Technological Forecasting & Social Change 193 (2023) 122645

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

AI-Augmented HRM: Literature review and a proposed multilevel framework for future research

Verma Prikshat [a], Mohammad Islam [b], Parth Patel [c], Ashish Malik [d,*], Pawan Budhwar [e], Suraksha Gupta [b]

[a] University of Wollongon in Dubai, UAE
[b] Newcastle University Business School, Newcastle University, 5 Barrack Road, Newcastle upon Tyne, Tyne and Wear, UK
[c] Department of HRM and Strategic Management, Australian Institute of Business, 1 King William Street, Adelaide 5000, South Australia, Australia
[d] Newcastle Business School, University of Newcastle, Corner of King and Auckland Street, Newcastle 2300, NSW, Australia
[e] Aston Business School, Aston University, 295 Aston Express Way, Birmingham B47ER, West Midlands, UK

ARTICLE INFO

Keywords:
Artificial intelligence
HRM
AI-Augmented HRM
Literature review
AI applications in HRM

ABSTRACT

The research using artificial intelligence (AI) applications in HRM functional areas has gained much traction and a steep surge over the last three years. The extant literature observes that contemporary AI applications have augmented HR functionalities. AI-Augmented HRM HRM$^{(AI)}$ has assumed strategic importance for achieving HRM domain-level outcomes and organisational outcomes for a sustainable competitive advantage. Moreover, there is increasing evidence of literature reviews pertaining to the use of AI applications in different management disciplines (i.e., marketing, supply chain, accounting, hospitality, and education). There is a considerable gap in existing studies regarding a focused, systematic literature review on HRM$^{(AI)}$, specifically for a multilevel framework that can offer research scholars a platform to conduct potential future research. To address this gap, the authors present a systematic literature review (SLR) of 56 articles published in 35 peer-reviewed academic journals from October 1990 to December 2021. The purpose is to analyse the context (i.e., chronological distribution, geographic spread, sector-wise distribution, theories, and methods used) and the theoretical content (key themes) of HRM$^{(AI)}$ research and identify gaps to present a robust multilevel framework for future research. Based upon this SLR, the authors identify noticeable research gaps, mainly stemming from - unequal distribution of previous HRM$^{(AI)}$ research in terms of the smaller number of sector/country-specific studies, absence of sound theoretical base/frameworks, more research on routine HR functions(i.e. recruitment and selection) and significantly less empirical research. We also found minimal research evidence that links HRM$^{(AI)}$ and organisational-level outcomes. To overcome this gap, we propose a multilevel framework that offers a platform for future researchers to draw linkage among diverse variables starting from the contextual level to HRM and organisational level outcomes that eventually enhance operational and financial organisational performance.

1. Introduction

The adoption of structured and unstructured data analysis techniques employing advanced artificial intelligence (AI) tools and techniques has seen an emergence of AI applications for human resource management (HRM) with significant implications for the HRM function (Saukkonen et al., 2019; Malik et al., 2021; Pereira et al., 2021; Vrontis et al., 2021). AI refers to a broad range of technologies that allow computers to perform tasks that would conventionally require human cognition and decision-making (Tambe et al., 2019). Recently, the Covid-19 pandemic situation created unprecedented challenges for human resource managers (i.e., recruitment, onboarding, and training) that have expedited AI application's adoption in HRM. There is a strong indication that the next normal in HRM practices will be characterized by high digitalization and increased virtualization aided by AI technologies for attaining sustainable competitive advantage based on superior human capital and HRM practices that embrace industry 4.0 (Mefi and Asoba, 2021), and increase in employees' experience and job

* Corresponding author.
E-mail addresses: m.j.islam2@newcastle.ac.uk (M. Islam), parth.patel@aib.edu.au (P. Patel), ashish.malik@newcastle.edu.au (A. Malik), p.s.budhwar@aston.ac.uk (P. Budhwar), suraksha.gupta@ncl.ac.uk (S. Gupta).

https://doi.org/10.1016/j.techfore.2023.122645
Received 4 September 2022; Received in revised form 10 April 2023; Accepted 15 May 2023
Available online 24 May 2023

satisfaction (Nguyen and Malik, 2022a; Malik et al., 2022a,b).

AI-augmented HRM is the capacity of the HRM function to integrate AI techniques within existing business intelligence systems in an organisation to ingest, process, and analyse data to aid problem-solving and decision-making for positive HRM-specific operational, relational and transformational consequences (Prikshat et al., 2023). Precisely, it connotes the combination of AI and intelligent automation (IA) and implies that AI can be useful for HRM from an IA perspective. It plays an assistive role by leveraging the latest techniques to enhance human intelligence in HRM functions and knowledge sharing through these tools (Malik et al., 2022c; Nguyen and Malik, 2022b). AI augmentation does not necessarily mean having the latest AI technologies to deliver functions of HRM. It is mostly about utilizing the latest AI techniques' untapped potential in HRM functions that enhance human-machine symbiosis to achieve higher HRM domain-specific outcomes, including enhancing the CXO's decision-making (Kondapaka et al., 2023).

An extensive review of state-of-the-art literature concerning AI-augmented HRM research (from now on referred to as $HRM^{(AI)}$) suggests that such research started in the early 1990s (Lawler and Elliot, 1996) and has gained much traction over the last couple of years (Jain et al., 2018; Meijerink et al., 2018; Buxmann et al., 2019; Alfes et al., 2020; Budhwar et al., 2022; Kaplan and Haenlein, 2020; Malik et al., 2023). However, despite this recent surge, $HRM^{(AI)}$ research is still underdeveloped, and there is limited evidence of extensive review of literature on $HRM^{(AI)}$ that systematically conceptualises the context and content of $HRM^{(AI)}$ research. While contextual research covers the chronological distribution, geographic spread, distribution of the research by industry/sector, theoretical perspectives, and research methodology/approaches, on the other hand, content analysis focuses on identifying research themes within a particular research domain (see Danese et al., 2018; Nolan and Garavan, 2016). Conceptualising the contextual and content-specific boundaries of previous $HRM^{(AI)}$ research assumes importance as it provides much-needed information concerning what previous researchers have done. Further, identifying and classifying research themes based on content analysis will help advance future research in this domain.

This systematic literature review (SLR from here on) reviews the extant literature within the context and content of $HRM^{(AI)}$ research and proposes a framework for future research. We start with capturing the context of extant $HRM^{(AI)}$ research (i.e., distribution, theoretical underpinnings, and research methodology/approaches used), followed by conducting a content analysis to identify and classify the emerging $HRM^{(AI)}$ research themes. Based on context and content analysis, we identify the knowledge gaps in the existing literature and then present a multilevel framework for further development of $HRM^{(AI)}$ to help practitioners and practitioners organise, conceptualise, and conduct research in $HRM^{(AI)}$ domain soon. The contribution of this research stems from context and content analysis of extant $HRM^{(AI)}$ research, identification of knowledge gaps in the existing $HRM^{(AI)}$ research and presenting a framework by synthesising past knowledge and gaps identification. This SLR attempts to present a basic framework for understanding how AI can be integrated into HRM based on extensive content and context analysis and identifying research gaps. The proposed multilevel framework can help researchers and industry experts understand the critical factors that can help them tread the transformation path to $HRM^{(AI)}$.

We begin this paper by summarising the research methodology and providing details of our literature search strategy, analysis, and assessment of the quality of the literature reviewed. We then report our context and content analysis findings. Following this, we identify the key research gaps in existing $HRM^{(AI)}$ research and suggest a multilevel research framework for further developing $HRM^{(AI)}$. The final section presents the managerial implications as well as concluding remarks.

2. Research methodology – a systematic literature review

We developed a comprehensive review protocol in line with established research methodologies described by Denyer et al. (2008) and Macpherson and Jones (2010), that has been termed 'systematic literature review', and this method is known to have numerous advantages compared with traditional unstructured reviews (Danese et al., 2018; Wang and Chugh, 2014). The adopted methodology for our SLR follows a replicable, scientific, and transparent process that minimises bias and errors (Tranfield et al., 2003), improves the quality of the review process and its validity by transparently following the exact steps, synthesises and organises the literature (Wang and Chugh, 2014) and further provides a platform for conceptualising frameworks that extend academic research (Kunisch et al., 2015).

In line with Danese et al. (2018), Nolan and Garavan (2016), and Wang and Chugh (2014), we adopted a structured and systematic literature review process as per the sequence of the stages described in Fig. 1. In line with the established practice of an SLR, multiple databases (eight) were searched for relevant articles. These include Scopus, Web of Science, Science Direct, Pro Quest, Google Scholar, EBSCO host, IEEE Xplore, and Emerald. This SLR analysed 56 published studies in the press from January 1990 to December 2021 in 35 ranked journals (see Appendix 1). This list comprised 49 articles from ranked journals listed in the Chartered Association of Business Schools (CABS) and Australian Business Deans Council (ABDC), in addition to some journals which have a practitioner slant addressing aspects of HRM and are widely recognised (such as MIT Sloan Management Review; Harvard Business Review) (see Table 1 for details). Four research articles published in unranked journals were included for the SLR based on their assumed importance for meeting the study's focus. These four articles, despite being unranked, contribute to the rigour of our SLR as unlike ABS/ABDC-listed articles, the unranked literature often a more neutral (Ndemewah and Hiebl, 2022) and sometimes novel perspective in exploring and/or examining the use of AI applications in HRM which further enriches our understanding of the latest developments in the field of $HRM^{(AI)}$. For example, the paper by Cesta et al. (2014) proposes a new learning environment system called PANDORA, which uses AI to help train crisis decision-makers, whereas the paper by Claus (2019) provides a theoretical perspective on the inclusion of new concepts and techniques like design thinking, agile management, behavioural analytics to develop a new breed of talent management (TM) practitioners which contribute to TM sustainability. Accordingly, due to the limited number of unpublished works in this field and the value addition they bring to our research theme, we have decided to include them in this paper.

2.1. Conceptual boundaries

As mentioned, we conceptualised this $HRM^{(AI)}$ SLR around contextual and content domains. The underlying rationale is that HRM(AI) research is somewhat fragmented and insufficiently defined, and exploring SLR along contextual and content domains will help streamline future research more comprehensively. More specifically, the context domain covered; (i) fuzzy logic, decision support systems and for listing the appropriate data for context and chronological distribution and geographic spread, (ii) distribution of the articles by industry/sector, (iii) theoretical perspectives, and (iv) research methodology/approaches used in the previous research. On the other hand, for content analysis, we explored the previous $HRM^{(AI)}$ research implementing AI in various HRM functions to identify common features among articles and further classify them into distinct research themes. Given the broader nature of AI techniques and applications used in $HRM^{(AI)}$ literature (i.e., algorithm, expert systems, content analysis), we used three sets of keywords in our search. The first group of keywords comprised descriptive items combining AI and HRM (e.g., AI and HRM, AI in HRM, Expert system and HRM, Algorithm and HRM, Fuzzy logic and HR). The

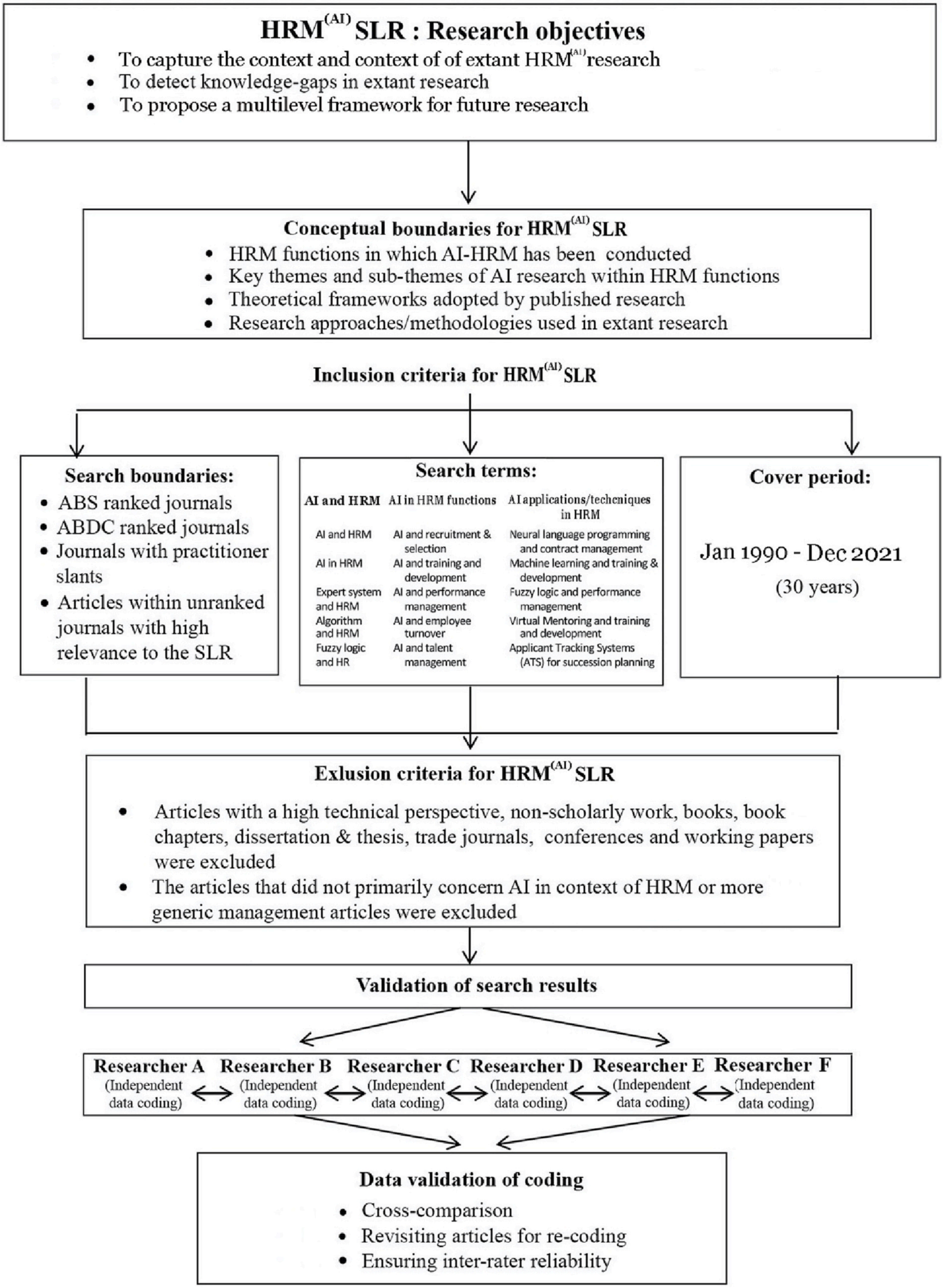

Fig. 1. A summary of the SLR process.

