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A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective

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ABSTRACT

Artificial intelligence (AI) can bring both opportunities and challenges to human resource management (HRM). While scholars have been examining the impact of AI on workplace outcomes more closely over the past two decades, the literature falls short in providing a holistic scholarly review of this body of research. Such a review is needed in order to: (a) guide future research on the effects of AI on the workplace; and (b) help managers make proper use of AI technology to improve workplace and organizational outcomes.

This is the first systematic review to explore the relationship between artificial intelligence and workplace outcomes. Through an exhaustive systematic review and analysis of existing literature, we ultimately examine and cross-relate 60 papers, published in 30 leading international (AJG 3 and 4) journals over a period of 25 years (1995–2020). Our review researches the AI-workplace outcomes nexus by drawing on the major functions of human resource management and the process framework of 'antecedents, phenomenon, outcomes' at multiple levels of analysis. We review the sampled articles based on years of publication, theories, methods, and key themes across the 'antecedents, phenomenon, outcomes' framework. We provide useful directions for future research by embedding our discussion within HR literature, while we recommend topics drawing on alternative units of analysis and theories that draw on the individual, team, and institutional levels.

1. Introduction

The world is witnessing the start of a new industrial revolution, which is expected to have a profound impact on industries across the globe (Aazam, Zeadally, & Harras, 2018; Soh & Connolly, 2020; Xu, David, & Kim, 2018). This is a new era of bridging the physical with the digital world (Xu et al., 2018), strengthening human-machine interactions (Eberhard et al., 2017; Ferreira, Oliveira, Silva, & da Cunha Cavalcanti, 2020) and fostering automation through integrations between smart machines and intelligent software (Ibarra, Ganzarain, & Igartua, 2018).

Artificial intelligence (AI), which has its roots in philosophy, mathematics, computation, psychology, and neuroscience (Kumar & Thakur, 2012), is becoming the 'new normal' in both manufacturing and service industries (Ibarra et al., 2018; Müller, Buliga, & Voigt,

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2020). AI is aimed at making machines think like humans but surpassing the way humans work (Misselhorn, 2018). It is equipping machines with the capacity to autonomously gather and process information from their environment to make decisions, solve problems, and undertake other actions where human reasoning is needed (Von Krogh, 2018). AI is increasingly incorporated at work to improve task execution and performance (Lee, Davari, Singh, & Pandhare, 2018; Von Krogh, 2018), and it is associated with computer-based systems and applications involving, among other things, machine learning (Chui, Manyika, & Miremadi, 2015), soft computing (Kumar & Thakur, 2012), fuzzy logic systems (Karatop, Kubat, and Uygun, 2015), smart robots (Liu, Shi, & Liu, 2017), and virtual and augmented reality (Abou-Zahra, Brewer, & Cooper, 2018).

The human resource management function of an organization has an important role to play in effectively incorporating AI at work (Lawler & Elliot, 1996; Strohmeier & Piazza, 2015). Integrating the processes of human resource management along with artificial intelligence can generate additional benefits for an organization (Minbaeva, 2020), such as improved managerial decisions (Liboni, Cezarino, Jabbour, Oliveira, & Stefanelli, 2019), faster and more effective employee recruitment processes (Reilly, 2018), better learning at work (Hamilton & Sodeman, 2020), employee engagement (Tripathi, Ranjan, & Pandeya, 2012), and employee retention (Samarasinghe & Medis, 2020).

In recent years, a new literature strand has begun to emerge, which looks into the actual and potential workplace effects from the use of AI within organizations (e.g., Strohmeier & Piazza, 2015). Scholars have started to acknowledge the benefits and risks from the use of AI at work and the impact that smart computer-based technologies can have for people and organizations alike (Ibarra et al., 2018; Müller et al., 2020). Although research work on the impact of AI on workplace outcomes is emerging and increasingly growing, the literature is also becoming fragmented. The interface between AI and workplace outcomes has been examined, drawing on different levels of analysis, disciplines, and organizational functions, leading to inconsistent results on the actual impact of AI at work. Improving clarity on the way AI influences people, teams, organizations, and the broader institutional domain is essential for practitioners looking to incorporate smart machines and smart computerized systems at work. At the same time, mapping the impact of AI at work in a consistent way can set a roadmap for future studies at the nexus between AI and workplace outcomes. Drawing on the above needs and gaps, the present study is set to answer the following research questions: RQ1: What has been researched on the nexus between AI and workplace outcomes?; RQ2: How can this nexus be conceptualized to provide practical implications for HRM practitioners?; and RQ3: How can multi-level understandings be incorporated in this conceptualization to provide research directions for HRM scholars?

The contributions of this review are fourfold. First, to the best of our knowledge, this is the first comprehensive, systematic analysis that links artificial intelligence with human resource management and outcomes at work. Second, we provide an analysis and future research directions by drawing on distinct HR functions. This is important, as it provides understanding on the way different HRM functions (e.g., human resource planning, training & development, recruitment & selection, etc.) can and are likely to use AI, and what outcomes can be generated out of this utilization. This line of work has been largely overlooked in HRM literature, but it is important in helping diverse HR functions to understand how to best incorporate smart technologies to improve their performance. Third, the present paper draws on a thematic analysis and offers insights on a process framework, which consolidates existing findings at different stages of a process: i.e., antecedents, phenomenon, outcomes. Through our analysis, we illustrate that AI influences can be better understood alongside relevant drivers that trigger AI use at work, relevant phenomena that underpin AI implementation at work, and relevant outcomes that illustrate the positive or negative consequences from AI implementation. Fourth, our study contributes to the HRM literature by isolating the influences of AI on workplace outcomes across different levels of analysis. Previous work has examined the influences of AI at work but not explicitly in relation to diverse units of analysis.

The section that follows defines key concepts and boundaries of the present study. The methodology used in systematically reviewing and analyzing the literature is then explained. The findings section provides a descriptive section and an analytical one, which offers a theme-based analysis of the articles according to the 'antecedents-phenomenon-consequences' logic. The discussion section provides directions for future research. The paper concludes by highlighting the contributions and practical implications of the present work.

2. AI in the workplace: the role of HRM

The term 'artificial intelligence', or AI, is used to describe advanced computerized systems and machines that mimic the 'cognitive' functions of the human brain, such as learning, reasoning, and planning (Lu, Li, Chen, Kim, & Serikawa, 2018; Ludger, 2009). AI is a category of intelligent technologies and tools (Lu et al., 2018) involving, among other things, machine learning (Glikson & Woolley, 2020), deep learning models Samek, Wiegand, & Müller, 2018), genetic algorithms (Lee, 2018), the Internet of Things (Ghosh, Chakraborty, & Law, 2018), artificial neural networks (Elkatatny, Tariq, Mahmoud, Mohamed, & Abdulraheem, 2018), smart robots (Liu et al., 2017), and virtual and augmented reality applications (Abou-Zahra et al., 2018). The increasing number of applications that encompass artificial intelligence exist on a continuum of weak and strong AI; where weak AI applications function as if they are intelligent, strong AI machines have identical intelligence to human beings (Nilsson, 2005; Raj & Seamans, 2019). However, the latter type, which involves automatic processes and algorithms that can autonomously perform all tasks without human intervention, is still an area under development (Glikson & Woolley, 2020).

Artificial intelligence is the steppingstone of industry 4.0 (Hecklau, Galeitzke, Flachs, & Kohl, 2016). While the literature falls short of substantial empirical evidence on the impact of artificial intelligence on the workplace (Rossini, Costa, Tortorella, & Portioli-Staudacher, 2019), it is widely acknowledged that the use of intelligent machines will bring a radical change in the way organizations function and tasks are executed (Hecklau et al., 2016; Huang & Rust, 2018). For instance, AI is envisioned to optimize production and its associated processes (Weichert et al., 2019), through robot-based smart manufacturing lines (Mohammadi & Minaei, 2019), intelligent scheduling systems (Kaab, Sharifi, Mobli, Nabavi-Pelesaraei, & Chau, 2019; Li, Hou, Yu, Lu, & Yang, 2017), and advanced production simulation activities (Yuldoshev, Tursunov, & Qozoqov, 2018). Further, AI can be used to solve a variety of complex engineering and financial problems within organizations, through the use of artificial neural networks (ANNs) (Bashiri & Geranmayeh, 2011) and fuzzy systems (Bělohlávek, Dauben, & Klir, 2017; Peraza, Valdez, Garcia, Melin, & Castillo, 2016), which are most applicable when input parameters are imprecisely defined and there is a need to process several inputs at the same time (Das, Pattnaik, & Padhy, 2014). In another instance, intelligent technologies in the form of machine learning can help predict workplace hazards by providing actionable feedback based on existing injury data within industries (Kakhki, Freeman, & Mosher, 2019). Past work also highlights direct employee outcomes linked to the use of AI in the workplace (Hughes, Robert, Frady, & Arroyos, 2019; Meisels & Schaerf, 2003). For instance, artificial neural networks can be used to assess and predict employee motivation and job satisfaction (Azadeh, Rouzbahmana, & Saberi, 2009). Intelligent techniques drawing on genetic algorithms can help solve employee timetabling problems at work (Meisels & Schaerf, 2003) and facilitate effective work scheduling (Simeunović, Kamenko, Bugarski, Jovanović, & Lalić, 2017). Further, artificial intelligence through machine learning and data mining techniques can be used in employee turnover prediction (Saradhi & Palshikar, 2011; Zhao, Hryniewicki, Cheng, Fu, & Zhu, 2018).

