Critical exploration of AI-driven HRM to build up organizational capabilities

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Abstract

Purpose:

HRM processes are increasingly AI-driven, and HRM supports the general digital transformation of companies' viable competitiveness. This paper points out possible positive and negative effects on HRM, workplaces, and organizations along the HR processes and its potential for competitive advantage in regard to managerial decisions on AI implementation regarding augmentation and automation of work.

Methodology:

A systematic literature review that includes 62 international journals across different disciplines and contains top-tier academic and German practitioner journals was conducted. The literature analysis applies the resource-based view (RBV) as a lens through which to explore AI-driven HRM as a potential source of organizational capabilities.

Findings:

The analysis shows four ambiguities for AI-driven HRM that might support sustainable company development or prevent AI application: job design, transparency, performance and data ambiguity. A limited scholarly discussion with very few empirical studies can be stated. To date, research has mainly focused on HRM in general, recruiting, and HR analytics in particular.

Implications:

The four ambiguities' context-specific potential for capability building in firms is indicated, and research avenues are developed.

Originality:

This paper critically explores AI-driven HRM and structures context-specific potential for capability building along four ambiguities that must be addressed by HRM to strategically contribute to an organization's competitive advantage.

Keywords

Artificial Intelligence, Literature Review, HRM, Resource-Based View; Ambiguity, Context

Introduction

Digital human resource management (HRM) includes the evolutionary development of technology-based HRM (Strohmeier, 2020). Artificial intelligence (AI) applications in HRM are one part of this evolution. Since the 1950s, AI has been discussed as a means of replacing the work of employees, and ever since, the application of AI has incrementally increased in many areas (Giering, 2021; Peña, 1988). Academic articles articulate the relative advantages of AI-driven HRM (King, 2016; Heinecken, 1993; Lackes and Mack, 1998). Consequently, applying AI in HRM changes the management of people in the workplace. To build up competitive advantage through inimitable core competencies integrating AI at an early stage leading to efficient processes, better decisions and satisfaction of employees seems to be a viable option for companies (Basu et al., 2023). Thus, AI application may bear potential for decent work and sustainable development of organizations.

Despite long-term interest in AI's substitution possibilities, for many years, scholarly discussion has remained limited (Budhwar et al., 2022; Chang et al., 2021; Vassilopoulou et al., 2022). Recently, the field may be characterized as "nascent but rapidly evolving" (Basu et al, 2023: 2). Challenges in AI-driven HR range from ethical to conceptual to practical (Tambe et al, 2019). In such an emerging and transdisciplinary field practitioner journals are showing actual cases, critical discussions and new developments in organization and may give valuable insights, even if the information is "often conventionally reported" (Basu, et al, 2023:13) and not verified on the same level as in peer-reviewed journals.

A gap has appeared between technological maturity and practical application (Gärtner, 2020; Gélinas et al., 2022). Moreover, in HRM, "there is already evidence of a research-practitioner divide" (Cheng and Hackett, 2019: 1), as practitioners have shown more interest in algorithms in HRM than academics, leaving the field at the "pre-theoretic stage" (Charlwood and Guenole, 2021: 738). To date, the possible contribution of AI in HRM to capability building remains unclear. Acting on the gaps identified by HRM scholars, this article aims to advance the knowledge about the potential of AI-driven HRM.

Currently, HRM is not only people-oriented but data-oriented and analytics-driven, resulting in transdisciplinary research (Gélinas et al., 2022). Thus, the objective of this paper is to critically explore AI-driven HRM along the HR process model through a systematic literature review of 62 international journals across the organization and human resources, business administration, and information systems disciplines, including international top-tier academic and German practitioner journals. In doing so, we intend to structure both positive and negative effects on HRM and workplaces that might foster or hinder building up organizational competitive advantage. The purpose is a meaningful extension of the scholarly discussion on effective management of AI applications' challenges and opportunities in HRM (Budhwar et al., 2022) validated in practice literature.

Considering the above-mentioned developments, this systematic literature review assesses the relevant literature for answering the research questions below:

1. What is the quality of the research-practice gap along the HR process perspective?
2. How can the technology-application gap in AI-driven HRM be delineated?
3. What are the ambiguities in AI-driven HRM to be considered when taking managerial decisions on improvements for HRM, employees at the workplace and therefore building up up-to-date core capabilities in firms to gain competitive advantages?
4. What are important considerations for future HR professionals' skills and future research avenues?

The paper is organized as follows: First, the article identifies the possibilities of AI-driven HRM in line with digital transformation and provides conceptual clarity on AI-driven HRM. In the following section, the resource-based view is expanded on AI applications in HRM.

Subsequently, following the methods section, this article provides a literature-based perspective on the application of AI along the HR process. Drawing on the resource-based view of the firm, we discuss the complexity of capability building along four ambiguities of AI-driven HRM inductively concluded from the literature review. As a practical contribution, implications for capability building and for HR practitioners' learning and development are discussed. Finally, research avenues along the ambiguities are indicated.

AI and Its Application in HRM

With the fourth industrial revolution (4IR) and the consequently increasing digitalization of companies, gaining sustainable competitive advantages that are hard for competitors to imitate includes aligning digital resources (Kindermann et al., 2020). HRM faces a twofold challenge: (1) digitalizing the processes of HRM and (2) supporting general digital transformation through the change processes and competence development needed for companies' viable competitiveness. Therefore, human resource (HR) practitioners might be expected to lead the way (Nankervis et al., 2019) and can contribute to how organizational resources are transformed into capabilities.

The nature of the relationship between technology and organizations is reciprocal (Wirtky et al., 2016). One consequence is that "rapid technological developments offer a new, smart, digital context for HRM practices" (Bondarouk and Brewster, 2016: 2652). AI is one segment of the technology landscape with growing relevance. AI is not easily defined (Giering, 2021; OECD, 2019) because the term covers a large field of diverse applications (Budhwar et al., 2022; Peña, 1988). Scholars characterize the field as multifaceted with impacts from various academic disciplines (Vrontis et al., 2021). Moreover, laymen often conflate AI with other technological achievements, such as filters in databases. A "machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments” (OECD, 2019: 7) is defined as an AI system. AI systems can operate with different levels of autonomy, and they can (1) use inputs from machines and/or humans to sense real and/or virtual environments; (2) build models on this basis; and (3) apply the implications of these models to provide options for action or information (OECD, 2019; Tambe et al, 2019). Consequently, automation of work processes, including the potential to replace human work on the one hand and the augmentation of human skill on the other hand, are possible (Markoff, 2016). These possibilities is underlined by the recent discussions about the language processing skills of ChatGPT and the fundamental changes to many organizational roles and functions that may be expected (Huffman, 2023).

