II: AI-driven workplace

The proliferation of AI-based applications has significantly influenced HR analytics, particularly emphasizing its potential to reshape workflow design and revolutionize organizational management practices (Raisch & Krakowski, 2021; Waldkirch et al., 2021). Our review suggests that the application of AI technology in various HR functions is contingent upon specific strategic emphases encompassing both *efficiency orientation AI use*, aimed at optimizing HR processes and minimizing costs, and *effectiveness orientation AI use*, targeted at elevating the quality and precision of HR decisions to achieve desired outcomes. These strategic directions determine AI-based applications' selection, implementation, and integration.

Efficiency orientation

Through the utilization of AI and automation technologies, tasks and data within organizations become more readily accessible, enabling HR departments to access data and make decisions efficiently (Chowdhury et al., 2023). Technology is able to handle vast amounts of information far beyond human capabilities, maximizing HR efficiency to the greatest extent (Duan et al., 2019; Tay et al., 2018). The utilization of advanced tools allows for the simultaneous collection of data from both the internal organization and the external market. They offer valuable recommendations to HR decision-makers through comprehensive data comparisons, thereby enhancing HR function efficiency. For instance, machine learning-based recruitment systems can add significant value to the data-intensive and time-consuming recruitment and selection process (Pessach et al., 2020; Sajjadijani et al., 2019). These tools provide higher efficiency in the recruitment process by pre-completing some of the screening and comparative tasks previously carried out by the HR department.

HR departments now utilize AI technology to streamline workflow processes. They can improve the candidate selection process by utilizing recommendation algorithms, which automatically match job offers with the most suitable candidates. This can reduce unnecessary interview expenses by prioritizing candidates who are both interested in and well-suited for the job. Augmented reality and virtual reality enable HR to address problems more effectively and help enhance the internal customer experience (Malik et al., 2022). The metaverse provides a dynamic platform allowing individuals to engage in remote work from any

geographical location across the globe, thereby ushering workplaces and HRM into an entirely new dimension of operational flexibility (Koohang et al., 2023). Reducing decision-making costs and increasing efficiency, in turn, propel the liberation of human resource experts to address more complex and contextual tasks. As Lindsay et al. (2014) and Huang et al. (2019) stated, the planning functions that involve recording information and scheduling routine tasks have been mainly taken over by machines, allowing human workers to focus more on cognitive tasks, such as evaluating data and analyzing implicit information. As technology is becoming integrated with human workers, HR planning no longer centers around job substitution but instead emphasizes the concept of human-robot symbiosis and collaboration to achieve complementarity (Vrontis et al., 2022).

Effectiveness orientation

AI technology outperforms human decision-making in terms of accuracy and objectivity (Jussupow et al., 2021). AI systems enable faster information collection and provide managers and HR experts with more comprehensive and relevant information to support accurate decision-making. For example, Allal-Chérif et al. (2021) generate some insights that predictive recruitment algorithms can facilitate the coordination of internal employee data with external labor market data within the organization. Converting candidates' skills and experiences into measurable data allows managers to make more precise decisions by comparing them with the performance data of reference employees within the organization. In recruitment, excluding human expertise reduces the chances of introducing bias and discrimination in hiring decisions, thereby fulfilling the commitment to enhance the objective of HR decisions (Köchling & Wehner, 2023). Automation technology transforms recruitment processes into more systematic and standardized procedures, eventually enhancing organizational management's quality and effectiveness (Pessach et al., 2020). AI-based performance management tools can facilitate more equitable performance evaluations of employees based on job requirements rather than other social standards, thus reducing unfairness (Gal et al., 2020; Newman et al., 2020).

AI technology enables the anticipation of employees' future behaviors by leveraging collected data, thereby enhancing the efficacy of HR practices when aligned with AI system recommendations (Leavitt et al., 2021; Sajjadi et al., 2019). According to Kellogg et al. (2020), managers use computational techniques to generate new performance metrics for employees and forecast their future performance. Examples include AI predicting employees' future intentions to leave using historical employee datasets and identifying instances of skill-job mismatch to forecast

employees' training needs (Chowdhury et al., 2023). AI tools are able to uncover implicit knowledge during decision-making, and disclosing such information will maximize knowledge sharing and enhance the organization's future decision intelligence (Metcalf et al., 2019).