Yet, a number of scholars view the adoption of AI by organizations with much skepticism (e.g., Acemoglu & Restrepo, 2020; Choi & Kang, 2019; Rampersad, 2020). They highlight the dangers associated with the use of intelligent technologies in the workplace, such as the reduction of the role of people in the production of goods and services (Choi & Kang, 2019), the reduction of labor in sectors where labor productivity has been low (Acemoglu & Restrepo, 2020), and labor replacement in middle-skill jobs where a high level of literacy, numeracy, and problem-solving ability is needed (David, 2015). Among the drawbacks of AI use within organizations are the negative attitudes and lack of trust that managers and employees maintain towards automation and intelligent technologies (Frey & Osborne, 2017; Raisch & Krakowski, 2021). Many people in organizations fear that AI will threaten their job (Makarius, Mukherjee, Fox, & Fox, 2020) and as a consequence, AI adoption can lead to increased employee stress, lower organizational commitment, and reduced productivity (Brougham & Haar, 2018). Subsequently, recent studies have called for a better understanding of the impact of AI on employees and the workplace in general to help organizations overcome some of the obstacles to AI adoption. The present study addresses this call by providing a systematic review on the impact of AI on workplace outcomes and by proposing directions for research and practice, which can enable a smoother organizational transition to industry 4.0. In achieving this, we frame our study within human resource management, which has been proposed as instrumental in facilitating the effective adoption of artificial intelligence machines and systems at work (Cheng & Hackett, 2019; Maduravoyal, 2018; Strohmeier & Piazza, 2015; Tambe, Cappelli, & Yakubovich, 2019). While HRM acts between employee and organizational outcomes (Su, Wang, & Chen, 2020), its role can be critical in understanding the ways organizations can facilitate the effective adoption of AI while mitigating risks and sustaining positive outcomes for employees.

Past work highlights that HRM can have a role in preparing employees to embrace and interact with intelligent technologies, which organizations need to adopt to sustain competitive advantages (DiClaudio, 2019). At the same time, studies illustrate that HRM, through its various functions, can make use of AI to produce benefits for employees and organizations (Sekhri & Cheema, 2019). For instance, the *recruitment and selection* function of HRM uses AI to process larger volumes of data via the internet (e.g., social media) in order to identify candidates that match certain job positions within organizations (Upadhyay & Khandelwal, 2018). The *training and development* function of HRM employs AI to suggest learning programs that are connected with work tasks and experience (Poquet & de Laat, 2021; Tripathi et al., 2012). AI learning programs can be used in order to foster employees' engagement, which can ultimately lead to an innovative way of learning among employees (Tripathi et al., 2012). Artificial intelligence can also have applicability in *performance management* by being used to reduce concerns regarding validity, reliability, and bias of controlling and managing performance (Schoorman, 1988). AI can be used for identifying patterns that lead to employees' departures and low performance, while through the appropriate feedback it can provide more accurate predictions (Samarasinghe & Medis, 2020).

Despite these developments, there is an absence of a unified framework that sets a role for HRM at the nexus between AI adoption and workplace outcomes. Current HRM literature does not provide an integrative understanding on the way diverse HR functions – such as 'human resource planning', 'recruitment and selection', 'training and development', 'compensation and rewards management', 'performance management and appraisal', 'employee and labor relations', and 'health, safety, and well-being' (Anakwe, 2002; Pucik, 1984) – can use AI technologies and their workplace outcomes, which are associated with this utilization. Since AI is likely to be employed differently within diverse HRM functions (Sekhri & Cheema, 2019), it is of practical importance to contextualize AI use within respective HR silos in order to understand workplace outcomes and risks associated with AI adoption. In the presence of this gap, and in answering our research questions, we provide a critical synthesis of AI and employee outcomes by considering the HR functions within which AI is utilized.

3. Methodology

Drawing on Tranfield, Denyer, and Smart (2003), the present study employs an evidence-informed systematic review methodology and synthesizes research in a systematic, thorough, and transparent manner. This approach is important in order to produce "a reliable knowledge stock" and develop "context-sensitive research" (Tranfield et al., 2003: p. 207). Our decision to employ a systematic review on this research topic was also based on the results of a scoping study in order to "access the size and relevance of literature and to delimit the subject area or topic" (Rajwani & Liedong, 2015; Tranfield et al., 2003, p. 214), to identify the current state of understanding of the subject area (Anderson, Allen, Peckham, & Goodwin, 2008), to comprehend the nature and extent of existing literature (Grant & Booth, 2009), and to determine the value of conducting a systematic literature review (Arksey & O'Malley, 2005; Rajwani & Liedong, 2015).

3.1. Selection of articles

As regards the scope of our review, we have focused on articles that are published in the leading journals in the business field, because high quality journals substantially contribute to academic development in the field (Luo & Zhang, 2016). Thus, we included journals that are considered to be premier publication outlets in business research. To achieve this, we followed examples of existing state-of-the-art systematic reviews (e.g., Atewologun, Kutzer, Doldor, Anderson, & Sealy, 2017; Franco-Santos & Otley, 2018), thereby limiting our review to studies in peer-reviewed journals ranked 3, 4 or 4* in the AJG (formerly ABS) 2018 journals. Added to this, this literature search restriction also ensures the quality of studies included in our review (Vrontis & Christofi, 2019; Franco-Santos & Otley, 2018; Atewologun et al., 2017). In line with previous systematic reviews in top journals in the field of management (e.g., Murnieks, Klotz, & Shepherd, 2020), we have complemented EBSCO Host Business Source Premier and Web of Science databases to identify and cross-check peer-reviewed articles. These databases provide a comprehensive portfolio of management, business, economics, and cognate journals (Kranzbühler, Kleijnen, Morgan, & Teerling, 2018; Stumbitz, Lewis, & Rouse, 2018).

Having selected our publication outlets, the next step was to define their nature and identify our final sample of articles. In line with our objectives and based on standard practice from state-of-the-art reviews in leading management journals (e.g., Gaur & Kumar, 2018; Okwir, Nudurupati, Ginieis, & Angelis, 2018; Pelz, 2019), we focused on full-length, peer-reviewed articles, but excluded letters, editorials, book reviews, conference proceedings, comments, and replies. We also decided to place no time restrictions because this is the first systematic review on the relationship between these two important research domains, thus we wanted to capture all possibly relevant studies from the first ever published article up to and including December 2020.

To conduct a comprehensive literature review on the impact of AI on the workplace, we carried out a broad search of artificial intelligence and workplace terms. Specifically, in line with Glikson and Woolley (2020), we used the following AI key words: AI, artificial intelligence, intelligent agent, human-agent interaction, robot–human interaction, and intelligent automation. We also used the following workplace terms: work, workplace, work environment, job, employee, organization, labor, personnel. Consequently, the following keyword formula was used: (AI OR 'artificial intelligence' OR 'intelligent agent' OR 'human-agent interaction' OR 'robot–human interaction' OR 'intelligent automation') AND (work OR workplace OR 'work environment' OR job OR employee OR organization OR labor OR personnel). We ran a keyword search on titles, abstracts, and keywords, in line with previous practice (Christofi, Vrontis, Thrassou, & Shams, 2019; De Keyser, Köcher, Alkire, Verbeeck, & Kandampully, 2019; Foss & Saebi, 2017). Drawing on past literature reviews of artificial intelligence (e.g., Glikson & Woolley, 2020), we narrowed down our search to articles published from 1995 onwards, to include published work that coincides with recent technological developments.

Following previous work (Atewologun et al., 2017; Franco-Santos & Otley, 2018), in order to keep our review manageable and synthesize state-of-the-art published studies, we limited our focus to the most impactful journals in the field of business and management. Therefore, we have limited our selection to include only articles published in 3, 4 or 4* journals in the AJG 2018. Initially using the EBSCO Host Business Source Premier database, and excluding duplicates, and non-academic, non-peer-reviewed, and non-English articles, we initially identified a list of 1337 unique articles published between 1995 and 2019. Articles were then screened to include only 3, 4 or 4* journal articles in the AJG 2018. This stage led to a reduction of selected articles to 211. Following Acar, Tarakci, and van Knippenberg (2019), we then analyzed the titles and abstracts of each article to determine whether the terms AI (or one of its associated techniques used in the keywords) and workplace outcomes were jointly considered. This led to a further reduction of the sample to 102. Finally, in line with Acar et al. (2019), we performed a full-text screening to examine each article in the refined sample for further relevance. In doing so, we screened out published work that did not explicitly address the relationship between AI and workplace outcomes. When screening articles based on the content (i.e., the links between AI and workplace outcomes), we followed the practice set by Glikson and Woolley (2020). Therefore, we excluded descriptions of algorithm/architecture (without reference to human or organizational outcomes). This round led to a sample of 56 articles. Further, considering that formal search techniques entering index terms or keywords in electronic databases may overlook important studies (Nielsen, Asmussen, & Weatherall, 2017), we also used a backward and forward snowballing procedure by searching the reference lists of the selected studies for additional works of relevance (e.g., Kranzbühler et al., 2018; Nielsen et al., 2017; Nofal, Nicolaou, Symeonidou, & Shane, 2018). This final round led to us identifying four more relevant articles. Our final sample was 60 articles, published between 1995 and 2020. Doubts regarding the inclusion or exclusion of a specific article in the final sample were resolved jointly by the authors of this study.

3.2. Coding

Given the purpose of our review and the need to deliver results based on a systematic analysis of the literature in a bias-free manner (Tranfield et al., 2003), we employed multi-step qualitative coding as our analytical method (Danese, Manfè, & Romano, 2018; Stumbitz et al., 2018; Gaur & Kumar, 2018). During the first step we documented the basic information of each article, including the publication outlet, year of publication, core topic investigated, type of paper (theoretical, empirical, or review), methodology applied (quantitative, qualitative, or mixed methods approach), industry context of empirical studies, and level of analysis (individual, team, organizational, societal/institutional, multilevel). We also documented the main theory(ies) that the selected studies used, including the geographic coverage of data and authors of the selected studies, as this analysis was useful when interpreting patterns of theory, content, and methodologies applied (Terjesen, Hessels, & Li, 2016). We also documented the practical implications from each article of the final sample, as well as the directions for further research, in order to identify the presence of recurring suggestions for further inquiry.