The concept of AI in HRM was explored by Strohmeier and Piazza (2015). They assumed that AI techniques have application potential in all areas of HRM if the AI techniques offer functionalities that correspond with the requirements of HR tasks (Strohmeier and Piazza, 2015). However, a gap between technological maturity and practical application is evident (Gärtner, 2020). In this paper, both the automation of HR tasks and the information derived to improve HR decisions generated via AI are considered applicable in transformations that help build capabilities. Following the employee life cycle in an organization, HR tasks and decisions can be structured in functional fields along the HRM process and cross-functional fields that may be transformed (Wirtky et al., 2016) (see figure 1). Thus far, it is not clear which AI techniques are already practically used and have been included in the scholarly discussion in the fields of HRM. Therefore, this literature review aims to provide insights into the quality of both the research-practice divide and the technology-application gap in the transformation.

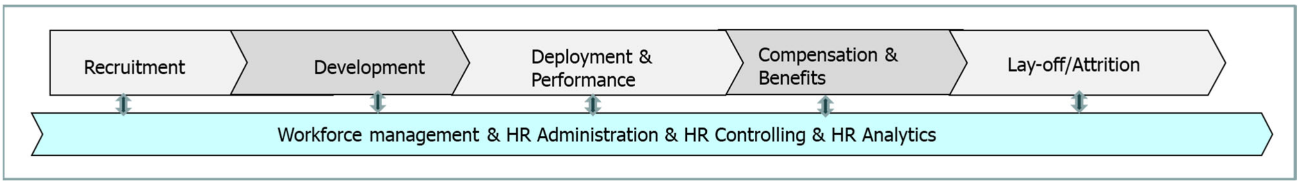

Figure 1: HRM process model (Source: Authors' creation based on Wirtky et al., 2016)

AI is generally considered a generic term for machines that possess abilities similar to human behaviour in analysing data and solving problems. If AI has the same intellectual skills as humans in all areas, such as logical thinking, creativity or decision making, these machines are considered 'strong' AI (Giering, 2021). To date, technological maturity has not reached this stage. Therefore, in HRM, 'weak' AI applications provide specific solutions for delimited processes in HRM, such as recruiting or selection. This developmental stage consequently leads to AI-augmented HRM, in which HR practitioners use algorithmic recommendations for decisions (Vassilopoulou et al., 2022). Nevertheless, extreme impacts on employment and workplaces mirrored in respective influences on HRM to be expected in the near future are still discussed (Vrontis et al., 2022).

Under AI, Gärtner (2020) includes subdisciplinary machine learning (ML), artificial neural networks including deep learning, analytics, robotic process automation and its extension to intelligence process automation for processing unstructured data, e.g., used in chatbots, and virtual and augmented reality (Gärtner, 2020). ML is one of the best-known subdisciplines and is highly relevant for HRM (Charlwood and Guenole, 2022). At the heart of ML is the generation of knowledge from experience through the use of algorithms. Algorithms are step-by-step instructions for solving mathematically describable problems, and they recognize patterns in data using inputs. Thus, the "feeding" of high-quality learning data for algorithms, i.e., the so-called training of AI (Gärtner, 2020: 17; Vassilopoulou et al., 2022), is essential for good results, meaning the identification of patterns. The identified patterns may then be used to generate predictions (Gärtner, 2020: 22).

Expanding the RBV model on AI applications in HRM

Considering the possibilities in AI-driven HRM, one major aspect is HR professionals' principal understanding of AI and knowledge of how to apply it (Vassilopoulou et al., 2022). Chang et al. (2021) underline the importance of managers' attitudes regarding AI implementation in HRM. The development and mastery of AI-driven HRM in an organization can be understood as a typical "bundle of tangible and intangible assets" discussed in the resource-based view (RBV) for sustainable competitive advantages (Barney et al, 2001: 625) because the related complexity needs an organizational learning journey that is not easily imitable. Developing competitive advantages includes organizational resource picking and capability building. Capabilities include "the capacity to deploy" (Mikalef et al., 2018: 58) organizational resources in the most suitable way; these capabilities in part consist of routines of learned behaviours, which fit into the organizational context and contain tacit knowledge, e.g., of HR managers. In organizational learning journeys, a new capability built via AI requires acceptance of AI tools in experimental stages. Technology acceptance can be fostered by perceived usefulness and perceived ease of use (Davis et al., 1989) not only by HR managers but also by line managers and employees. Thus, taking the discussion of AI potential for positive and negative organizational outcomes into account, organizations must moderate competing and opposing requirements of management and employees when AI is implemented (Griering, 2021).

Building up an AI-driven HRM architecture includes a transformation process, leading to organizational learning instead of competencies bound to a single person. Therefore, these capabilities—and the information and knowledge that derives from them—can be controlled by the organization and may be difficult for competitors to imitate. Managers' decisions in uncertainty for or against AI application at an early stage depend on their attitude towards this technology. Taking into account the path dependency of managerial decisions, today's

the review did not consider (chapters of) books or newspaper articles. Publications written in English or German up to March 2020 were included.

Second, the keywords for the review were developed following Wirtky et al. (2016), who used six basic HRM functions based on the literature as the framework for their review of electronic human resource management (e-HRM). Their approach was augmented to include the following functional process steps: recruitment, development, deployment and performance, compensation and benefits and terminations. Additionally, the cross-functional categories workforce management, HR administration and HR controlling were used (Figure 1). The following keywords for the review were developed from these categories:

- HR/HRM, human resources/human resource management, internal staffing, recruiting, hiring, HR administration, HR marketing, HR controlling, compensation management, employer branding, talent management, employee training, employee workplace, workforce planning, lay-off.