Cluster III: AI-enabled business models

Algorithm-driven AI technologies are being applied in the context of the gig economy. The gig economy creates a novel form of labor by connecting workers with consumers (Connelly et al., 2021; Wood et al., 2019). Scholars have notably recognized the profound transformation of HR functions within the gig economy business model (Cheng & Hackett, 2021). HRM no longer prioritizes nurturing labor relationships and maintaining relationships with employees (Duggan et al., 2020). Instead, HR is currently engaged in reassessing and shaping interactions among key entities within a platform that employs algorithmic control to guide workers' behavior (Keegan & Meijerink, 2023). Workers subsequently exhibit diverse attitudes toward algorithmic control and employ various coping strategies (Orhan et al., 2022). In essence, the current emphasis of HRM lies in the control and coordination of the triadic relationship among gig workers, platform users, and intermediary platform organizations.

Enforced algorithmic control

Algorithms primarily employ diverse technological mechanisms to offer distinct affordances to employees (Kellogg et al., 2020; Möhlmann et al., 2023). Previous research categorizes algorithmic control into two primary types, guidance algorithms and constraint algorithms. Guidance algorithms revolve around recommendations and suggestions. These algorithms govern what actions employees can undertake by delineating the process of the actions and assigning tasks (Kellogg et al., 2020; Veen et al., 2020). Diverging from conventional control mechanisms, algorithmic recommendations frequently leverage automated pattern discovery within data to furnish employees with finer-grained propositions and workflow directives (Burbano & Chiles, 2022). For instance, GPS systems and sensor technology track drivers and provide real-time information, such as weather and traffic conditions, to optimize routes and prevent accidents (Abraham et al., 2019). This automated recommendation system enhances HR resource flexibility by optimally addressing employees' specific job requirements and preferences across diverse scenarios (Wright & Snell, 1998). Conversely, the other type, constraint algorithms, are operated by curtailing the extent of organizational information exposure and limiting the worker's information availability, thus dictating the realm of activities in which employees are 'not allowed' to partake (Kellogg

et al., 2020; Wiener et al., 2023). The autonomy and discretion of workers are constrained, as they typically make decisions and take actions based on signals provided by algorithms (Leicht-Deobald et al., 2019).

The online labor platform represents a novel business model driven by algorithms, where most HR management decisions are entirely automated to organize short-term tasks and facilitate market transactions efficiently (Alacovska et al., 2024; Duggan et al., 2020). Based on information modeling, prescriptive algorithms not only predict future outcomes to enhance decision-making but also possess the capability to fully autonomously recommend diverse courses of action, enabling organizations to derive maximum benefits from alternative scenarios (Leicht-Deobald et al., 2019). Uber drivers who receive complaints automatically experience a reduction in the number of assigned orders, and they might even lose their driving privileges or be permanently removed from the platform (De Stefano, 2015). Such automated decision-making strengthens the coordination flexibility of HR, enabling the rapid and efficient implementation of HR practices aligned with organizational strategic goals (Wright & Snell, 1998).

Workforce adaptability

Algorithm-enhanced workplace control extends beyond conventional organizational boundaries and is often characterized as an electronic panopticon due to its unrestricted temporal and spatial nature (Parent-Rochelleau & Parker, 2022). The restricted transparency of algorithmic control has created tension between workers and platforms (Gal et al., 2020; Leclercq-Vandelannoitte, 2023). Möhlmann et al. (2023) state that platform workers exhibit two primary response mechanisms, ranging from an organization-like response, where workers display compliance with algorithmic control and enjoy their work, to a market-like reaction, where workers resist and oppose the algorithm's guidance. Due to the misalignment of interests between workers and platforms, these two common types of responses are not always positive or negative, as workers might feign loyalty while gaming the algorithmic control by manipulating system scores (Möhlmann et al., 2023).