Second, in order to map the links between AI and workplace outcomes and identify the key themes at their intersection, we drew on a process logic, and particularly the 'antecedents-phenomenon-consequences' logic (e.g., Newman, Ucbasaran, Zhu, & Hirst, 2014;

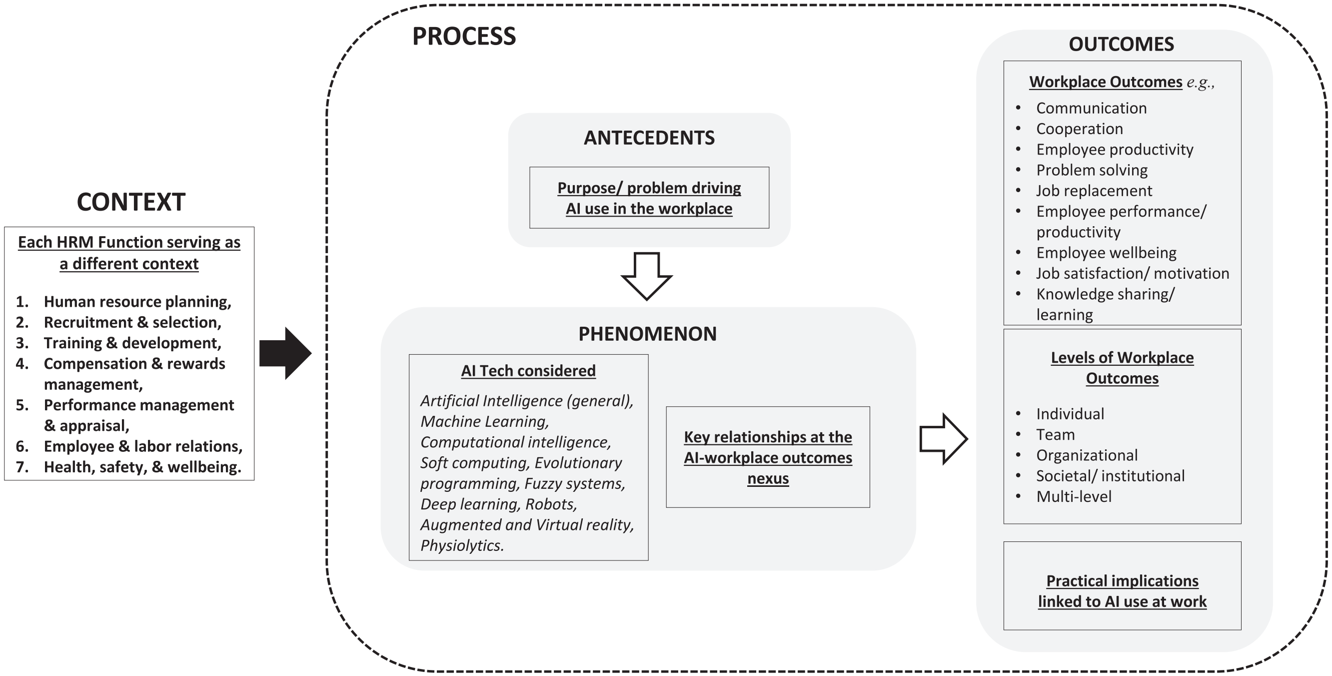

Fig. 1. Theme-guided 'antecedents-phenomenon-outcomes' framework.

Pisani, Kourula, Kolk, & Meijer, 2017; Pisani & Ricart, 2016). In line with Pisani et al. (2017), 'antecedents' refer to the main drivers of a phenomenon; 'phenomenon' refers to a practice, its implementation, and key features; and 'consequences' involve the main effect stemming from the implementation of the phenomenon. Considering this as a framework, and in order to understand the key themes and relationships to be included in this framework, a thematic mapping of the articles was done (Sarto & Veronesi, 2016). This process allowed us to distinguish the key themes, codes, and relationships under the 'antecedents-phenomenon-consequences' framework, as follows: (i) Antecedents: 'purpose/problem driving AI use at work' (i.e., what drives organizations to use artificial intelligence at work); (ii) Phenomenon: 'AI tech considered' (i.e., what technology in the AI family is considered); Themes associated with the

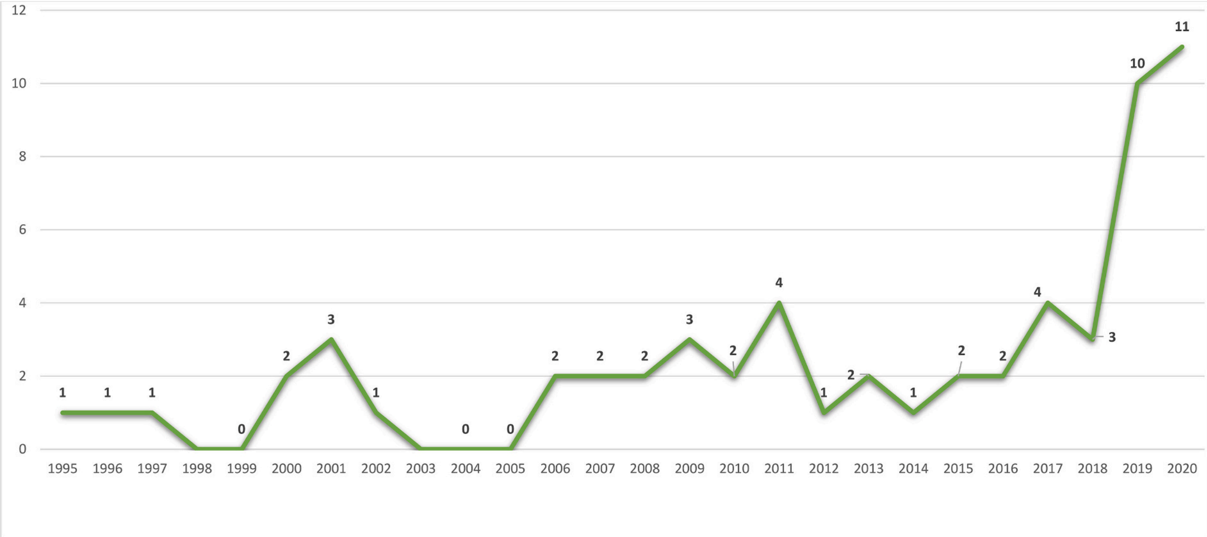

Fig. 2. Year of publication for selected studies.

Table 1
Article distribution across academic journals.

Journal	(AJG 2018) rank	Entries
American Economic Review	4*	2
British Journal of Management	4	2
California Management Review	3	4
Cambridge Journal of Regions, Economy and Society	3	3
Computers in industry	3	1
Decision Support Systems	3	6
Economic Inquiry	3	1
Harvard Business Review	3	1
Human Relations	4	1
Human Resource Management (USA)	4	1
IEEE Transactions on Engineering Management	3	1
IEEE Transactions on systems, man, and cybernetics	3	3
Industrial Marketing Management	3	1
Information and Organization	3	1
Information Systems Journal	3	1
Information Systems Research	4*	2
International Journal of Production Research	3	3
Journal of Business Ethics	3	2
Journal of Business Research	3	3
Journal of Economic Perspectives	4	3
Journal of Management	4*	1
Journal of Management Information Systems	4	6
Journal of Management Inquiry	3	1
Journal of Service Research	4	3
Journal of the American Society for Information Science	3	1
Journal of the operational research society	3	2
MIS Quarterly	4*	1
Organizational Research Methods	4	1
Research Policy	4*	1
Strategic Management Journal	4*	1
Total		60

* AJG, world's elite journals

Table 2
Years, theories, methods, and themes across levels of analysis.

	Total	Level of analysis				
		Individual	Team	Organizational (Firm)	Societal/ Institutional	Multi-level
1. Publication Years						
1995–2000	5	–	–	4	1	–
2001–2005	4	–	3	1	–	–
2006–2010	11	–	1	5	2	3
2011–2015	10	–	–	4	2	4
2016–2020	30	4	1	11	5	9
Total	60	4	5	25	10	16
2. Theory						
Affordance theory	1	1	–	–	–	–
Balance Theory	1	–	1	–	–	–
Behavioural Decision Theory	1	–	–	1	–	–
Contemporary work–life theory	1	–	–	–	1	–
Contingency theory	1	–	–	1	–	–
Critical theory	3	–	–	2	–	1
Design Theory	1	–	1	–	–	–
Dynamic Capabilities View	1	–	–	1	–	–
Economic growth theory	1	–	–	1	–	–
Human capital theory	2	–	–	1	1	–
Knowledge-based View	3	–	–	1	–	2
Moral theory	1	–	–	1	–	–
Network Theory	1	–	1	–	–	–
Organization Theory	1	–	–	1	–	–
Resource-based view	1	–	1	–	–	–
Role theory	1	1	–	–	–	–
Detection theory	1	–	–	1	–	–
Social network theory	1	–	–	–	1	–
Sociotechnical Systems theory	1	–	–	1	–	–
Structuration theory	1	–	–	1	–	–
System Theory	2	–	–	–	–	2
Theory of mind	2	–	–	–	–	2
No theory	31	2	1	12	7	9
Total	60	4	5	25	10	16
3. Method						
Qualitative Research	5	1	–	2	–	2
Quantitative Research	33	1	4	12	7	9
Mixed methods	1	–	–	1	–	–
Non-empirical (Literature Review/conceptual)	21	2	1	10	3	5
Total	60	4	5	25	10	16
4. Theme 1: Type of AI						
Artificial Intelligence (in general)	17	1	2	10	–	4
Robots/Chatbots	8	1	–	2	1	4
Machine learning/deep learning	22	1	2	9	6	4
Computational intelligence/evolutionary programming	4	–	–	1	1	2
Virtual/Augmented reality	1	–	–	1	–	–
Soft computing/fuzzy systems	7	–	1	2	2	2
Physiolytics (wearable tech)	1	1	–	–	–	–
Total	60	4	5	25	10	16
5. Theme 2: workplace outcomes						
Effective/ineffective communication interactions, & relations at work	5	–	–	1	3	1
Cooperation at work	3	–	2	–	–	1
Decision-making and problem-solving	3	–	1	2	–	–
Employee motivation/satisfaction	1	–	–	–	–	1
Employee productivity/performance/effective task execution	8	1	–	4	2	1
Well-being and work-life balance	3	2	–	–	1	–
Employment/employee replacement/job loss	9	1	1	4	–	3
Innovation capabilities	1	–	–	–	–	1
Improved task execution	6	–	–	2	3	1
Learning, knowledge sharing/transfer	19	–	1	12	–	6
Work-related injuries	2	–	–	–	1	1
Total	60	4	5	25	10	16
6. Theme 3: HR practice						
Human Resource Planning	9	–	2	2	4	1