Each HRM-specific keyword was combined with AI or artificial intelligence as a keyword to conduct this research. In addition, the following research combinations were considered:

- HR analytics and AI/artificial intelligence
- People analytics and AI/artificial intelligence
- Predictive analytics and HR(M)/human resources/human resource management
- Big Data and HR(M)/human resources/human resource management
- Machine learning and HR(M)/human resources/human resource management
- Artificial neural networks and HR(M)/human resources/human resource management

For journals published in Germany, the German equivalents of the keywords were used.

Additional HRM-IRFVVL practitioners journals (Germany)	Zfo - Zeitschrift für Führung + Organisation	1996-2020	3
	PERSONALquarterly	2011-2020	7
	Personalmagazin	2005-2020	18
	Personalwirtschaft	2007-2020	15
	Number of publications: 56		

Table 1: List of the reviewed journals with the Number of Publications (if any) (Source: Authors' creation)

The analysed articles included qualitative, quantitative, mixed methods, and conceptional approaches. Along with conceptional papers, the top-tier journal articles comprised four empirical studies and four literature reviews. The number of papers focussing on questions of AI technology and human perspectives is balanced here.

Results

Analysis along the HR Process

To further analyse the content of the publications, papers could be mapped onto one or more functional and cross-functional HRM fields (Table 2). It stands out that the academic discussion has not touched on some fields of HRM at all and mainly focuses on HRM in general or HR analytics. Interestingly, the candidates' or employee perspective is rarely discussed, while the HR professionals' competencies and potential skill gaps are discussed in five top-tier papers (e.g., Nankervis et al., 2019; King, 2016).

Artikel	academic	practicioners	total*
HRM (general)	8	23	31
Recruiting	3	18	21
Human Resource Development	1	10	11
Deployment & Performance	1	4	5
Compensation & Benefits	0	3	3
Lay-off/Attrition	1	3	4
Workforce Management	1	6	7
HR Administration	0	3	3
IT-Methodes/Tools	0	12	12
HR-Analystics	4	10	14

Table 2: Frequency of Articles in the Fields of HRM (Source: Authors' creation)

With 31 articles, the overarching category, human resource management, is the largest, and eight of the academic publications can be mapped onto this category. In 1993, the first publication took an approach to AI in HRM in the form of knowledge-based systems (Heinecke, 1993). Some of the papers from nonacademic journals (Kaiser and Kraus, 2014; Pesch, 2017b, 2019) as well as one academic paper (Bondarouk and Brewster, 2016) discuss the potential of AI in HRM in general; others present the current status quo in Germany (Endres and Kestel, 2017; Furkel, 2019; Seegmüller, 2019). Several papers in this category address limitations such as ethical boundaries (Straub, 2020), legal boundaries with a special focus on data protection (Blum and Kainer, 2019; Huff and Götz, 2020; Kaiser and Kraus, 2014), practical limitations concerning the readiness of companies, and the competencies of HR professionals (Biemann, 2019; Brüggemann and Schinnenburg, 2018). The academic publication by Angrave et al. (2016) also addresses barriers to the current adoption of AI in HRM and notes that HR lags behind other functional areas. With a special focus on Australia, the article by Nankervis et al. (2019) is one of the few academic empirical studies focussing on the preparedness of organizations and HRM professionals. As one of their results, they emphasize a lack of AI adoption in Australian organizations. Moreover, two studies published in practitioners' journals focus on AI acceptance, showing that, in general, decisions made by humans are preferred over decisions made by algorithms (Kaibel et al., 2019) and that, for higher acceptance, employees themselves need a basic understanding of algorithms (Grotenhermen et al., 2020).

With 21 papers, the recruitment category is the largest field covered during the HR process. Here, the few academic publications (4) indicate the increasing practical importance of AI in recruiting in comparison to the limited scientific interest represented in the literature. As early as 1998, Lackes and Mack researched how neural nets can be used to assess the suitability of applicants. Currently, publications describe several more opportunities, such as the use of chatbots, assistance with job advertisements and suitable recruiting channels, CV parsing and application analysis, active sourcing or CV matching (Laumer et al., 2019; Pesch, 2019; Petry, 2019; Petry and Jäger, 2018; Siemann, 2017).

In academic research, van den Broek et al. (2019) empirically show the potential ethical dilemmas of AI in recruitment. Pessach et al. (2020) present an analytical framework for recruiters to improve recruitment success rates, placement decisions and diversity through ML. Schmoll and Bader (2019) examine the influence of algorithmic social media screening for personality analysis on applicants' job pursuit intention.

Eleven articles could be mapped in the human resource development category. The only academic research focussing on this category is a case study on how HR analytics are used in HR development (King, 2016). In practitioners' journals, some articles address the field of learning analytics, e.g., to visualize learning progress, to predict dropouts and final results or to individualize learning processes through recommendation systems for employees (Pinkwart and Rüdian, 2020).

The HR analytics category includes 14 papers, while four papers in academic journals show outstanding scientific interest. In their critical paper on the use of analytics in HRM, Angrave et al. (2016) conclude that for "[…] bridging the analytics/HR gap […]" (Angrave et al., 2016: 8), support from academia for HR professionals is needed. Additionally, in her HRM study, King (2016) refers to this conclusion, as HR professionals often lack an understanding of analytical approaches, while analytical professionals often do not fully understand HR. Therefore, academia should provide support by transferring methods from other areas to HRM. On the other hand, publications from more practice-oriented journals discuss exemplary fields of HR analytics application in HRM (Pesch, 2019) and highlight its legal restrictions because of data protection, especially in the German context (Bertram and Pesch, 2017; Huff and Götz, 2020). They indicate that HRM as a whole will be much more data driven in the future; currently, however, the data quality in companies is still one of its main challenges (Bertram and Pesch, 2017).

