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Do Humans Trust AI in HRM? Why Do? Why Not? — Insights from a Decade of Research

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Abstract

This literature review investigates the complex issue of trust in the context of Artificial Intelligence (AI) applications in Human Resource Management (HRM). Adopting the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, we systematically reviewed 43 research articles published between 2013 and 2023 to examine the attitudes towards AI as a disruptive technology in HRM practices, the ethical and legal challenges that influence trust, and the strategies for building a trustworthy future. The findings reveal a mixed picture of trust, with growing adoption of AI in various HRM practices, such as recruitment, selection, performance management, and employee development, accompanied by significant concerns related to bias, transparency, privacy, and job displacement. The review identifies key factors that affect trust in AI, including perceived usefulness, ease of use, and fairness, as well as the ethical and legal challenges that erode trust, such as data privacy, algorithmic bias, and lack of explainability. Furthermore, it discusses the implications for HRM professionals and proposes strategies for enhancing trust, such as ensuring human oversight, promoting transparency, and developing AI literacy skills. This review contributes to the research on AI in HRM by providing a nuanced understanding of the trust dynamics, challenges, and opportunities associated with this disruptive technology, offering valuable insights for both researchers and practitioners.

Keywords: industry 4.0, disruptive technology, HRM, HRM practices, Artificial Intelligence (AI), PRISMA, AI applications in HRM

1. Introduction

Human Resource Management (HRM) has evolved from a primarily administrative role to a strategic partner in the organizational success (Ulrich & Dulebohn, 2015). This evolution has been driven by various factors, including globalisation, technological advancements, and shifting workforce demographics (Stone et al., 2015a). In recent years, the integration of disruptive technologies, particularly Artificial Intelligence (AI), has emerged as a critical driver of change in HRM practices (Bondarouk & Brewster, 2016). Disruptive technologies, such as AI, big data analytics, and blockchain, fundamentally change how organizations operate and manage their workforce (Agarwal et al., 2023a; Bondarouk & Brewster, 2016; Fenech et al., 2019; Nocker & Sena, 2019; Strohmeier, 2020).

Dabić et al. (2023) contend that within the dynamic context of the fourth industrial (Industry 4.0) revolution, disruptive technologies have taken a front-row seat, revolutionising HRM practices. Industry 4.0 is characterized by integrating technologies like AI, the Internet of Things (IoT), and big data analytics into production systems, enabling intelligent factories and connected supply chains (Schwab, 2017; Xu et al., 2018). However, these technologies are also fundamentally changing the nature of work, requiring new skills and challenging traditional HRM approaches (The Future of Jobs Report 2020, 2020). As Ulrich & Dulebohn (2015) argued, integrating these technologies into HRM has become a strategic imperative for organisations to stay competitive and innovative. Aligning HRM and technology strategy is crucial for organizational success in the digital age, although challenges such as ethics and employee resistance must be addressed (Bondarouk & Brewster, 2016).

Among these disruptive technologies, AI stands out as a transformative force reshaping HRM (Albassam, 2023). AI has the potential to revolutionize various aspects of HRM, from talent acquisition and employee engagement to performance management and learning and development (Minbaeva, 2021). By leveraging machine learning, natural language processing, and predictive analytics, AI-enhanced HRM systems can streamline processes, improve decision-making, and enhance the employee experience (Strohmeier, 2020). However, adopting AI in HRM also raises significant ethical, legal, and privacy concerns that must be addressed to ensure the responsible and trustworthy use of these technologies (Dennis & Aizenberg, 2022).

The strategic implementation of disruptive technologies in HRM is evident through their capacity to streamline and optimize various functions (Minbaeva, 2021). From talent acquisition, where predictive analytics enable more informed recruitment decisions (Stanley & Aggarwal, 2019), to the customization of training initiatives via adaptive learning algorithms (Bobrovskyi et al., 2023), the influence of disruptive technologies is extensive. AI-powered chatbots and virtual assistants transform employee experience and support (Josh Bersin, 2018), while people analytics enables data-driven decision-making in talent management (Marler & Boudreau, 2017). Moreover, these technologies have significantly bolstered employee engagement by introducing chatbots and virtual assistants that foster a more interactive and supportive workplace (Naim, 2023).

These innovations align perfectly with the core tenets of Industry 4.0, which champions automation, interconnectivity, machine learning, and real-time data processing (Bedi et al., 2024; Treviño-Elizondo & García-Reyes, 2023; Yunus, 2021). Modern HRM practices are being transformed by disruptive technologies, providing organizations with the necessary tools to effectively manage a modern workforce with improved efficiency and foresight within the new industrial paradigm (Priyashantha, 2023).

Despite the potential benefits, adopting these technologies in HRM requires time and effort. Ethical concerns (Sharif & Ghodoosi, 2022), privacy issues (Nocker & Sena, 2019) and the legal implications of employment contracts (Michailidis, 2021) must be carefully navigated. Furthermore, employee resistance and the need for reskilling pose significant challenges (Bondarouk & Brewster, 2016; Strohmeier, 2020). Overcoming these obstacles necessitates a strategic approach that aligns technological implementation with organizational values, employee well-being, and regulatory compliance.

In light of these developments, this literature review aims to explore the current state of AI applications in HRM, the key challenges faced, and potential methods to overcome these challenges. Specifically, it seeks to answer the following research questions:

- LRQ1: What is the current attitude towards AI applications in HRM?
- LRQ2: What are the key ethical, legal, and privacy challenges of AI in HRM?
- LRQ3: What are the methods of overcoming these challenges to build trustworthy AI-enhanced HRM systems?

The literature review will follow a structured approach to address these research questions. First, the Method section will outline the search strategy and selection criteria for relevant literature. Next, a Literature Analysis of the selected literature will be conducted, focusing on the current applications of AI in HRM, the challenges faced, and the proposed solutions. The Results and Key Research Gaps section will synthesize the key findings and identify research gaps. Finally, the Implications for Practice section discusses the implications for HRM practice, followed by concluding remarks.

By exploring the intersection of AI and HRM, this literature review aims to contribute to the ongoing discourse on the strategic role of disruptive technologies in shaping the future of work and organizational practices. It will provide valuable insights for HRM professionals, organizational leaders, and researchers seeking to navigate the opportunities and challenges presented by AI in the dynamic landscape of HRM.

2. Method

This Literature Review delves into the scholarly and professional discussions on incorporating AI in HRM. It provides a comprehensive synthesis of existing knowledge, which is invaluable for academics and practitioners. By collating and analysing the collective wisdom on AI in HRM, this review offers a joined view that can inform current practices and future research directions. The literature review helps to identify patterns, key challenges, and gaps in the literature that may not be apparent when considering individual studies in isolation (Wang & Chugh, 2014). This literature review adheres to a structured literature review process, executed in the sequential stages summarised in Figure 1.

The literature review began by setting objectives and defining the conceptual framework, as recommended Denyer et al.(2008). Therefore, the review includes papers from various industries and sectors, examining the use of AI tools in multiple contexts, such as finance, service, and healthcare, and including different HR processes like recruitment, training, and talent management.

Additionally, the content analysis provides an understanding of the main challenges faced in integrating AI within HRM, focusing primarily on ethical, legal, and privacy issues. The analysis strives to pinpoint common themes and categorise them into specific research areas. It also examines the range of authors' attitudes towards the studied topic of AI-augmented human resource processes. These attitudes include Support, Caution, or Neutral, alongside the prevalent sentiment.