(*continued on next page*)

Table 2 (*continued*)

	Total	Level of analysis				
		Individual	Team	Organizational (Firm)	Societal/ Institutional	Multi-level
Recruitment & Selection	4	–	1	1	–	2
Training & Development	25	1	1	15	–	8
Performance Management/Appraisal	7	1	1	3	1	1
Health, safety, & wellbeing	10	2	–	3	3	2
Employee and labor relations	5	–	–	1	2	2
Total	60	4	5	25	10	16

implementation of AI in the workplace (i.e., in the form of relationships and research questions at the AI-workplace outcomes nexus); and (iii) Outcomes: workplace outcomes (what specific job/workplace outcomes are associated with the use of AI at work) and practical implications (what are the managerial and HR implications from the use of AI at work). In addition to the above, 'HRM function' was identified as a guiding or overarching theme to contextualize the 'antecedents-phenomenon-consequences' process. Each HR function provides a diverse context with specific technical aspects (Wright & Snell, 1991). Examining, therefore, the 'antecedents-phenomenon-consequences' process with respect to each HR function differently can provide a more holistic understanding of the links between AI and workplace outcomes.

This enabled us to impose a systematic framework in the presentation and analysis of the sampled studies (see Appendix A for the full list of selected studies). Under each theme, we included respective codes to allow a meaningful categorization of the information in the final set of articles (see Fig. 1 for details).

4. Descriptive analysis at the intersection between artificial intelligence and workplace outcomes

4.1. Years of publication and article distribution across academic journals

As Fig. 2 illustrates, the AI-workplace outcomes nexus is relatively under-researched, with only a handful of studies being published in top-tier journals every year. It is just in the past 2 years (2019 and 2020) that a rise of interest in artificial intelligence as a research topic has been observed within the field of business and management. Indeed, one in three articles sampled were published in the last 2 years.

Table 1 provides information on the academic journals in which the 60 sampled articles were published. As shown in this table, the sampled articles have been published in a diverse set of academic journals from various fields of study. The highest concentration of articles (six articles) is found in the Journals of *Management Information Systems* and *Decision Support Systems*, followed by *California Management Review* (four articles). A closer look at the findings illustrates that the majority of articles were published in journals in the fields of information management (19 articles) and ethics/CSR and management (14 articles). Yet, just one article was published in the field of HRM, and this was in the *Human Resource Management Journal* (USA). Further, a portion of the sampled articles (10 in total) have been published in premium AJG 4* journal venues, including *Information Systems Research, American Economic Review, Research Policy*, *Strategic Management Journal,* and *Journal of Management.*

4.2. Years, theories, methods, and themes across levels of analysis

Table 2 provides a closer look at the years, theories, methods, and themes across different levels of analysis for the 60 sampled articles. The analysis illustrates that the individual (four articles) and team (five articles) levels of analysis are largely understudied. Studies adopting the individual as a unit have recently been published, between 2016 and 2020. The institutional level was adopted by 17% (10 articles) of the sample, with half of the studies drawing on this unit, which has been published recently, between 2016 and 2019. Multilevel analysis occurred in 27% of the sample, which has again become popular in recent years (after 2006). The unit of analysis that is dominant in the AI-workplace outcomes nexus is the organizational level. Our analysis illustrates that 42% of the sample (25 articles) drew on the organizational level to study the influences exerted by AI in the workplace. Table 2 illustrates that the organization has become increasingly popular as a level of analysis since 2006.

Further, the analysis indicates that about half (31 articles) of the sampled articles do not draw on a theoretical lens, and this pattern is stronger among studies drawing on an organizational level of analysis (12 articles). Regarding the sampled articles that draw on a theory, our analysis indicates a large diversity on the theories being considered, such as moral theory (two articles), systems theory (two articles), critical theory (two articles), theory of mind (two articles), and numerous other theories that have been used by a single study. Our analysis indicates that the sampled articles draw on theories from various disciplines, including psychology, sociology, organization studies, economics, management, and engineering.

In terms of research methods, 63% of the sampled articles are empirical (39 articles), which draw primarily on quantitative research designs (33 articles), including experiments, survey, and panel analysis. Our findings indicate that the individual and team units of analysis have received relatively little consideration by quantitative scholars examining AI in the workplace. From the sampled articles, only five studies are qualitative, and these draw on case studies and in-depth interviews. The mixed-methods approach is also relatively under- researched, with only one study drawing on this approach.

Table 3
AI in the Workplace: HR Functions across the 'Antecedents, Phenomenon, Outcomes' logic

HR Practice	REPRESENTATIVE REFERENCES	ANTECEDENTS		PHENOMENON	OUTCOMES	
		Purpose/ problem addressed	AI Tech considered	Central RQs/ Relationships examined	Workplace Outcomes associated with AI	Practical Implications from the use of AI at work
Human Resource Planning	Atack et al. 2019; Huang et al. 2019; Robinson et al., 2020; Warner, 2008; Ye et al. 2001; Yoon and Guimaraes, 1995	• Improving task design; • Improving task execution; • Workers' skills-tasks matching; • Minimization of labor expenses; • Enhancement of distant team member interactions and collaboration.	• AI in general; • Soft computing; • Evolutionary programming; • Robots; • Machine Learning; • Deep Learning.	• How collaborative activities in virtual settings facilitate effective task execution?; • How can kaizen case-base philosophy and visual management (VM) integration facilitate continuous improvement? • What is the impact of AI tech advances on job creation? • What is the impact of AI on tasks and work? • How may human capital complement Machine Learning (ML) in the workplace? • How can AI socialization in the workplace help alleviate negative expectations of employees towards AI and amplify the human-AI collaboration? • How can robots assist humans in previously manual manufacturing processes? • What are the organizational performance gains from human-smart machines collaboration? • Will AI affect how and where we work? • How can AI support organizational team formation?	• Improved task execution; • Improvement of employees' cooperation; • Employee productivity; • Employee performance; • Employee replacement/ job loss.	• AI can be used to continually assess task assignments to ensure matching with employee needs. • AI can lead to improved awareness among team members and enhance team performance. • Managers must adapt the nature of jobs to compensate for the use of AI. • Company roles should be redesigned to enable employee-machine interactions. • Intelligent systems need to be incorporated into employees' workload so that they become more acceptable to employees. • Upgrade human capital by increasing the number of employees with postgraduate education to reap the benefits of AI.
Training & Development	Kane, 2017; Lengnick-Hall and Lengnick-Hall, 2006; Metcalf et al. 2019; Murata and Katayama, 2010; Wang et al. 2009; Zhu et al. 1997	• Maximizing learning and knowledge sharing within organizations; • Improving decision-making skills; • Need to improve virtual collaboration in teams; • Improve organizational capabilities; • Optimize interactions & learning between people and machines.	• AI in general; • Machine Learning; • Deep Learning; • Computational Intelligence; • Evolutionary programming.	• What is the impact of job automation on middle-level skill employee replacement? • What is the relationship between AI-related technologies and human skills? • What are the effects of AI-infused social media on knowledge sharing within organizations? • Can AI enhance humans' cognitive skills and creativity, and free workers from low-level tasks? • When, how, and to what extent should service be provided by AI, and how will the use of AI reshape service provision and the job skills	• Learning; • Skill development; • Knowledge sharing between employees; • Innovation capabilities; • Decision-making capabilities; • Problem-solving capabilities	• AI can be employed to develop people's decision-making and technical expertise in the workplace. • Corporations need to be organized around different types of skills rather than around rigid job titles. • Virtual settings for collaboration can lead to the creation or discovery of tacit knowledge. • Human workers must place emphasis on the development of empathetic and emotional dimensions of their work, which are difficult to be replicated by AI. • Redesign of company roles to enable employee-machine

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Table 3 (*continued*)

HR Practice	REPRESENTATIVE REFERENCES	ANTECEDENTS		PHENOMENON	OUTCOMES	
		Purpose/ problem addressed	AI Tech considered	Central RQs/ Relationships examined	Workplace Outcomes associated with AI	Practical Implications from the use of AI at work
				required by employees? • How can AI amplify the intelligence of organizational teams?		interactions and knowledge sharing at work.
Health, safety, & wellbeing	Acemoglu and Restrepo, 2020; Chalfin et al. 2016; Erickson et al. 2010; Lazzerini and Pistolesi, 2017; Mettler and Wulf, 2019; Munoko et al. 2020	• Minimizing risk factors associated with work-related musculoskeletal disorders; • Improvement of employee safety and satisfaction at work; • Addressing work–family conflict/ imbalance; • Addressing employees' psychological and social needs; • Advancements in the workplace may lead to increased distractions and injuries; • Psychological and sociological aspects of manufacturing systems are poorly supported	• Computational Intelligence; • Soft computing; • Machine Learning; • Fuzzy Systems; • Physiolytics (wearable tech); • Robots; • Automation; • Evolutionary programming	• Can adoption of AI enhance both safety and convenience in the workplace? • What do employees think about using physiolytics at the workplace? • What affordances and constraints do they associate with physiolytics in their occupational environment? • Do employees share the same technoenthusiasm as organizations wanting to implement AI technologies? • What are the potential ethical issues at work as organizations adopt AI technologies? • How intelligent environments can adapt and learn employees' habits to provide them a better everyday life? • What factors influence the work–family interface and its associated outcomes for workers in organizations adopting AI?	• Injuries at work; • Employee motivation; • Enhanced/ diminished interactions & relations at work; • Job satisfaction; • Employee task execution; • Enhanced/ diminished employee wellbeing; • Psychological harms from wage reduction.	• Using genetic algorithms to obtain rotation schedules can help prevent work-related musculoskeletal disorders at work.. • Fuzzy systems can be useful on analyzing and predict workers' behavior in the presence of risk. • AI can improve managerial awareness of safety issues in work environments characterized by diverse levels of hazardousness. • Employees need to be adequately trained to minimize individual hazards from the use of intelligent technologies at work.
Performance Management/ Appraisal	Aztiria et al., 2013; Barkhi, 2002; Lawler and Elliot, 1996; Markus, 2001; Schepers and Van der Borgh, 2020; Somers and Casal, 2009	• Optimization of job performance; • Limited understanding on the way Knowledge Management Systems (KMS) use can improve individual and firm performance; • Improvement of employees' extra-role behavior; • Raising employee productivity	• AI in general • Deep learning • Soft computing • Machine Learning • Evolutionary programming • Robots	• In what ways can machine learning help to improve worker productivity? • Are we investing in the "right" type of AI, the kind with the greatest potential for raising employee productivity? • How AI use can improve individual employee performance? • How does organizational support based on new service technologies (e.g., robots, artificial intelligence) • relate to employees' extra-role behavior? • How can intelligent Knowledge Management Systems (KMS) improve employee and organizational performance?	• Employee performance; • Employee productivity; • Problem solving effectiveness; • Employee Motivation; • Job Satisfaction	•Smart (intelligent) environments in the workplace can learn via AI to react to the actions and needs of users, and to provide personalized and adapted services which can improve their productivity. • Managers should opt for the use of AI KMS to improve employee performance, but considering at the same time the temporal factor and the role of experience.