Current Ambiguities in AI-driven HRM Regarding the RBV

The application of new technologies in HRM is often discussed as a double-edged sword in several ways (Figure 2; Bader and Kaiser, 2020: 37; Gärtner, 2020: 5). Consequently, managers' attitudes towards AI-driven HRM might be based more strongly on one or the other edge when taking implementation decisions to build up organizations' capabilities. In the literature review, four ambiguities regarding the potential to build up an organizations' (intangible) assets and therefore influencing these decisions were categorized inductively (see figure 2): (1) Human capabilities can be supported by AI and consequently grow, on the one hand, and be replaced by AI to increase efficiency, on the other hand (*job design ambiguity*). (2) Tailor-made information distribution can be extended because algorithms can increase transparency, but their mechanism can also lead to black boxes and reduce the users' understanding of data, decision-making, and predictions (*transparency ambiguity*). (3) Human performance can be optimized, and AI can pressurize employees by closely monitoring performance (*performance ambiguity*). (4) Furthermore, big data may be AI-driven to generate new results from structured and unstructured data. Acquiring data volumes with high velocity and variety great enough to fully apply AI apps may be difficult (Garcia-Arroyo and Osca, 2019) and can foster conflicts with human rights, data protection, and storage principles in HRM (*data ambiguity*). These ambiguities impact HRM, the employees at their workplace, and the whole firm with its inimitable, rare, valuable, and non-substitutable manner to develop sustainable competitive advantages.

The following section explains how these ambiguities in building up capabilities are derived from the literature. All four ambiguities in AI-driven HRM are debated at different intensities: Practitioners' journals frequently describe marketable HR applications that partly include anecdotal descriptions. Therefore, following an evidence-based approach, the analysis of the more rigorous discussions in the top-tier journals is used first and supplemented by the practitioners' journals.

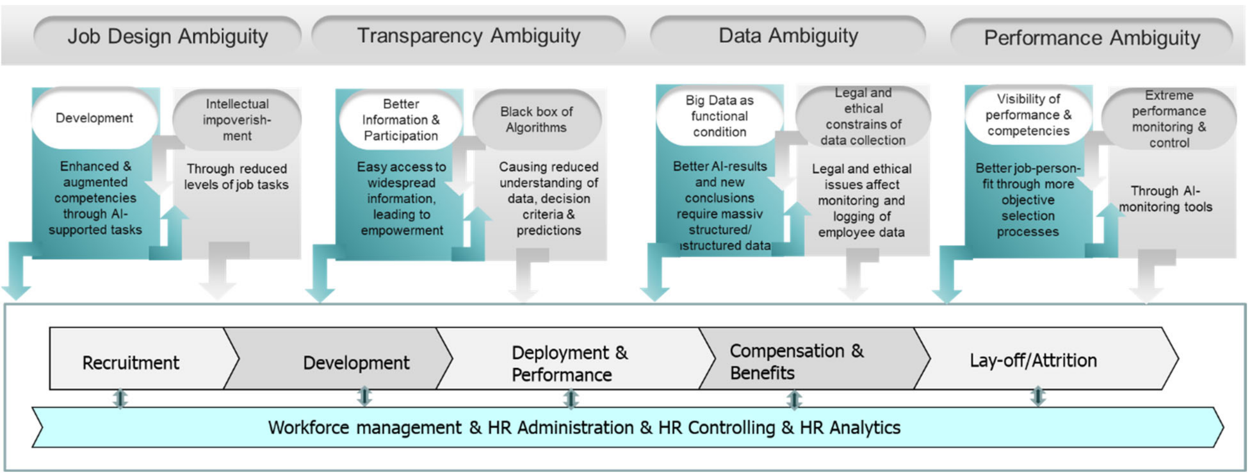

Figure 2: Capability-relevant Ambiguities in AI-driven HRM (Source: Authors' creation)

(1) Job Design Ambiguity: AI can describe and summarize high data volumes, predict trends and calculate scenarios, and propose optimized decisions (Pessach et al., 2020; Garcia-Arroya and Osca, 2019). Consequently, AI can take over tasks formerly performed by workers and destroy jobs or reduce task complexity, leading to intellectual impoverishment of work. Bondarouk and Brewster (2019) question whether new opportunities are created or work is destroyed. With their question, they focus on *job design ambiguity* faced by managers when assessing AI implementation. Picturing the selection process as an example, the final decision for or against a candidate can be made by AI based on a broad information base and the integration of diverse sources. Pessach et al. (2019) state the potential for recruiting decisions to be more successful when AI-augmented. One consequence of AI would be a different job design in recruiting because a (weak) AI application can perform analytical tasks instead of HR practitioners. This exemplifies why making recruitment decisions based on the AI proposal requires new, different skills. Nankervis et al. (2019) conclude that HR professionals require an upgrade in attitudes, capabilities, and competencies, while van den Broek et al. (2019) state how decision quality can be augmented by AI in the selection process. The relevance of this ambiguity is indicated by more than half of the scientific articles discussing it. Remarkably, regarding job design ambiguity, the focus of the articles is mostly on HR professionals' competencies, even though the strategically important decision to make use of this AI potential can be applied to any job in a company.

(2) Transparency Ambiguity: Pessach et al. (2019) indicate that using AI applications is meant to lead to better, e.g., fairer and nondiscriminatory, decisions. Moreover, Angrave et al. (2016) state AI's potential to capture strategic value formerly hidden in HR data. Information that was not extractable by workers becomes available with AI applications, leading to new capacities of knowledge management (Angrave et al., 2016). Furthermore, Biemann and Weckmüller (2016) argue that AI applications ensure a more comprehensive distribution of better

information, provide deep data insights and are said to improve the quality of delimited decisions. Overall, these effects may foster employee empowerment. The other side of the coin is that sensible workers' data potentially contain hidden biases and can be manipulated (Pessach et al., 2020; Garcia-Arroya and Osca, 2019). One possible consequence is decisions that are increasingly not transparent or verifiable by HR practitioners. Research also shows that applicants currently still prefer selection decisions by humans (Bundesverband der Personalmanager, 2019). Therefore, AI application might reduce employer attractiveness. These AI characteristics may either increase or decrease transparency and therefore lead to *transparency ambiguity.*

Transparency ambiguity is mentioned in the majority of articles and is characterized as a challenge in more recent articles (Pessach et al., 2020; Cheng and Hackett, 2019), while early articles see the potential for more transparency and knowledge generation because more data and criteria can be considered (Lackes and Mack, 1998; Heineke, 1993). Few articles discuss the perspective of applicants or employees and their perception of more transparency due to AI application in HRM (Schmoll and Bader, 2019).