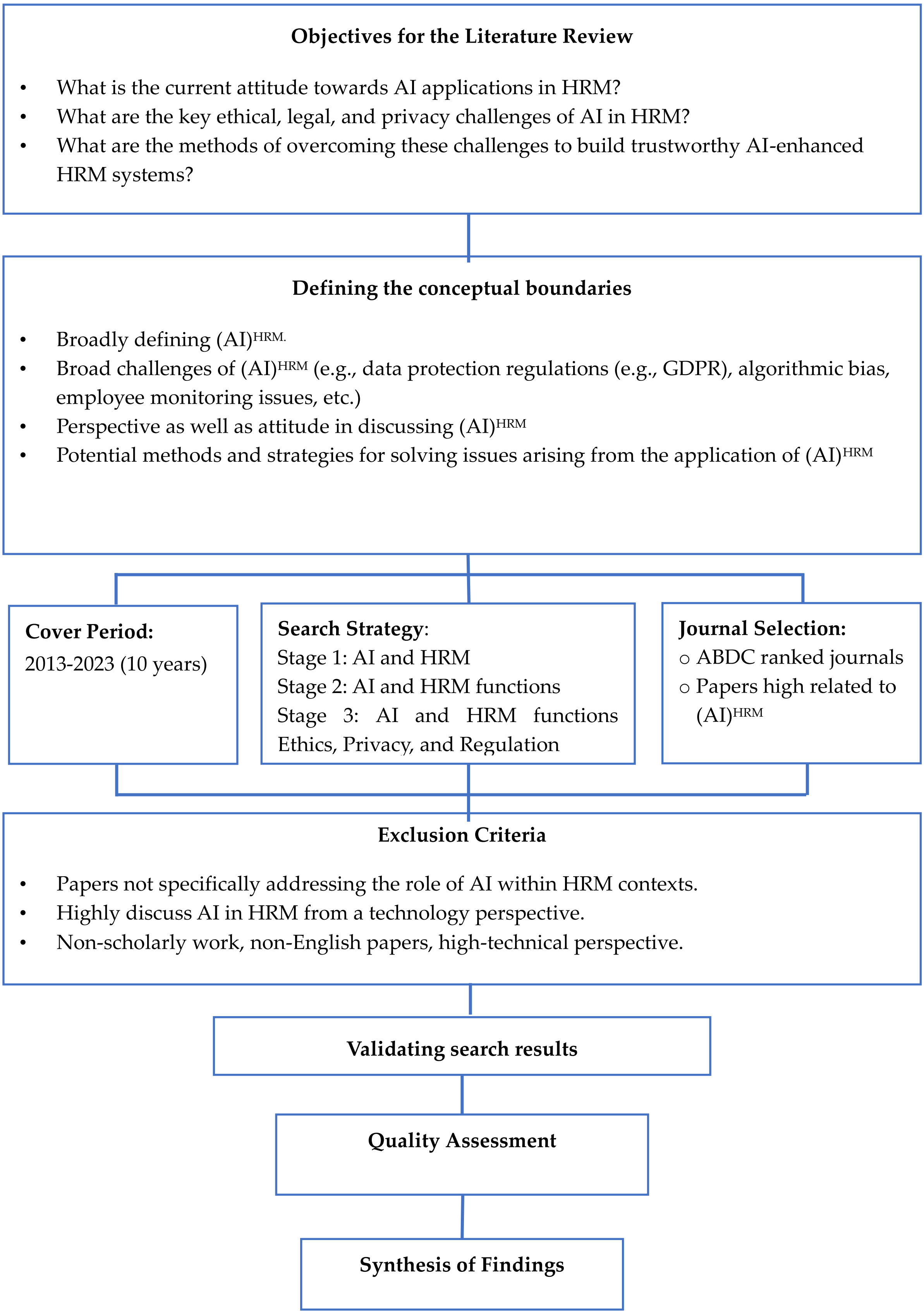


Figure 1. A summary of the literature review process

This literature review intersects three interconnected conceptual realms: HRM, Information systems, and Challenges. Table 1 outlines the search keywords employed. This literature review focuses on rigorously researched HRM issues identified by specific key terms while excluding tangentially related topics such as algorithms and Information Technology Law To identify relevant literature, a comprehensive search was conducted using a combination of keywords and Boolean operators. Boolean operators, such as "AND", "OR", and "NOT", are used to combine or exclude keywords in a search, allowing for more precise and efficient results (MIT Libraries, 2022). The following search string was employed:

(TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "natural language processing" OR "machine learning" OR "big data") AND TITLE-ABS-KEY ("human resource management" OR "HR Technology" OR "HR analytics" OR "Employee Recruitment" OR "Talent Retention" OR "recruitment and disposition") AND TITLE-ABS-KEY ("Challenges" OR "Ethical Considerations" OR "Privacy Issues" OR "Regulation" OR "Ethical" OR "Bias")).

In this search string, the "OR" operator was used to include synonyms or related terms, ensuring a comprehensive coverage of the topic. The "AND" operator combined different concepts, narrowing down the results to studies that address the intersection of artificial intelligence, human resource management, and ethical challenges.

Table 1. Keywords used for the literature review

Artificial intelligence	Human resource management	Challenges
"Artificial intelligence"	"Human resource management"	"Ethical Considerations"
Or "AI"	Or "HR Technology"	Or "Privacy Issues"
Or "natural language processing"	Or "HR analytics"	Or "Regulation"
Or "machine learning"	Or "Employee Recruitment"	Or "Ethical"
Or "big data"	Or "Talent Retention"	Or "Bias "
	Or "recruitment and disposition"	

2.1 Literature Analysis Strategy

The content analysis followed a systematic coding process. First, the selected papers were carefully read, and relevant content related to the research questions was highlighted. Then, the highlighted content was coded into initial categories based on the specific challenges or issues discussed (e.g., bias, privacy, transparency). These initial categories were then grouped into broader themes (e.g., technological challenges, ethical challenges) through an iterative process of comparing, contrasting, and refining the categories. The coding process was conducted independently by two researchers to ensure reliability, and any discrepancies were resolved through discussion and consensus.

This section aims to establish a comprehensive database, which will serve as the foundation for the literature analysis (Thomé et al., 2016) (Appendix S1). In pursuit of this objective, this literature review adhered to specific inclusion and exclusion parameters detailed in Figure 1, which guided the selection process concerning the journals, the time frame, and the papers chosen from within the sampled publications. The baseline for observed trends and developments was set in 2013, corresponding with a noticeable upsurge in academic exploration and practical usage. The findings from a thorough literature review during this era indicate an increased scholarly interest, focusing on the emerging integration of Artificial Intelligence (AI) within Human Resource Management (HRM). SCOPUS, Google Scholar, and Web of Science (WoS) have been chosen as the preferred search engines widely recognised and esteemed in scholarly circles, meeting the established requirements for conducting this review (Hiebl, 2023). These three databases have been utilised for ten years. For sourcing high-quality, peer-reviewed scholarly papers, the initial point of focus should be the Web of Science (WOS), renowned for its comprehensive and authoritative collection. Initial screening focused on titles, keywords, or abstracts, after which literature was chosen for its relevance to LRQ1, LRQ2 and LRQ3.

2.2 Papers Selection and Retention Process

Initially, the literature review traced relevant citations located within papers that had been previously identified to track additional references and then further utilised the collected references to determine related papers. Manual searches were conducted in addition to the primary strategy to guarantee the thoroughness of this research, utilising the backward and forward citation tracking approach as outlined Snyder (2019). This literature review initially identified 251 papers pertinent to the research focus. Using Zotero's deduplication feature, 47 duplicate and retracted entries were removed, leaving 204 papers. Within these records, each paper underwent a further review of its title and the classification of literature to which it belonged. Books were excluded from the list of cited materials to preserve source timeliness and uphold the references' academic credibility. On this basis, papers deemed insufficiently related to (AI)HRM research or those analysing (AI)HRM from a purely technical perspective were excluded, culminating in a final selection of 87 papers. Remember that this research revolves around the key ethical, legal, and privacy challenges of (AI)HRM. At this stage, 44 papers were excluded, leaving 43 papers to be used for the literature review. This literature review adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Moher et al., 2010) outlined in our literature review. The process applied for the reviews is depicted in Figure 2.

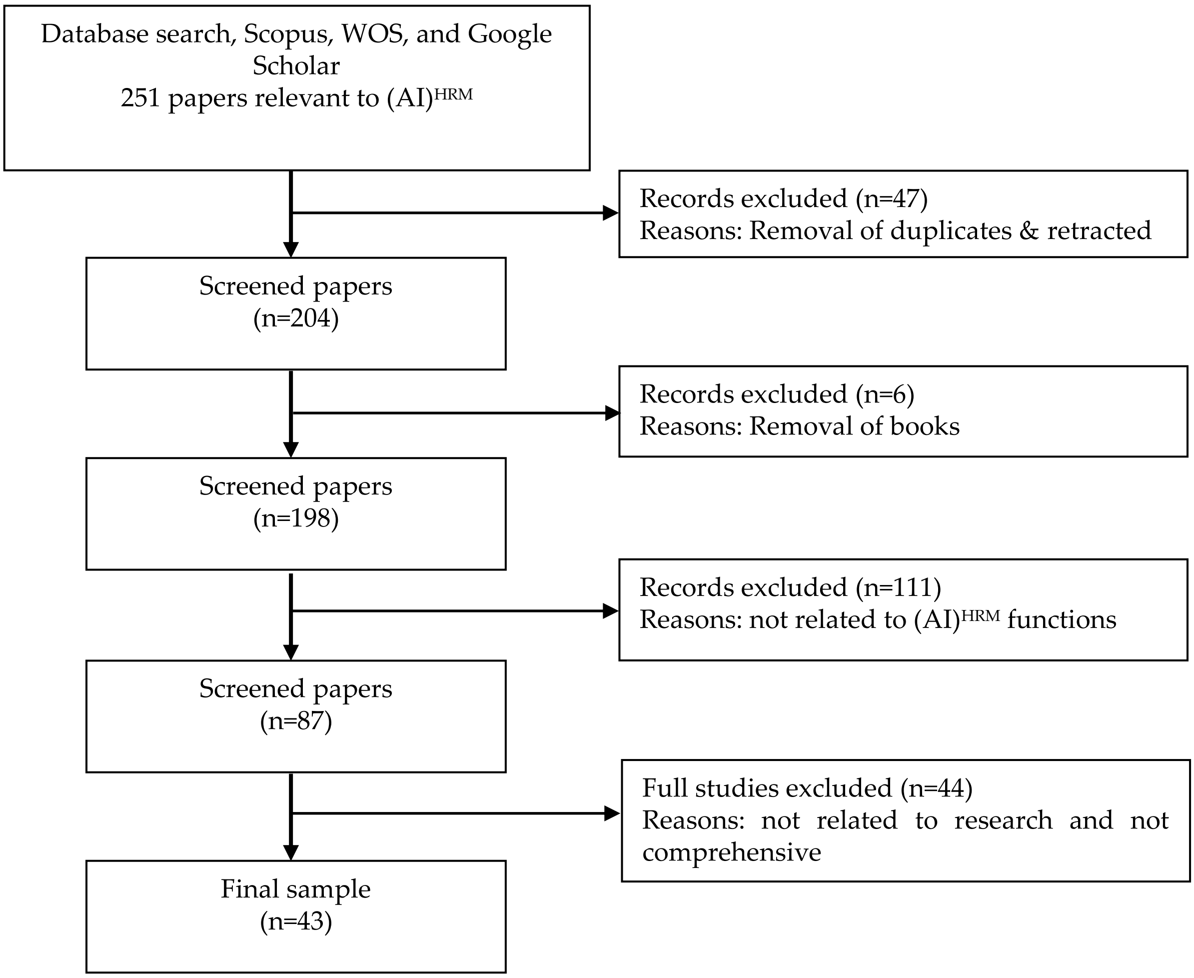


Figure 2. Papers selection and retention process

3. Literature Analysis

This section presents the context analysis and content analysis regarding the challenges faced by (AI)^{HRM} and an overview of the literature data collected. Analysing data from the literature on (AI)^{HRM} is crucial for understanding the evolution of research interests and focal points within this field. This covers the chronological spread, geographical dispersion, research dimensions, theoretical perspectives, literature author(s) attitudes towards the use of AI in

HRM, and the array of challenges currently faced in (AI)^{HRM}.