The advent of AI and algorithms has led to a transformative shift in the labor process (Heiland, 2022; Huang, 2023). According to Duggan et al. (2020), algorithmic management limits human involvement and oversight in the labor process. Veen et al. (2020) examine how labor process control is implemented in Australian food delivery platforms. The process encompasses the panoramic configuration of algorithms, the utilization of asymmetric information to restrict worker choices, and ambiguous performance standards to enforce workers' adherence to platform rules. In response to new algorithm-driven forms of labor control,

workers' digital resistance has become an integral part of the labor process (Cameron & Rahman, 2022). Workers balance the power disparities in the gig economy by expressing active solidarity, which serves as a collective response to the underlying conflicts in the labor process (Lei, 2021; Tassinari & Maccarrone, 2020).

AI has the potential to bring substantial benefits, it also facilitate intensified surveillance and control pressures in the workplace. Algorithmic management increases the risk of discrimination, as it often conceals biases within a seemingly objective technical framework (Dagnino & Armaroli, 2019). Given the unprecedented challenges gig workers face in defending their rights, seeking to impose collective control over algorithmic management and preserve workers' voices—such as through collective bargaining—has naturally become a priority for unions and labor movements (Doellgast & Wagner, 2022). Collective bargaining presents an adaptable framework for negotiating algorithmic controls, allowing for customized agreements that address the specific needs of management within individual companies or sectors (De Stefano, 2015). A cross-national study on digital labor platforms highlights that riders with sector-specific collective agreements benefit from greater transparency and predictability regarding essential employment conditions (Leschke & Scheele, 2024). These findings emphasize that including platform workers in collective bargaining is a crucial lifeline for sustaining the necessary regulatory capacity of social dialogue (Piasna, 2024).

Cluster IV. AI-Powered innovation

The adoption of AI enhances an organization's productivity (Del Giudice et al., 2022), knowledge capabilities (Wang & Wu, 2021), creativity (Mikalef & Gupta, 2021), and innovation (Verganti et al., 2020). Organizations can utilize AI-enabled tools to maintain a high level of balance between *exploitation-orientated practices*, which involves improving employee experiences and upgrading customer services by leveraging existing resources, and *exploration-orientated practices*, which aim to achieve optimal strategic business outcomes (Simsek, 2009). The importance of ambidexterity is evident among the many prescriptions for organizations to adapt and thrive in the digital age.

The exploitation of existing resources

As one of the intangible assets within a firm, knowledge is regarded as the core element for gaining a competitive edge. AI technology has propelled knowledge management systems to a new level, especially in driving knowledge-guided innovation and inspiring holistic decision-making. Botega and da Silva (2020) demonstrate that AI can support knowledge

management in selecting creative and innovative techniques, thereby fostering the development of innovative products. Furthermore, due to the wealth of organizational knowledge resources, AI can efficiently facilitate or replace human decision-making through interactive and integrated knowledge systems (Duan et al., 2019).

Exploitative resources are fundamental factors for the successful operation of businesses, involving the judicious allocation of various resources. The emergence of AI enhances organizational flexibility by enabling agile assessments of the market and competitors that drive rapid transformation (Teece et al., 1997). Tarafdar et al. (2019) delineate that through the implementation of enterprise cognitive computing, which integrates algorithms into applications supporting organizational processes, routine and formulaic tasks are delegated to technology, leading to substantial enhancements in the reliability and accuracy of outcomes. Furthermore, smart factories can leverage real-time data and AI to achieve autonomous and flexible operations (Ancarani et al., 2019). AI-driven HR analytics enables organizations to quickly bridge skill gaps with competitors and develop the necessary knowledge, enhancing flexibility in managing human capital resources.