Table 1
Publications by journals.

Journals	CABS ranking	ABDC ranking	Number of articles
Australasian Marketing Journal (AMJ)	1	A	1
Business Horizons (BH)	2	B	3
Business Research Quarterly (BRQ)	–	B	1
California Management Review (CMR)	3	A	3
Career Development International (CDI)	1	B	1
Computers in Human Behavior (CHB)	3	A	2
Computers and Industrial Engineering (CIE)	2	A	4
Expert System with Applications (ESA)	3	C	5
Harvard Business Review (HBR)	3	A	7
Human-Computer Interaction (HCI)	1	A	1
Human Resource Management Journal	4	A	1
Human Resource Management Review (HRMR)	3	A	1
Information Resources Management Journal (IRMJ)	1	C	1
Information System Frontiers (ISF)	3	A	1
International Journal of Emerging Trends in Engineering Research	–	–	1
International Journal of Information Management (IJIM)	2	–	1
International Journal of Organizational Analysis (IJOA)	–	B	1
International Journal of Manpower (IJM)	2	A	1
International Studies of Management and Organisation (ISMO)	2	B	1
Journal of Applied Psychology (JAP)	4*	A*	1
Journal of Business Ethics (JBE)	3	A	1
Journal of Information Technology-Teaching Case (JITTC)	1	–	1
Journal of Labor Research (JLR)	2	B	1
Journal of Management (JM)	4*	A*	1
Journal of Management Development (JMD)	1	C	1
Knowledge-Based Systems (KBS)	–	A	1
Management Decisions (MD)	2	B	1
Management Research Review	1	C	1
MIT-Sloan Management Review (MSMR)	3	A	1
The International Journal of Human Resource Management (IJHRM)	3	A	4
Technology in Society (TIS)	–	C	1
Tourism Management (TM)	4	A*	1
Arkansas Law Review(ALR)	–	–	1
Strategic HR Review(SHR)	–	–	1
Advanced Trends in Computer Science and Engineering(ATCS)	–	–	1
		Total:	56

second group of keywords included AI concerning different HRM functions (e.g., AI and recruitment & selection, AI and training and development, and AI and performance management). The last set of keywords encompassed specific AI techniques/applications within different HR functions (e.g., neural language programming and contract management, machine learning and training and development, fuzzy logic, and performance management) (see sample search terms section in Fig. 1).

2.2. Inclusion and exclusion criteria

To build a comprehensive HRM$^{(AI)}$ research database, the authors applied inclusion/exclusion criteria to ensure that the research articles are relevant and stay within the research foci boundaries (Kitchenham, 2004). As shared above, the aim was to identify peer-reviewed journals on different topics relating to HRM$^{(AI)}$, AI concerning different HRM functions, and AI techniques within the scope of different HR functions. The main reason for choosing the 1990s as a starting point was the growing evidence of research starting in this domain in the early 1990s (Lawler and Elliot, 1996). The search parameters were set to focus on peer-reviewed academic journal articles listed in the lists mentioned above (Harvey et al., 2010) and articles from unranked journals considered necessary to meet the study's research objectives. The articles that were not available in full, book chapters, discussion notes, editorials and reports, highly technical articles, and duplicated articles were excluded from the review.

2.3. Articles selection and retention process

To further ensure the completeness of the research, we additionally conducted manual research by adopting the backward and forward approach (Webster and Watson, 2002). In this approach, we first traced the relevant citations from identified articles to trace additional references, and then, the collected references were further used to identify relevant articles. The research study identified 217 articles relevant to the focus of the research. The data was recorded into Microsoft Excel files, and the other cautious process was followed to ensure the accuracy and reliability of the data collected (Wang and Chugh, 2014; Nolan and Garavan, 2016). Each co-author went through each paper and collected and codified data manually in their database. The databases were compared, and we discussed the differences to find a shared attribution (Danese et al., 2018). Finally, the authors validated the coded data where the articles were first cross-compared to remove any potential duplication. Second, we revisited the articles and re-coded them to improve the accuracy of the coding process and to improve its rigour and authenticity. Subsequently, our objective was also to improve the inter-rater reliability given the multiple coders involved and to ensure consistency and clarity at the screening and coding stages (Belur et al., 2021).

We further examined the title and abstract of each article, and based on this analysis, some articles that were found to be inadequate in the context of HRM$^{(AI)}$ research were excluded from the SLR (Thorpe et al., 2005). Thus, 108 articles were excluded in the first step, reducing the number of articles to 109. Further, based on examining these articles' introductions and conclusions, the final list was refined to 56 articles. Fig. 2 shows the processual articles selection and retention process.

3. Context analysis

This section presents the context of HRM$^{(AI)}$ research. It covers chronological distribution, geographic spread, distribution of the articles by industry/sector, theoretical perspectives, and research methodology/approaches used in extant HRM$^{(AI)}$ literature.

3.1. Chronological distribution and geographic spread

Capturing the scope of what HRM$^{(AI)}$ comprises is quite broad. Analysis of the chronological distribution of extant research across the year of publication, journals, and geographic region is critical for understanding how the HRM$^{(AI)}$ research is picking up, which journals are pursuing the AI agenda in HRM, and as well as to emphasise the need for diversification of future HRM$^{(AI)}$ research into geographic regions that need more scholarly attention. This approach has been previously used in the context of business intelligence system adoption reviews and emerging market multinational enterprises (MNEs) (Luo and Zhang, 2016; Ain et al., 2019). Though the research on HRM$^{(AI)}$ started in 1990, the most relevant research articles in line with this study's focus were published between 1995 and 2021. In particular, HRM(AI) research witnessed increasing growth, specifically after 2018. A steep rise in research articles on HRM$^{(AI)}$ was noted in the 2018–2020 period. For example, 2019 alone accounted for the maximum number of articles (22); ten were published in 2018 and 2020, and three were published in 2021. In total, 21 articles were published before 2018; all were published in top-class journals. These 21 research articles account for 100 % of the total publications from 1995 to 2017. This review demonstrates that HRM$^{(AI)}$ did capture top-class scholarly journals' attention since the

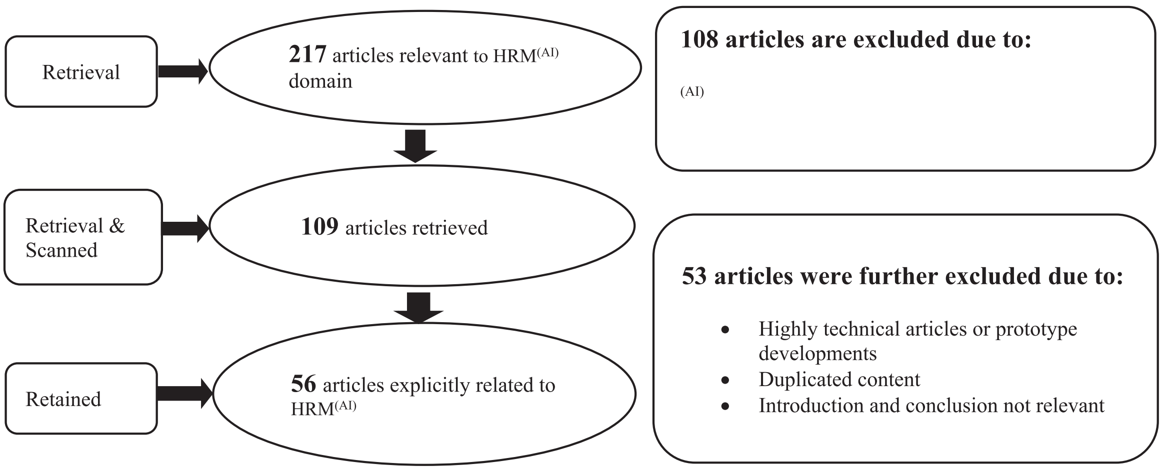

Fig. 2. Articles selection and retention process.

mid of 1990s; however, these research articles failed to provoke much interest or follow-up research until the call of special issues in top journals.

The analysis suggests that 87.50 % of the relevant research articles in the HRM$^{(AI)}$ domain are published in top-ranked journals. Only 12.50 % of the articles are published in non-ranked journals (see Table 1 for more details). Harvard Business Review - HBR ($n = 7$) leads the way as most of the articles in HBR are critical reviews and make a case for the use of AI in HRM and other issues (e.g., ethics, legal, biases). However, most other articles are in computer journals (i.e., Expert System with Applications, Computer and Industrial Engineering, Computers in Human Behaviour), mainly observing trends and using AI applications and techniques in HRM. Noticeably, HRM$^{(AI)}$ research evidence is now more visible in typically high-ranked HRM journals (for example, IJHRM and HRMR).

We further examined the number of articles for geographical distribution based on each author and the author's country. The analysis reveals that the 56 research articles selected for this SLR covered 18 countries. The findings suggest that the number of research articles from the United States of America was relatively high, with 26 articles. India's contribution was second with (6 articles), followed by China (5 articles), Turkey (3 articles), the UK (2 articles), Germany (2 articles), Canada (2 articles), and Taiwan (2 articles), respectively. Besides, among the developed economies, the US (25 articles), UK (2 articles), Taiwan (2 articles), Greece, Canada, Switzerland, Italy, Belgium, Australia, Hong-kong, and Japan each had 1 article. The main reason for the high number of studies in the US, China, and India can be attributed to the fact that these countries have an extremely well-developed and highly skilled labour pool comprising academics, research institutions, and organisations that continue to push the boundaries of what is capable with AI techniques and applications (Walch, 2020). In summary, most research on AI-driven HRM was conducted in the USA, India, China, Turkey, the UK, and Taiwan.

3.2. Distribution of the studies by sector

Out of the total 56 articles reviewed for this SLR, only seventeen articles were sector-specific (30.36 %), and the remaining 39 articles (70 %) were not explored in the context of any particular sector. It was found that the education, banking, manufacturing, human resource, and information technology sectors are the key industries in which HRM$^{(AI)}$ research has been conducted (two articles each), followed by a single article for semiconductor, telecommunication, hospitality, and oil and gas sectors.

3.3. Theoretical perspectives

This section explores the theoretical foundations of the articles listed in the SLR. The theory is a building block for answers to questions about what, why, who, when, and how (Sutton and Staw, 1995). We identified the theoretical perspectives in HRM$^{(AI)}$ research in line with the approach followed by Nolan and Garavan (2016) and Danese et al. (2018). Of 56 studies, twenty-one articles utilised existing theories, models, and frameworks to examine HRM$^{(AI)}$ research. Out of 21 theoretical-based studies, most of the studies used psycho-social theories ($n = 6$), such as behavioural decision theory, social exchange theory, and social information processing theory, to examine the influence of AI in HR functions of recruitment and selection (Suen et al., 2019; Van Esch et al., 2020), performance management (Abubakar et al., 2019; Robert et al., 2020), training and development (Cesta et al., 2014), and job evaluation (Lawler and Elliot, 1996) (see Table 2 for more details).

Four of the studies used fuzzy set theory using fuzzy approaches and many-valued logic (Gottwald, 1999) to investigate the influence of AI on decision-making and decision support for recruitment and selection (Polychroniou and Giannikos, 2009), employee turnover risk management (Wang et al., 2011), AI for biased free performance appraisal (Manoharan et al., 2011), and talent management (Karatop et al., 2015). Data mining theories were employed in three of the studies to examine the advent of AI in HR functions of recruitment and selection and retention (Chien and Chen, 2008), employee turnover (Fan et al., 2012), and performance management (Strohmeier and Piazza, 2013). Surprisingly, there was less onus on innovation diffusion theory (only two studies - Coeurderoy et al., 2014 and Brock and Von Wangenheim, 2019) as the adoption of AI in different management disciplines is usually discussed in innovation diffusion theories. These two studies explored the assistance of AI in HR functions of training & development and performance management. While two studies by Cascante et al. (2002) and Khosla et al. (2009) used expert systems theories to explore the diffusion of AI in performance management and recruitment and selection, Golec and Kahya (2007) embraced the theory of constructing hierarchies for competency-based evaluation and selection of job applicants in the recruitment and selection process. More recently, Pan et al. (2021) and Jaiswal et al. (2021) used the technology-organization-environment framework (TOE) and job replacement theory, respectively, to examine the contextual factors' influence on AI adoption in recruitment and selection and to explicate employees' upskilling.

3.4. Research methodologies used in previous HRM$^{(AI)}$ research

This section synthesises the findings related to methodology in terms of research methodology/approaches used in extant HRM$^{(AI)}$ research.

Table 2
Theoretical perspective in previous HRM$^{(AI)}$ research.

Theoretical perspectives	Authors/years	HR functions
1. Psycho-social theories		
• Behavioural decision theory	Lawler and Elliot (1996)	Job evaluation
• Psycho-physiological experiment	Cesta et al. (2014)	Training & development
• Psychological ownership and social exchange theory	Abubakar et al. (2019)	Performance management
• Social information processing theory/Media richness theory	Suen et al. (2019)	Recruitment and selection
• Organisational justice theory	Robert et al. (2020)	Performance management
• Subjective intention theory	Van Esch et al. (2020)	Recruitment and selection
2. Fuzzy set theory		
• Fuzzy approach	Polychroniou and Giannikos (2009)	Recruitment and selection
• Fuzzy approach	Manoharan et al. (2011)	Performance management
• Fuzzy approach	Karatop et al. (2015)	Talent management
• Decision support Theory	Wang et al. (2011)	Employee turnover
3. Data mining theories		
• A data mining framework for personnel selection	Chien and Chen (2008)	Recruitment and selection/ retention
• Clustering analysis and data mining methodology	Fan et al. (2012)	Employee turnover
• Domain-driven data mining framework	Strohmeier and Piazza (2013)	Recruitment and selection/ performance management/ employee turnover
4. Innovation diffusion theory		
A unified theory of acceptance and the use of technology	Coeurderoy et al. (2014)	Training and development
Innovation-adoption-implementation theory TOE framework/ Transaction cost theory	Brock and Von Wangenheim (2019) Pan et al. (2021)	Performance management Recruitment and selection
5. Expert system theories		
• Performance, user satisfaction and learning	Cascante et al. (2002)	Performance management
• Expert system model	Khosla et al. (2009)	Recruitment and selection
6. Miscellaneous theories		
• Theory of constructing hierarchies	Golec and Kahya (2007)	Recruitment and selection
• Artificial intelligence-based Design platform (AID) • Neo-human capital/AI job replacement theory	Lee and Ahn (2020) Jaiswal et al. (2021)	Recruitment and selection Upskilling/development

The review highlighted the adoption of several research methodologies, including critical reviews, experimental design qualitative and quantitative methodology, the analytical hierarchy process, and mixed-research methodology in HRM$^{(AI)}$. The distribution of research types, namely critical reviews, qualitative, quantitative, experimental design, the analytical hierarchy process, and mixed methods (quantitative + qualitative), is presented in Fig. 3. The majority of the research studies used a critical review approach comprising 24 articles, 46.15 % of the total research studies reviewed. In comparison, 15 articles used a quantitative/empirical approach (28.84 % of the total), and five used experimental design (9.61 %); the remaining 11.52 % of the articles used qualitative, mixed methodology, and the analytical hierarchy approach. Moreover, 26.41 % of the articles used the survey, 9.43 % used an experimental design, 3.77 % of articles used interviews, and the remaining 5.75 % of articles used the analytical hierarchy and both survey and interviews.