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Table 3 (*continued*)

HR Practice	REPRESENTATIVE REFERENCES	ANTECEDENTS		PHENOMENON	OUTCOMES	
		Purpose/ problem addressed	AI Tech considered	Central RQs/ Relationships examined	Workplace Outcomes associated with AI	Practical Implications from the use of AI at work
Employee and labor relations	Chua et al. 2019; Fjermestad, 2000; • Liu and Lai, 2011; Sack, 2000; Von Groddeck, 2011	• Drawing value from large-scale written conversations at work. • Solving communication problems within larger organizations • Improvement of interactions at work • Helping organizations deal with uncertainty and complexity.	• AI in general • Machine Learning • Evolutionary programming • Computational intelligence	• To what extent is Artificial Intelligence (AI) fundamentally reshaping employee relations at work? • How can intelligent group support systems improve interactions within organizations? • How can AI be used at work to extract value from very large-scale email conversations at work? • How can automated data mining accurately infer meaning from social media text to enhance communication?	• Effective/ ineffective communication at work • Cooperation/ cooperative work • Relationship-building/ • interpersonal relations	Use of machine learning to select employees and predict worker productivity can enhance social gains at work. • AI-based metanalysis of communication text can improve communication within larger organizations. • Use of machine learning and data mining to extract semantic lexical chains from single social media accounts (e.g. customers) to enhance communication. • Incorporation of AI into Group Support Systems can lead to improved interactions.
Recruitment & Selection	Leigh et al. 2020; Malinowski et al., 2008; Pessach et al., 2020; Tambe et al. 2019	• Making employee selection more effective. • Mastering the digital coevolution of talent and technology. • Facilitation of organizational transformation. • Seeking innovative experts to lead the use of AI/machine learning (ML) in organizations.	AI in general • Machine Learning • Soft computing • Evolutionary programming • Robots	• How AI can be used in HR recruitment procedures? • How can the selection of individuals for organizations and teams be supported by AI? • What is the relationship between robots and employment at the industry-region level?	• Employee performance • Employee productivity • Employment/ unemployment	• AI infused decision support systems can aid the automated pre-selection of candidates that fit existing teams and future team members. • Organizations should nurture internal AI/ML capabilities to effectively mitigate risks, identify and nurture talent, and facilitate organizational sustainability. • Machine Learning can facilitate effectively and efficiently the HR functions of recruitment and selection.

'Theme 1' in Table 2 contains techniques and applications under the AI family, which have been categorized by drawing on coding analysis (see 'Methods'). Among the sample articles, the majority consider machine learning (20 articles) and AI in general (17 articles), largely at the organizational level of analysis (nine and ten articles, respectively). Other AI techniques and applications that have been leveraged include robots (eight articles), soft computing (seven articles), computational intelligence (four articles), virtual and augmented reality (one article), and physiolytics (one article). The analysis reveals serious gaps in applying or considering AI techniques and applications at levels beyond the organization, particularly the individual and team levels. For instance, it makes sense to consider the individual or the team as a unit of analysis, since individually or collectively, people are likely to be affected by the use or interaction of intelligent technologies in the workplace (Ferreira et al., 2020).

'Theme 2' categorizes the workplace outcomes, which have been researched by the sampled articles in conjunction with AI use. While the findings reveal a diverse set of outcomes, the most popular topic (under outcomes) is 'learning, training, and knowledge sharing' (19 articles). This is not surprising, given that managers in organizations largely conceive AI as a valuable resource for establishing learning and knowledge management infrastructures within an organization (Salge & Vera, 2013). What is surprising is the fact that studies focusing on this topic have ignored units of analysis such as the individual and the team, despite learning being human-centric within the workplace. Further, our findings illustrate that topics less investigated include, among others, employee productivity and performance, well-being and work-life balance, employee motivation and satisfaction, work-related injuries, communication, cooperation, and problem solving at work.

Finally, 'Theme 3' categorizes articles in terms of the HR function,[1] through which we can observe the AI-workplace outcome nexus. Almost half of the sampled articles (25 articles) fall under training and development. Again, it is surprising that studies under this function have ignored the individual and the team as levels of analysis, given that the primary resources in HR planning and learning endeavours are the individual employees, who are often called to work and learn in organizational teams (Markus, 2001). Other HR functions such as human resource planning (10 articles), health, safety, and well-being (10 articles), recruitment and selection (14 articles), performance management and appraisal (seven articles), and employee and labor relations (five articles) are HR dimensions that have received less consideration. The compensation and rewards management function has not been represented by any of the sampled articles.

5. Framing the 'antecedents-phenomenon-outcomes' process within HR functions

This subsection includes a theme-based analysis of the articles, according to the 'antecedents-phenomenon-consequences' logic, and considers this logic separately for each of the six respective HR functions. Framing the 'antecedents-phenomenon-consequences' process within each HR function separately is important for engaging in a meaningful discussion of the findings in the sampled articles, given that each HR function operates within idiosyncratic technical aspects (Wright & Snell, 1991). A discussion, as such, can then provide a more holistic understanding of the way HR makes use of AI in the workplace, the drivers behind this use, and the outcomes that are pursued from AI utilization. Within each HR function (which acts as an overarching theme), we present the findings alongside the 'antecedents-phenomenon-consequences' logic, as summarized in Table 3. The sub-themes included under the 'antecedents', 'phenomenon', and 'outcomes' themes have emerged as part of the coding process and are described in the methods section and Fig. 1.

5.1. *Human resource planning*

A portion (10 out of 60) of the sampled articles cluster under the 'human resource planning' function. While studies complementing human resource planning aspects with AI have been limited, these have drawn on the team (two), organizational (two), institutional (two), and multiple (one) levels of analysis. Phenomena associated with the use of AI in the workplace, particularly at the individual level, are absent (See Table 2).

Antecedents being addressed by studies at the nexus between human resource planning and AI include the improvement of task design (Huang, Rust, & Maksimovic, 2019), the minimization of labor expenses (Atack, Margo, & Rhode, 2019), workers' skills-tasks matching and job execution, (Yoon & Guimaraes, 1995), plus the enhancement of distant team member interactions and collaboration (Ye, Boies, Huang, & Tsotsos, 2001). Studies at this nexus have addressed phenomena drawing on AI techniques and applications, such as machine learning (Li, Xu, Zhang, & Lau, 2014), deep learning (Huang et al., 2019), soft computing (Yoon & Guimaraes, 1995), evolutionary programming (Warner, 2008), and robots (Atack et al., 2019) (see Table 3).

As exhibited in Table 3, the sampled studies at the HR planning-AI nexus have examined *phenomena associated with the use of AI* to redesign employee tasks in an efficient and effective manner (Huang et al., 2019), to complement human with AI capital in the workplace (Agrawal, Gans, & Goldfarb, 2019), to improve human-machine collaboration (Ye et al., 2001), to understand how robots can assist humans in previously manual manufacturing processes (Atack et al., 2019), and to facilitate effective team formation (Ye et al., 2001). The cluster of articles (under the human resource planning function) has looked at *workplace outcomes* associated with AI use, including effective task execution (Yoon & Guimaraes, 1995), employee cooperation (Ye et al., 2001), employee performance (Huang et al., 2019), employee replacement/job loss (Robinson, Orsingher, Alkire, De Keyser, Giebelhausen, Papamichail, & Temerak, 2020), and AI-employee synergies (Agrawal et al., 2019). Further, the sampled articles convey essential practical implications from the use of AI at work (see Table 3). For instance, Agrawal et al. (2019) argue that it is important to upgrade human capital to reap the

[1] The HR function is not explicitly addressed in the sampled articles. Instead, the functions have been deemed important during the thematic mapping process and the articles have been categorized retrospectively in an inductive fashion.

benefits of AI technologies, and this can be done by increasing the number of employees with postgraduate education.

5.2. Training and development

The sampled articles under the 'training and development' function are 25 in total (42% of the articles in this review). The majority of the articles under this category have focused on the organizational level (15 articles) and multilevel (eight), while levels of analysis such as the individual (one), team (one), and institutional (0) are underrepresented.