3.1 Paper Distribution and Geographic Spread

The selected 43 papers for the literature review consist of 31 from journals ranked by the Australian Business Deans Council (ABDC), as well as some widely recognised journals that cover various aspects of HRM and are aimed at practitioners, such as the Harvard Business Review (for more details, see Table 2). Additionally, 12 studies published in journals that were not included in the ABDC listings were included in the Literature Review. These unlisted journals were considered because they offer a broader perspective and enhance the thoroughness of the literature review (Prikshat et al., 2023). According to Ndemewah & Hiebl (2022), these non-ABDC-listed publications provide a neutral viewpoint. Particularly valuable are those published between 2020 and 2023, which are instrumental in tracking (AI)^{HRM} development trends and are thus highly relevant to the research focus.

Table 2. Publications used for the literature review

Journal	ABDC ranking	Number of papers
Ad Alta-Journal of Interdisciplinary Research	—	2
Advances in Intelligent Systems and Computing	—	1
Benchmarking	B	1
Business Horizons	B	1
California Management Review	A	1
Computers in Human Behaviour	A	1
Employee Responsibilities and Rights Journal	C	1
Ethics and Information Technology	C	2
Expert Systems with Applications	C	1
Harvard Business Review	A	2
HELIYON	—	1
Human Resource Management Journal	A	3
Human Resource Management Review	A	4
Human–Computer Interaction	—	1
IEEE Access	B	1
Interacting with Computers	C	1
International Development Planning Review	B	1
International Journal of Business Continuity and Risk Management	—	1
International Journal of Human Resource Management (IJHRM)	A	1
International Journal of Manpower	A	3
International Journal of Organizational Analysis	B	1
International Journal of Quality & Reliability Management	B	1
Journal of Business Ethics	C	1
Journal of Information Technology Education: Research	—	1
Journal of Organizational and End User Computing (JOEUC)	—	1
Journal of Responsible Technology	—	1
Lecture Notes in Computer Science	—	1
Lecture Notes in Networks and Systems	—	1

Journal	ABDC ranking	Number of papers
Management Research Review	C	1
Organizational Behaviour and Human Decision Processes	A	1
Pacific Asia Journal of the Association for Information Systems	B	1
Procedia Computer Science	—	1
Technology in Society	C	1
The International Arab Journal of Information Technology	—	1
	Total	43

Analysing the annual volume of literature on (AI)HRM highlights shifts in scholarly focus and provides insights into the field's evolving research trends. It identifies key growth areas and pivotal moments and offers a deeper understanding of the field's dynamics. As shown in Figure 3, although the search was limited to the period between 2013 and 2023, it was not until around 2018 that it began to be studied by more researchers. During the decade from 2013 to 2023, the overall volume of literature on (AI)HRM has shown an upward trend. Before 2018, there needed to be more scholarly research on (AI)HRM. Still, there was an explosive increase in 2019 (n=6), which aligns with the findings reported in Stanford University's The 2019 AI Index Report, indicating a significant global surge in artificial intelligence research between 2018 and 2019. Particularly after 2020, there has been an increasing yearly trend. Between 2020 and 2023, research papers on (AI)HRM increased dramatically. Notably, in 2023 (n=16), contributions accounted for 37% of the literature values reviewed in this literature review, double the number of publications in 2022 (n=8) and more than three times that of 2020 (n=5).

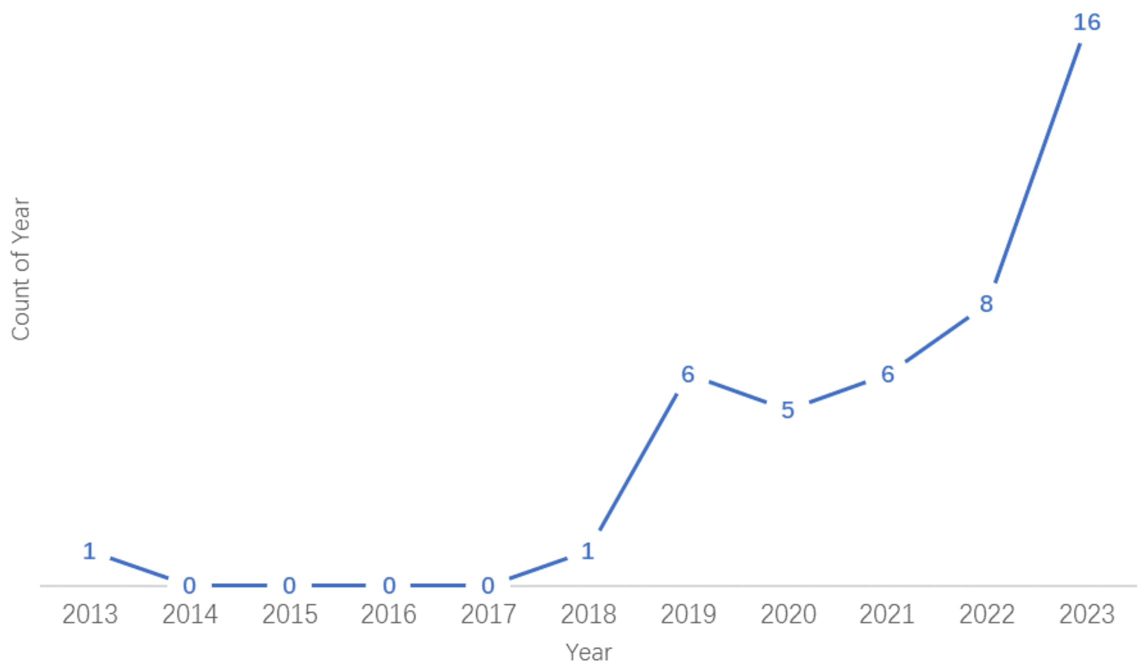


Figure 3. Number of Selected Papers Published Per Year

This literature review also examines the background of the authors. This analysis highlights the leading countries in (AI)HRM research and sheds light on international collaboration patterns and the influence of regional resources on research outputs.

American scholars appear in 20 papers, meaning that 46% of the literature selected for this literature review involves American scholars. Australian scholars also perform well in (AI)HRM research, contributing five papers.

Additionally, incorporating an analysis of the author's country into the literature review helps to map out the global contribution to the field, finding key centres of research excellence and potential gaps in geographical representation. The literature review analysed the geographical distribution of the papers, considering the number of papers published by each author and the countries in which the authors are located. The analysis results show that 121 authors of 43 research papers come from 21 countries (see Figure 4 for details). Among the 121 authors, 33 were from the United States. Indian and British scholars follow closely, occupying the second and third positions, respectively. Scholars from Spain, Netherlands, Canada, Malaysia, New Zealand, Ireland, and Singapore each participated in one paper. The active participation of scholars from the United States, the United Kingdom, and Australia in (AI)HRM research can be attributed to these countries' advanced high-skilled labour resources, including scholars, research institutions, funding support, and broad practical environments (Kaushal et al., 2023). This literature review has also compiled data on the collaborative efforts among authors within these publications. Out of the 43 papers analysed, only 11 were co-authored by teams of two or more researchers, while the remaining 74%, equating to 32 papers, were authored independently by scholars from single countries. In conclusion, the United States is leading in (AI)HRM research.