4. Content analysis

Previous scholarly work in HRM$^{(AI)}$ is diverse and heterogeneous and explores many issues in different contexts. The content analysis aims to identify common features among articles to classify them into distinct research themes based on the unit of analysis. To do so, we focused on AI research in different functions of HRM and the key AI themes within these functions. Building upon the results of the content analysis of 56 selected articles, we classified four major research themes covered in the extant HRM$^{(AI)}$ research in line with the application of AI techniques across different functions of HRM, as shown in Table 3. Following is a detailed discussion about HRM$^{(AI)}$ research efforts in these classified themes.

4.1. Theme 1: application of AI techniques in HRM

AI has been observed as a multifarious computer domain, and often AI techniques are heterogeneous and are not appropriately categorised (Kahraman et al., 2010). This might be the reasoning behind why extant literature on HRM$^{(AI)}$ has mostly indulged in a heterogeneous set of suggestions as to how specific AI techniques could be applied for specific HRM functions (Strohmeier and Piazza, 2015). Most of the HRM$^{(AI)}$ research that has dealt with AI applications in HRM has AI techniques of data mining, expert systems, fuzzy logic, and algorithm techniques for their suitability in distinct HRM functions. For example, the data mining technique has been examined to improve selection, and performance management, reduce employee turnover and enhance human capital (Chien and Chen, 2008; Strohmeier and Piazza, 2013). While expert systems have been perused in the context of the selection and job evaluation process (Lawler and Elliot, 1996; Mehrabad and Brojeny, 2007), fuzzy logic has been explored to examine whether it enhances reward management and talent management (Karatop et al., 2015; Escolar-Jimenez et al., 2019). Similarly, the applications of AI algorithms have been explored in the context of recruitment and selection and training and development functions (Danieli et al., 2016; Cheng and Hackett, 2019; Van Esch and Black, 2019). The extant HRM$^{(AI)}$ literature also reports on other AI techniques (i.e. benchmarking, AID framework) for further highlighting the application of generic AI in the context of other important functions of HRM such as job design, employee engagement and retention (Burnett and Lisk, 2019; Huang et al., 2019; Jaiswal et al., 2021).

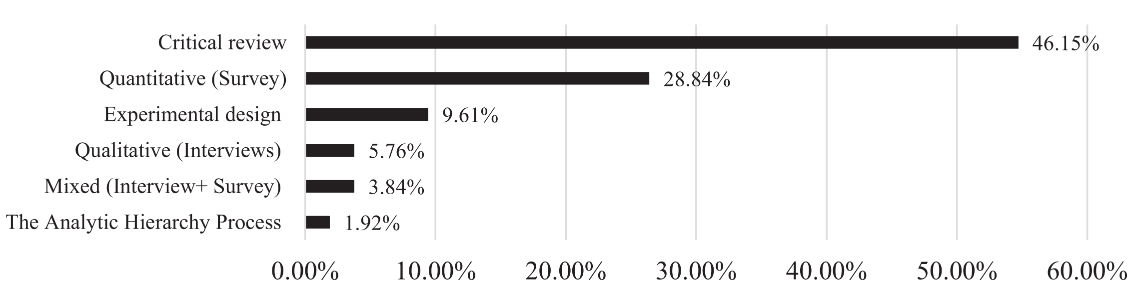

Fig. 3. Distribution of research methods.

Table 3
HRM$^{(AI)}$ themes in previous literature.

AI in HRM (Classified themes)	HRM function	Key AI themes	Authors
1. Application of AI techniques in HRM	• Recruitment and selection	• Expert system for the selection process	Mehrabad and Brojeny (2007)
		• Data mining to improve personnel selection	Chien and Chen (2008), Strohmeier and Piazza (2013)[a]
		• Benchmarking system in AI-based recruitment	Lee and Ahn (2020); Khosla et al. (2009)
		• Artificial Intelligent Design (AID) framework for the selection	Kuncel et al. (2014)
		• Algorithm for recruitment and selection	Danieli et al. (2016); Van Esch and Black (2019)
	• Training and development	• Training software 'Pandora' for crisis decision making	Cesta et al. (2014)
		• HRM algorithm decision-making in training	Cheng and Hackett (2019)[a]
		• AI's assistance in re-skilling and upskilling	Gratton (2019)
	• Performance Management	• Applicability of data mining in performance management	Strohmeier and Piazza (2013)[a]
		• Designing fair AI for performance management	Robert et al. (2020)
	• Talent management	• Fuzzy logic for gap reduction between the desired level of capabilities and the existing capabilities of HR professionals	Karatop et al. (2015)[a]
		• Digital transformation of talent management	Guinan et al. (2019)
		• Talent analytics for talent management	Sivathanu and Pillai (2019)[a]
		• Data mining for enhancing human capital.	Chien and Chen (2008)[a]
	• Employee turnover	• AI techniques for employee turnover prediction	Fan et al. (2012); Li et al. (2019)
		• Applicability of data mining in employee turnover	Strohmeier and Piazza (2013)[a]
		• AI for employee turnover risk	Wang et al. (2017)
	• Reward management	• Fuzzy logic/artificial neural network for employees' reward management	Escolar-Jimenez et al. (2019)
	• Job design	• AI for job design	Huang et al. (2019)
	• Job evaluation	• AI as an expert system for the job evaluation system	Lawler and Elliot (1996)
	• Employee engagement	• AI and digital engagement	Burnett and Lisk (2019)
	• Retention	• Employees upskilling and the future of work.	Jaiswal et al. (2021)
2. HRM$^{(AI)}$ outcomes	• Training and development	• HR analytics is beneficial for training and development	Davenport (2019)
		• AI's use in personalized training	Maity (2019)
	• Performance management	• Knowledge hiding behaviour and performance management	Abubakar et al. (2019)
		• HR decision-making for workplace monitoring	Leicht-Deobald et al. (2019)
	• Talent management	• Fuzzy logic for gap reduction between the desired level of capabilities and the existing capabilities of HR professionals	Karatop et al. (2015)[a]
		• People analytics for talent management	Leonardi and Contractor (2018)
		• Talent analytics for organisational performance	Sivathanu and Pillai (2019)[a]
		• Impact of AI techniques on talent management	Claus (2019)
3. Ethical concerns in the use of HRM$^{(AI)}$	• Recruitment and selection	• Eliminating unconscious human bias in recruitment	Cheng and Hackett (2019)[a]
		• AI for job applicants' fairness perceptions	Suen et al. (2019)
		• AI's role in eliminating unconscious human bias	Polli (2019)
	• Performance management	• AI for biased free performance appraisal	Manoharan et al. (2011)
	• Talent management	• Ethical AI for talent management	Chamorro-Premuzic et al. (2019)
4. Challenges and adoption of HRM$^{(AI)}$	• Recruitment and selection	• Challenges of blockchain technology for recruitment	Michailidis (2018)
		• Drivers, barriers, and social considerations for AI adoption	Cubric (2020)

[a] Denotes the author's contributions across different HRM functions.

4.2. Theme 2: HRM$^{(AI)}$ outcomes

Given that most recent research has reported that managing the interdependencies of human and artificial intelligence will become a key strategy of an organisation's digital transformation initiative in the future (Lichtenthaler, 2020), understanding the benefits and outcomes of AI techniques in HRM becomes crucial. Surprisingly, very little research has been conducted highlighting the outcomes and benefits associated with the application of AI in different HRM functions. While Davenport (2019) and Maity (2019) underline the benefits of the use of AI in training and development, some researchers have focused on how AI helps in detecting knowledge-hiding behaviour (Abubakar et al., 2019) and enhancing HR decision-making for performance management functions (Leicht-Deobald et al., 2019). Similarly, studies by Claus (2019), Leonardi and Contractor (2018), and Sivathanu and Pillai (2019) discuss the impact of AI-assisted talent management analytics for enhancing organisational performance. Thus, much groundwork needs to be covered in this research domain. Without a clear understanding of outcomes and benefits associated with the use of AI in HRM, it is not easy to impress upon the organisation stakeholders to fully reap the substantial benefits through investment in AI in HRM.

4.3. Theme 3: ethical concerns in the use of HRM$^{(AI)}$

Despite the great prospects presented by implementing AI applications in distinct HRM functions, many ethical concerns are associated with using AI in HRM, constituting a darker side of AI (Arslan et al., 2021; Prikshat et al., 2023; Varma et al., 2022). Although some of the previous research (Chamorro-Premuzic et al., 2019; Cheng and Hackett, 2019; Polli, 2019; Manoharan et al., 2011) has focused on ethical issues regarding the use of AI in functions of recruitment and selection, performance management, and talent management, the specific understanding of various ethical issues that need to be addressed concerning the advent of AI in distinct functions of HRM is limited. Previous research has suggested numerous ethical principles in the generic HRM domain; however, there is a serious issue of extending these principles further in the domain of HRM$^{(AI)}$. Thus, it becomes essential to underline the various ethical concerns associated with the use of AI in different functions of HRM as well as how to address those concerns.

4.4. Theme 4: challenges and adoption of HRM$^{(AI)}$

Despite the ever-increasing evidence of an upsurge in HRM$^{(AI)}$ research regarding the use of AI applications for different HRM functions, a detailed understanding of challenges and the adoption process of diverse AI applications is somewhat missing. We could only find two specific studies (Cubric, 2020; Michailidis, 2018) focused on challenges, drivers, barriers, and social considerations for AI adoption in the function of HRM. The necessity of understanding the challenges and the adoption process of AI techniques in different HRM functions gains much traction as recent research has also observed this void and urged for underlining the challenges as well as highlighting the drivers and barriers for their smooth adoption (Kiron and Schrage, 2019; Fountaine et al., 2019). In essence, a detailed understanding of challenges faced by organisations and HR professionals and comprehensive adoption processes or frameworks has the potential to understand the prerequisites for using AI applications and provide a platform to scholars for future research efforts and best practice recommendations.

5. SLR results and key research gaps

The extensive HRM$^{(AI)}$ research context analysis suggests that most previous research corresponds to generic sectors (70 %) and is not country-specific. Even though few country-specific studies (30 %), the previous research lacks a cross-country comparison focus. Moreover, very few studies (37.50 %) relied on theoretical models and frameworks, and the use of theory-building and extension approaches was limited. It was pretty surprising to note that there was little reliance on technology adoption theories, given that HRM$^{(AI)}$ can be categorised as radical innovation primarily related to technology adoption and must be linked with technical innovation literature. Further, most previous studies have used critical review methodology (46 %), implying the lack of empirical evidence due to a few studies using qualitative, qualitative, or mixed methods approaches.

On the other hand, the HRM$^{(AI)}$ research content analysis depicted that previous research has primarily indulged in heterogeneous AI techniques used in the context of varied HRM functions. The research on using specific AI techniques (i.e. data mining, expert systems, fuzzy logic, and algorithms) has been conducted in the context of distinct HRM functions. For example, most of the applicability of these AI techniques have been undertaken in recruitment and selection training and development and very sparingly for other functions. This leaves a massive vacuum in the previous A-HRM research on whether all these techniques are not applicable or can assist other HRM functions. Similarly, suppose we want to capture all the prevalent AI techniques that can assist business functions. In that case, the obvious question is whether they are useful for diverse HRM functions. This conveys that much ground needs to be covered where future researchers have to systematically identify all the AI techniques and then decide whether they can be applied to distinct HRM functions. Moreover, the SLR suggests limited research on the outcomes associated with the use of HRM$^{(AI)}$. There is a huge gap in the previous research concerning the analysis of the linkage of the perceived HRM outcomes based on the implementation of HRM$^{(AI)}$ and their connection with organisational outcomes as a whole.

Another notable concern is that previous research scholars working in HRM$^{(AI)}$ have not suggested a robust ethical framework that clearly explains the role and responsibilities of the different stakeholders. There have been sparse efforts to raise awareness or impact of various ethical concerns in recruitment and selection, performance management, and talent management. Still, there is the absence of a holistic approach comprising principles or dimensions where the ethical issues presented by AI in different HRM functions can be wholly captured. Last but not least, given that HRM$^{(AI)}$ is based on technology innovation, AI adoption or assimilation process within HRM assumes much significance. As observed through this SLR, very few systematic research efforts exist in this domain.

Given that every AI technique may offer different propositions and an altogether unique set of challenges for diverse functions of HRM, it becomes necessary to understand the challenges organisations and HRM professionals face to develop a comprehensive understanding of the AI adoption or assimilation process. Table 4 captures the main gaps and supporting data based on the context and content analysis of SLR. We will further use the proposed multilevel framework for developing HRM$^{(AI)}$ to provide research ideas that can help fulfill these notices gaps in previous literature.

6. A multilevel framework for the development of HRM$^{(AI)}$

In light of the above-highlighted gaps in previous themes pursued in HRM$^{(AI)}$ literature, the question arises of how AI can be suitably implemented and verified in human resource management. Given that every organisation might have different characteristics and somewhat dissimilar HRM goals and objectives, the desired AI augmentation of HRM departments or functions might have to map the areas of strategy, culture, technology facilitators, and reconfiguration challenges. To streamline these challenges, we propose a multilevel framework for developing the HRM$^{(AI)}$ field that can inform change managers about the basic AI augmentation approach that will help them develop a transformation roadmap for successful HRM$^{(AI)}$ endeavours. This multilevel framework serves to fill in the gaps in the existing HRM$^{(AI)}$ research and, at the same time, provides a platform for future researchers to examine the interplay of different factors in prescribed levels to extend the research further in this domain. We will elaborate on the multilevel framework for the development of HRM$^{(AI)}$ next. The significant factors within prescribed levels will be discussed using the attributes used to categorise and review the literature. The details of the multilevel framework comprising different factors are displayed in Fig. 4.