According to Table 3, phenomena at the nexus between AI and 'training and development' have been triggered by *antecedents* such as the maximization of learning and knowledge sharing within organizations (Davenport, Harris, De Long, & Jacobson, 2001; Wang, Gwebu, Shanker, & Troutt, 2009; Zhu, Prietula, & Hsu, 1997), the improvement of decision making skills in the workplace (Metcalf, Askay, & Rosenberg, 2019), the need to improve virtual collaboration in teams (Kane, 2017; Paul, 2006), the improvement of organizational capabilities (Criscuolo et al., 2007), and the optimization of interactions and learning between people and machines (Wilson & Daugherty, 2018). Studies at this nexus have considered a range of AI techniques and applications, including machine learning (Wilson & Daugherty, 2018; Zhu, Baesens, Backiel, & vanden Broucke, S. K., 2018), evolutionary computation (Nan, 2011), robots/automation (Choi & Kang, 2019), and virtual and augmented reality (Kane, 2017).

As exhibited in Table 3, the sampled studies under 'training and development' have examined AI-linked *phenomena,* such as the way AI (such as AI used in machine learning and data mining) can facilitate organizational learning (Zhu et al., 1997), knowledge sharing (Wang et al., 2009), employee knowledge accumulation (Metcalf et al., 2019), and the impact of automation on middle-level employee skills (David, 2015). For instance, Metcalf et al. (2019) looked into the way machine learning can amplify the knowledge of people within organizations to make more effective predictions and decisions. Criscuolo et al. (2007) and Paul (2006), in turn, have looked into the influence of AI (such as neural networks, soft computing, and machine learning) on the way firms can enhance their capabilities through intelligent systems to develop the skills and knowledge of their employees.

The cluster of articles drawing on 'training and development', has looked at *workplace outcomes* associated with AI use, such as learning and skill development (Davenport et al., 2001; Nan, 2011; Salge & Vera, 2013), knowledge sharing/transfer (Haug, Hvam, & Mortensen, 2012; Murata & Katayama, 2010; Wang et al., 2009), the development of problem solving (Zhu et al., 1997), and decision-making capabilities (Metcalf et al., 2019). Further, the sampled articles under 'training and development' convey essential practical implications from the use of AI at work, as indicated in Table 3. For instance, Haug et al. (2012), Lengnick-Hall and Lengnick-Hall (2006), and Metcalf et al. (2019) suggest that AI incorporation at work can help develop people's decision-making and problem-solving expertise. Further, Wilson and Daugherty (2018) suggest a redesign of company roles to enable employee-machine interactions and knowledge sharing at work.

5.3. Health, safety, and well-being

The sampled articles (10 articles) at the nexus between AI and 'health, safety, and well-being' have focused on the individual (two articles), organizational (three articles), institutional (three articles), and multi-level (two articles) of analysis. The team has not been considered as an analytical unit.

The sample of articles under this category examined phenomena triggered by *antecedents,* such as the minimization of risk factors associated with work-related musculoskeletal disorders (Aouadni & Rebai, 2017; Asensio-Cuesta, Diego-Mas, Cremades-Oliver, & González-Cruz, 2012), the improvement of employee safety and satisfaction at work (Mutlu & Özgörmüş, 2012), the need to address work–family balance (Erickson, Martinengo, & Hill, 2010), the need to consider employees' psychological and social needs when designing work (Chalfin et al., 2016; Elkosantini & Gien, 2009; Lazzerini & Pistolesi, 2017), and the problem associated with the implementation of technological advancements in the workplace, which may often lead to increased distractions and injuries (Yi, Su, Liu, & Chen, 2017).

Studies on this function have considered a range of AI techniques, including genetic algorithms (Aouadni & Rebai, 2017; Asensio-Cuesta et al., 2012), fuzzy systems (Lazzerini & Pistolesi, 2017; Mutlu & Özgörmüş, 2012), machine learning (Chalfin et al., 2016; Yi et al., 2017), soft computing (Erickson et al., 2010), and computational intelligence (Elkosantini & Gien, 2009). Additionally, varied *phenomena* have been examined under this category, including the way AI adoption can enhance the safety of employees and reduce the risk of work-related injuries (Yi et al., 2017), factors influencing the work–family interface and its associated outcomes for workers in organizations dealing with artificial intelligence (Erickson et al., 2010), the potential ethical issues consequences for employees within organizations adopting AI technologies (Munoko, Brown-Liburd, & Vasarhelyi, 2020), the way intelligent environments can adapt to learn employees' habits in order to provide them with a better everyday life (Yi et al., 2017), employees' views about using physiolytics in the workplace, and the affordances and constraints associated with physiolytics at work (Mettler & Wulf, 2019).

The cluster of articles under 'health, safety, and well-being' has looked at *workplace outcomes* associated with AI, such as work-related injuries/hazards (Lazzerini & Pistolesi, 2017; Yi et al., 2017), job satisfaction (Aouadni & Rebai, 2017; Asensio-Cuesta et al., 2012), employee well-being (Chalfin et al., 2016; Erickson et al., 2010), and employee motivation and enhanced social gains (Elkosantini & Gien, 2009; Yi et al., 2017). Lastly, this article cluster provides a number of important practical implications. For instance, Chalfin et al. (2016) argue that the consideration of machine learning to select employees and predict worker productivity can enhance social gains at work. Further, Acemoglu and Restrepo (2020) suggest that a consortium of ethicists, technologists, and policymakers should consider the development of the appropriate accreditation to accompany AI adoption within organizations in order to safeguard the rights of employees.

5.4. Performance management and appraisal

The sampled articles (seven articles) that fall under the 'performance management and appraisal' category have investigated AI-linked phenomena at the individual (one article), team (one article), organizational (three articles), institutional (one article), and multi-level (one article) strata of analysis. *Antecedents* being considered under this category include the optimization of job performance (Lawler & Elliot, 1996; Somers & Casal, 2009), the limited understanding on the way KMS (knowledge management systems) can improve individual and firm performance (Ko & Dennis, 2011), the improvement of employees' extra-role behavior (Schepers & Van der Borgh, 2020), and the need to raise employee productivity (Somers & Casal, 2009). The 'performance management and appraisal' cluster examined various AI techniques in association with workplace outcomes, including deep learning and soft computing (Barkhi, 2002; Markus, 2001), artificial neural networks and genetic algorithms (Lawler & Elliot, 1996; Somers & Casal, 2009), and machine learning (Aztiria, Augusto, Basagoiti, Izaguirre, & Cook, 2013).

Additionally, a number of phenomena have been examined by the articles under this theme, including the way artificial neural networks can help model the job satisfaction—job performance relationship (Somers & Casal, 2009), the way intelligent knowledge management systems can improve employee and organizational performance (Ko & Dennis, 2011), and the way organizational support based on new AI service technologies (e.g., robots) can relate to employees' extra-role behavior (Schepers & Van der Borgh, 2020). Barkhi (2002), in turn, examined the way AI-driven problem-modeling tools can support team decisions that cross boundaries of functional areas within the business to improve performance. In terms of outcomes, this cluster of articles focused on job performance (Barkhi, 2002; Somers & Casal, 2009), problem-solving effectiveness (Lawler & Elliot, 1996; Markus, 2001), job satisfaction (Somers & Casal, 2009), and employee engagement (Ko & Dennis, 2011).

Lastly, this cluster provides practical implications at the nexus between AI and 'performance management and appraisal'. For instance, Ko and Dennis (2011) call for managers to use AI knowledge management systems to monitor and improve employee performance, but considering at the same time the temporal factor and the role of experience. Aztiria et al. (2013), in turn, advise that smart (intelligent) environments in the workplace can learn via AI to provide personalized and adapted services that can improve user productivity.

5.5. Employee and labor relations

The sampled articles under the 'employee and labor relations' function number five in total, focusing on the organizational (one article), institutional (two articles), and multi-level (two articles) strata of analysis. The individual and team levels have not been considered as units of analysis. Articles under this function have examined phenomena triggered by antecedents, such as the presence of communication obstacles and problems at work (Sack, 2000), the improvement of interactions between employees (Jerry Fjermestad, 2000), drawing value from large-scale written conversations at work (Sack, 2000), and helping organizations deal with uncertainty and complexity (Von Groddeck, 2011). The 'employee and labor relations' cluster examined a diverse set of AI techniques, including computational intelligence (Jerry Fjermestad, 2000), machine learning (Chua, Storey, Li, & Kaul, 2019; Sack, 2000), and genetic algorithms (Liu & Lai, 2011).

Further, this article cluster looked at a number of phenomena at the nexus between AI and 'employee and labor relations'. Jerry Fjermestad (2000) looked into how intelligent group support systems can improve interactions within organizations, while Slack (2000) examined the way AI can be used at work to extract value from very large-scale email conversations at work. Chua et al. (2019), in turn, examined the way automated data mining can accurately infer meaning from social media text to enhance communication. In terms of outcomes, effective communication and interactions at work (Chua et al., 2019; Jerry Fjermestad, 2000), as well as cooperation/cooperative work (Liu & Lai, 2011; Sack, 2000), emerged as core workplace outcomes. Lastly, this cluster provides practical implications linked to 'employee and labor relations'. For instance, Sack (2000) argues for the use of machine learning and data mining to extract semantic lexical chains from single social media accounts (e.g., customers) to enhance communication. Jerry Fjermestad (2000) suggests that the incorporation of AI into group support systems can lead to improved interactions.

5.6. Recruitment and selection

This is the smallest set of articles ($N = 4$), focusing on the team (one article), organizational (one article), and multi-level (2 articles) units of analysis. The individual and the institutional have not been considered as analytical units. Antecedents that have been considered under this theme include the need to make employee selection more effective (Malinowski, Weitzel, & Keim, 2008), the management of digital coevolution of talent and technology (Pessach et al., 2020), the facilitation of organizational transformation (Tambe et al., 2019), and the identification of innovative experts to lead the use of AI/ML in organizations (Pessach et al., 2020). Under 'recruitment and selection', the sampled articles examined AI techniques and applications such as soft computing (Malinowski et al., 2008), machine learning (Pessach et al., 2020; Tambe et al., 2019), smart robots (Leigh, Kraft, & Lee, 2020), and big data algorithms (Malinowski et al., 2008).