Practitioners' assumed scepticism regarding transparency ambiguity is taken seriously by the authors. Thus, 34 of 44 papers in practitioners' journals explain dilemmas around transparency. Partly, this is done with the help of anecdotal stories of hidden bias in big data that lead to applicant or employee discrimination in pioneer companies such as Amazon or Google (Tambe et al., 2019).

(3) Data ambiguity: AI mostly requires great data volumes that may contain structured and unstructured information. As early as 1993, Heinecke discussed data 'ponds' as a challenge; today, data lakes are pertinent. They might include a long history of employee performance reviews as well as activities in diverse social media platforms and networks. In the analysed

articles, the hurdle to generating enough data of suitable quality in the current legal framework is paramount (Pessach et al., 2020; Cheng and Hackett, 2019; King, 2016). Consequently, the basic need for data velocity and variety is not easily met by HR data, especially in the EU with its EU's General Data Protection Regulation (GDPR) in place. Moreover, King (2016) underlines the 'garbage in – garbage out' rule, reflecting the importance of data quality for AI apps. Therefore, the third ambiguity when considering the potential to build up organizational assets derived from the literature analysis is *data ambiguity*.

(4) Performance Ambiguity: In general, AI is applied in HRM to optimize the work environment. This optimization goes hand in hand with the clear visibility and transparency of work processes and employee performance through AI applications. Bondaroak et al. (2016) state that formerly nonobservable aspects such as work stress become observable. Another current example is the measurement, storage, and analysis of employee time-off tasks as a (negative) performance indicator. Garcia-Arroya and Osca (2019) indicate that the associated optimization of human performance inevitably leads to a new, higher level of performance control. Simultaneously, the inclusion and protection of employee needs gain new importance and require compliance. Consequently, in the literature analysis, performance ambiguity surfaced as one category: companies' competitiveness increases because of a better visibility of employee performance and competencies on the one hand, while employees face extreme performance monitoring and control that may increase sick rates on the other hand.

To date, performance ambiguity is discussed least and with a rather critical voice, such as Angrave et al. (2016), who warn that there might be disadvantages for the monitored staff if HR professionals do not manage to build up new skills. When performance ambiguity is discussed in practitioners' journals, authors especially combine it with ethical issues and corporate codetermination (Straub, 2020; Strohmeyer, 2020).

Author	Year	Title	Journal	Purpose	key findings	job design ambiguity	transparency ambiguity	performance ambiguity	data ambiguity
Pessach, Dana; Singer, Gonen; Avrahami, Dan; Ben-Gal, Hila Chalutz; Shmueli, Erez; Ben-Gal, Irad	2020	Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming	Decision Support Systems	Propose a comprehensive analytics framework to support HR recruiters in (1) optimizing single job placements and (2) organizational recruitment processes	"A hybrid decision support system for HR professionals in the operations of recruitment and placement" (13) that can be implemented as an application for HR professionals without deeper technical or machine learning skills.	x	x		x
Cheng, Maggie M.; Hackett, Rick D.	2019	A critical review of algorithms in HRM: Definition, theory, and practice	Human Resource Management Review	Bridge the gap between academics and management practice	Research paper differ from traditional HRM research - theory modelled not developed; algorithms serve as heuristic (Def. developed in this paper)		x		x
Garcia-Arroyo, José; Osca, Amparo	2019	Big data contributions to human resource management: a systematic review	The International Journal of Human Resource Management	what does Bid Data mean for HRM (in terms of innovations and challenges) and what are academic inputs	General issues are discussed mainly from a resource-based view, specific applications and studies are scarce	x	x	x	x
Nankervis, Alan; Connell, Julia; Cameron, Roslyn; Montague, Alan; Prikshat, Verma	2019	'Are we there yet?' Australian HR professionals and the Fourth Industrial Revolution	Asia Pac J Hum Resour (Asia Pacific Journal of Human Resources)	Find out how well prepared Australian HR professionals are for 4IR	Upgrade in attitudes, capabilities, competencies needed, organ. In different developmental stages	x			
Schmoll, René; Bader, Verena	2019	Who or what screens which one of me? The differential effects of algorithmic social media screening on applicants' job pursuit intention	ICIS 2019 Proceedings	Clarify role of SM screening on job pursuit intention of candidates regarding private or business network and screening agent (human or AI)	Self-learning AI is perceived more negatively than human screening agents by candidates	x	x		
van den Broek, Elmira; Sergeeva, Anastasia; Huysman, Marleen	2019	Hiring Algorithms: An Ethnography of Fairness in Practice	ICIS 2019 Proceedings	Find out to what extend does AI shape what is consider ethical.	AI brings to the fore the role of fairness in organizational decision-making	x	x		
Jiang, Kaifeng; Messersmith, Jake	2018	On the shoulders of giants: a meta-review of strategic human resource management	The International Journal of Human Resource Management	Show current state of SHRM	Theoretical fields and empirical findings over three decades			x	x
Angrave, David; Charlwood, Andy; Kirkpatrick, Ian; Lawrence, Mark; Stuart, Mark	2016	HR and analytics: why HR is set to fail the big data challenge	Human Resource Management Journal	Show that HR needs to develop new skill to avoid HR Analytics being of disadvantage for employees and companies	So far developers/HR professionals don't understand each other, academia doesn't deliver enough to bridge the gap	x	x	x	x
Bondarouk, Tanya; Brewster, Chris	2016	Conceptualising the future of HRM and technology research	The International Journal of Human Resource Management	Regarding the interface between HRM and technology, to find out if it is contextually bound and what outcomes can stakeholders can expect.	E-HRM has to consider stakeholders, context & long-term effects	x	x	x	
King, Kylie Goodell	2016	Data Analytics in Human Resources	Human Resource Development Review	Show how analytics can be applied in HRM.	New skills needed to use current technology (bridge programming and HRM), important because of the huge part of company value in intangible HR, HR professionals should overcome skepticism and use analytics for improvements		x		x
Lackes, Richard; Mack, Dagmar	1998	Innovatives Personalmanagement? Möglichkeiten und Grenzen des Einsatzes Neuronaler Netze als Instrument zur Eignungsbeurteilung	German Journal of Human Resource Management	Explore in which way neuronal Networks can be used in performance management	Neuronal networks can be used in performance management to support HRM prof. decisions		x		
Heinecke, Albert	1993	Das Potential von Expertensystemen im Rahmen der Personalwirtschaft	German Journal of Human Resource Management	Narrow down where it is suitable to use AI in HRM	Acceptance as major hurdle, knowledge management as major advantage, no general usability prognosed		x		x

Table 3: Overview of the discussion of ambiguities in AI-driven HRM (authors' own creation)

Each scientific article includes at least one, and some consider all four ambiguities. Table 3 gives an overview of the analysed articles stating their purpose, main findings and addressed ambiguities.