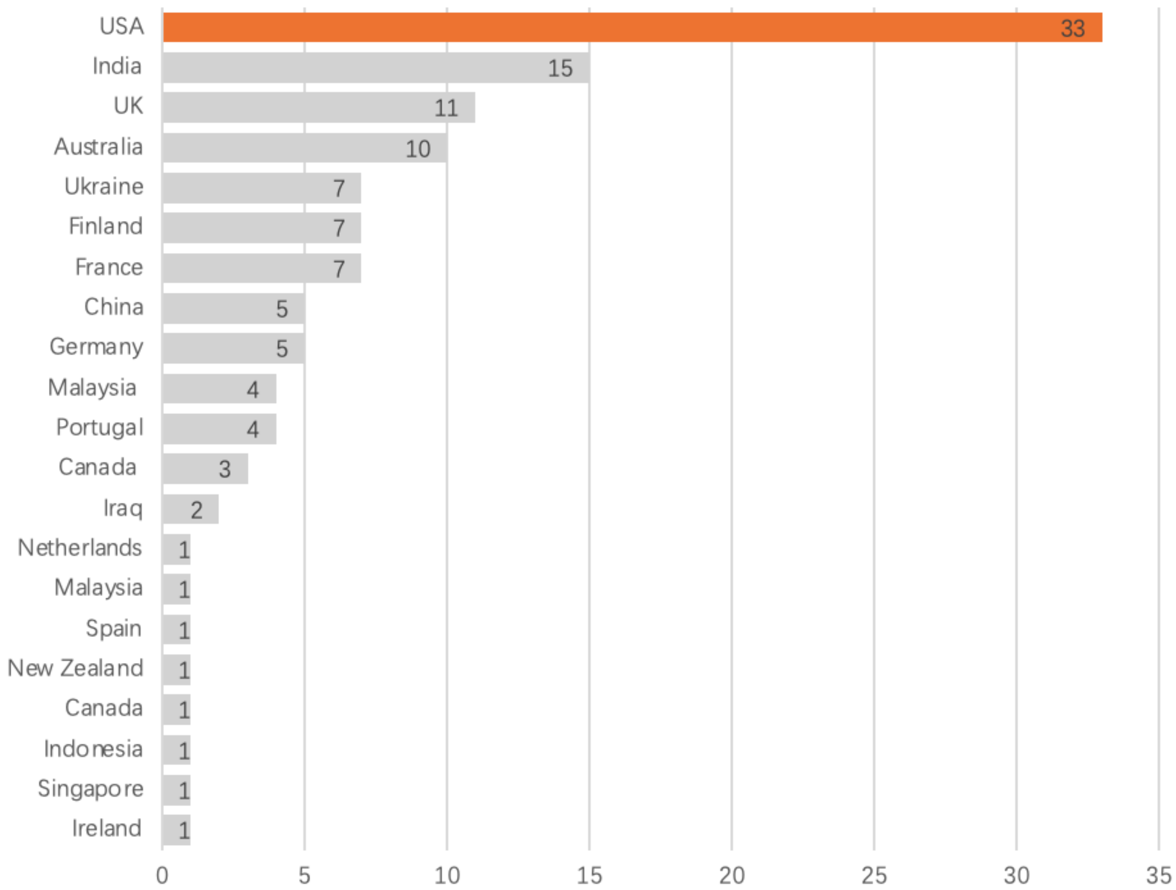


Figure 4. Distribution of all 121 authors by nationality

3.2 Analysis of Established theories for (AI)^HRM Research

Theoretical frameworks are essential for analysing (AI)HRM in this literature review. They provide the basis for generating hypotheses, designing research methodologies, and interpreting findings. This ensures that the literature review is methodologically rigorous and significantly contributes to the broader academic discourse. This section examines and assesses the application of theoretical frameworks in previous (AI)HRM studies. Consistent with foundational works (Sutton & Staw, 1995), the literature review deemed a study theoretically robust if it provided clear justifications for 1) the chosen conceptual framework, 2) the methodology employed, and 3) the reasons the framework is expected to be practical. This literature review mapped out the theoretical frameworks applied in (AI)HRM studies, adhering to the methodologies followed by Wright & McMahan (1992), Nolan & Garavan (2016), Danese et al. (2018), and Farndale et al. (2020). This literature review of 43 papers uncovered a variety of theoretical perspectives underpinning Artificial Intelligence-Human Resource Management research (see Table 3 for details). Of these, 27 papers employed established theories, frameworks, and models, with some papers utilising multiple theoretical supports.

Table 3. Theories used in LR

Theoretical perspectives	Theories / Frameworks/ methodologies	Authors/years
Critical theory and HRM (n=4)	Digital Taylorism	Birnbaum & Somers (2023)
	Labour Process Theory	Charlwood & Guenole (2022)
	Moral Principles Framework	Manroop et al. (2024)
	Human Rights Theoretical Frameworks	Oravec (2022)
Economic theory and HRM (n=2)	Game Theory	Sharif & Ghodoosi (2022)
	Psychological And Economic Theory of Fairness	Delecraz et al. (2022)
Industrial sociology, IR theory and HRM (n=2)	Labour Process Theory	Charlwood & Guenole (2022)
	Stakeholder Theory	Prikshat et al. (2023)
	Ethical Frameworks	Prikshat et al. (2023)
Psychological theory and HRM (n=5)	Organizational Justice Theories	Newman et al. (2020)
	Psychological And Economic Theory of Fairness	Delecraz et al. (2022)
	Person Fit Theory	Malik et al. (2022)
	Social Exchange Theory	Budhwar et al. (2023)
	Grounded Theory	Budhwar et al. (2023)
	Management Mental Health Framework	Oravec (2022)
Strategic management theory and HRM (n=13)	Throughput Model (TP Model) Framework	Rodgers et al. (2023) Kamal & Kokila (2023)
	3-Fold Framework	Koivunen et al. (2023)
	Media Richness Theory	Suen et al. (2019)
	Social Interface Theory	Suen et al. (2019)
	aiSTROM framework	Herremans (2021)
	Patternmatching Theory	Kshetri (2021)
	Decision-Making Framework	Bankins (2021)
	Technology-Organization-Environment (TOE) framework	Agarwal et al. (2023) Pillai & Sivathanu (2020)
	Task-Technology Fit (TTF) model	Pillai & Sivathanu (2020)

	HR Life Cycle framework	Gélinas et al. (2022)
	HRIS frameworks	Masum et al. (2018)
	Employee Retention Models	Gryncewicz et al. (2023)
	Evidence-Based Management (EBMgmt)	Tambe et al. (2019)
International business and HRM (n=2)	Fuzzy Set Theory	Manoharan et al. (2011)
	Organizational Justice Theory	Robert et al. (2020)
	Social Theory	Robert et al. (2020)

In the literature review on (AI)HRM, 27 papers were identified as employing theoretical frameworks to guide their analysis and discussion. These papers were categorised into six theoretical perspectives, with varying contributions from each category. The distribution is as follows: Strategic Management Theory and HRM (13 papers, approximately 48.1%), Psychological Theory and HRM (5 papers, nearly 18.5%), Critical Theory and HRM (4 papers, about 14.8%), Economic Theory and HRM (2 papers, roughly 7.4%), Industrial Sociology and IR Theory and HRM (2 papers, about 7.4%), and International Business and HRM (2 papers, around 7.4%).

The prevalence of Strategic Management Theory, constituting over 30% of the total 43 pieces of literature, underscores a significant academic inclination towards integrating HRM with organisational strategy, highlighting the importance of aligning HR practices with business objectives for optimal organisational performance. Conversely, Economic Theory and International Business perspectives are less represented in the current literature, each accounting for less than 5% of the total, suggesting potential areas for further exploration and research. Critical Theory and HRM critique conventional HR practices, advocating for more ethical and human-centric approaches. At the same time, Psychological Theory provides insights into individual-level processes within organisations, such as justice, fit, and social exchanges. Industrial Sociology and IR theories contribute to understanding the socio-economic context of employment relations. This categorisation reflects a multifaceted approach to (AI)HRM research that is theoretically grounded in diverse academic traditions, as suggested by Boon et al. (2019) and Wright & McMahan (1992).

The literature review investigates the role of AI in HRM, assessing various HR functions and the theoretical frameworks that support them. Table 4 encapsulates theoretical frameworks aligned with specific HR functions identified from a literature review on AI in HRM. It maps out the relevance of various theories to key HR areas.

Table 4. Theoretical Frameworks Aligned with HR Functions

HR Functions	Theoretical Concepts/Frameworks
Job Evaluation	• Digital Taylorism • Human Capital Management (HCM)
Training & Development	• Game Theory • Psychological and Economic Theory of Fairness • HR Life Cycle framework • Management Mental Health Framework
Performance Management	• Game Theory • Pattern matching theory • Organizational Justice Theories • Evidence-Based Management (EBMgmt) • Fuzzy Set Theory

HR Functions	Theoretical Concepts/Frameworks
Recruitment and Selection	• Throughput Model (TP model) framework • aiSTROM framework • Game Theory • Human Rights Theoretical Frameworks • TOE Framework • Person Fit Theory • Social Exchange Theory • Media Richness Theory
Talent Management	• Social Exchange Theory • Game Theory • 3-fold Framework • Social Interface Theory • TOE Framework • HRIS Frameworks • Task-Technology Fit (TTF)
Employee Turnover	• Game Theory • Employee turnover • Grounded Theory • Stakeholder Theory

Several theories can be applied to investigate the application of AI in HRM, providing a theoretical foundation and analytical framework for future research. When AI is applied, the review acknowledges the diversity of theoretical perspectives that inform job evaluation, training and development, performance management, recruitment and selection, talent management, and employee turnover. The Task-Technology Fit Theory analyses the degree of fit between AI technology and HRM tasks and its impact on the effectiveness of AI applications (Ma & Wang, 2021). Stakeholder Theory emphasises balancing the interests of various stakeholders when applying AI in HRM (A. Malik et al., 2023). The exploration of different HR functions reveals a trend toward integrating complex, interdisciplinary theories that align with the innovative capabilities of AI, signifying a shift from conventional approaches to a more dynamic and analytically driven HRM practice.