Phenomena being considered at the nexus between AI and 'recruitment and selection' include the way the recruitment and selection of individuals for organizations and teams can be supported by AI (Malinowski et al., 2008) and the nature of the relationship between robots and employment at the industry-region level (Leigh et al., 2020). In terms of workplace outcomes, employee performance, productivity (Malinowski et al., 2008; Pessach et al., 2020), and employment (Leigh et al., 2020) have been considered. Lastly, this article cluster provides practical implications for the use of AI in recruitment and selection. For instance, Malinowski et al. (2008) suggest that AI-infused decision support systems can aid the automated pre-selection of candidates that fit existing teams and

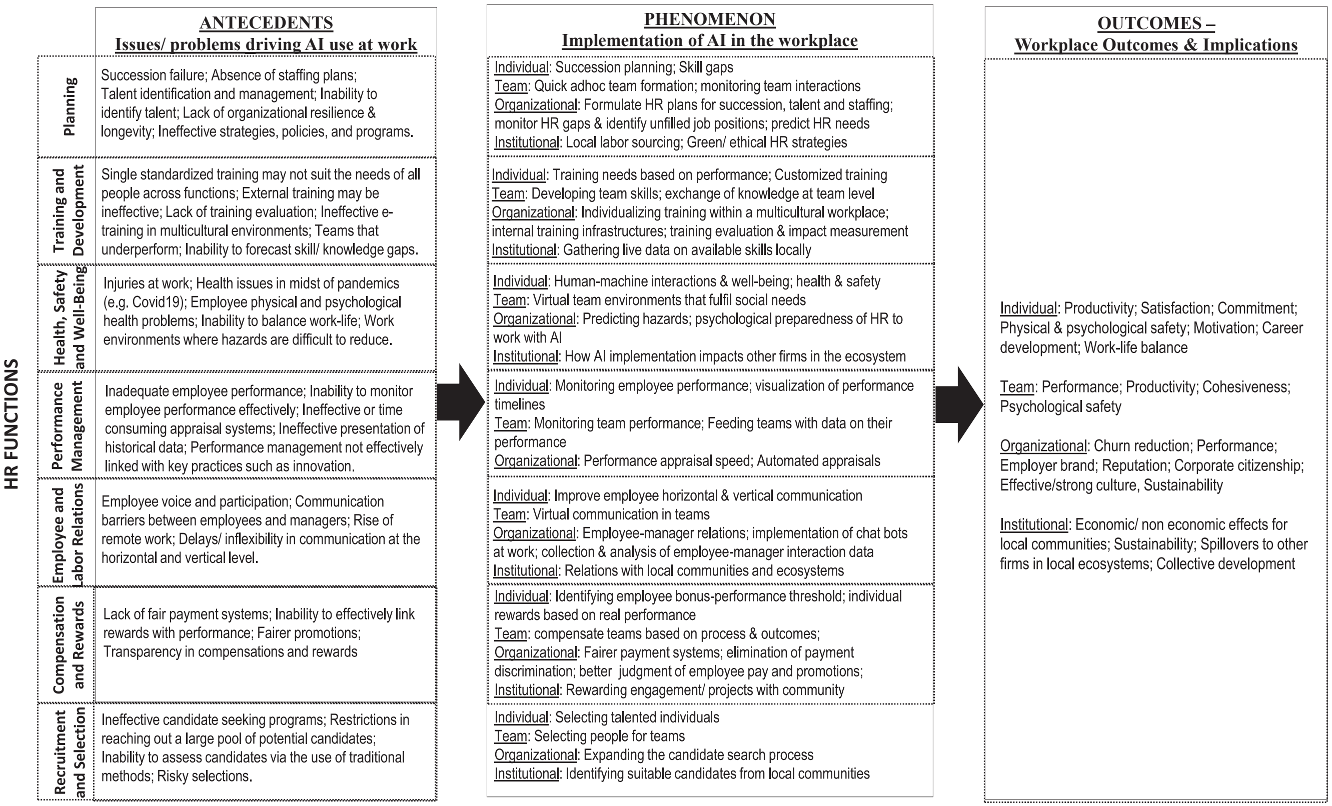

Fig. 3. Suggestions for future research.

future team members.Pessach et al. (2020), in turn, recommends that organizations should nurture internal AI/ML capabilities to effectively mitigate risks, recruit talent, and facilitate organizational sustainability.

6. Future research directions

In this section we provide useful future research directions along two main pillars: i) HR-related topics and future research work; ii) theories and levels of analysis in future work.

6.1. HR-related topics and future research work

The analysis in the previous sections illustrates that the nexus between AI, HRM, and workplace outcomes has been largely examined in relation to training and development within organizations. Yet, most studies under this function have focused on phenomena and outcomes linked to knowledge sharing (Metcalf et al., 2019; Wang et al., 2009). Further, research phenomena implicating artificial intelligence and other HR functions, such as 'recruitment and selection', 'employee and labor relations', 'performance management', 'health, safety, and well-being', and 'human resource planning' have not been sufficiently featured in the literature. Driven by the above limitations and the scarcity of evidence that exists on the nexus between AI, HRM, and workplace outcomes, we draw on the directions set by the sampled articles ($N = 60$) and recent HRM literature to provide hot research topics for future studies. Fig. 3 lists research directions across the seven HRM functions – 'human resource planning', 'recruitment and selection', 'training and development', 'compensation and rewards', 'performance management and appraisal', 'employee and labor relations', and 'health, safety, and well-being' – and across the antecedents, phenomenon, outcomes continuum.

The inability to properly manage talent (Garavan, Carbery, Rock, Nilsson, & Ellström, 2012; Van den Brink, Fruytier, & Thunnissen, 2013), the ineffectiveness in identifying suitable successors for leadership positions, the lack of staffing plans (Chakraborty & Biswas, 2019), and task assignment inefficiencies (Atack et al., 2019) are major problems that fall under the umbrella of human resource planning and are important for organizational survival. These issues could ideally serve as drivers for the exploration of the way AI could be applicable in formulating more effective talent management strategies, succession plans, staffing plans, and in organizing employee tasks more effectively across the organization. For instance, evolutionary computation and data mining can be employed to explore large databases or social media (Chen, Vorvoreanu, & Madhavan, 2014), where potential talented individuals can be found. Machine learning could be useful in re-analyzing and recognizing patterns from data (Mohri, Rostamizadeh, & Talwalkar, 2018) collected from existing decision support systems within organizations to help organizations improve their strategic (HR) planning processes. In turn, Atack et al. (2019) highlight that future research could look into the way artificial intelligence can reduce the cost of reassigning and reorganizing tasks, allowing for more efficient dynamic optimization of organizational functions in response to changing conditions.

The 'training and development' function of HRM is currently facing complexities regarding the approach to be used in training organizational personnel (de Brito Neto, Smith, & Pedersen, 2014; Dierdorff, Surface, & Brown, 2010). This is a facet of this HR function, which has not been reflected in the sampled articles of the present review. Frequently, organizations opt for the less costly delivery of a single standardized training program or the services of external organizations to deliver training (Dierdorff et al., 2010). Customizing training to fit the needs of diverse people within a range of functions is often the least desired option, since it takes longer to implement and is more costly than the other options (de Brito Neto et al., 2014; Dierdorff et al., 2010). At the same time, training programs that are delivered within organizations are not properly followed up and evaluated (Phillips & Phillips, 2016). Similar challenges apply for the increasingly used e-learning platforms by organizations, which are ineffective to address needs within an increasingly diverse multicultural work environment (de Brito Neto et al., 2014). These are important drivers, which can trigger research work on the integration of AI technologies in making physical and online training more effective, through proper customization to fit the needs of a diverse workforce and through proper evaluation that allows impact measurement. For instance, machine learning can be effective in customizing training within organizations, based on the profile, historical performance, appraisal data, and skill gaps of each employee. An additional area of future work under 'training and development' involves the use of machine learning and big data algorithms to identify the optimal bundle of skills, which can be capitalized on to facilitate the development of individuals, teams, and the organization as a whole (Akhtar, Frynas, Mellahi, & Ullah, 2019; Criscuolo, Salter, & Sheehan, 2007).

The 'health, safety, and well-being' function is increasingly concerned with employee well-being at work, which is particularly linked to the psychology of employees at work and their attempts to establish a proper work-life balance (Erickson et al., 2010; Fotiadis, Abdulrahman, & Spyridou, 2019; Zheng, Kashi, Fan, Molineux, & Ee, 2016). At the same time, there is an ever-increasing consideration of the protection of the health of employees in the midst of worsening global health conditions linked to the Covid-19 pandemic (Boeri, Caiumi, & Paccagnella, 2020). These drivers call for the consideration of the use of artificial intelligence to provide effective solutions. For instance, machine learning is good for automating repetitive tasks within organizations (Prado, Michałek, & Cheein, 2018). By avoiding 'grunt' work, employees can pursue more enjoyable and meaningful tasks within organizations, which add positively to their well-being at work. Additionally, as suggested by Lazzerini and Pistolesi (2017), fuzzy systems and models drawing on genetic algorithms can a set a path for future work looking into the optimization of safety at work. Such AI techniques can be useful in predicting workers' behavior when in the presence of risks and assigning high-risk tasks to employees who are more likely to exert caution in the presence of hazardous conditions.

Concerning performance management, major contemporaneous issues that could be addressed by AI include the need to link individual performance management within organizations with cognitive and emotional aspects of the individual at work, such as creativity (Audenaert, Decramer, George, Verschuere, & Van Waeyenberg, 2019) and perceived well-being (Franco-Santos & Doherty, 2017). AI, in the form of deep learning systems, if properly fed with behavioural and performance data on employees at work, can help managers make better judgments on the way performance management can be linked with individual psychological dimensions at work. Another hot issue is problems associated with the delay, ineffectiveness, and transparency of appraisal systems within organizations, which can be solved through the use of artificial intelligent techniques such as fuzzy set logics and machine learning (Ojokoh et al., 2020). AI can progressively allow a shift to efficient automated appraisal systems, with high analytical and predictive abilities, which can enable completion of appraisals in a timely manner and with high transparency.