Overall, practitioners' journals can be seen as a communication channel for AI-driven HRM systems that describes the four ambiguities as major characteristics of this innovative technology. In addition to the neural voices of scientists, there are many papers that aim to persuade companies to apply AI.

Discussion

Researchers state that HRM will be much more data driven in the future, opening the door for AI applications in HRM and the workplace. Overall, (a) the reviewed discussion on AI and HRM mostly takes place in journals with a more practice-oriented view. (b) Through March 2020, some areas of HRM along the process perspective have hardly been addressed. The main focus is on HRM in general and on recruiting, which mirrors the practical usage of weak AI in HRM. (c) Only a few of the available articles have an empirical research background. Thus, to date, journals covering the interface between theory and practice in Germany have more strongly focused on the topic of AI in HRM than academic journals.

Nevertheless, the number of academic publications is rapidly growing. Since few empirical studies were found, the scholarly discussion is dominated by conceptional papers and literature reviews, whereas practitioner journals explain and report practical possibilities for AI applications in HRM. Cheng and Hackett (2019) emphasize that there is a gap between practice and academia, which is underlined by this literature review. Moreover, the gap between technological maturity and practical application is indicated in the number of practitioner papers that describe application usefulness, while case studies of successful implications and application are scarce. The discussion of future possibilities or options prevails with detailed insights in case study companies. The field of AI-driven HRM in practitioners' journals is dominated by authors from start-ups – which are mostly technological experts – and scientists explaining the field, its promises and borders. Technological experts from start-ups promote their tools and aim to help practitioners understand the ambiguities discussed above. Scientists mainly use anecdotal examples from blue chip companies and AI pioneers—such as Google, Microsoft, or Amazon—to illustrate AI ambiguities. In general, their contribution to the practitioners' sphere does not include their own empirical findings.

Even though familiarity with the innovations of AI and its outcomes increases as more papers are published and read, its compatibility with the individual company context is hard to gather by practitioners as long as articles provide few case studies of successful implementation and application. Especially in Germany, with a high quota of small- and medium-sized companies, doubts regarding the advantages of AI applications resulting from data ambiguity may hinder its further diffusion.

The future of HRM professionals will likely consist of mixed decision-making with AI as support or even as a partner that enhances and augments human competencies (Neuburger and Fiedler, 2020), leading to job design ambiguity. This ambiguity partly derives from the diversity of AI tools and applications that range from services (leading to a higher level of automation, such as help-desk chatbots) to sophisticated solutions based on NLP and ML. Thus, AI can support human decisions, replace them, degrade humans to objects with reduced job task levels or enable innovative and new approaches through efficient collaboration (Gärtner, 2020: 6).

To put it in concrete terms, AI has the technological maturity to conduct job interviews and analyse and interpret job-seeker behaviour. For this reason, in the future, recruiters will no longer be needed to lead standardized interviews and may lose some of their interviewing skills. At the same time, they need the right competencies to develop new AI applications for interviews in cross-functional teams. The example shows job design ambiguity because the future recruiter needs a deeper understanding of selection tools, including their advantages, disadvantages, biases and side effects, while operative interview skills are no longer needed.

Research shows that there is scepticism regarding a broad application of AI systems in German HR departments (Bundesverband der Personalmanager, 2019) and that this scepticism derives from a limited acceptance of AI.

AI-enabled better information usage empowers employees on the one hand, while business risks increase because of the nontransparency of AI-supported decisions on the other hand. The lack of transparency of AI applications derived from their high levels of autonomy has been critically discussed (Straub, 2020). The results from ML algorithms that provide new patterns from massive data pools may serve as an example. Human cognition cannot reproduce such AI results, and the way in which an AI system "learned" and came to conclusions remains a black box. This lack of transparency can affect technology acceptance because it requires HR practitioners to learn methods of checking opaque AI results and understanding the basics of ML programming and algorithms. Therefore, the perceived ease of use is limited.

Data ambiguity surfaces when not only AI needs but also employee necessities are considered. More specifically, employee rights, e.g., regarding their personal data, right of privacy, requirements to minimize data and to delete it after a reasonable period of time, restrict possibilities for data storage and reduce fields of AI application. Especially the possibility to predict via AI can therefore be restricted (Tambe et al., 2019). Moreover, in small- and medium-sized companies, this ambiguity can prevent expedient AI usage in HRM.

Motivational, ethical, and fairness issues as well as data protection regulations gain importance and lead to complex decision-making processes regarding AI-augmented performance management. Therefore, HRM is required to balance optimizing and monitoring performance. Consequently, to gain acceptance, AI needs to be trustworthy not only for HR practitioners but also for line managers and employees with their representatives, e.g., worker boards and unions. Performance ambiguity requires refocusing the role of HR to achieve broad AI acceptance, especially considering the current discussion of trust, employee autonomy and self-regulation in flatter hierarchies.

AI applications as a potential source of competitive advantages

Resources being combined in an inimitable, rare, valuable, and nonsubstitutable manner to develop sustainable competitive advantages is at the core of the RBV and has been widely used to state the positive impacts of HRM systems and organizational performance (Barney et al., 2001; Jiang et al., 2017). Considering the ambiguities of AI-driven HRM stated above, these ambiguities need careful consideration in managerial decisions on AI-implementation regrading augmentation or automation of work.