3.3 Context Analysis

3.3.1 Research Types in the Reviewed Literature

The literature review identified 24 papers (56%) that were purely Empirical, reflecting a dominant trend in data-driven studies within the (AI)HRM field (see Figure 5 for details). Purely Theoretical papers accounted for 17 papers (39%), contributing to the conceptual and framework development necessary for advancing theoretical discourse in HRM research. A smaller subset of 2 papers (5%) employed a mixed-methods approach, integrating empirical data with theoretical insights to analyse the phenomena under study better. These classifications were informed by academic standards for methodological differentiation in scholarly research, as prominent methodologists such as Charli et al. (2022) and Montello (2002) suggested. This distribution underscores a multifaceted approach to exploring (AI)HRM, with most studies favouring empirical methods to conclude observed realities. At the same time, a significant proportion also emphasises the importance of theoretical contributions to the field. To this end, this literature review focuses on research on accepting AI applications in HRM and the challenges that arise.

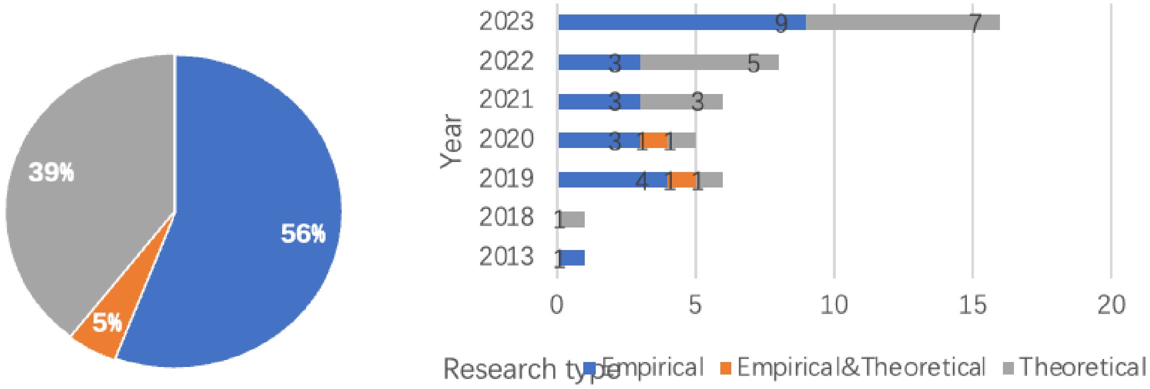
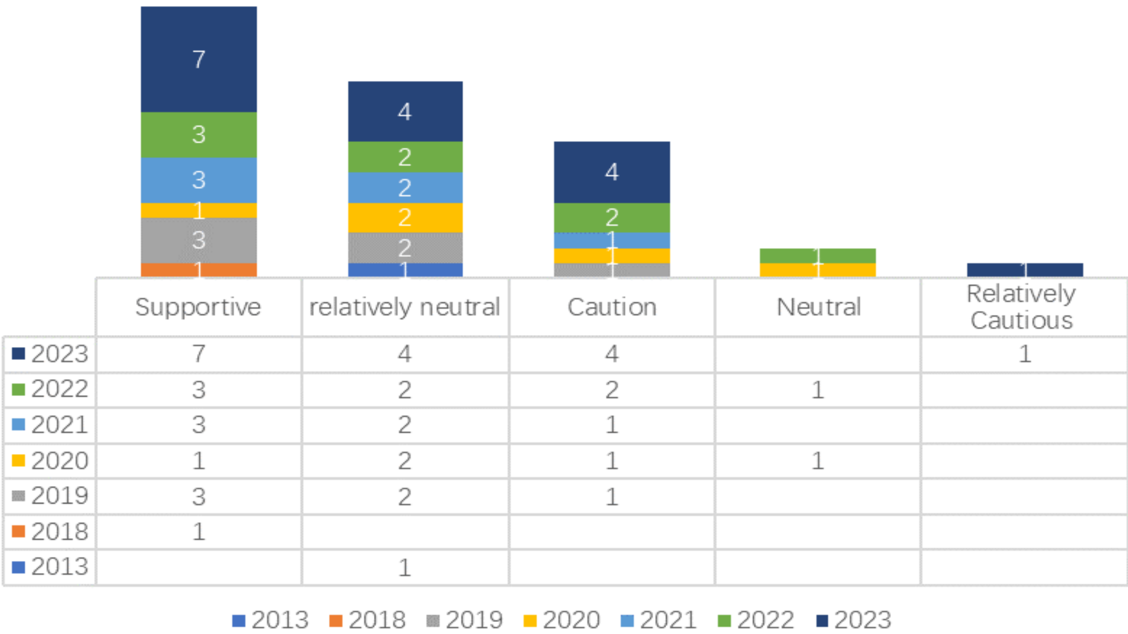


Figure 5. Distribution of research types

3.3.2 Analysing Authors' Attitudes in the Literature

This review inferred the authors' attitudes towards AI applications in HRM from a qualitative content analysis of 43 scholarly papers. Attitude is a psychological concept that refers to an individual's evaluative judgment towards a specific object, person, or matter. Supportive, neutral, and critical statements were used as indicators of positive, neutral, and negative attitudes, respectively. The authors' attitudes towards AI applications in HRM were inferred through a thorough reading of each study, focusing on analysing the stances, opinions, and conclusions expressed regarding the use of AI in human resource management. Specifically, the analysis involved identifying and categorizing statements as Supportive (e.g., affirmation of AI's advantages and potential), Neutral (e.g., objective analysis of pros and cons), or Caution (e.g., questioning AI's limitations). Based on the prevalence and strength of these statements, the authors' attitudes were classified as positive, neutral, or caution towards the application of AI in HRM.

The analysis revealed that 18 papers expressed explicit support for AI applications in HRM, while 13 papers maintained a relatively neutral stance (see Figure 6 for details). This suggests a predominantly positive attitude among scholars. A temporal analysis further indicated increased academic acceptance and support for AI's role in HRM after 2019.



	Supportive	relatively neutral	Caution	Neutral	Relatively Cautious
2023	7	4	4		1
2022	3	2	2	1	
2021	3	2	1		
2020	1	2	1	1	
2019	3	2	1		
2018	1				
2013		1			

Figure 6. Distribution of authors' attitudes

3.3.3 Analysis of Established Research Methods For (AI)HRM Research

Various research methods have been employed to investigate the application of AI in HRM. The distribution of research methodology, encompassing Critical Reviews, Qualitative, Quantitative, Experimental design, and Mixed methods, is presented in Figure 7. Quantitative methods, such as surveys and experiments, are commonly used to examine the factors influencing the adoption and effectiveness of AI in HRM. For instance, Jia et al.(2018) surveyed to investigate the factors affecting HR professionals' intention to use AI tools. Agarwal et al. (2023b) used an experimental design to study the impact of AI on HR decision-making. Qualitative methods like case studies and interviews are valuable for exploring HR professionals' and employees' experiences and perceptions regarding AI in HRM. Combining quantitative and qualitative approaches, mixed-methods research can provide a more comprehensive understanding of AI in HRM. Kshetri (2021b) used a mixed-methods approach, combining a survey and interviews, to investigate the institutional pressures driving AI adoption in HRM.

Critical review methodology emerges as the most prevalent (n=14), comprising 33% of the methodologies utilised. This approach is characterised by a comprehensive appraisal and synthesis of literature to evaluate the current state of knowledge on a topic, often identifying gaps for future research. Hamilton & Davison (2022), for example, take a critical look at existing knowledge, which not only enhances the theoretical depth of the research but also improves the quality of the research design and the rigour of implementation. Following this, Qualitative research methodologies (n=11) are employed in 26% of the studies. Mixed methods research accounts for 23% of the methodologies applied, underscoring a significant trend towards integrating qualitative and quantitative approaches. Six papers used a Quantitative research method (14%), focusing on numerical data and statistical analysis to test hypotheses or answer research questions. Lastly, experimental design is the least represented methodology (n=2), making up only 5% of the studies. This method's lower representation could suggest a potential area for further development in future research endeavours.

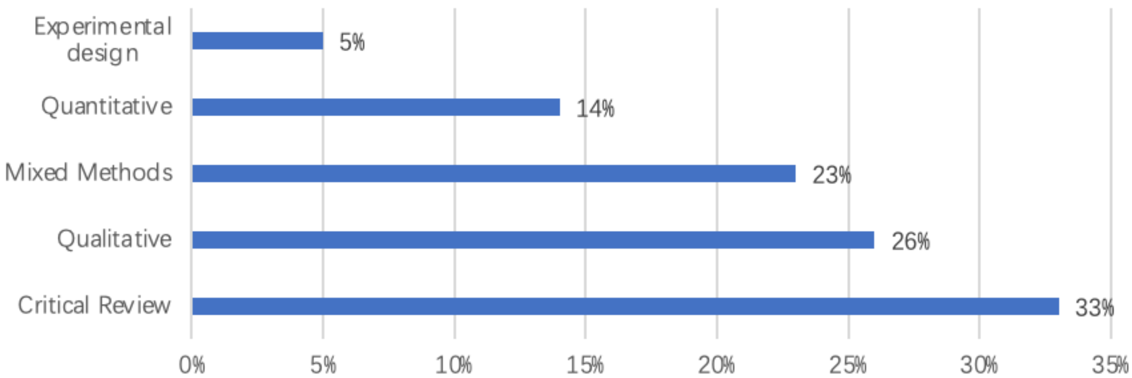


Figure 7. Distribution of research methods

3.4 Content Analysis

Previous academic literature on the challenges of (AI)HRM has been wide-ranging and diverse, exploring many issues in different contexts. Content analysis aims to identify standard features in the paper and divide them into various research topics according to the unit of study.