6.1. *Contextual level*

Researching the domain of HRM$^{(AI)}$ does not necessarily mean covering only the use of AI techniques in HRM. While doing meaningful research, choosing the appropriate research methodology and supporting theories is a must. While conducting research, the significant consideration is to borrow theories originating from reference disciplines and use them appropriately to contribute something additive back to the reference disciplines from which we borrow (Truex et al., 2006). Similarly, the choice of research method and the various research designs are used to ensure that the research is being carried out within the established frameworks and following existing guidelines (Williams, 2007). Keeping this in mind, the first level of our framework discusses the gap in existing HRM$^{(AI)}$ literature in terms of theories and research methodologies used. It provides future directions for using different theories and research methods. We also delve into the gaps in previous HRM$^{(AI)}$ research concerning the selection of samples (i.e., in terms of countries and industries) and prescribe future research to fill this gap.

6.1.1. *Prescribed theories for HRM$^{(AI)}$ research*

We go beyond the existing HRM literature and look into theories from technical innovation and social psychology literature to prescribe future HRM$^{(AI)}$ research theories. For example, the 'Technology Acceptance Model' (TAM) by Davis (1989) can help assess the perceived ease of use and usefulness of the latest AI technologies in different HRM functions from the perspective of HR professionals. On the other hand, using the theoretical lens of the 'Theory of reasoned action (TRA)' (Ajzen, 1991) can help research scholars to determine the human behavioural patterns in the decision-making strategy to utilise AI techniques in HRM. Similarly, 'Theory of planned behaviour (TPB)' (Ajzen, 1991) and 'Unified Theory of Acceptance and Use of Technology (UTAUT)' (Venkatesh et al., 2003) can help scholars to examine behaviour intentions for AI adoption based on an HR professional's attitude and intentions towards innovative behaviour by examining HR professionals' behaviour, subjective norms, and perceived behavioural control.

Information management theories such as 'Technology-Organization-Environment (TOE)' (Tornatzky et al., 1990), 'Technological,

Table 4
Main gaps and supporting data based on the context and content analysis of SLR.

Previous HRM$^{(AI)}$ research	Reference variable	Main gaps	Supporting data
Context	Sectors	• A small number of sector-specific studies • Very few studies in the service sector	• Only 30 % of studies ($n = 17$) are sector-specific. The remaining 70 % ($n = 39$) are not sector specific. • The key focused sector in this research was the IT sector, followed by education, banking, and human resource services.
	Country/ies of the research	• A small number of country-specific studies • Lack of cross-country comparisons	• Seventy per cent of studies (n = 39) are not country-specific. • Most of the studies have a single-country narrative.
	Theoretical perspectives	• Lack of theoretical frameworks • Use of a few theories building and theory extension approaches. • Lack of technology adoption theories	• Only 37.50 % ($n = 21$) used theories, models, or frameworks. • Only 8.93 % ($n = 5$) of studies used the primary method of the theory construction process, 23.21 % ($n = 13$) studies used the theory-testing process, while only 5.35 % (n = 3) used the theory extension process. • HRM$^{(AI)}$ can be categorised as radical innovation primarily related to technology adoption and must be linked with technical innovation literature.
	Research methodology/ approaches	• A small number of studies used a qualitative, qualitative, or mixed-methods approach, implying the lack of empirical evidence	• About 46 % ($n = 24$) of the total research articles used a critical review approach
Content	Limited research in the context of AI techniques	• Only AI techniques of data mining, expert systems, fuzzy logic, and algorithms	• There is no systematic knowledge of whether all these AI techniques can be used for all HRM functions
	HRM$^{(AI)}$research in different HRM functions	• Unequal distribution of HRM$^{(AI)}$ research concerning all the functions of HRM.	• Most of the HRM(AI) research is in recruitment & selection and training & development.
	Significantly less research concerning adoption and challenges	• There is an absence of prescribed adoption or assimilation processes	• Lack of knowledge of challenges faced in developing a comprehensive understanding of AI adoption or assimilation process
	Linkage with HRM level and organisational outcomes	• Limited research on the outcomes associated with the use and implementation of HRM$^{(AI)}$	• No synthesis among HRM level and organisational level outcomes based on HRM$^{(AI)}$ implementation
	Absence of ethical frameworks	• No prescribed ethical frameworks regarding the application of AI in distinct HRM functions	• The absence of a robust ethical framework explaining the role and responsibilities of the different stakeholders clearly

Organisational or People framework (TOP)' (Bondarouk et al., 2017) and 'Decision Maker-Technology-Organisation-Environment (DTOE)' (Thong, 1999) theories can help future research scholars to explain contextual factors relating to organisation's people, top management and technological environment for influencing AI's adoption in HRM. The 'Innovation Diffusion Theory (IDT)' (Rogers, 1995) can assist researchers in understanding how, why and at what rate innovative AI technologies can spread in the social fabric of the HRM department. In addition, the more recent 'Theory of Assimilation Innovation (TAI)' (Zhu et al., 2006) can help organisations to understand the process and contexts of technology diffusion through an integrative model to examine three assimilation stages, namely, initiation, adoption, and routinisation of AI techniques in HRM functions.

Further, given that researchers have also investigated the relationships between 'Social Exchange' and 'Social Identity' theories with technology adoption intentions (Chu and Chen, 2016), future HRM$^{(AI)}$ research can use these theories to elucidate motivational factors for knowledge sharing concerning various AI applications and techniques and AI adoption in different HRM functions.

6.1.2. *Prescribed research methods for HRM$^{(AI)}$ research*

The research methods that have been employed so far in previous HRM$^{(AI)}$ research are mostly critical reviews (46.15 %), followed by quantitative research methodology (28.84 %) and experimental design (9.61 %) (see Table 3). Qualitative and mixed-method studies are limited in number. We believe this is a significant omission in the current literature as qualitative exploratory research and mixed-method research can play an essential role in better understanding the impact of AI on HRM, given that HR practices and systems vary significantly from one country and industry to another (Wijesinghe, 2011; Lee, 2016). We strongly recommend further research using more qualitative exploratory research and mixed-method research.

6.1.3. *Selection of samples*

Based on this SLR, we found out that the existing HRM$^{(AI)}$ research body is minimal in terms of the countries covered and the included industries. Second, most HRM$^{(AI)}$ research has been conducted in developed countries. There is an almost total absence of studies from developing countries, particularly from Asia and Africa. Some research studies are from China, India, Turkey, and the UK, but most previous research concerning HRM$^{(AI)}$ has its roots in the US. It seems justifiable enough, given that the US tops the AI readiness index (AI Readiness Index Report, 2020). However, it is also disconcerting that despite the high AI readiness index in four Western European nations (the UK, Finland, Germany, and Sweden), significantly less HRM$^{(AI)}$ research is reported in these countries. Moreover, there is a shortage of cross-country comparisons regarding the implementation and adoption of AI in different HRM functions.

Moreover, the SLR demonstrates that 70 % of HRM$^{(AI)}$ studies are not sector specific. The absence of sector-specific research leaves gaps in contextual knowledge and a holistic perspective regarding using AI in HRM. Given the increasing influence of AI in financial, healthcare, education, digital governance, retail, manufacturing, and smart city operations worldwide (Deloitte, 2019; McKinsey, 2020), we assume that there might be a much broader impact on HR departments of the mentioned sectors, which need to be reported. We argue that this is a significant limitation as sector and country-specific studies are crucial in responding to such a massive change in HRM and firms (e.g., filling the gaps in the employee's existing skillset, redesigning sector-specific jobs and training, hiring new talent for sector-specific needs). Unless existing research addresses AI's impact on different sectors, research in this domain will not progress further. Organisations will not develop distinct, sector-specific responses to tackle AI implementation issues.

6.2. *Organisational level*

Using AI techniques in HRM is not only based on the discretion of the HRM department. It is mostly about aligning AI augmentation of HRM with the organisation's strategic objectives to realise the untapped potential of the HRM function as a whole. In addition to an HRM$^{(AI)}$ strategy that is firmly aligned with the organisation's strategic vision, there has to be present an AI-oriented culture and support in the form of

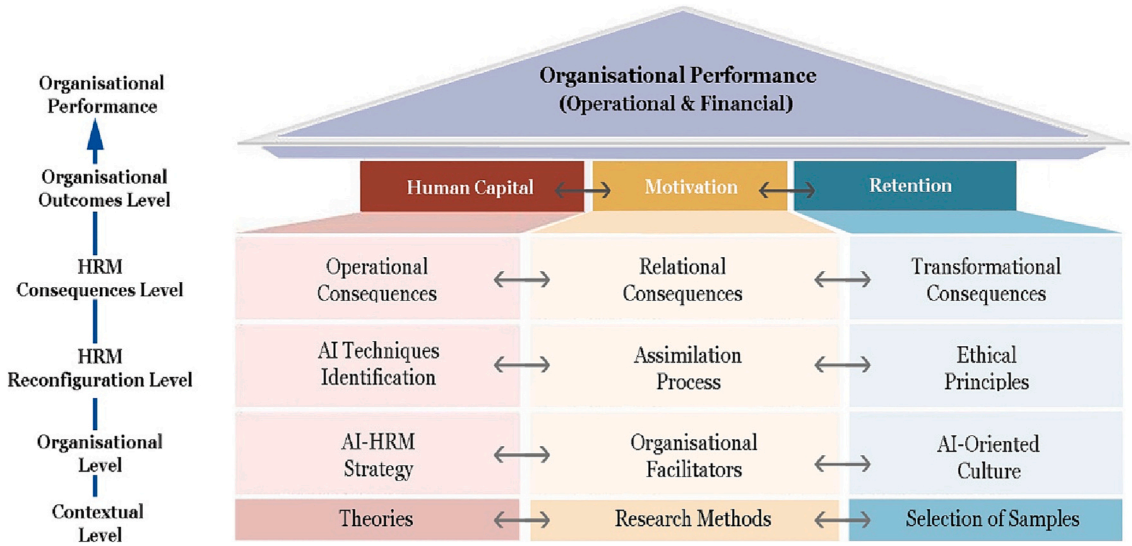

Fig. 4. A multilevel framework for the development of HRM(AI).

technological enablers. Thus, this level encompasses three areas: *AI-HRM strategy*, AI-*oriented culture,* and *organisational facilitators*. At the AI-HRM strategic level, we prescribe two types of integration between organisations' strategy and HRM(AI) strategy (Henderson and Venkatraman, 1999). The first, termed *strategic alignment*, is the link between business strategy and HRM(AI) strategy that helps explain how HRM(AI) helps shape and support business strategy. The second, termed operational integration, should have the capacity to explain the linkage between HRM(AI) infrastructure (i.e., HRM data hubs or marts) and how it flows into the organisational business intelligence infrastructure (i.e., cloud data lake or warehouse).

The second organisational factor - *AI-oriented culture* - refers to employees, managers, and leaders' attitudes towards implementing AI techniques and can be a strong determining factor for adopting AI in an organisation. Previous research has highlighted the importance of organisation culture in accepting and adopting innovative information system techniques (Twati and Gammack, 2006). Thus, to understand the dynamics of HRM(AI), the current organisational culture and how the organisation culture can be improved or transformed into an AI-oriented culture needs to be examined in more detail. Culture has been recognised as one of the most influential factors responsible for technology acceptance in organisations (Duan et al., 2019). For example, a study by Dora et al. (2021) found that organisational culture played a vital role in AI adoption in the food supply chain. Further, research in information systems focusing on technology adoption indicates that individual adoption of technology and the latest innovations also depends upon *organisation facilitators* within the folds of the organisations. These facilitators are often provided through AI leadership and top-level management through diverse policies and actions for the smooth implementation of technological innovations (Schillewaert et al., 2005). The leaders have to actively endorse and root for the organisation's AI projects and continuously communicate the status and progress of AI activities across internal and external stakeholders (Brock and Von Wangenheim, 2019). Similarly, the present status of technological infrastructure, technology enablers (i.e., user training, technical user support, top management support), project management system and human-technology relationship are some of the organisational level factors that need to be studied in detail in the context of HRM(AI).

6.3. HRM reconfiguration level

HRM configuration level is prescribed to understand better the operational enablers of using HRM(AI) at the HRM domain level. An analysis of AI techniques augmenting different HRM functions, the *AI assimilation* process in HRM functions, and the *ethical principles* that assume importance in HRM(AI). *AI technique* identification within the HRM reconfiguration level involves identifying AI techniques applied in distinct HRM functions. The previous literature provides a heterogeneous set of AI techniques (i.e., data mining, fuzzy logic, expert systems) that have been employed in a range of HRM functions (Strohmeier and Piazza, 2015). Thus, for HRM(AI), diverse and detailed insights into the potential of various AI techniques for individual HRM tasks need to be analysed. For a system capable of reconfiguring the HRM functions in an organisation, we strongly suggest that there has to be a mix of AI techniques that can be employed across different HRM functions instead of using or focusing on one technique or a particular function of HRM. For example, how to use the data mining technique in employee selection, intelligent agent technique in career development or information extraction technique in employee recruitment (Strohmeier and Piazza, 2015). Such a variety of AI techniques are crucial for HRM in efficiently and effectively executing its broad range of functions and tasks and thus are valuable.

Further, given that migration from initial adoption to the diffusion of AI techniques might be complex and may involve additional steps of diffusion, routinization, and extension of assimilation (Prikshat et al., 2023), thus understanding the processual assimilation mechanism comprising these stages is warranted for further development of HRM(AI). Understanding such a mechanism will ensure a deeper integration of AI techniques and lay down a foundation process for inculcating AI techniques in various HRM functions. Moreover, identifying AI techniques for specific HRM functions and their assimilation would arguably add a new set of role demands, professional challenges, and management expectations for organisations and HRM professionals, necessitating critical analysis of these challenges' ethical implications (Leikas et al., 2019). The new HRM(AI) scenario may present challenges varying from data privacy issues, security, ethical/moral judgment and decision-making, goal alignment between AI and human beings, and ethical problems related to agency and fairness of AI (Du and Xie, 2021). All these mentioned exemplary risks and challenges highlight the need for detailed ethical principles that should cover the challenge posed by different AI techniques in the context of distinct HRM functions and clear responsibilities of stakeholders associated with those employing these techniques to enhance HRM decision-making.