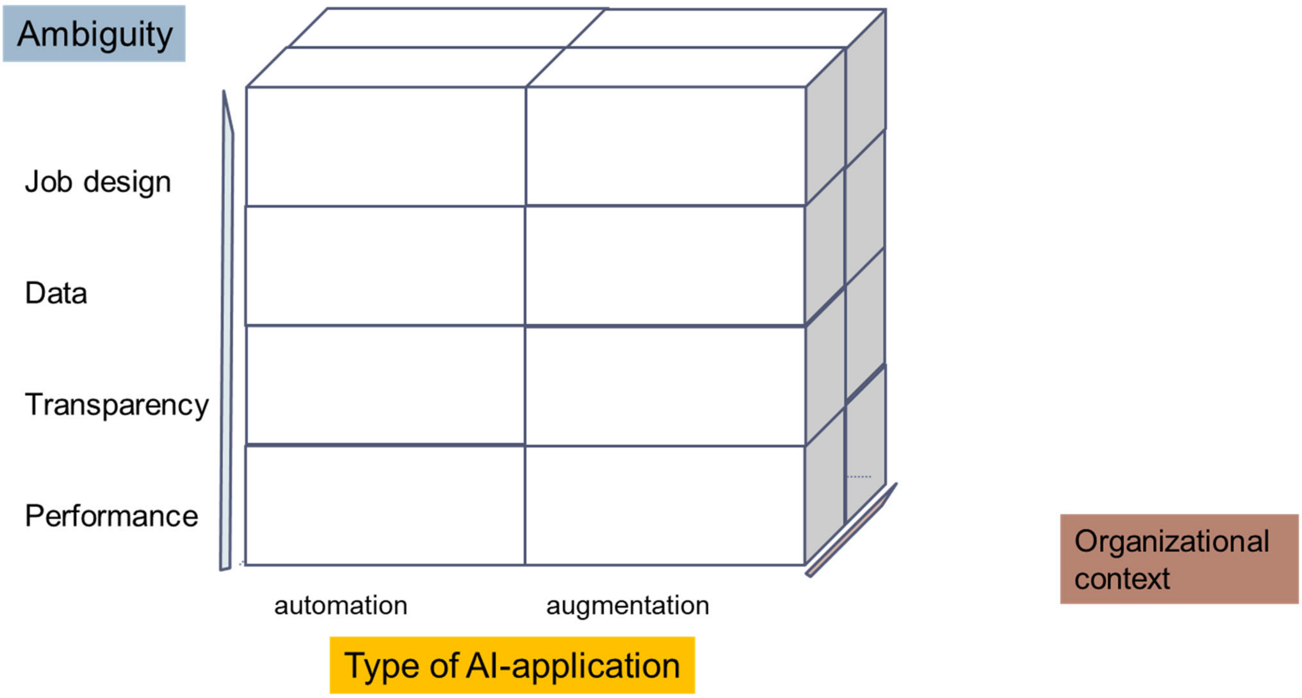

Table 3: Capability-building context-analysis cube (authors' own creation)

The characteristics and skills of the users, namely, HR specialists, line managers, applicants, and employees, at the current state can be seen as an impediment to AI implementation because the traditional competence set needs alteration and new adjustment (Angrave et al., 2016; King, 2016). Depending on the context of the AI application, ambiguities may lead to an increase or decrease in motivation, performance, and attrition of employees. An early decision for AI-driven HRM processes may lead to a new and distinct combination of competencies and resources in the company that is unique in its industry and prospectively leads to an inimitable first mover advantage. Figure 3 illustrates that when HR managers aiming at capability building make decisions for automation or augmentation via AI, the four ambiguities as well as the internal and external context may be considered.

In this section, the four ambiguities found in the literature review are considered to decide which way of deploying resources may lead to competitive advantage in the specific organizational context if HRM wants to use AI in capability building. Regarding job design, chat bots to provide employee assistance in standard situations may serve as an example for automation via AI. The number of personal inquiries that the bot is supposed to handle can be measured. With these metrics, the working hours saved in HRM can be calculated to decide if the investment in acquiring and adjusting the AI application generates a return on investment. At the same time, this automation gives HR staff the chance to tend to more complex inquires that require personal counselling to keep employee satisfaction on the aspired level. This AI application changes the job design in HRM to more demanding counselling tasks, e.g., regarding employee career decisions or work-life-balance issues. While the counselling itself can profit from more complex AI applications that augment the analytical skills of the HR staff, developing the necessary AI application would require more resources and eventually different competencies in HRM. Consequently, the number of staff, the counselling requirements in the professional field or industry, and the connected HR issues influence capability building via AI. Ultimately, workforce management can exemplify that job requirements change with AI-driven HR task automation and AI-augmented HR decisions. Finally, new (higher or impoverished) job requirements may lead to positive and negative effects on attracting new employees.

Regarding data ambiguity, the volume, variety, and velocity of the data provided can be used as an indicator of whether this organizational resource is valuable, inimitable, rare, and suitable for capability building via AI. The digitization of data, such as personnel files, can be identified as a decisive organizational context factor for both automation and augmentation via AI. However, using information previously inaccessible to build up data pools and analysing formerly non-observable employee characteristics and patterns may collide with employees' ethics and values and have negative performance effects instead of capability building.

Even though technological advantage may reduce the challenges of Black-Box-AIs (Charlwood and Guenole, 2021), due to the current gap between technological maturity and practical applications as well as context-specific deviating acceptance of AI applications, transparency ambiguity needs intense consideration when AI applications are implemented. Capability building in recruiting might be impossible as long as applicants and line managers mistrust AI-supported (automated or augmented) selection processes. Moreover, in several country contexts, recruiting decisions solely taken by AI conflict with the legal framework.

Considering performance ambiguity, employees with a good labour market position and a strong union might leave the company when feeling overly monitored in their performance. The destruction of core competences might in this case be higher than the gain through AI in performance management and control.

Consequently, when considering path dependency, a good timing and intense evaluation of the four ambiguities becomes a base metaphor for strategic decision-making regarding capability building via AI-driven HRM processes.

Implications

In summary, on the one hand, by applying AI along the entire HRM process chain, HR practitioners can increase their competencies using AI technologies, redefine their role in the company, and enhance their importance for company development; on the other hand, if HRM does not enact its role in 4IR, other organizational functions or external consultancies might take over and push HR from a pole position to a peripheral position in driving digital transformation.