Exploitative innovation entails upgrading or incrementally refining existing services or products (Piao & Zajac, 2016). The application of AI in service-oriented organizations has been demonstrated to optimize resource utilization while upgrading customer services at reduced costs. For example, service robots can swiftly retrieve customer information, and through collaborative interaction with humans, these robots can foster a more positive customer experience while assisting in establishing robust customer relationships (Prentice & Nguyen, 2020). The metaverse represents a convergence of complementary technologies, including AI, augmented reality, and virtual reality. It amalgamates advanced technologies within an organization onto a unified platform, facilitating efficient resource utilization and service upgrades (Wong et al., 2024).

The exploration of new ventures

Exploratory innovation requires firms to develop entirely new products or services to meet the demands of emerging customers and markets (Piao & Zajac, 2016). The introduction of AI technology offers exciting business innovation opportunities (Fountain et al., 2019). On the one hand, technologies such as geolocation, virtual reality, and biometric identification offer opportunities for extensive service innovations (Wirtz, 2020). Firms use service robots to adapt to a continuously evolving environment and maintain a competitive edge through service innovations, including establishing novel service concepts, new customer interaction, new business partnerships, and revenue models. On

the other hand, the integration of technology has driven the digital transformation of enterprises, facilitating the development of novel digital business models that help to create more value for the organization (Verhoef et al., 2021). For instance, firms can leverage mobile augmented reality (AR) to assist customers in simulating product experiences, thus innovatively fostering customer engagement and satisfaction (Poushneh & Vasquez-Parraga, 2017). Moreover, as a geographically unconstrained resource, recommendation algorithms provide a vast stage for developing innovative business models within enterprises. Ma and Hu (2021) indicate that through robust AI algorithm systems, TikTok creatively utilizes existing localized content resources to present globally distinctive products, thereby creating unique value in internationalization and economic transformation.

Researchers assert that we are currently at the forefront of a new industrial revolution, where the adoption of technologies such as humanoid robots is guiding enterprises into the new era of Industry 5.0 (Del Giudice et al., 2022). With robust governmental support, integrating AI capabilities and strategic agility significantly enhances firms' new product creativity and new service development performance (Ameen et al., 2024). An organizational-level research gap that must be addressed is how AI can facilitate innovation and greater customization within the business. While data-driven AI serves as the foundation for influential AI implementation, leadership provides the transformative energy that enables organizations to succeed in AI initiatives (Brock & Von Wangenheim, 2019; Philippart, 2022). Transformational leadership represents a strategic response that allows organizational members to overcome perceived threats of AI and engage with it constructively (Yin et al., 2024). Innovations in AI technology require businesses to embrace the uncertainty of technology and approach potential intelligent machine innovation with an open mindset (Odugbesan et al., 2023).

Limitations of AI integration

The Pandora's box of AI has been unleashed, with its breathtaking potential surging forth. Every step of AI and HRM integration is fraught with intertwined hopes and dangers. The motivations for adopting AI in HR functions are multifaceted, yet they consistently reflect a strategic perspective aimed at optimizing organizational resources for competitive advantage (Haenlein & Kaplan, 2019). However, despite its strategic potential, it is crucial to acknowledge that AI introduces latent risks within HR that are inherently difficult to mitigate.

First, AI exhibits myopia in its capacity to recognize the interdependencies between tasks within an organization (Kemp, 2024). The

limitations of algorithms in understanding the broader context of activities highlight the need for HR departments to prioritize human agency, as humans possess a greater ability to interpret context and generate novel, creative solutions. In this regard, integrating AI in the loop into human-centered creative problem-solving processes represents the most effective approach (Boussioux et al., 2024).

Second, the technological nature of AI inherently lacks human characteristics, leading to mixed or even negative impacts on employee well-being (Tong et al., 2021). Employees exhibit concerns regarding machines' potential displacement of their roles while lacking confidence in the outcomes of intelligent decision-making (Braganza et al., 2021; Schlicker et al., 2021). The deployment of automated systems within organizations is seen as a negative signal regarding their job capabilities, detracting from employees' task performance (Tang et al., 2023). Perception of technological uncertainty among employees raises their levels of technostress and diminished job satisfaction. Merely treating humans as data streams for personnel analysis may underestimate the complexity and autonomy of humans, thereby reducing managerial efficiency (Gal et al., 2020).