6.4. HRM consequences level

Previous research has conceptualised macro-level consequences of technology-driven HRM into operational, relational, and transformational consequences (Obeidat, 2016; Parry and Tyson, 2011). We further suggest examining the consequences of AI assimilation in HRM along with these domains. For *operational consequences*, we recommend investigating the impact of HRM$^{(AI)}$ on HR efficiency, HRM system strength, and HR service quality. The rationale for this is based on the fact that previous studies have observed a positive influence of technology-assisted HRM on HRM system strength (Bondarouk et al., 2017), HR efficiency (Bissola and Imperatori, 2020), and HR service quality (Bondarouk and Ruël, 2009). In fact, as per Malik et al. (2023), HRM$^{(AI)}$ has been shown to improve productivity gains, cost reduction, safety improvements and other operational efficiencies like accuracy, speed and resource employment in a wide range of industry sectors. Hence, the operational consequences of HRM$^{(AI)}$ emphasise efficiency and overall performance outcomes (Vrontis et al., 2021). We further pitch HR empowerment, trust in the HR department, and an internal relational social capital as *relational consequences* that need to be examined in much detail to observe the impact of HRM$^{(AI)}$. While implementing AI techniques in HRM can improve the relationship between HR and line managers and result in empowering individual employees, line managers, and senior managers to perform HR tasks themselves, thus reducing response time and improving service levels (Parry and Tyson, 2011), on the other hand, the relational factor of trust can be enhanced by AI implementation in HRM, to help employees perceive activities and criteria underlining HR policies that strengthen their trust in the HR department, thus legitimating their role and credibility (Bissola and Imperatori, 2020). Based on the assumption that advanced AI technologies have the potential to change the basic nature of HRM's fundamental nature from a 'descriptive and diagnostic' to a 'prescriptive and predictive' nature (Di Claudio, 2019), that can help strengthen relational coordination among employees and enhance internal relational social capital.

Transformational consequences refer to improvements in the business support and strategic orientation of HRM via the implementation of AI techniques transforming HRM into a more strategic function (Strohmeier and Piazza, 2015). We propose enhanced human resource analytics capability (Enhanced HRAC), strategic involvement, and HR global orientation as transformational consequences of HRM$^{(AI)}$. Through the implementation of AI techniques in HRM, an organisation can enhance their 'Big data analytical capabilities' (see Wang et al., 2016), serving as capacity building mechanism that helps in absorbing large amounts of the data (volume), maintaining structural heterogeneity (variety), enhancing the speed of data generation (velocity), ensuring data quality (veracity), and reaping economic benefits (value) of big data (Arunachalam et al., 2018). Further, implementing AI techniques in HRM may relieve HR professionals from essential administrative functions and empower them to portray a stellar role in the strategic matters of the organisation, thus contributing to HR strategic involvement. We also include HR global orientation - the standardisation of HR functions across units or departments within an organisation (Parry and Tyson, 2011) as one of the transformational consequences, as previous research has observed that technology-driven HRM can improve the global orientation of an organisation through standardisation of HR processes across units or departments. AI techniques can help managers standardise HRM practices across different organisational units and subsequently help managers improve the management process, resulting in a strategic contribution towards the organisation (Parry and Tyson, 2011).

6.5. Organisation-level outcomes impacting organisational performance

This level focuses on the organisation-level outcomes linked to the HRM outcomes level of HRM$^{(AI)}$. Based on Jiang et al. (2012), we categorise organisational outcomes into three factors, namely human capital (the composition of employee skills, knowledge, and abilities), employee motivation (reflected through collective job satisfaction, organisational commitment, organisational climate, perceived organisational support, and organisational citizenship behaviour) and retention (percentage of employees who tend to stay for longer-term). This categorisation is primarily based upon the ability-motivation-opportunity model of HRM, which divides HR outcomes into human capital, motivation, and opportunity to contribute (Guest, 1997). We anticipate that the HRM-level outcomes (i.e., operational, relational and transformational) will positively impact these organisation-level factors. There will be a resultant impact on the operational performance (productivity, quality, service, innovation, and overall operational performance) and financial performance (return on assets, return on equity, market return, sale growth, and overall financial performance) of the organisation. We also anticipate that interplay of human capital, employee motivation, and retention might have varying levels of impact on the operational and financial performance of the organisation that can be analysed through the interplay of these factors through mediating mechanisms. For instance, human capital is the organisation's most important resource as it consists of the workforce's collective knowledge, attributes, skills, experience, and health.

On the other hand, employee motivation drives the quality of work and boosts performance in an organisation. When organisations keep their employees motivated, they enable their workforce to become highly productive, and the workflow becomes more efficient. Finally, employee retention is important for an organisation's growth as it helps prevent burnout and can save an organisation from productivity losses. Hence, we assume that human capital, motivation, and retention interplay will impact HRM-level outcomes.

7. Theoretical implications

The main objective of this SLR was to conduct context and content analysis within the domain of HRM$^{(AI)}$ to identify gaps and develop a framework for future research. The SLR based on context and content analysis of 56 journal articles highlighted that there is a scarcity of sector and country-specific studies within the domain of HRM$^{(AI)}$ research, and there is a lack of robust theoretical framework for the development of HRM$^{(AI)}$ as a distinct field within the ambit of HRM. The findings that extant research around HRM$^{(AI)}$ displays an absence of underpinning theoretical frameworks and use of a few theories building and theory extension approaches, we recommend researchers/scholars use prescribed theories for future HRM$^{(AI)}$ research in Section 6.1.1. Applying the recommended tested techno-innovation theories such as TAM, UTAUT, IDT, DTOE, and TOP can overcome this conspicuous gap and can further provide a robust platform for examining diverse research themes in HRM$^{(AI)}$ research. Further, the assimilation of AI into HRM functions of an organisation involves complex processes and challenges, and there is a lack of a framework that systematically identifies and links diverse contextual and organisational level variables with organisational operational and financial performance. This SLR presents a robust framework that links diverse variables at different organisational levels to understand AI's assimilation into HRM. The multilevel framework provides a platform for researchers to conduct further empirical research to test the relationships among proposed variables.

The novel approach of presenting organisation-level factors (i.e. AI-HRM strategy, organisational facilitators, AI-oriented culture) and how it helps reconfigure the existing HRM department provides a base for exploring multiple empirical research themes that have the potential to help understand the assimilation of AI into HRM. Similarly, the linkage proposed between reconfigured HRM department and domain-level HRM consequences provides a platform to further conduct research regarding outcomes of HRM$^{(AI)}$. Last but not least, the underlying rationale for proposing the linkage between HRM consequences level and organisational outcomes and further organisational performance presents a novel proposition for HRM$^{(AI)}$ researchers to explore future research avenues.

8. Managerial implications

We also point out some important managerial implications based on this SLR. First, this research proposes a detailed framework that clearly outlines the organisational-level factors that can help top management and managers reconfigure their HRM to be AI-ready. The top management can delve into re-strategizing their approach to inculcate AI-oriented culture with the help of organisational facilitators to reconfigure their HRM department. The top managers need to re-evaluate their strategic analysis and formulation and strategy implementation to engage internally and external stakeholders in advancing AI-related gains in HRM. The newly formulated strategy should aim at understanding the requisite transformed culture and the environment needed to adapt to the AI-driven changes in the HRM department. We posit that the approach should be putting in place organisation-level facilitators (i.e. top management support, user training, technical user support), based upon a thorough analysis of the current state of the level of automation in different departments of the organisations. Top management support comprising vision sharing (or impressing HRM staff to understand the strategic benefits of HRM$^{(AI)}$), ensuring apt resource provision (e.g., funds, latest AI software, and HR staff with data science and analytical acumen) and change management (interventions related to HRM$^{(AI)}$ acceptance) can go a long way for ensuring understanding of the core objectives and ideals for HRM$^{(AI)}$ assimilation (Dong et al., 2009). Additionally, robust user training and constant technical support comprising collaborative efforts between HRM and IT professionals in an organisations to conduct workshop and coaching sessions and also provision of continuous training support from AI experts who specialise in HRM$^{(AI)}$ applications can ensure smooth HRM$^{(AI)}$ assimilation in the HRM department. Knowledge building communities/repositories, creation of IT department and HRM professionals dyads, implementation guides, smart toolkits, hot lines, and standard operating procedures for implementing different HRM$^{(AI)}$ applications can lay a solid platform for assimilating HRM$^{(AI)}$ in an organisation (Prikshat, 2022).These organisational facilitators will help the workforce to enhance their awareness of the functioning of AI applications, their usefulness and their fit with the job.

Developing an understanding of optimal HRM$^{(AI)}$ applications that can be utilised for diverse functions of HRM, the assimilation process of these applications, and ethical concerns regarding the use of different AI techniques can enhance the knowledge and awareness of managers to use AI in HRM to realise their full potential without any adverse impacts. We will like to highlight the less researched domain of significance of business analysts in plugging the client-developer gap for ensuring smooth assimilation of HRM$^{(AI)}$ in an organisation. The recruitment of competent business analysts who can translate the needs of diverse HR functions to AI experts can help in designing HRM$^{(AI)}$ applications that can be customed-fit into specific HR tasks. Moreover, business analysts can actually liaise among top management, HRM professionals and AI experts to check the most suitable HRM$^{(AI)}$ applications for HRM department or can explain to the experts to design specific applications to suit strategic HR needs. Further, previous research has observed numerous challenges (i.e., issues of data privacy, security, ethical/moral judgment goal alignment between AI and human beings) that raises ethical concerns related to assimilation of HRM$^{(AI)}$ (Prikshat et al., 2022). An organisation's managers must identify the likely ethical issues arising from the use of HRM$^{(AI)}$ applications in each HR function and develop robust standard operating procedures and mechanisms to eliminate or minimize the adverse effects and dark side issues of HRM$^{(AI)}$. The willingness of senior management to actively engage with ethical issues and responsibly addressing them can reduce its adverse impact and ensure smooth assimilation of HRM$^{(AI)}$. Policy level initiatives, such as guidance mechanisms that can help steer HR policies to develop ethical HRM$^{(AI)}$ practices, and implementation of the principles of ethical corporate governance for HRM$^{(AI)}$ practices can go a long way to ensure ethical use of HRM$^{(AI)}$ in organisations (Stahl et al., 2022).

Understanding the potential of different AI-enabled smart database management for various levels and functions of the HRM department may help managers offer isolated and end-to-end intelligence HRM services within the organisation. Similarly, understanding the HRM assimilation process (i.e. initiation, adoption, routinization and extension) will help the managers to achieve HR domain-level operational, relational and transforaminal consequences. Last but not least, the linkage of operational, relational, and transformation consequences with organisational-level outcomes (i.e., operational and financial performance) provides managers with an understanding of how HRM$^{(AI)}$ translates in terms of achieving the desired operational and financial performance.

9. Limitations & future directions

This SLR has not captured new research that falls outside of the review and provided a higher level overview of the literature. Particularly coverage of content that must be included, should represent a broader spectrum of industries, sectors and geographical locations. Moreover, the presence of a rigid criteria for paper selection might have also led to the exclusion of some relevant studies. Further, though our research presents a multilevel framework for the development of HRM$^{(AI)}$, we could not focus in depth on the specific outcomes of transformation, operational and relational consequences of assimilation of HRM$^{(AI)}$ in an organisation. Future qualitative research comprising specific and much more precise outcomes, such as HR manager's experiences of using HRM$^{(AI)}$, performance enhancement and inter-connected impact of HRM$^{(AI)}$ on other functions of the organisation. Regarding research avenues for exploring future research, we recommend HR domain-specific research and that researchers/scholars build upon prescribed technology adoption theories borrowed from technical innovation literature that is uniquely applicable to the HRM$^{(AI)}$ context. For examining the composite impact of HRM$^{(AI)}$, more empirical investigations are needed in less studied functions of HRM, such as compensation and benefits and learning and development. In the absence of such research, we might not be aware of the limited capability of HRM$^{(AI)}$ applications in assisting only some of the HR functions. Future empirical studies capturing the essence and applicability of HRM$^{(AI)}$ applications for each of HRM functions will help widen the understanding of composite impact of HRM$^{(AI)}$. Moreover, this will also serve as a catalyst for AI application developers to concentrate on HRM$^{(AI)}$ applications that are cater to the less neglected HR functions.

In regard to the proposed multilevel framework, more research on different layers and components can help develop the domain of HRM$^{(AI)}$. Specific research on AI-HRM strategy nexus (such as factors for facilitating strategic technological alignment between business strategy and HRM department, mechanism to develop linkage of HRM$^{(AI)}$ with organisational business intelligence infrastructure), research to see the impact of mentioned organisational facilitators or investigating more facilitators for assimilation of HRM$^{(AI)}$ with in HRM department, and research related to establishing a culture of AI leadership, conscience and responsibility can contribute a lot to take the organisational level components understanding further. Another important area of future research might be pertaining to AI techniques identification, where we see important role of development of business analysts who can understand the needs of HRM professionals and at the same time have the ability to convey to the AI experts to develop suitable HRM$^{(AI)}$ applications. More precise research on how organisations explore different HRM$^{(AI)}$ applications or various gaps in terms of identifying the exact HRM$^{(AI)}$ software would add great value to research in this domain. Though, Prikshat et al. (2023) have advanced a conceptual framework for assimilating AI in HRM, further quantitative research is needed to test the propositions advanced. Similarly, a preliminary ethical framework proposed by Prikshat et al. (2022) can be tested with empirical research. Finally, the future researchers can include new aspects that have operational, relational and transformational consequences of HRM$^{(AI)}$ and translate in enhanced operational and financial performance.

10. Conclusion

This SLR presents a gist of HRM$^{(AI)}$ research through a rigorous content and context analysis. Based on the findings of this SLR, our multilevel research framework serves as a platform to fully explore multilevel empirical research themes in HRM$^{(AI)}$. The extensive SLR highlights and captures the progress towards understanding influence, diverse themes, and gaps in the existing HRM$^{(AI)}$ literature. The SLR illustrates the diversity of HRM$^{(AI)}$ research foci in the extant research and based on the gaps noted in this SLR, we recommend a balanced coverage of HRM$^{(AI)}$ pertaining to all the functions of HRM, selecting from a vast but related bundle of theories/frameworks for undertaking empirical research on the linkage between HRM$^{(AI)}$, and HRM domain-level and organisational consequences. Such research can enhance the validity and viability of HRM$^{(AI)}$ research.

Research involving human participants and/or animal

This research does not contain any studies involving human or animal participants performed by any of the authors.