3.4.1 Analytical Perspectives on (AI)HRM Challenges in Literature

The literature analysis regarding the challenges faced when implementing AI in HRM reveals that 19 papers (44%) initiate discussions from an Organizational perspective (see Figure 8 for details). Ten papers approach the subject from the viewpoint of individual Employees, and another ten contemplate both Employee and Organizational dimensions. Only four papers exclusively focus on the Department Sector (HR) challenges.

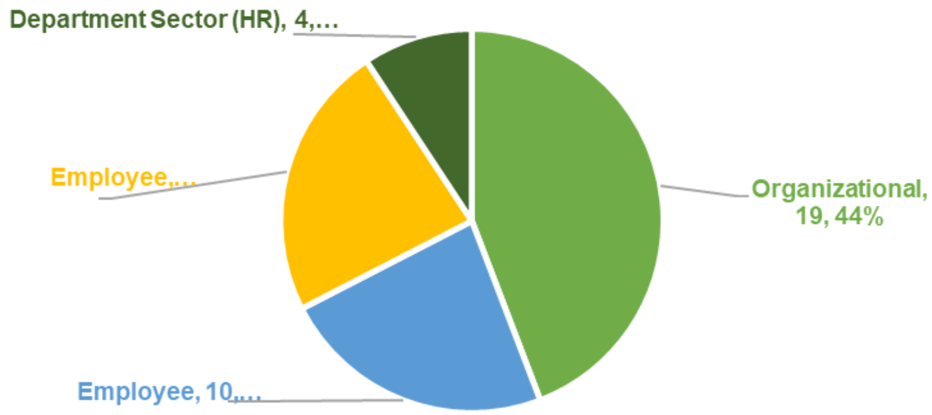


Figure 8. Distribution of administrative units

3.4.2 Examining Dimensions of (AI)HRM Challenges in Literature

Upon analysing the content, it has been observed that past literature does not limit itself to examining (AI)HRM from a purely managerial perspective but also considers the ethical, legal, and regulatory issues involved. Six papers provide a multi-faceted analysis of the challenges in (AI)HRM, such as combining managerial with technological aspects or with both policy and technical aspects (see Figure 9 for details). 36 papers predominantly analyse (AI)HRM challenges from an organisational perspective. Intriguingly, no literature solely discusses (AI)HRM challenges from a policy standpoint. This categorisation of analytical layers is not unexpected, as the application of AI in HRM is a complex topic that cannot be viewed from a single perspective; it invariably necessitates a multidisciplinary discourse involving Management, Technology, Regulation, and Ethics.

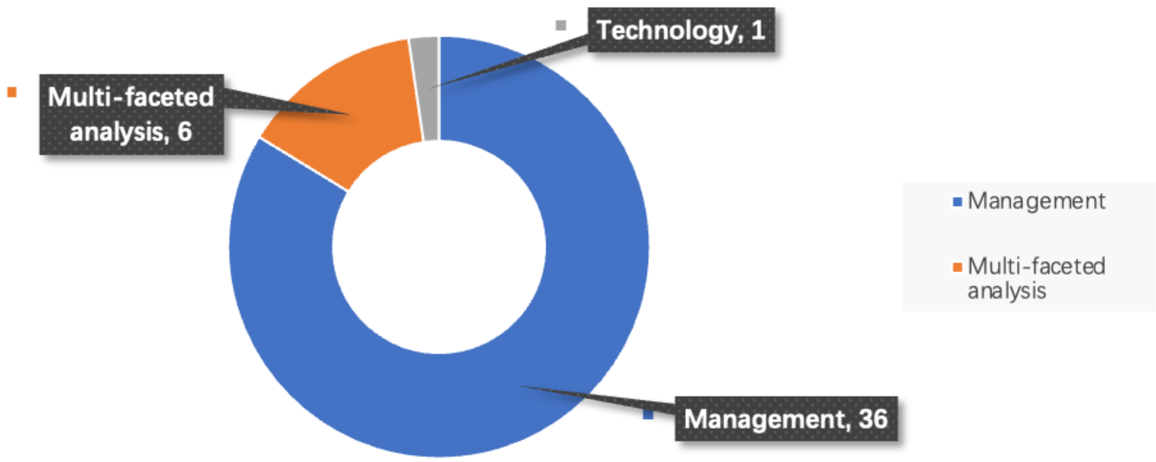


Figure 9. Analysed Perspective

4. Synthesis of Findings and Underexplored Areas in the Literature

4.1 Findings

The context analysis of the literature review shows that most previous studies correspond to the broad field of (AI)HRM rather than just specific industries. Although scholars from 21 countries, 121 authors have contributed to the research content. Single-country authors contributed 32 papers to the literature review, accounting for 74%, so past research needs to pay attention to cross-cultural perspectives. Additionally, out of the 121 authors reviewed, 33 are scholars from the USA, limited by cultural background and industry experience, defining the research on (AI)^{HR}. Although 63% of the studies (n=27) rely on theoretical models and frameworks, most use Strategic management theory (n=13). Only a total of 6 papers use Economic theory, Industrial sociology IR theory and international business theory, so there is a limitation in theory building. In addition, most of the previous research used Critical Review methods (n=14), followed by Qualitative (n=11), which means that scholars focus on theory construction and in-depth understanding.

On the other hand, the research content of (AI)^{HRM} has been analysed. Most of the literature, 86% (n=36), studies (AI)^{HRM} from a management perspective only, with only seven papers analysing (AI)^{HRM} from two or more perspectives (including management, technology, ethics, and regulations), indicating there is a significant imbalance in the perspectives from which (AI)^{HRM} is studied. Therefore, the choice of research methods for (AI)^{HRM} may change over time. It was also found that 24 papers used Empirical research (accounting for 56% of the total literature reviewed), which shows that scholars also pay attention to empirical data and actual observations. Also, most of the studies, constituting 72%, which is 30 in number, utilised exploratory methods. This could reflect a demand for exploring new theories or concepts within the field, with researchers employing experimental methods to uncover new phenomena, build theories, or identify new variables. Empirical research also demonstrates that researchers actively collect and analyse data to validate these findings or hypotheses.

This literature review also looked at which data collection methods scholars used. After examining the methodologies for data collection reported in the literature, it was found that the frequency of using Interviews, Company Documents, and Material from Field Sites Relevant to the Phenomena of Interest was the most significant. Although these data can reflect the application of (AI)^{HRM}, the disadvantages are also exposed, that is, these data may be outdated or only reflect the (AI)^{HRM} trends of some companies or some fields and cannot reflect the overall situation of (AI)^{HRM}.

The results of the literature review suggest that there is still significant room for exploration in (AI)^{HRM} research. The following discussion will address the 3 questions posed earlier for the literature review and figure out in which areas further research is required to augment future research on (AI)^{HRM}.

LRQ 1: What is the current attitude towards AI applications in HRM?

Examining the attitudes expressed in studies helps identify research trends, prevailing sentiments, and potential gaps in the field (Jane Webster & Richard T. Watson, 2002; Vrontis et al., 2022). Understanding these attitudes is essential for positioning the research within the broader context, aligning it with prevailing sentiments or challenging existing assumptions (Smith, 2018). Furthermore, examining attitudes encourages a critical analysis of the literature, considering underlying assumptions, biases, and limitations, leading to a more nuanced review (Torraco, 2005).

Most studies support the use of AI in HRM. 18 studies (LR No. 1, 2, 4, 9, 13, 15, 19, 20, 27, 31, 32, 33, 34, 36, 38, 39, 40, 41) provide an in-depth analysis of the positive role of AI in HRM. Much of the research (15 studies) maintains a neutral/relatively neutral stance, yet 10 studies adopt a cautious/relatively cautious approach. The supportive literature demonstrates the value and potential of AI technology from various aspects, including enhancing efficiency, aiding decision-making, optimising recruitment processes, and emphasising ethics and fairness. AI can automate repetitive and time-consuming tasks such as resume screening and preliminary interviews, thereby allowing HR professionals to allocate more time and resources to strategic tasks. For instance, Manoharan et al. (2011) showcase a decision support model that integrates multiple attributes to assist in employee performance evaluations, illustrating the application of AI in facilitating decision-making processes. França et al. (2023) explore how AI can aid in the more efficient and equitable identification and evaluation of potential talent, thereby optimising recruitment. As industries continue to advance their digital transformation efforts, Klietsova et al. (2023) discuss how AI supports the digitalisation of HRM, highlighting the role of AI in facilitating the transition towards more digitalised HR practices.