Third, AI is inherently derivative in nature, functioning solely within the boundaries of pre-existing data and patterns and thus lacking the ability for true innovation or original thought. Bringing AI technologies into the workplace introduces additional decision agents within organizations. While these decision agents offer the potential to ease the workload of managers by standardizing decision procedures, they also present challenges to managers in interpreting opaque and complex AI systems (Ötting & Maier, 2018). For instance, managers are obligated to explain the outputs and decision processes of AI systems to decision-makers and employees and continually monitor the systems to ensure their proper functioning (Makarius et al., 2020). Improper utilization of AI-integrated business analysis can result in suboptimal decisions that have the potential to impede the firms' operations and diminish their business value (Rana et al., 2022). These issues underscore the critical need to enhance skill adaptability and technological literacy to navigate digital challenges effectively.

Future research agenda

Drawing upon our prior discourse on clusters, this review offers a comprehensive framework illustrating that these four clusters encapsulate distinct dimensions of AI's varied directional impacts within the field of HRM. The horizontal axis emphasizes the evolution between technology-driven applications and the transformation of business

models. In contrast, the vertical axis represents the increasing levels of collaboration and innovation between AI and human agency. Overall, AI serves as a bridge for transforming HRM. It supports specific operational processes while also driving comprehensive organizational transformation. This section draws on our framework and themes to present future research agendas. A comprehensive overview of the developmental logic and its correlation with the preceding themes is presented in [Figure 4](#).

Theme 1: Embracing the AI-driven adaptability in the HR ecosystem

While AI, driven by efficiency and effectiveness, confers substantial advantages in enhancing the quality of HRM, we propose a more comprehensive, adaptability-oriented perspective. Specifically, we advocate adopting a ‘loose coupling’ strategy (Beekun & Glick, 2001; Nambisan & Luo, 2021), granting HR significant discretion and relying on establishing shared values and expectations related to technology for effective management. At the organizational level, loose coupling signifies interconnectivity and swift responsiveness among HRM functions, involving the flexible adjustment of human resource strategies to adapt to rapidly changing environments (Orton & Weick, 1990). In addition to HR’s general functions of attracting, retaining, and developing talents, we suggest that future HR research explore deeper into the dynamic adjustments and coordination among these functions to maximize the potential of AI technology applications (Pereira et al., 2023). The more critical point inspired by Snell and Morris (2021) is establishing an HR ecosystem to achieve consistency and synergy among workforce, capabilities, and cultures.

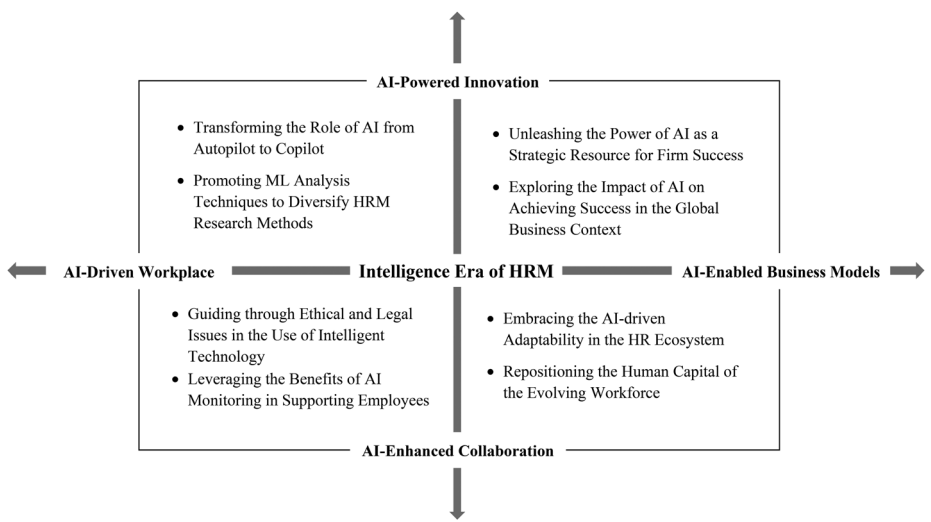


Figure 4. Reflecting on past and future trends in AI and HRM research.