Informed consent

Since it is a systematic literature review that's why this research didn't require informed consents.

CRediT authorship contribution statement

Verma Prikshat: Conceptualization, Data curation, Formal analysis, Investigation, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mohammad Islam:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Parth Patel:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ashish Malik:** Data curation, Formal analysis, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Pawan Budhwar:** Data curation, Formal analysis, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Suraksha Gupta:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

We confirm that there are no competing interests that are directly or indirectly related to the work submitted for this publication.

Data availability

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

Appendix A

Appendix 1
A summary of AI-HR publications.

SL no	Authors/Year	Title	Country	Journal	CABSRank	Theoretical concepts/ frameworks	Research methodology/ approaches	HR function	Key theme
1	Abubakar et al. (2019)	Applying artificial intelligence technique to predict knowledge hiding behaviour	Turkey	IJIM	3	Psychological ownership and social exchange theory	Quantitative (Survey)	Performance Management	Knowledge hiding behaviour impact on performance management
2	Bell et al. (2008)	Current issues and future directions in simulation-based training in North America	USA	IJHRM	3	No Theory	Critical Review	Training and Development	Simulation-based training on skill development.
3	Black and van Esch (2020)	AI-enabled recruiting: What is it, and how should a manager use it?	USA	BH	3	No Theory	Critical Review	Recruitment and Selection	AI-enabled recruitment necessity and key strategic steps
4	Brock and Von Wangenheim (2019)	Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence	USA	CMR	3	Innovation-adoption-implementation theory	Quantitative (Survey)	Performance Management	Human intelligence, skilled staff, employee engagement
5	Burnett and Lisk (2019)	The future of employee engagement: Real-time monitoring and digital tools for engaging a workforce	USA	ISMO	2	No Theory	Critical Review	Employee Engagement	Employee engagement with digital tools
6	Cascante et al. (2002)	The impact of expert decision support systems on the performance of new employees	USA	IRMJ	1	Expert system(ES) theory - Performance, user satisfaction and learning	Experimental design	Performance Management	Knowledge, expertise, performance, and satisfaction
7	Cesta et al. (2014)	Training for crisis decision making–An	Italy	KBS	–	Psycho-physiological experiment	Experimental design	Training and Development	Training for crisis decision making

(continued on next page)

Appendix 1 (*continued*)

SL no	Authors/Year	Title	Country	Journal	CABSRank	Theoretical concepts/ frameworks	Research methodology/ approaches	HR function	Key theme
		approach based on plan adaptation							
8	Chamorro-Premuzic et al. (2019)	Building ethical AI for talent management	USA	HBR	3	No Theory	Critical Review	Talent Management	AI-based talent management practices
9	Cheng and Hackett (2019)	A critical review of algorithms in HRM: Definition, theory, and practice	Canada	HRMR	3	No Theory	Critical Review	Recruitment, Training & Development, Compensation	Eliminating unconscious human bias in recruitment, HRM algorithms for decision-making in training, Flexible adjustments to compensation packages
10	Chien and Chen (2008)	Data mining to improve personnel selection and enhance human capital: A case study in the high-technology industry	Taiwan	ESA	3	A data mining framework for personnel selection	Quantitative (Survey)	Recruitment and Selection & Retention	Association between personnel characteristics and work behaviours & retention
11	Claus (2019)	HR disruption—Time already to reinvent talent management	USA	BRQ	–	No Theory	Critical Review	Talent Management	Impact of AI techniques on talent management
12	Coeurderoy et al. (2014)	Explaining factors affecting technological change adoption: A survival analysis of an information system implementation	Belgium	MD	2	A fuzzy model for competency-based employee evaluation and selection	Quantitative (Survey)	Training and Development	Role of AI in self-efficacy and supervisor influence
13	Cubric (2020)	Drivers, barriers, and social considerations for AI adoption in business and management	UK	TS	–	No Theory	Critical Review (SLR)	Training and Development	Implications of AI-adoption on development
14	Danieli et al. (2016)	How to hire with algorithms	USA	HBR	3	No Theory	Critical Review	Recruitment and Selection	Algorithm for recruitment and selection
15	Dattner et al. (2019)	The legal and ethical implications of using AI in hiring	USA	HBR	3	No Theory	Critical Review	Recruitment and Selection	AI-based recruitment and employees privacy concern
16	Davenport (2019)	Is HR the most-analytics driven function	USA	HBR	3	No Theory	Quantitative (Survey)	Training and Development	HR analytics is beneficial for training and development.
17	Deobald et al. (2019)	The challenges of algorithm-based HR decision-making for personal integrity	Switzerland	JBE	3	No Theory	Critical Review	Performance Management	Algorithm-based HR Decision-Making for Workplace monitoring
18	Escolar-Jimenez et al. (2019)	Data-Driven Decisions in Employee Compensation utilizing a Neuro-Fuzzy Inference System	Japan	IJETER	–	No Theory	Quantitative (Survey)	Reward Management	The usefulness of fuzzy logic and artificial neural network in designing employees' reward
19	Fan et al. (2012)	Using hybrid data mining and machine learning clustering analysis to predict the turnover rate for technology professionals	Taiwan	ESA	3	Clustering analysis data mining methodology	Quantitative (Survey)	Employee Turnover	Hybrid data mining, machine learning clustering- analysis for employee turnover prediction.
20	Golec and Kahya (2007)	A fuzzy model for competency-based employee evaluation and selection	Turkey	CIE	3	Theory of constructing hierarchies	The Analytic Hierarchy Process (AHP)	Recruitment and Selection	Employee evaluation and selection
21	Gratton (2019)	New frontiers in re-skilling and upskilling	UK	MSMR	3	No Theory	Critical Review	Training and Development	AI's assistance in re-skilling and upskilling
22	Guinan et al. (2019)	Creating an innovative digital project team: Levers to enable digital transformation	USA	BH	3	No Theory	Critical Review	Talent Management	Digital transformation of talent management
23	Gupta et al. (2018)	Automation in recruitment: a new frontier	India	JITTC	1	No Theory	Quantitative (Survey)	Recruitment and Selection	AI-enabled recruitment

(continued on next page)

Appendix 1 (*continued*)

SL no	Authors/Year	Title	Country	Journal	CABSRank	Theoretical concepts/ frameworks	Research methodology/ approaches	HR function	Key theme
24	Huang et al. (2019)	The feeling economy: managing in the next generation of artificial intelligence (AI)	USA	CMR	3	No Theory	Critical Review	Change in job design in wake of AI	Job design at the feeling economy will be based on intelligence skills instead of analytical and thinking skills
25	Jaiswal et al. (2021)	Rebooting employees: upskilling for artificial intelligence in multinational corporations.	India	IJHRM	3	Dynamic skill, neo-human capital	Qualitative	Upskilling/ Development	Upskilling in wake of AI in MNCs
26	Karatop et al. (2015)	Talent management in a manufacturing system using fuzzy logic approach	Turkey	CIE	3	Fuzzy Set Theory	Critical Review	Talent Management	Fuzzy for putting right people with proper talents to the right positions
27	Khosla et al. (2009)	Separating the wheat from the chaff: An intelligent sales recruitment and benchmarking system	Australia	ESA	3	Expert system model	Mixed Methods	Recruitment and Selection	AI-based recruitment and benchmarking system
28	Kuncel et al. (2014)	In hiring, algorithms beat instinct	USA	HBR	3	No Theory	Critical Review	Recruitment and Selection	Artificial Intelligent Design (AID) framework for selection
29	Lawler and Elliot (1996)	Artificial intelligence in HRM: an experimental study of an expert system	USA	JM	4*	Behavioural Decision Theory	Experimental design	Job Design	AI as an expert system for the job evaluation system
30	Lee and Ahn (2020)	Industrial Human Resource Management Optimization based on Skills and Characteristics	South Korea	CIE	3	Artificial Intelligence based Design platform (AID)	Quantitative (Survey)	Recruitment and Selection	AI-based recruitment and benchmarking system
31	Leonardi and Contractor (2018)	Better people analytics	USA	HBR	3	No Theory	Critical Review	Talent Management	People analytics for talent management
32	Leicht-Deobald et al. (2019)	The challenges of algorithm-based HR decision-making for personal integrity	Switzerland	JBE	3	No Theory	Critical Review	Performance Management	Algorithm-based HR Decision-Making for Workplace monitoring
33	Liebowitz (2001)	Knowledge management and its link to artificial intelligence	USA	ESA	3	No Theory	Critical Review	Training and Development	Future of knowledge management with AI for organisation and leadership development
34	Li et al. (2019)	Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate	China	TM	4	No Theory	Quantitative (Survey)	Employee Turnover	AI for predicting employee's turnover
35	Maity (2019)	Identifying opportunities for artificial intelligence in the evolution of training and development practices	India	JMD	1	No Theory	Qualitative (Interviews)	Training and Development	AI's use in personalised training
36	Manoharan et al. (2011)	An integrated fuzzy multi-attribute decision-making model for employees' performance appraisal	India	IJHRM	3	Fuzzy Set Theory	Mixed Methods	Performance Management	AI for biased free performance appraisal.
37	Martinsons (1997)	Human resource management applications of knowledge-based systems	Hongkong	IJIM	2	No theory	Critical Review	Training and Development	Knowledge based systems for training & development
38	Mehrabad and Brojeny (2007)	The development of an expert system for effective selection and	Iran	CIE	3	No theory	Critical Review	Recruitment and Selection	Expert system for intelligent selection

(continued on next page)

Appendix 1 (*continued*)

SL no	Authors/Year	Title	Country	Journal	CABSRank	Theoretical concepts/ frameworks	Research methodology/ approaches	HR function	Key theme
		appointment of the jobs applicants in human resource management.							and appointment process
39	Michailidis (2018)	The Challenges of AI and Blockchain on HR Recruiting Practices	Cyprus	TIS	–	No theory	Critical Review	Recruitment and Selection	Blockchain technology in recruitment
40	Pan et al. (2021)	The adoption of artificial intelligence in employee recruitment: The influence of contextual factors.	China	IJHRM	3	TOE framework and transaction cost theory	Quantitative (Survey)	Recruitment and Selection	AI adoption
41	Polli (2019)	Using AI to Eliminate Bias from Hiring	USA	HBR	3	No theory	Critical Review	Recruitment and Selection	AI's role in eliminating-unconscious human bias
42	Polychroniou and Giannikos (2009)	A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank	Greece	CDI	1	Fuzzy Set Theory	Experimental design	Recruitment and Selection	AI technique for sound decision-making in selection
43	Raub (2018)	Bots, bias and big data: artificial intelligence, algorithmic bias and disparate impact liability in hiring practices	USA	ALR	–	No Theory	Critical Review	Recruitment and Selection	Benefits of AI to increase hiring efficiency
44	Robert et al. (2020)	Designing fair AI for managing employees in organizations: a review, critique, and design agenda	USA	HCI	1	Organisational Justice Theory	Critical Review	Performance Management	Designing fair AI for managing employees
45	Sajjadiani et al. (2019)	Using machine learning to translate applicant work history into predictors of performance and turnover	USA	JAP	4*	No theory	Quantitative (Survey)	Recruitment and Selection	AI technique for improving the quality of selection process
46	Singh and Finn (2003)	The effects of information technology on recruitment	USA	JLR	2	No theory	Critical Review	Recruitment and Selection	Impact of AI on recruitment
47	Sivathanu and Pillai (2019)	Technology and talent analytics for talent management–a game-changer for organizational performance	India	IJOA	1	No Theory	Qualitative (Interviews)	Talent Management	Talent analytics for talent management
48	Strohmeier and Piazza (2013)	Domain-driven data mining in human resource management: A review of current research	Germany	ESA	3	Domain driven data mining framework	Critical Review	Recruitment and Selection, Performance Management, Employee Turnover	Applicability of data mining for HR functions
49	Suen et al. (2019)	Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes	China	CHB	3	Media richness theory and social interface theory	Experimental design	Recruitment and Selection	Job applicants' fairness perception between the AVI setting and the AVI setting using an AI decision agent (AVI-AI)
50	Tambe et al. (2019)	Artificial intelligence in human resources management: Challenges and a path forward.	USA	CMR	3	No theory	Critical Review	Generic HRM	Challenges of AI in HRM
51	Upadhyay and Khandelwal (2018)	Applying artificial intelligence: implications for recruitment.	India	SHR	–	No theory	Critical Review	Recruitment and Selection	AI-enabled recruitment
52	Van Esch et al. (2019)	Marketing AI recruitment: The next phase in the job application and selection	USA	CHB	3	No theory	Quantitative (Survey)	Recruitment and Selection	AI-enabled recruitment

(*continued on next page*)

Appendix 1 (*continued*)

SL no	Authors/Year	Title	Country	Journal	CABSRank	Theoretical concepts/ frameworks	Research methodology/ approaches	HR function	Key theme
53	Van Esch and Black (2019)	Factors that influence new-generation candidates to engage with and complete digital, AI-enabled recruiting	USA	BH	3	No Theory	Quantitative (Survey)	Recruitment and Selection	Algorithm for recruitment and selection
54	Van Esch et al. (2020)	AI-enabled biometrics in recruiting: Insights from marketers for managers	USA	AJM	2	Subjective intention theory	Quantitative (Survey)	Recruitment and Selection	AI-enabled biometrics for attracting candidates
55	Wang et al. (2011)	Constructing a decision support system for management of employee turnover risk	China	ITM	B	Decision Support Theory	Critical Review	Employee Turnover	Decision support system for employee turnover risk management
56	Wang et al. (2017)	Developing an employee turnover risk evaluation model using case-based reasoning	China	ISF	3	No theory	Critical Review	Employee Turnover	AI for employee turnover risk

References

Abubakar, A.M., Behravesh, E., Rezapouraghdam, H., Yildiz, S.B., 2019. Applying artificial intelligence technique to predict knowledge hiding behavior. Int. J. Inf. Manag. 49, 45–57. https://doi.org/10.1016/j.ijinfomgt.2019.02.006.

AI Readiness Index Report, 2020. Oxford insights. Available at: https://www.oxfordinsights.com/government-ai-readiness-index-2020 (Accessed 27 October 2021).

Ain, N., Vaia, G., DeLone, W.H., Waheed, M., 2019. Two decades of research on business intelligence system adoption, utilization, and success–a systematic literature review. Decis. Support. Syst. 125, 113113 https://doi.org/10.1016/j.dss.2019.113113.

Ajzen, I., 1991. The theory of planned behaviour. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211.