The cautious or relatively cautious stance towards using AI in HRM reflected in these studies (LR No. 5, 10, 16, 17, 18, 24, 25, 26, 28, 37) can be attributed to several key concerns. Firstly, ethical and privacy issues highlighted by Manroop et al. (2024) raise alarms about potential privacy breaches and data misuse when employing big data and AI in HRM, especially in talent acquisition, evaluation, and monitoring. Secondly, fairness and bias are critical critique points. Robert et al. (2020) indicate how existing (AI)^{HRM} systems may perpetuate biases and inequalities, particularly in recruitment and promotion processes, inadvertently favouring particular groups. Moreover, as Koivunen et al. (2023) explored, considerations around digital ethics underscore the need for a thoughtful approach to integrating (AI)^{HRM} practices. This includes addressing potential ethical dilemmas and ensuring that the deployment of AI technologies aligns with broader organisational values and societal norms.

LRQ 2: What are the key ethical, legal, and privacy challenges of AI in HRM?

LRQ 3: What are the methods of overcoming these challenges to build trustworthy AI-enhanced HRM systems?

Based on the content analysis of 43 papers, the main research topics of (AI)^{HRM} research are divided into four categories according to the application of AI in different HRM management units, as shown in Table 5. Notably, all papers address associated privacy, ethical, and regulatory concerns, with authors proposing potential solutions and strategies, regardless of paper length. However, despite the myriad of problems researchers have identified, there needs to be a comprehensive solution framework in existing (AI)^{HRM} scholarship that addresses the multifaceted issues reflected in AI practices within HRM. Statistical analysis reveals that the frequency of (AI)^{HRM} challenges mentioned by scholars are in order: 1) Bias & Discrimination, 2) Data Security, 3) Automation Errors, 4) Transparency & Accountability, 5) Legal Compliance, 6) Privacy Concerns, 7) Consent & Choice, 8) Explainability 9) Surveillance & Autonomy and 10) AI audits and auditability. This categorisation, while helpful, still encompasses numerous sub-issues.

Table 5. Challenges and antidote

AI in HRM	Key AI concern	HRM challenges	Suggested solutions/ antidote
Technology Level	• Bias and Discrimination • Data Security • Automation Errors	• AI systems might replicate or amplify existing biases, such as gender or racial biases. • The challenge of protecting employee data from unauthorized access or breaches. • AI systems can make mistakes that could lead to unfair HR decisions.	• AI systems are trained on unbiased data. • Improving the fairness of HR algorithms by considering qualitative information and contextual factors. • A machine-learning-powered solution is suggested: scoring algorithms to avoid bias and prevent discriminatory outcomes. • Design the system from the perspective of HR professionals to understand their subjective insights and experiences. • TP model's algorithms.
Regulation Level	• Privacy Concerns • Legal Compliance	• The need to comply with privacy laws and regulations when handling personal data. • Ensuring that the use of AI in HRM complies with labor	• Call for specialised laws. • Incorporating AI audits to meet legal and regulatory requirements. • Implementing strict policies and enforcement regarding data privacy, usage, and access. • incorporating organizational

AI in HRM	Key AI concern	HRM challenges	Suggested solutions/ antidote
		laws and other relevant legislations.	"environmental variables" within HRM algorithms.
Ethical Level	• Transparency and Accountability • Consent and Choice • Surveillance and Autonomy	• The transparency of AI decision-making processes and accountability for the outcomes. • Employees' rights to be informed and to choose how their data is used by AI systems. • The potential for AI in the workplace to infringe on employee autonomy and privacy.	• Contractarianism—focusing on ex-ante expectations of individuals regardless of status. • Ensuring transparency and fairness in the AI decision-making agent process. • Ensuring transparency with employees about data collection. • Securing employees' data and preventing unauthorized use. • Creating a code of ethics for AI-related initiatives
Management Level	• Explainability • AI audits and auditability	• How AI makes decisions, and whether those decisions are understandable and explainable by humans. • Regular assessments of AI systems to ensure they are fair, effective, and in line with established policies.	• AI-Human balanced. • HR building of trust and mutual respect among participants. • Should let human make human decisions. • Access to data should be limited to a small number of key position holders. • Providing explainability for AI decisions to employees • Involving stakeholders in the design and deployment of AI systems and advocating for statutory regulation to provide necessary safeguards. • Collaboration between I-O Psychology and HRM scholars • Fostering organisational environments where machines and humans coexist • Businesses establish talent incentives and constraints aligned with management mechanisms. • Incorporating ethical considerations, decision-making processes, and managers' knowledge into AI algorithms.

4.1.1 Technological Challenges in $(AI)^{HRM}$

While the current literature effectively highlights the technological challenges associated with $(AI)^{HRM}$, it needs to provide concrete solutions. For instance, Gryncewicz et al. (2023) and Langer & König (2023) discuss the issue of AI perpetuating biases. Still, they do not offer clear strategies for mitigating this problem. Similarly, Herremans (2021) addresses data security concerns but lacks a comprehensive framework for ensuring data protection. The literature would benefit from more practical, actionable recommendations for overcoming these challenges.

4.1.2 Regulatory Challenges in $(AI)^{HRM}$

The literature on regulatory challenges in $(AI)^{HRM}$ needs to be expanded in scope. While Sharif & Ghodoosi (2022) discussing privacy concerns and legal compliance, they need to provide a thorough analysis of the specific laws and regulations that apply to AI in HR. Future research should delve deeper into the legal landscape, examining how existing laws may need to be adapted or new laws created to address the unique challenges posed by AI.

4.1.3 Ethical Challenges in $(AI)^{HRM}$

The literature on ethical challenges in $(AI)^{HRM}$ is more comprehensive, with studies like Newman et al. (2020), Herremans (2021) and Farndale et al. (2020) addressing issues of transparency, employee rights, and surveillance. However, these studies are primarily theoretical and lack empirical evidence to support their claims. Future research should focus on collecting data from real-world AI implementations in HRM to understand the ethical implications better.

4.1.4 Management challenges in $(AI)^{HRM}$

The literature on management challenges in $(AI)^{HRM}$, including Chamorro-Premuzic et al., (2019), Delecraz et al. (2022), Robert et al. (2020), Van Esch & Black (2019) and Delecraz et al. (2022), provides valuable insights into the importance of explainability and regular audits. However, these studies must sufficiently address the practical challenges of implementing these measures. Future research should explore the barriers to adoption and guide on overcoming them.

4.2 Underexplored Areas in the Literature

The analysis of existing literature reveals several key research gaps in the application of AI in human resource management, spanning aspects such as technology, regulation, ethics, and management. These gaps highlight the limitations of current research and areas requiring further investigation. The specific application and definition of Artificial Intelligence (AI) in Human Resource Management (HRM) remains a significant challenge. Research into AI applications in HRM can be dated back to the early 1990s, with foundational studies such as that by Lawler & Elliot (1993). Despite the growth in literature over the past decade, the field exhibits substantial diversity and needs to be more cohesive. Prikshat et al. (2022) have argued for context- and content-specific research to facilitate the streamlining of future studies, which aligns with the goals of this review. Identifying these research gaps is crucial for advancing the field, as it allows researchers to focus on overlooked or insufficiently addressed areas, develop more comprehensive approaches, and ultimately lead to effective strategies for implementing AI in HR practices. Table 6 provides a concise overview of the identified gaps and supporting data based on context and content analysis, facilitating a clearer understanding of the current state of research and areas requiring further investigation.

Table 6. Main gaps and supporting data based on the context and content analysis

Reference	Main gaps	Supporting data
Theoretical perspectives	• Insufficient use of established theories • Unbalanced view of $(AI)^{HRM}$	• 63% (n=27) utilized existing consolidated theories. • Most Strategic Management Theory (n=13), but only 2 used Economic Theory, Industrial Sociology & IR Theory, and International Business Theory respectively.
Context of the research	• Information is outdated. • Lack of direct practical guidance for employees and departments (HR). • There are measurement errors, sampling biases, or data collection	• Most studies, 56% (n=24), employed Empirical. • Most of the data collection methods were sourced from Company Documents. • Nearly half (n=19) of the literature focuses

	issues that may affect the reliability of research conclusions. • Lack of standardized analysis	on Organizational yet there are only 4 papers focuses on Department Sector (HR).
Country/ies of the research	• Lacking a cross-cultural perspective. • Research perspective is limited. • Limited diversity of research contexts.	• 32 papers (74%) were completed by scholars from a single country. • Of the 121author sources, 48 % were from the United States.
Content	• Lack of discussion on the conversion of technical methods into practical standards for applying existing AI technologies in HRM. • Lack of detailed regulatory regulations specifically governing AI applications in HRM. • Lack of clarity in ethical standards concerning the use of AI in HRM. • Lack of management tools for guiding the use of AI in HRM and a lack of clear regulations for management decisions. • Narrow understanding of (AI)^{HRM} and its implications.	• Regulatory standards may evolve continuously with technological advancements. • For privacy issues in HRM, there are no uniform strict boundaries, and despite the high demand for ethical guidelines, none are clearly established. • There is disagreement on the use of AI tools to manage HRM, and the delineation of responsibility is unclear. • 86% of papers focus solely on the management perspective.

5. Limitations and Future Research Directions

In summary, this Literature Review is a pivotal resource that maps out the intellectual territory of AI applications in HRM while illuminating the path forward concerning privacy, ethics, and regulation. Through this meticulous scholarly investigation, stakeholders can better understand and navigate the complex landscape of AI in HRM.

5.1 Limitations

While this literature review provides valuable insights into the current state and future directions of AI applications in HRM, it has several limitations that should be acknowledged.