At the individual level, loose coupling implies retaining a certain uniqueness, involving the provision of differentiated management approaches for different employees (Orton & Weick, 1990). Rostain and Huising (2024) indicate that occupational characteristics influence employees' engagement with digital representations. For instance, computer engineers may fully immerse themselves in digitized technologies, while assembly line workers may distance themselves from technology. We recommend that future research focus on how individuals and organizations from different industries approach technological challenges adaptively.

Theme 2: Repositioning the human capital of the evolving workforce

Traditionally, the HR domain perceived these contracting workers engaged in flexible tasks as having low human capital value (Lepak & Snell, 1999). However, the gig economy platforms increasingly governed by algorithms have brought a turning point. On the one hand, it eliminates the requirement for human supervisors and managers, thereby keeping marginal and labor costs relatively low (Meijerink et al., 2021). On the other hand, with the growing expansion of digital platform organizations, more high-skilled professionals, such as marketing professionals and programmers, are recruited for gig work on these platforms, contributing to the intangible capital stock of the platforms (Meijerink & Keegan, 2019). Therefore, the rise of gig economy platforms creates a pathway to maximize returns and prompts scholars to reconsider the potential of gig workers as an emerging form of human capital that generates value for businesses.

More research is needed to understand how gig worker human capital contributes to the long-term development of businesses. For instance, how these gig workers bring essential expertise resources to the organization and promote knowledge sharing across the entire enterprise (Alacovska et al., 2024). Additionally, as gig economy platforms involve collaboration among workers from different fields and locations, future research should focus on how gig workers seamlessly integrate into organizational workflows and culture. An essential discussion here revolves around the conditions under which enhancing the human capital of gig workers is most effective for organizations, as businesses often face a trade-off between upgrading the skills of existing employees or hiring gig workers (Jaiswal et al., 2022).

Theme 3: Transforming the role of AI from autopilot to copilot

Automation technologies allow organizations to employ AI-based solutions as autopilots for managerial tasks (Raisch & Krakowski, 2021).

However, the emergence of powerful new model foundations in generative AI, along with easily accessible natural language interfaces, brings about an exciting transformation in the landscape of AI. The role of AI is shifting from being an autopilot to becoming a copilot. Human involvement in the AI working process is shifting from ideation to guidance and evaluation, establishing human workers as gatekeepers of creative value (Magni et al., 2024).

As generative AI transitions from behind the scenes to the forefront, increasing employees utilize these tools to assist in their work (Budhwar et al., 2023). There is a need for a deeper understanding of how generative AI promotes employee well-being, such as using chatbots to provide mental health support, as this could become a new way to enhance employee motivation and job satisfaction in the digital age. At the organizational level, the extensive use of generative AI may consume more energy, and future research should investigate how to optimize the usage of generative AI to achieve resource and energy efficiency in HR management processes (Wang et al., 2023). On a societal level, researchers should explore how governments, non-governmental organizations, and firms can collaborate to create a more positive and efficient work experience for the whole society while reducing potential data leaks or privacy infringements (Angrave et al., 2016).

Theme 4: Promoting ML analysis techniques to diversify HRM research methods

In alignment with Felten et al. (2021), despite the exploration of numerous intriguing concepts related to AI, these concepts lack sufficient empirical testing. A primary criticism lies in the prevalent use of cross-sectional designs and the confinement to context-limited analytical environments in the existing studies (Vrontis et al., 2022). Therefore, we suggest that future research should address these potential gaps. AI solutions are essentially data-driven, and the quality and quantity of available data are closely tied to the context. This underscores the need to validate existing theories and research findings across broader scenarios.