Alfes, K., Avgoustaki, A. Alexandra, Beauregard, T., Cañibano, A., Muratbekova-Touron, M., 2020. Call for papers for the special issue on 'New ways of working: understanding the implications for employees across different cultural and organizational contexts.'. In: 16th International Journal of Human Resource Management Conference. ESCP, Paris.

Arslan, A., Cooper, C., Khan, Z., Golgeci, I., Ali, I., 2021. Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies. Int. J. Manpow. 43 (1), 75–88. https://doi.org/10.1108/IJM-01-2021-0052.

Arunachalam, D., Kumar, N., Kawalek, J.P., 2018. Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice. Transport Res E-Log 114, 416–436. https://doi.org/10.1016/j.tre.2017.04.001.

Bell, B.S., Kanar, A.M., Kozlowski, S.W., 2008. Current issues and future directions in simulation-based training in North America. Int. J. Hum. Resour. Manag. 19 (8), 1416 1434. https://doi.org/10.1080/09585190802200173.

Belur, J., Tompson, L., Thornton, A., Simon, M., 2021. Interrater reliability in systematic review methodology: exploring variation in coder decision-making. Social Methods Res. 50 (2), 837–865. https://doi.org/10.1177/0049124118799372.

Bissola, R., Imperatori, B., 2020. "Prelims", HRM 4.0 for Human-centered Organizations. Advanced Series in Management, 23. Emerald Publishing, Bingley, pp. 1–22. https://doi.org/10.1108/S1877-636120190000023001.

Black, J.S., van Esch, P., 2020. AI-enabled recruiting: what is it, and how should a manager use it? Bus. Horiz. 63 (2), 215–226.

Bondarouk, T.V., Ruël, H.J., 2009. Electronic human resource management: challenges in the digital era. Int. J. Hum. Resour. Manag. 20 (3), 505–514. https://doi.org/10.1080/09585190802707235.

Bondarouk, T., Parry, E., Furtmueller, E., 2017. Electronic HRM: four decades of research on adoption and consequences. Int. J. Hum. Resour. Manag. 28 (1), 98–131. https://doi.org/10.1080/09585192.2016.1245672.

Brock, J.K.U., Von Wangenheim, F., 2019. Demystifying AI: what digital transformation leaders can teach you about realistic artificial intelligence. Calif. Manag. Rev. 61 (4), 110–134. https://doi.org/10.1177/1536504219865226.

Budhwar, P., Malik, A., De Silva, T., Thevisuthan, P., 2022. Artificial intelligence - Challenges and opportunities for International HRM: a review and research agenda. Int. J. Hum. Resour. Manag. 33 (6), 1065–1097.

Burnett, J.R., Lisk, T.C., 2019. The future of employee engagement: real-time monitoring and digital tools for engaging a workforce. Int. Stud. Manag. Organ. 49 (1), 108–119. https://doi.org/10.1080/00208825.2019.1565097.

Buxmann, P., Hess, T., Thatcher, J., 2019. Call for papers, issue 1/2021. Bus. Inf. Syst. Eng. 61 (4), 545–547. https://doi.org/10.1007/s12599-019-00606-2.

Cascante, L.P., Plaisent, M., Maguiraga, L., Bernard, P., 2002. The impact of expert decision support systems on the performance of new employees. Inf. Resour. Manag. J. 15 (4), 64–78.

Cesta, A., Cortellessa, G., De Benedictis, R., 2014. Training for crisis decision making–an approach based on plan adaptation. Knowl.-Based Syst. 58, 98–112. https://doi.org/10.1016/j.knosys.2013.11.011.

Chamorro-Premuzic, T., Polli, F., Dattner, B., 2019. Building ethical AI for talent management. Harv. Bus. Rev. (21 November) https://egn.com/dk/wp-content/uploads/sites/3/2020/06/Building-Ethical-AI-for-Talent-Management.pdf (21 November) Accessed 24 December 2020.

Cheng, M.M., Hackett, R.D., 2019. A critical review of algorithms in HRM: definition, theory, and practice. Hum. Resour. Manag. Rev. 31 (1), 100698 https://doi.org/10.1016/j.hrmr.2019.100698.

Chien, C.F., Chen, L.F., 2008. Data mining to improve personnel selection and enhance human capital: a case study in high-technology industry. Expert Syst. Appl. 34 (1), 280–290. https://doi.org/10.1016/j.eswa.2006.09.003.

Chu, T.H., Chen, Y.Y., 2016. With good we become good: understanding e-learning adoption by theory of planned behaviour and group influences. Comput. Educ. 92, 37–52. https://doi.org/10.1016/j.compedu.2015.09.013.

Claus, L., 2019. HR disruption—time already to reinvent talent management. BRQ Bus. Res. Q. 22 (3), 207–215. https://doi.org/10.1016/j.brq.2019.04.0.

Coeurderoy, R., Guilmot, N., Vas, A., 2014. Explaining factors affecting technological change adoption: a survival analysis of an information system implementation. Manag. Decis. 52 (6), 1082–1100. https://doi.org/10.1108/MD-10-2013-0540.

Cubric, M., 2020. Drivers, barriers, and social considerations for AI adoption in business and management: a tertiary study. Technol. Soc. 62, 101257 https://doi.org/10.1016/j.techsoc.2020.101257.

Danese, P., Manfè, V., Romano, P., 2018. A systematic literature review on recent lean research: state-of-the-art and future directions. Int. J. Manag. Rev. 20 (2), 579–605. https://doi.org/10.1111/ijmr.12156.

Danieli, O., Hillis, A., Luca, M., 2016. How to hire with algorithms. Harv. Bus. Rev. 17 October https://hbr.org/2016/10/how-to-hire-with-algorithms Accessed 20 December 2020.

Dattner, B., Chamorro-Premuzic, T., Buchband, R., Schettler, L., 2019. The legal and ethical implications of using AI in hiring. Harv. Bus. Rev. 25 April https://egn.com/dk/wp-content/uploads/sites/3/2020/06/The-legal-and-ethical-implications-of-using-AI-in-Hiring.pdf Accessed 23 July 2020.

Davenport, T., 2019. Is HR the most analytics-driven function? Harv. Bus. Rev. 19 April https://hbr.org/2019/04/is-hr-the-most-analytics-driven-function Accessed 10 August. 2020.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319–339.

Deloitte, 2019. Global artificial intelligence industry whitepaper. https://www2.deloitte.com/cn/en/pages/technology-media-andtelecommunications/articles/global-ai-development-white-paper.html (Accessed November. 22, 2020).

Denyer, D., Tranfield, D., Van Aken, J.E., 2008. Developing design propositions through research synthesis. Organ. Stud. 29 (3), 393–413. https://doi.org/10.1177/0170840607088020.

Di Claudio, M., 2019. People analytics and the rise of HR: how data, analytics and emerging technology can transform human resources (HR) into a profit centre. Strateg. HR Rev. 18 (2), 42–46. https://doi.org/10.1108/SHR-11-2018-0096.

Dong, L., Neufeld, D., Higgins, C., 2009. Top management support of enterprise systems implementations. J. Inf. Technol. 24 (1), 55–80.

Dora, M., Kumar, A., Mangla, S.K., Pant, A., Kamal, M.M., 2021. Critical success factors influencing artificial intelligence adoption in food supply chains. Int. J. Prod. Res. 60 (14), 4621–4640. https://doi.org/10.1080/00207543.2021.1959665.

Du, S., Xie, C., 2021. Paradoxes of artificial intelligence in consumer markets: ethical challenges and opportunities. J. Bus. Res. 129, 961–974. https://doi.org/10.1016/j.jbusres.2020.08.024.

Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. Int. J. Inf. Manag. 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021.

Escolar-Jimenez, C.C., Matsuzaki, K., Okada, K., Gustilo, R.C., 2019. Data-driven decisions in employee compensation utilizing a neuro-fuzzy inference system. Int. J. Emerg. Trends Eng. Dev. 7 (8), 163–169. https://doi.org/10.30534/ijeter/2019/10782019.

Fan, C.Y., Fan, P.S., Chan, T.Y., Chang, S.H., 2012. Using hybrid data mining and machine learning clustering analysis to predict the turnover rate for technology professionals. Expert Syst. Appl. 39 (10), 8844–8851. https://doi.org/10.1016/j.eswa.2012.02.005.

Fountaine, T., McCarthy, B., Saleh, T., 2019. Building the AI-powered organization technology isn't the biggest challenge, culture is. Harv. Bus. Rev. 97 (4), 62–73.

Golec, A., Kahya, E., 2007. A fuzzy model for competency-based employee evaluation and selection. Comput. Ind. Eng. 52 (1), 143–161. https://doi.org/10.1016/j.cie.2006.11.004.

Gottwald, S., 1999. Many-valued logic and fuzzy set theory. In: Mathematics of Fuzzy Sets. Springer, Boston, MA, pp. 5–89.

Gratton, L.C., 2019. New frontiers in re-skilling and upskilling. MIT Sloan Manag. Rev. 61 (1). https://sloanreview.mit.edu/article/new-frontiers-in-re-skilling-and-upskilling/ (Accessed 21 October 2021).

Guest, D.E., 1997. Human resource management and performance: a review and research agenda. Int. J. Hum. Resour. Manag. 8 (3), 263–276. https://doi.org/10.1080/095851997341630.

Guinan, P.J., Parise, S., Langowitz, N., 2019. Creating an innovative digital project team: levers to enable digital transformation. Bus. Horiz. 62 (6), 717–727.

Gupta, P., Fernandes, S.F., Jain, M., 2018. Automation in recruitment: a new frontier. J. Inf. Technol. Teach. 8 (2), 118–125. https://doi.org/10.1057/s41266-018-0042-x.

Harvey, C.R., Liechty, J.C., Liechty, M.W., Müller, P., 2010. Liechty and P. Müller. Portfolio selection with higher moments. Quant. Finan. 10 (5), 469–485. https://doi.org/10.1080/14697681003756877.

Henderson, J.C., Venkatraman, H., 1999. Strategic alignment: leveraging information technology for transforming organizations. IBM Syst. J. 38 (2.3), 472–484. https://doi.org/10.1147/sj.382.0472.

Huang, M.H., Rust, R., Maksimovic, V., 2019. The feeling economy: managing in the next generation of artificial intelligence (AI). Calif. Manag. Rev. 61 (4), 43 65. https://doi.org/10.1177/0008125619863436.

Jain, H., Padmanabhan, B., Pavlou, P.A., Santanam, R.T., 2018. Call for papers—special issue of information systems research—humans, algorithms, and augmented intelligence: the future of work, organizations, and society. Inf. Syst. Res. 29 (1), 250–251. https://doi.org/10.1287/isre.2018.0784.

Jaiswal, A., Arun, C.J., Varma, A., 2021. Rebooting employees: upskilling for artificial intelligence in multinational corporations. Int. J. Hum. Resour. Manag. 33 (6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114.

Jiang, K., Lepak, D.P., Hu, J., Baer, J.C., 2012. How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. Acad. Manag. J. 55 (6), 1264–1294. https://doi.org/10.5465/amj.2011.0088.

Kahraman, C., Kaya, İ., Çinar, D., 2010. Computational intelligence: past, today, and future. In: Computational Intelligence in Complex Decision Systems. Atlantis Press, pp. 1–46.

Kaplan, A., Haenlein, M., 2020. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Bus. Horiz. 63 (1), 37 50. https://doi.org/10.1016/j.bushor.2019.09.003.

Karatop, B., Kubat, C., Uygun, Ö., 2015. Talent management in manufacturing system using fuzzy logic approach. Comput. Ind. Eng. 86, 127–136. https://doi.org/10.1016/j.cie.2014.09.015.

Khosla, R., Goonesekera, T., Chu, M.T., 2009. Separating the wheat from the chaff: an intelligent sales recruitment and benchmarking system. Expert Syst. Appl. 36 (2), 3017–3027. https://doi.org/10.1016/j.eswa.2008.01.090.

Kiron, D., Schrage, M., 2019. Strategy for and with AI. MIT Sloan Manag. Rev. 60 (4), 30–35.

Kitchenham, B., 2004. Procedures for Performing Systematic Reviews, 33. Keele University, Keele, UK, pp. 1–26.

Kondapaka, P., Khanra, S., Malik, A., Kagzi, M., Hemachandran, K., 2023. Finding a fit between CXO's experience and AI usage in CXO decision-making: evidence from knowledge-intensive professional service firms. J. Serv. Theory Pract. 33 (2), 280–308.

Kuncel, N.R., Klieger, D.M., Ones, D.S., 2014. In hiring, algorithms beat instinct. Harv. Bus. Rev. 92 (5), 32.

Kunisch, S., Menz, M., Ambos, B., 2015. Changes at corporate headquarters: review, integration, and future research. Int. J. Manag. Rev. 17 (3), 356–381. https://doi.org/10.1111/ijmr.12044.

Lawler, J.J., Elliot, R., 1996. Artificial intelligence in HRM: an experimental study of an expert system. J. Manag. 22 (1), 85–111. https://doi.org/10.1177/014920639602200010.

Lee, J.E., 2016. Qualitative approach in research on human resource management. J. Korea Content. Assoc. 16 (10), 188–195.

Lee, D., Ahn, C., 2020. Industrial human resource management optimization based on skills and characteristics. Comput. Ind. Eng. 144, 106463 https://doi.org/10.1016/j.cie.2020.106463.

Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., Kasper, G., 2019. The challenges of algorithm-based HR decision-making for personal integrity. J. Bus. Ethics 160 (2), 1–16. https://doi.org/10.1007/s10551-019-04204-w.

Leikas, J., Koivisto, R., Gotcheva, N., 2019. Ethical framework for designing autonomous intelligent systems. J. Open Innov. Technol. Mark. Complex 5 (1), 18. https://doi.org/10.3390/joitmc5010018.

Leonardi, P., Contractor, N., 2018. Better people analytics. Harv. Bus. Rev. 96 (6), 70–81.

Li, J.J., Bonn, M.A., Ye, B.H., 2019. Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: the moderating roles of perceived organizational support and competitive psychological climate. Tour. Manag. 73, 172–181. https://doi.org/10.1016/j.tourman.2019.02.006.

Lichtenthaler, U., 2020. Beyond artificial intelligence: why companies need to go the extra step. J. Bus. Strateg. 41 (1), 19–26. https://doi.org/10.1108/JBS-05-2018-0086.

Liebowitz, J., 2001. Knowledge management and its link to artificial intelligence. Expert Syst. Appl. 20 (1), 1–6. https://doi.org/10.1016/S0957-4174(00)00044-0.