The current academic discussion indicates gaps in most fields of HRM and takes a general and HR analytics perspective. In addition, few empirical studies have been published thus far. One reason for this limited number of studies may be the transdisciplinary approach needed to develop a watertight research design to study AI. Data scientists are required as much as HR scholars. However, transdisciplinary work is strenuous and not always successful (Tambe et al., 2019). This difficulty enhances the hurdle for mutual research ambitions. In the same way as in practice, HR professionals need data scientists and vice versa to further develop practical AI implementation, and HR scholars need to collaborate with data scientists to dare new research avenues in AI along the HR process model. If both sides narrow the skill gap, empirical AI research in the field of HRM may flourish.

When faced with the four ambiguities, HR practitioners need to broaden their methodological competencies with a basic understanding of software, programming, and algorithms as well as data and analytic techniques (Pesch, 2019) and the corresponding terminology. Moreover, a higher level of statistical skills is required to understand the consequences of data analytics and their predictions. At the same time, social competencies and networking skills become more important as they distinguish (weak) AI from humans. Regarding personal competencies, HR practitioners need to further develop their values, ethics, and professional identity, which have always been important in their profession. HR professionals need to develop their competencies if they want to adjust to the requirements of AI-driven HRM. It can be argued that a general AI mindset is the basic prerequisite and is mandatory for a fulfilling professional life in the future. This AI mindset includes a general openness and growth attitude that embraces mutual learning in cross-functional teams and continuously considers what happens beyond company boundaries (Farrow, 2020).

Conclusion and Research Agenda

This article contributes to the scholarly discussion by delineating the current research-practice-divide and the gap between technological maturity and practical application along the HRM process model. The demanding role of HRM in the digitalization process when building up organizational capabilities was outlined with a focus on HRM automation and augmentation with AI. On this basis, implications for HR experts in terms of learning and development requirements were concluded.

Considering the slightly better performance of AI in HRM compared to humans, on the one hand, and the continuing lack of acceptance of some AI applications, on the other hand (Biemann and Weckmüller, 2016), common sense and efforts to achieve efficiency will probably lead to increasing areas of AI application in the future. To date, substantial HR support regarding general digital transformation that companies may need for viable competitiveness is generally not provided. The future potential of AI in HRM appears vast (Gärtner, 2020), but at least, currently, not all HRM fields have been addressed by academia and practice. Increasing technological maturity will trigger further practical applications that might foster decent work in some contexts or endanger it in others. This literature review indicates that, to date, empirical studies are almost absent in pertinent scientific HR journals. Conceptional papers and the currently growing number of literature reviews such as the present article help to frame the field and make the scholarly discussion more robust. However, the high altitude of the scholarly discussion provides too little support for the development in companies to date. At the same time, to address the challenges posed by AI in HRM, HR practitioners can benefit from and need some support from academia to adopt future tools and techniques (Nankervis et al., 2019). Consequently, (a) the application and impacts of AI throughout all fields of the HRM process, (b) the four ambiguities contributed to the scholarly discussion with this paper, and (c) the impact of AI tools and applications on future skills of HR professionals, line managers and employees to build up inimitable, rare, valuable, and non-substitutable competitive advantages demand research avenues to close the academia-practice gap.

(a) To date, scientific research has focused on recruiting and HR analytics. In awareness of the technological maturity that provides AI solutions for all areas along the HR process, different research approaches are applicable. (1) The efficiency of AI in each HR process can be surveyed in qualitative research designs such as case studies comparing AI-driven HR systems with non-AI-driven HR systems. (2) To bridge this gap, the implementation of new applications can be scientifically supported, evaluated, and serve as a base for overdue theory development (Charlwood and Guenole, 2021). (3) Since app development is still mostly driven by technological experts, research on the perception of these applications by HR specialists can help to understand whether they see hurdles that might hinder AI diffusion in HRM. Considering the doubts about the preparedness of HRM and its professionals for AI-driven systems, research might also include studying the position of HRM regarding digital transformation in general and AI specifically. In researching this field, it would be important to measure HRM’s progress in comparison to other functional areas in companies. This would help to understand whether HRM actually supports others or is pushed and consequently influenced by other functional areas. The latter scenario includes the risk of being deskilled (Charlwood and Guenole, 2021) or losing influence on organizational development.

(b) If the broad application of AI is part of 4IR, one conclusion is that the impacts of technology on job design will lead to fundamental changes. As a major driver of this corporate digital transformation, HRM needs to be aware of this connection. Therefore, research is needed regarding job design, transparency, data, and performance ambiguities. Research designs that enable scientists to bring to the fore evidence about the balance between the positive and negative effects of each ambiguity would provide practitioners with a sound base for a decision for or against AI implementation.

(c) Furthermore, research might focus on exploring actual staff competencies in a longitudinal study. The outcomes might indicate a broad general qualification and, therefore, the employability of staff or a further polarization into low- and high-skill workers with very different labour market possibilities. With the help of AI, past, present, and future skills and competencies in job advertisements can be explored to forecast skill trends. Such trends may help individuals develop their careers in promising directions. In macro talent management, governments might use results to develop educational programmes for future generations.

Moreover, a quantitative survey of current AI applications in HRM studying companies of different sizes and different industries might help to analyse how well-prepared sectors are for an AI-interwoven future and, consequently, foresee the rise and decline of industries. Furthermore, the structural changes that will be experienced by the economy and by workers may become obvious, and the societal hardships that were experienced in other industrial revolutions might be prevented.

In conclusion, some limitations of this review need acknowledging. Only publications written in English and German up to March 2020 were included. Researching in an emerging and transdisciplinary field bears the risk that the search keywords did not capture all relevant articles. Thus, this review does not give an all-embracing picture. Moreover, the scope leads to a focus on Western industrialized countries with a special focus on Germany. Therefore, at this point, it is important to underline that the differences in country contexts were not used to identify country-specific factors (Vrontis et al., 2022) because the centre of this research was not on global HRM and the discussion on convergence or divergence in AI-augmented HRM. Finally, linking our contribution to the current scholarly discussion and considering the growing academic discussion on AI in HRM only within the last months, some additional articles (Basu et al., 2023; Budhwar et al., 2022; Charlwood and Guenole, 2021; Gélinas eta al., 2022; Vrontis et al., 2022) were included in the selected sections.

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