Some scholars suggest embracing emerging multi-level analysis techniques in HRM research. Machine learning tools, including text classification and natural language processing, offer possibilities for exploring extensive unstructured text. For example, supervised machine learning techniques are employed to classify patent text documents, and the variables generated through this approach can be used for subsequent regression analysis (Miric et al., 2023). Furthermore, machine learning can be a powerful toolbox for identifying robust patterns within complex datasets.

For instance, Choudhury et al. (2021) use supervised machine learning to analyze employee turnover in a large tech firm, revealing potential patterns of employee attrition. What is particularly noteworthy is that machine learning introduces fresh prospects for advancing organizational theory. By efficiently analyzing large volumes of data and uncovering latent patterns, machine learning can be a tool for testing and refining mid-level theories and promoting grand theories that are applicable across various contexts and timeframes (Leavitt et al., 2021).

Theme 5: Unleashing the power of AI as a strategic resource for firm Success

AI is widely regarded as the primary source of future business value. As we discussed, AI aids businesses in fully exploiting existing resources and exploring new opportunities. Despite businesses initiating investments in AI applications, research indicates that organizations have not fully experienced the benefits of adopting AI (Fountain et al., 2019). From a resource-based view, firms achieve competitive performance by establishing unique, difficult-to-imitate capabilities (Bharadwaj, 2000). These capabilities are formed by combining and deploying various complementary enterprise resources (Mikalef & Gupta, 2021). Therefore, we suggest that unlocking the value of AI requires treating it as a strategic resource and developing distinctive AI capabilities.

Future research needs to intricately detail the dynamic combination of resources required to build AI capabilities—how technological resources complement other resources to create value for businesses. Chowdhury et al. (2023) present eleven key research questions related to unlocking AI capabilities, urging organizations to develop a conducive organizational context and effective strategies for AI adoption. In alignment with these meaningful questions, we propose that future HR research focus on the crucial non-technical resources required for AI adoption and how to configure these organizational resources to unleash the value of AI capabilities.

Theme 6: Exploring the impact of AI on achieving success in the global business context

The key to success for multinational firms in the global business context lies in their ability to effectively transfer and reconfigure knowledge in various forms of knowledge (Chang et al., 2012). Knowledge-based systems are considered one of the most successful applications of AI, thereby adding significant value to the success of multinational firms in the global context (Malik et al., 2021). We suggest that future research should

plan the adoption of AI by MNEs from a more comprehensive perspective.

First, future research should explore how AI-supported knowledge systems can facilitate the sharing and replication of critical knowledge within the networks of the MNEs. Globalization and advancements in information and communication technologies have led to the creation of global virtual teams, which are increasingly adopted by the MNEs. There is a lack of sufficient understanding of how multinational corporations can use AI tools to improve global task efficiency and reduce collaboration costs. Second, scholars have noted that MNEs that adopt AI algorithmic technologies can cater to a global talent pool with more refined and customized experiences while improving needed skills (Malik et al., 2022). However, despite AI reducing the need for human labor in MNEs, achieving effective integration with outcomes requires a thorough understanding of the AI-related capabilities of organizational members (Jaiswal et al., 2022). Furthermore, future research in international HRM should recognize the significant role of AI technology in promoting the development of expatriates.

Theme 7: Leveraging the benefits of AI monitoring in supporting employees

As sensor technology embeds into smartphones and wearable equipment, the introduction of monitoring devices supported by intelligent algorithms has sparked widespread societal concerns. The central argument in the long-standing debate is that while AI monitoring has the potential to enhance employee safety and improve job performance, it also poses significant risks, such as diminishing autonomy in the workplace and undermining trust in management (Abraham et al., 2019). However, in the middle of difficulty lies opportunity. AI-driven tracking technology will ultimately become the new norm and standard in the workplace. We suggest that research should not solely focus on its potential risks; instead, it should concentrate on establishing social norms of technology, for example, defining the scope of monitoring and establishing data collection criteria to balance the advantages brought by supervision and the negative impacts arising from employee opposition (Burbano & Chiles, 2022). Additionally, we encourage future research to explicitly identify the reasons behind employee acceptance or resistance to AI monitoring (Cameron & Rahman, 2022; Deng et al., 2025). For instance, understanding which factors influence employees to accept new AI tracking technologies or what concerns lead to resistance against AI monitoring is crucial (Abraham et al., 2019; Deng et al., 2025).