The areas below outline the limitations:

- The literature review primarily relied on conceptual and theoretical discussions and lacked empirical evidence on the implementation and outcomes of AI applications in HRM. While some case studies and surveys were included, more empirical research is needed to validate the proposed frameworks and propositions and to provide practical insights for organisations.
- The literature review did not consider the potential moderating or mediating factors influencing the relationship between AI applications and HRM outcomes. Factors such as organisational culture, leadership, employee attitudes, or external environment may play important roles in shaping the effectiveness and consequences of AI applications in HRM.
- Most studies mainly focused on the organisational level of analysis and did not examine the individual-level impacts of AI applications on employees. AI may have significant implications for job design, work relationships, employee well-being, and ethical issues, which warrant further investigation.
- Most studies treated AI as a monolithic concept and did not differentiate between various AI technologies or applications in HRM. AI encompasses various tools and systems, such as machine learning, natural language processing, and robotic process

automation, each with unique features and potential applications in HRM.

5.2 Future Research Directions

In conclusion, while the current literature provides a solid foundation for understanding the challenges associated with AI in HRM, it has several limitations. Future research should focus on delivering more concrete solutions, delving deeper into the legal and regulatory landscape, collecting empirical evidence to support theoretical claims, and addressing the practical implementation challenges. By addressing these gaps, the literature can better inform the successful adoption of AI in HRM practices.

While the current literature provides valuable insights into the attitudes towards (AI)^{HRM}, it could benefit from a more systematic examination through the lens of the Technology Acceptance Model (TAM). Developed by Davis (1989), TAM posits that users' acceptance of new technology is primarily determined by perceived usefulness and ease of use. Applying TAM to the (AI) ^{HRM} context could offer a more nuanced understanding of HR professionals' attitudes towards AI, considering efficiency gains, decision support capabilities, and user-friendliness of AI tools. Furthermore, TAM acknowledges the role of external variables, such as organisational environment and social norms, in shaping users' attitudes (Marangunić & Granić, 2015). Future research could draw upon TAM to systematically examine how these factors influence HR professionals' acceptance of AI technologies.

Future research should also incorporate the Perceived Ease of Use (PEOU) construct from TAM as a key factor influencing individuals' attitudes towards AI. PEOU refers to the degree to which an individual believes that using a particular system would be free of effort. In the context of AI applications in HRM, PEOU may be particularly relevant. HR professionals' willingness to adopt AI tools could be influenced by their perceptions of how easy these tools are to use and integrate into their daily work processes. By examining the role of PEOU and other relevant factors, such as trust, privacy concerns, and ethical considerations, future research can provide a more comprehensive understanding of the factors shaping HR professionals' attitudes towards AI.

In future (AI)^{HRM} research, selecting appropriate research methodologies and supporting theories is crucial (Stone et al., 2015). Researchers should borrow theories from reference disciplines and apply them correctly to make value-added contributions (Marler & Parry, 2016). To set the stage for the detailed exploration of future research directions in (AI)^{HRM}, it is essential to acknowledge the dynamic and multifaceted nature of this field of technologies (see Table 7 for details). Integrating AI into HRM presents challenges and opportunities that require a comprehensive and nuanced approach. As researchers look to expand the boundaries of (AI)^{HRM} research, several key areas emerge as pivotal for advancing the understanding and application of these technologies. These range from comparative, cross-cultural studies that scrutinise the diverse applications of AI in different cultural contexts to the incorporation of a wide array of theoretical frameworks that can deepen our insights into the economic, sociological, and business dimensions of AI in HRM.

Table 7. Future research areas and directions

Research Area	Future Directions
Cross-Cultural Studies	Conduct comparative studies across different countries to explore how AI-HRM is applied in various cultural contexts
Theoretical Diversity	Incorporate a broader range of theories, including economic, industrial sociology, and international business theories, to enrich AI-HRM research.
Research Methods	Increase the use of quantitative and mixed-methods research to enhance the generalizability and comprehensiveness of findings.
Multi-Perspective Analysis	Adopt a holistic approach by analysing AI-HRM from multiple perspectives such as management, technology, ethics, and regulation.
Empirical & Longitudinal Studies	Conduct more empirical and longitudinal studies to understand the long-term effects of AI on HRM and track changes over time.

Research Area	Future Directions
Under-Researched HR Functions	Focus on less-studied HR functions like Employee Relations, Health and Safety, and Diversity Management in the context of AI-HRM.
Data Collection Techniques	Develop innovative data collection methods, including real-time analytics and social media analysis, for current AI-HRM practices.
Implementation Guidance	Provide practical implementation guidance for HR professionals on the use of AI tools, encompassing best practices and decision-making frameworks.
Ethics & Regulation	Investigate the development of ethical standards and regulatory frameworks for AI applications in HRM.
Technological Methodology	Translate technical AI methods into practical standards for HRM application, ensuring relevance and usability for practitioners.

Furthermore, enhancing research methodologies by adopting quantitative and mixed-method approaches will improve the generalizability and depth of our findings. A multi-perspective analysis encompassing management, technology, ethics, and regulation is vital to grasp AI's role in HRM. In addition, there is a pressing need for more empirical and longitudinal studies to capture the long-term impacts of $(AI)^{HRM}$ practices and observe evolutionary trends.

Focusing on under-researched HR functions such as Employee Relations, Health and Safety, and Diversity Management within the $(AI)^{HRM}$ framework will fill existing knowledge gaps. Advancements in data collection techniques, including real-time analytics and social media analysis, are crucial for keeping pace with evolving $(AI)^{HRM}$ practices. Practical implementation guidance on AI tools for HR professionals will ensure that best practices and decision-making frameworks are readily available.

Lastly, exploring the ethical dimensions and regulatory requirements surrounding AI applications in HRM will safeguard against potential misuse and foster trust in these technologies. Translating complex technological methodologies into practical standards will facilitate their adoption in HR practices, ensuring they are relevant and user-friendly for practitioners. These directions represent the breadth of research opportunities and underscore the importance of a strategic and thoughtful approach to integrating AI into the fabric of HRM.

6. Implications for HRM Practice

The findings of this literature review offer several implications for HRM practitioners. First, organizations should develop clear AI strategies and policies aligning with their business goals and values. This includes establishing principles and guidelines for the ethical and responsible use of AI in HRM and creating governance mechanisms to ensure compliance and accountability (Tambe et al., 2019). Organisations should also develop cross-functional coordination mechanisms to ensure that the application of AI in HRM aligns with the overall organisational strategy and culture (Pillai & Sivathanu, 2020).

Second, organisations need to pay close attention to change management in AI applications. The introduction of AI may significantly impact organisational structure, work processes, and employees (Cheng & Hackett, 2021). Organisations need to proactively assess and plan for these impacts and take effective communication, training, and support measures to help employees adapt to the changes. HRM professionals need to acquire new AI-related skills and knowledge, such as data analytics, algorithmic design, machine learning, and ethical risk assessment, to effectively design, implement, and evaluate AI systems (Dwivedi et al, 2021).

Third, organizations should foster a culture of transparency, trust, and collaboration between humans and machines. This can be achieved through inclusive governance mechanisms that involve employees in the process of AI adoption and adaptation, transparent communication about the purpose and functioning of AI systems, and fair incentive structures that reward human-machine collaboration (Siau & Wang, 2018). Organisations should also provide adequate training and support to help employees understand and work effectively with AI systems.

Finally, HRM practitioners should continuously monitor and assess the impacts of AI on workforce outcomes, such as diversity, fairness, and well-being. They should establish clear metrics and processes for assessing these impacts, such as regularly auditing AI systems for bias, conducting employee surveys and focus groups to gather feedback, and analysing workforce data to identify any disparate impacts on different employee groups (Tambe et al., 2019). HRM practitioners should also develop proactive strategies to mitigate any identified risks or unintended consequences, such as adjusting AI models, providing additional employee support, or revising HR policies and practices as needed.

In conclusion, the effective application of AI in HRM requires a holistic approach that encompasses strategic alignment, change management, human-machine collaboration, and continuous monitoring and improvement. By proactively addressing these key areas, organisations can harness the potential of AI to enhance HRM processes and outcomes while mitigating potential risks and challenges.

7. Conclusion

This literature review provides a comprehensive review and synthesis of the current research on AI applications in HRM, highlighting the key opportunities, challenges, and future directions in this rapidly evolving field. The findings suggest that AI has the potential to revolutionise various HRM functions, such as recruitment and selection, performance management, training and development, and employee engagement. By automating routine tasks, providing data-driven insights, and enhancing decision-making processes, AI can improve the efficiency, fairness, and effectiveness of HRM practices. However, the study also identifies several challenges and limitations associated with AI adoption in HRM. Organisations must develop robust data governance frameworks to address these challenges, ensure transparency and accountability in AI decision-making, invest in employee reskilling and upskilling, and foster a culture of trust and collaboration between humans and machines.

In conclusion, this literature review contributes to the growing knowledge of AI applications in HRM by synthesising the current research landscape, identifying gaps, and proposing a multilevel research framework. As organisations increasingly adopt AI technologies in their HRM processes, it is crucial to continue exploring the multifaceted impacts of AI on HRM outcomes at various levels of analysis. By addressing the identified gaps and pursuing the recommended research directions, scholars and practitioners can advance our understanding and effective use of AI in HRM, ultimately contributing to developing more efficient, fair, and human-centric workplaces in the digital age.

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