Luo, Y., Zhang, H., 2016. Emerging market MNEs: qualitative review and theoretical directions. J. Int. Manag. 22 (4), 333–350. https://doi.org/10.1016/j.intman.2016.05.001.

Macpherson, A., Jones, O., 2010. Strategies for the development of international journal of management reviews. Int. J. Manag. Rev. 12 (2), 107–113. https://doi.org/10.1111/j.1468-2370.2010.00282.x.

Maity, S., 2019. Identifying opportunities for artificial intelligence in the evolution of training and development practices. J. Manag. Dev. 38 (8), 651–663. https://doi.org/10.1108/JMD-03-2019-0069.

Malik, A., De Silva, M.T., Budhwar, P., Srikanth, N.R., 2021. Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: evidence from an IT-multinational enterprise. J. Int. Manag. 27 (4), 100871 https://doi.org/10.1016/j.intman.2021.100871.

Malik, A., Budhwar, P., Patel, C., Srikanth, N.R., 2022a. May the bots be with you! Delivering HR cost-effectiveness and individualized employee experiences in an MNE. Int. J. Hum. Resour. Manag. 33 (4), 1–31. https://doi.org/10.1080/09585192.2020.1859582.

Malik, A., Budhwar, P., Mohan, H., Srikanth, N.R., 2022b. Employee experience –the missing link: insights from an MNE's AI-based employee engagement ecosystem. Hum. Resour. Manag. https://doi.org/10.1002/hrm.22133.

Malik, A., Nguyen, M., Budhwar, P., 2022c. Antecedents and consequences of an artificial intelligence mediated knowledge-sharing social exchange: towards a conceptual model. IEEE Trans. Eng. Manag. https://doi.org/10.1109/TEM.2022.3163117.

Malik, A., Budhwar, P., Kazmi, B.A., 2023. Artificial intelligence (AI)-assisted HRM: towards an extended strategic framework. Hum. Resour. Manag. Rev. https://doi.org/10.1016/j.hrmr.2022.100940.

Manoharan, T.R., Muralidharan, C., Deshmukh, S.G., 2011. An integrated fuzzy multi-attribute decision-making model for employees' performance appraisal. Int. J. Hum. Resour. Manag. 22 (3), 722–745. https://doi.org/10.1080/09585192.2011.543763.

Martinsons, M.G., 1997. Human resource management applications of knowledge-based systems. Int. J. Inf. Manag. 17 (1), 35–53. https://doi.org/10.1016/S0268-4012(96)00041-2.

McKinsey, 2020. The state of AI in 2020. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020. Accessed November. 12, 2020.

Mefi, N.P., Asoba, S.N., 2021. Sustainable human resource practices for organizational competitiveness post the covid-19 pandemic. Acad. Entrep. J. 27 (2), 1–7.

Mehrabad, M.S., Brojeny, M.F., 2007. The development of an expert system for effective selection and appointment of the jobs applicants in human resource management. Comput. Ind. Eng. 53 (2), 306–312. https://doi.org/10.1016/j.cie.2007.06.023.

Meijerink, J., Boons, M., Keegan, A., Marler, J., 2018. Special issue of the international journal of human resource management: digitization and the transformation of human resource management. Int. J. Hum. Resour. Manag. 1-6 https://doi.org/10.1080/09585192.2018.1503845.

Michailidis, M.P., 2018. Hie challenges of AI and Blockchain on HR recruiting practices. Cyprus Rev. 30 (2), 169–170.

Ndemewah, S.R., Hiebl, M.R., 2022. Management accounting research in Africa. Eur. Account. Rev. 31 (4), 1029–1057. https://doi.org/10.1080/09638180.2021.1897025.

Nguyen, T.M., Malik, A., 2022a. A two-wave cross-lagged study on AI service quality: the moderating effects of the job level and job role. Br. J. Manag. 33 (3), 1221–1237. https://doi.org/10.1111/1467-8551.12540.

Nguyen, M., Malik, A., 2022b. Knowledge sharing in enhancing employee service quality in the hotel industry: the moderating role of artificial intelligence. Int. Mark. Rev. 39 (3), 482–508. https://doi.org/10.1108/IMR-02-2021-0078.

Nolan, C.T., Garavan, T.N., 2016. Human resource development in SMEs: a systematic review of the literature. Int. J. Manag. Rev. 18 (1), 85–107. https://doi.org/10.1111/ijmr.12062.

Obeidat, S.M., 2016. The link between e-HRM use and HRM effectiveness: an empirical study. Pers. Rev. 45 (6), 1281–1301. https://doi.org/10.1108/PR-04-2015-0111.

Pan, Y., Froese, F., Liu, N., Hu, Y., Ye, M., 2021. The adoption of artificial intelligence in employee recruitment: the influence of contextual factors. Int. J. Hum. Resour. Manag. 1-23 https://doi.org/10.1080/09585192.2021.1879206.

Parry, E., Tyson, S., 2011. Desired goals and actual outcomes of e-HRM. Hum. Resour. Manag. J. 21 (3), 335–354.

Pereira, V., Hadjielias, E., Christofi, M., Vrontis, D., 2021. A systematic literature review on the impact of artificial intelligence on workplace outcomes: a multi-process perspective. Hum. Resour. Manag. Rev., 100857 https://doi.org/10.1016/j.hrmr.2021.100857.

Polli, F., 2019. Using AI to eliminate bias from hiring. Harv. Bus. Rev. https://hbr.org/2019/10/using-ai-to-eliminate-bias-from-hiring (29 October, Accessed 25 September 2020).

Polychroniou, P.V., Giannikos, I., 2009. A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank. Career Dev. Int. 14 (4), 372–387. https://doi.org/10.1108/13620430910979853.

Prikshat, V., 2022. An integrated strategic architectural framework for AI-augmented HRM. In: Academy of Management Proceedings, Vol. 2022. Academy of Management, Briarcliff Manor, NY 10510, p. 15370 (No. 1).

Prikshat, V., Patel, P., Varma, A., Ishizaka, A., 2022. A multi-stakeholder ethical framework for AI-augmented HRM. Int. J. Manpow. 43 (1), 226–250.

Prikshat, V., Malik, A., Budhwar, P., 2023. AI-augmented HRM: antecedents, assimilation, and multilevel consequences. Hum. Resour. Manag. Rev., 100860 https://doi.org/10.1016/j.hrmr.2021.100860.

Raub, M., 2018. Bots, bias, and big data: artificial intelligence, algorithmic bias, and disparate impact liability in hiring practices. Ark. L. Rev. 71 (2), 529–570.

Robert, L.P., Pierce, C., Marquis, L., Kim, S., Alahmad, R., 2020. Designing fair AI for managing employees in organizations: a review, critique, and design agenda. Hum. Comput. Interact. 35 (5–6), 545–575. https://doi.org/10.1080/07370024.2020.1735391.

Rogers, E.M., 1995. Diffusion of Innovations, 4th Ed. The Free Press, New York.

Sajjadiani, S., Sojourner, A.J., Kammeyer-Mueller, J.D., Mykerezi, E., 2019. Using machine learning to translate applicant work history into predictors of performance and turnover. J. Appl. Psychol. 104 (10), 1207–1225. https://doi.org/10.1037/apl0000405.

Saukkonen, J., Kreus, P., Obermayer, N., Rodriguez Ruíz, O., Haaranen, M., 2019. AI, RPA, ML, and other emerging technologies: anticipating adoption in the HRM field. In: Griffiths, P., Kabir, M.N. (Eds.), Proceedings of the European Conference on the Impact of Artificial Intelligence and Robotics. EM-Normandie Business School Oxford, UK, pp. 287–296 (31 October–1 November).

Schillewaert, N., Ahearne, M.J., Frambach, R.T., Moenaert, R.K., 2005. The adoption of information technology in the sales force. Ind. Mark. Manag. 34 (4), 323–336. https://doi.org/10.1016/j.indmarman.2004.09.013.

Singh, P., Finn, D., 2003. The effects of information technology on recruitment. J. Lab. Res. 24 (3), 395–408. https://doi.org/10.1007/s12122-003-1003-4.

Sivathanu, B., Pillai, R., 2019. Technology and talent analytics for talent management–a game changer for organizational performance. Int. J. Organ. Anal. 28 (2), 457–474. https://doi.org/10.1108/IJOA-01-2019-1634.

Stahl, B.C., Antoniou, J., Ryan, M., Macnish, K., Jiya, T., 2022. Organisational responses to the ethical issues of artificial intelligence. AI & Soc. 37 (1), 23–37.

Strohmeier, S., Piazza, F., 2013. Domain-driven data mining in human resource management: a review of current research. Expert Syst. Appl. 40 (7), 2410–2420. https://doi.org/10.1016/j.eswa.2012.10.059.

Strohmeier, S., Piazza, F., 2015. Artificial intelligence techniques in human resource management—a conceptual exploration. In: Intelligent Techniques in Engineering Management, Intelligent Systems Reference Library, 87. Springer, Cham. https://doi.org/10.1007/978-3-319-17906-3_7.

Suen, H.Y., Chen, M.Y.C., Lu, S.H., 2019. Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? Comput. Hum. Behav. 98, 93–101. https://doi.org/10.1016/j.chb.2019.04.012.

Sutton, R.I., Staw, B.M., 1995. What theory is not. Adm. Sci. Q. 40 (3), 371–384.

Tambe, P., Cappelli, P., Yakubovich, V., 2019. Artificial intelligence in human resources management: challenges and a path forward. Calif. Manag. Rev. 61 (4), 15–42. https://doi.org/10.1177/0008125619867910.

Thong, J.Y., 1999. An integrated model of information systems adoption in small businesses. Manag. Inf. Syst. 15 (4), 27–31.

Thorpe, R., Holt, R., Macpherson, A., Pittaway, L., 2005. Using knowledge within small and medium-sized firms: a systematic review of the evidence. Int. J. Manag. Rev. 7 (4), 257–281.

Tornatzky, L.G., Fleischer, M., Chakrabarti, A.K., 1990. The Processes of Technological Innovation Lexington Books. Lexington, MA.

Tranfield, D., Denyer, D., Smart, P., 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br. J. Manag. 14 (3), 207–222. https://doi.org/10.1111/1467-8551.00375.

Truex, D., Holmström, J., Keil, M., 2006. Theorizing in information systems research: a reflexive analysis of the adaptation of theory in information systems research. J. Assoc. Inf. Syst. 7 (12), 797–821.

Twati, J.M., Gammack, J.G., 2006. The impact of organizational culture innovation on the adoption of IS/IT: the case of Libya. J. Enterp. Inf. Manag. 19 (2), 175–191. https://doi.org/10.1108/17410390610645076.

Upadhyay, A.K., Khandelwal, K., 2018. Applying artificial intelligence: implications for recruitment. Strateg. HR Rev. 17 (5), 255–258. https://doi.org/10.1108/SHR-07-2018-0051.

Van Esch, P., Black, J.S., 2019. Factors that influence new-generation candidates to engage with and complete digital, AI-enabled recruiting. Bus. Horiz. 62 (6), 729–739. https://doi.org/10.1016/j.bushor.2019.07.004.

Van Esch, P., Black, J.S., Ferolie, J., 2019. Marketing AI recruitment: the next phase in the job application and selection. Comput. Hum. Behav. 90, 215–222. https://doi.org/10.1016/j.chb.2018.09.009.

Van Esch, P., Black, J.S., Franklin, D., Harder, M., 2020. AI-enabled biometrics in recruiting: insights from marketers for managers. Australas. Mark 29 (3), 225–234. https://doi.org/10.1016/j.ausmj.2020.04.003.

Varma, A., Dawkins, C., Chaudhuri, K., 2022. Artificial intelligence and people management: a critical assessment through the ethical lens. Hum. Resour. Manag. Rev. 33 (1), 100923 https://doi.org/10.1016/j.hrmr.2022.100923.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425–478.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., Trichina, E., 2021. Artificial intelligence, robotics, advanced technologies, and human resource management: a systematic review. Int. J. Hum. Resour. Manag. 33 (3), 1–30. https://doi.org/10.1080/09585192.2020.1871398.

Walch, K., 2020. Why the race for AI dominance is more global than you think, Forbes. https://www.forbes.com/sites/cognitiveworld/2020/02/09/why-the-race-for-ai-dominance-is-more-global-than-you-think/?sh=2219ebd0121f. Accessed 19 June 2021.

Wang, C.L., Chugh, H., 2014. Entrepreneurial learning: past research and future challenges. Int. J. Manag. Rev. 16 (1), 24–61. https://doi.org/10.1111/ijmr.12007.

Wang, X., Wang, H., Zhang, L., Cao, X., 2011. Constructing a decision support system for management of employee turnover risk. Inf. Technol. Manag. 12 (2), 187–196. https://doi.org/10.1007/s10799-011-0093-6.

Wang, G., Gunasekaran, A., Ngai, E.W., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: certain investigations for research and applications. Int. J. Prod. Econ. 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014.

Wang, X., Wang, L., Zhang, L., Xu, X., Zhang, W., Xu, Y., 2017. Developing an employee turnover risk evaluation model using case-based reasoning. Inf. Syst. Front. 19 (3), 569–576. https://doi.org/10.1007/s10796-015-9615-9.

Webster, J., Watson, R.T., 2002. Analyzing the past to prepare for the future: writing a literature review. MIS Q. 26 (2) (Xiii-XXiii).

Wijesinghe, S., 2011. From interpretivism to positivism: a methodological approach to the research in human resource management (HRM). In: 8th International Conference on Business Management, University of Sri Jayewardenepura, Sri Lanka, December, pp. 434–438.

Williams, C., 2007. Research methods. J. Bus. Econ. Res. 5 (3), 1–8. https://doi.org/10.19030/jber.v5i3.2532.

Zhu, K., Kraemer, K.L., Xu, S., 2006. The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business. Manag. Sci. 52 (10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487.

Verma Prikshat is an Associate Profesor at the University of Wollongong, Dubai, UAE.

Mohammad Islam is a PhD Candidate at Newcastle University Business School Newcastle University, UK.

Parth Patel is a Senior Lecturer in Management, Department of HRM and Strategic Management, Australian Institute of Business.

Ashish Malik is the Head of the Management Discipline and Associate Professor at Newcastle Business School, University of Newcastle, NSW, Australia.

Pawan Budhwar is a Professor of IHRM and Head of the Aston Business School, Aston University, UK.

Suraksha Gupta is a Professor of Marketing at Newcastle University Business School Newcastle University, UK.