Theme 8: Guiding through ethical and legal issues in the use of intelligent technology

While many regions have implemented crucial regulations to restrict businesses in their use and exploration of AI, the gap between the execution of technical supervision and the outlined guidelines has complicated issues (Budhwar et al., 2022). Based on our cluster analyses of AI tools in managing gig platform workers, we emphasize two potential research directions for the future: addressing the emergence of algorithmic bias and mitigating the negative impacts it brings. To minimize algorithmic bias, it is crucial to explicitly define decision agents—specifying which decisions can be delegated to algorithms and which must involve human decision-making, along with a clear understanding of the outcomes. The optimal approach to avoiding algorithmic bias may not lie in attempting to regulate AI itself but rather in establishing universally accepted standards for the training and testing of algorithms to ensure fair and unbiased outcomes (Haenlein & Kaplan, 2019). To reduce the negative impact of unethical AI use, we propose that future research clearly outlines responsible AI decision models to support businesses in openly and transparently disclosing their utilization of AI systems (Rodgers et al., 2023).

Conclusion

This research addresses the fundamental question of how the integration of AI can enhance research and practice in HRM. In this review, we present a temporal framework delineating the evolution of literature and synthesize key theories that underpin current research. We elucidate the four pathways through which AI can be strategically harnessed to generate competitive advantages in HR. Lastly, we consolidate our findings and propose a forward-looking research agenda.

The study makes several contributions to the intersection of HRM and AI. First, in response to scholarly calls for a more systematic exploration of the potential opportunities and challenges of AI (Grote et al., 2024; Raisch & Fomina, 2024), we pave the way for new avenues of future research across various directions. The future research agenda outlined in this review sparks future studies in exploring how AI-driven HRM generates value across different dimensions of scope and depth. Second, we delineated the theoretical landscape by contrasting how theories are applied in research, which has led to the initiation of theoretical dialogues to advance our understanding of AI-HRM (Pan & Froese, 2023). This discussion serves as a guide for aspiring researchers seeking a broader understanding of the latest advancements and uncovering opportunities for further theoretical development. Third, this study possesses

certain methodological advantages by combining systematic review and in-depth bibliometric analysis. The bibliometric analysis provides results that help construct scientific structures for cross-disciplinary research topics while minimizing bias in literature search and synthesis (van Eck & Waltman, 2010; Zupic & Čater, 2015).

This review is subject to several limitations. First, it is confined to journal articles, excluding books, book chapters, and conference proceedings. Given the emerging nature of AI research, most of the recent advancements are primarily published in journals, and full access to conference papers is often restricted. Second, due to the interdisciplinary nature of AI and HRM, there may be relevant technology-oriented articles on workplace management that were not captured in this review. Third, our analysis did not incorporate some early influential works in the field, especially those written in other language, as limitations in search and mapping technologies hindered a comprehensive examination of these foundational contributions.

While the research field is relatively nascent, our study affirms the potential for further investigation into how AI interacts with HR. New research opportunities abound to explore how to tame artificial intelligence and ensure it becomes more beneficial for everyone. Similar to all technological innovations, AI tools are a double-edged sword. They have the potential to foster positive changes in organizational structures and employee roles, but they may also exacerbate vulnerabilities in management decisions and ethical challenges. This underscores the urgent need for responsible integration and the development of best practices. We recommend that future research closely tracks AI technological advancements to address the dynamic changes brought to the workplace and business environment.

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Data availability statement

The data that support the findings of this study are openly available in publications included in the reference list.

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