Classical issues such as employee voice and participation are diachronically important concerns of the 'employee and labor relations' function (Budd, Gollan, & Wilkinson, 2010). More modern issues involve the rise of remote work, which makes face to face contact between managers and employees increasingly scarce in some workplaces (Miele & Tirabeni, 2020). By eliminating exhaustive repetitive tasks through machine learning, deep learning, and other AI techniques, organizations can give space to employees to voice their ideas and participate in key practices such as the creation of new products within organizations. In this way, AI can lead to more fulfilling employee experiences at work and can bring employees and managers closer to one another. Moreover, Von Groddeck (2011) calls for future work on communication within organizations under fuzzy circumstances. Computational intelligence and soft computing techniques can be further researched for their applicability in evaluating value activities within organizations and in optimizing value-driven communication between employees across departments.

Hot topics in recruitment and selection are effective candidate seeking and selection of high performing and productive individuals (Breaugh, 2013; Carlson, Connerley, MECHAM, & R. L., 2002). AI, in the form of big data algorithms, can be instrumental in allowing organizations to expand their searching processes and breadth (Alasadi & Bhaya, 2017; Rahim et al., 2018). Big data algorithms can also be important in the selection process, since they can go beyond the searching of documents supplied by candidates to examine their social media and other online profiles to help management make judgments of a candidate's fit with organizational culture and teamwork practices. It remains to be seen, however, how AI can lead to more effective recruitment and selection programmes within organizations. Additionally, Leigh et al. (2020) touch on the topic of robot diffusion and use within organizations, linking this practice with the selection of employees who feature the characteristics and demographics to achieve it.

Compensation and rewards are an area that was not discussed in the previous section, since the sampled studies have not touched on issues concerning compensation. There are contemporaneous issues with which this function currently deals, such as the lack of fair payment systems (Hancock, Schaninger, & Rahilly, 2018) and the inability to effectively link rewards with performance (Kuvaas, Buch, & Dysvik, 2020). AI, through evolutionary programming, neural networks, and other techniques that use optimization models, can be effective in terms of creating metrics and models that can enable organizations to reward employee efforts in a more effective and fairer manner.

6.2. Levels of analysis and theoretical perspectives in future work

Our analysis reveals that most studies have drawn on the organizational level to examine AI phenomena linked to the workplace. Evidently, there is a need to undertake future research that draws on the individual, the team, the institution, and even the inter-organizational level of analysis. At the same time, future studies can benefit from the consideration of multiple levels of analysis, given that AI, when applied within the workplace, can influence not only outcomes at the level of the organization, but can also lead to changes at the individual and the team levels. Fig. 3 provides a number of topics, which can help future studies delve beyond the organizational level when examining the AI-workplace outcomes nexus.

For instance, at the individual level, future studies could consider phenomena such as the way AI, through machine learning and deep learning, can help customize individual employee training or the way genetic algorithms can help managers optimize individual employee compensations and bonuses that match real individual employee performance at work. Further, at the team level, future work could look into the way AI, through data mining and machine learning, can automatically search and form teams on an ad hoc basis within larger organizations, based on the project that is pursued. Another example is the use of AI such as machine learning and deep learning in virtual team environments, and the way this technology can help replicate social environments that fulfil the needs of interacting team members. Finally, at the institutional level, future research could focus on the way AI can assist organizations in searching and sourcing local talent through evolutionary computation and data mining or in pursuing strategies that match the needs and idiosyncrasies of the external entrepreneurial ecosystem. Fig. 3 suggests workplace outcomes at multiple levels, which have not been sufficiently examined at the AI-workplace outcomes nexus and could set the basis for future research work.

Further, as can be extracted from Table 2, the sampled articles in the present review have drawn theories from multiple disciplines, including information management, operations, economics, psychology, and sociology. However, despite the heterogeneity and pluralism in the theories being considered, there is a lack of a theoretical base from which to understand and interpret the influence of AI on individuals and teams in the workplace, including the organization at large. The dynamic capabilities view, for instance, can be applied to understand how individual managers, teams, or the firm can nurture sensing, seizing, and transforming capacities (Helfat & Peteraf, 2015; Teece, Pisano, & Shuen, 1997) in the use of AI techniques and applications for generating positive workplace outcomes such as individual and team productivity, and improved cooperation at work. On the contrary, critical theories, such as critical organization theory (Alvesson, 1985; Jermier, 1998) and critical theory of technology (Feenberg, 1991) can be used to 'demystify' the benefits of AI technology in the workplace. Drawing on the ideas of Karl Marx and Jurgen Habermas, future studies can conceptualize the way the increased adoption and use of AI technologies by organizations can lead to negative workplace outcomes such as increased inequality and oppression. At the same time, a critical theoretical base can pave the way for future studies on how individual employees can be empowered to reflect and challenge an oppressive technological rationality, which is applied to serve narrow class interests (Marcuse, 2013).

Moreover, there is an absence of HRM theories, or theories that have been applied in the field of human resource management, to explain phenomena at the nexus of AI and workplace outcomes. Considering such theories, future research can be in a better position to explain AI-linked phenomena and outcomes that relate to individual behavior and the behavior of teams within organizations. For instance, social capital (Nahapiet & Ghoshal, 1998), social network (Krause, Croft, & James, 2007), and social-exchange (Emerson, 1976) theories can be employed to identify the way AI is influencing more qualitative and social aspects, such as trust and distrust, in a workplace environment of human-machine interactions. Such theories could be applicable in examining the way AI is mediating or replicating social interactions between individuals within virtual work environments. Moreover, HRM theories such as Theory X and Theory Y (McGregor, 1960), as well as Herzberg's two-factor theory (Alshmemri, Shahwan-Akl, & Maude, 2017), could be considered in researching phenomena at the nexus of AI and workplace outcomes. These theories can be useful in understanding how AI is linked to essential workplace outcomes such as motivation, satisfaction, commitment, and engagement, which are important for an individual's performance and productivity at work. Lastly, it would be wise to consider theories such as the institutional theory (Scott, 1987), structuration theory (Giddens, 1991), and embeddedness theory (Granovetter, 1985), which view the role of the individual within a broader system or place and the way individual actors influence and are influenced by the structures of the systems in which they are embedded. Such theories could be useful in determining the way AI use within organizations can influence the structures of the context or broader institution in which the actor is embedded, and vice versa.

7. Contributions and conclusions

The present study has reviewed systematically the literature at the nexus between artificial intelligence (AI) and workplace outcomes. It has reviewed literature published in 30 leading international (AJG 3 and 4) journals over a period of 25 years (1995–2020). Our review is comprehensive, researching the AI-workplace nexus by drawing on the major functions of human resource management and the process framework of 'antecedents, phenomenon, outcomes' at multiple levels of analysis. We have reviewed the sampled articles based on years of publication, theories, methods, and key themes across the 'antecedents, phenomenon, outcomes' framework. We provide useful directions for future research by embedding our discussion in the recent HR literature, while we recommend studies drawing on alternative units of analysis and theories that draw on the individual, team, and institutional levels.

7.1. Main contributions

Our study makes four key contributions to human resource management and the management field in general. First, to the best of our knowledge, this is the first comprehensive, systematic analysis that links artificial intelligence and workplace outcomes. We identify and analyse all key articles that have been published on this research nexus, while we provide both a descriptive and deep thematic analysis of the sampled articles. Given the extensiveness with which we have approached our systematic literature, we argue that our review is the first to analyse the body of literature pertaining to the use of AI in the workplace. Second, we provide an analysis and future research directions by drawing on distinct HR functions. This novel analysis has allowed us not only to add thoroughness to our investigation, but to effectively contextualize our review into distinct HRM silos. Our analysis illustrates that different HR functions treat AI differently and tend to explore diverse phenomena at the AI-workplace nexus. Consequently, our review contributes to the HRM field by stressing the need to consider each HR function in isolation when looking at the influence of AI at work. This line of work has been largely overlooked in HRM literature, but it is important in helping diverse HR functions to understand how to best incorporate intelligent technologies to improve their performance.

Third, we used a thematic analysis across the 'antecedents-phenomenon-outcomes' logic, which enabled us to emphasize the process nature of AI influences at work. Through our analysis, we illustrate that AI influences can be better understood alongside relevant drivers that trigger AI use at work, relevant phenomena that underpin AI implementation at work, and relevant outcomes that illustrate the positive or negative consequences from AI implementation. These results help in providing a solid foundation for future studies in HRM that examine the use or influences exerted by AI at work. Fourth, we contribute to the field of HRM by highlighting respective gaps and proposing future research directions for studies, drawing on deferent units of analysis to examine the AI-workplace nexus.

7.2. Implications for practice

Our work can provide useful implications for practitioners within the HRM function, such as HR managers and people in charge of diverse HR activities such as recruitment, compensation, well-being, labor relations, planning, training, and performance management. For instance, HR professionals in charge of recruitment and selection could consider the use of data mining techniques to become more thorough in their quest to identify the right candidates and to assess candidate profiles in order to ensure a perfect match between candidate and organization. Additionally, HR experts in the field of compensation could draw on algorithms at work to find the most effective payment formula that optimizes the balance between individual performance and compensation. At the same time, managers in charge of training and development could draw on machine learning and deep learning to establish bespoke approaches to the training of their employees. Additional practical implications falling under diverse HRM functions are presented in Table 3.

In conclusion, this systematic literature review provides a comprehensive outlook and a critical analysis on the state-of-the-art research on AI and employee outcomes by considering the HR functions within which AI is utilized. Our critical analysis and synthesis have enabled us to: a) provide an integrative, multi-dimensional framework that encapsulates and provides a better understanding of current literature; and b) identify several research streams of how future research could further enhance the conceptual basis of this research domain, by suggesting and stimulating theoretical and conceptual inputs from various fields. Our critical analysis and synthesis have also enabled us to fill in gaps in existing literature through empirical research that draws on various scientific domains and contexts. We hope that this comprehensive and timely review will provide the basis for new and exciting research towards this research domain, which is likely to be of interest to a wide range of scholars and practitioners alike.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.hrmr.2021.100857.

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