Mapping the Intellectual Structure of Artificial Intelligence in HRM

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Abstract: Artificial intelligence (AI) is reshaping how organisations create, validate, share and use workforce knowledge. Despite rapid growth, research on AI in human resource management (HRM) remains fragmented across HRM, information systems and knowledge management. This study maps the intellectual structure of the Scopus-indexed literature and interprets its major research streams through a knowledge management lens. Drawing on 693 peer-reviewed journal articles published between 1991 and 2025, it combines performance analysis, bibliographic coupling, keyword co-occurrence mapping and thematic evolution with a focused qualitative reading of influential works in each cluster. The findings show rapid growth since 2019 and three dominant but weakly integrated streams: AI adoption and HR analytics; algorithmic decision-making, fairness and governance; and human-AI collaboration. The qualitative interpretation shows that these streams differ not only in topic but also in their assumptions about workforce knowledge: whether it is treated as data to be codified and optimised, as a source of bias and ethical risk, or as a human capability that intelligent systems can augment. The study contributes to knowledge management by showing that AI-HRM research is organised around competing processes of knowledge codification, validation, transfer and use, while giving less attention to knowledge creation, tacit expertise and employee-side knowledge agency. It concludes with a research agenda on knowledge governance, employee experience and cross-database validation. The Scopus-only corpus is acknowledged as a limitation.

Keywords: Artificial intelligence, Human resource management, Knowledge management, Bibliometric analysis, Science mapping, Workforce knowledge

1. Introduction

The integration of artificial intelligence (AI) into human resource management (HRM) is changing not only HR tasks but also the way organisations know their workforce. Recruitment algorithms convert applicant information into predictions, HR analytics platforms aggregate performance data, and generative systems produce feedback, learning content and decision support. These systems therefore mediate the codification, validation and application of workforce knowledge, positioning HRM as a strategic knowledge process rather than a purely administrative function (Nonaka, 1994; Grant, 1996; Vrontis et al., 2022).

This intersection matters to several scholarly communities. Knowledge management research offers concepts for examining how AI transforms knowledge creation, sharing, transfer and use (Argote and Ingram, 2000; Szulanski, 1996). HRM scholarship examines how algorithmic systems affect job design, employee experience and HR roles (Malik et al., 2022; Pereira et al., 2023). Information systems research highlights problems of trust, transparency and system design in people-management contexts (Kong et al., 2021; Van den Broek et al., 2021). The resulting literature is valuable but fragmented across disciplines with different assumptions about what counts as valid workforce knowledge.

This fragmentation poses a significant obstacle to cumulative knowledge development. Without a clear understanding of how the field is structured, which works provide its intellectual foundations, and which themes organise its research activity, scholars risk working at cross-purposes or duplicating efforts. The present study addresses this gap by providing a bibliometric and qualitative analysis of Scopus-indexed AI-HRM research. Drawing on 693 publications indexed in Scopus between 1991 and 2025, the study applies established science-mapping techniques to address three research questions:

RQ1: *What is the bibliometric profile of AI in HRM research in terms of publication trends, productive sources, authors, and countries?*

RQ2: *What intellectual and conceptual clusters organise the field, and how have these clusters evolved over time?*

RQ3: *What structural gaps and emerging frontiers can be identified to guide future research?*

By treating the literature itself as a knowledge asset, this study contributes in three ways. First, it provides a reproducible map of the Scopus-indexed AI-HRM field. Second, it complements formal bibliometric indicators with a qualitative interpretation of the major research streams. Third, it reframes AI in HRM as a knowledge management problem, showing how debates about adoption, ethics and collaboration reflect deeper tensions over knowledge codification, human judgement, employee agency and organisational control.

2. Literature Review

2.1 AI in HRM: Conceptual Foundations

The application of AI to HRM builds on earlier work in HR data mining and people analytics, which conceptualised employee data as a resource for prediction and evidence-based decision-making (Strohmeier and Piazza, 2013; Marler and Boudreau, 2017). More recent research extends this logic to machine learning for candidate screening, natural language processing for employee sentiment, and generative AI for HR service delivery (Chowdhury et al., 2023). These applications make workforce knowledge more visible and calculable, but they also raise questions about data quality, contextual judgement and managerial capability (Tambe et al., 2019).

Several contributions have shaped the field. (Huang and Rust 2018) distinguish mechanical, analytical, intuitive and empathetic intelligence, clarifying where human and machine capabilities may differ. (Vrontis et al., 2022) synthesise key themes in AI-enabled HRM, while (Chowdhury et al., 2023) propose an AI capability framework for creating value in HR. Together, these works establish the foundations for examining AI-HRM as both a technological and organisational knowledge phenomenon.

2.2 Knowledge Management Perspectives

From a knowledge management perspective, AI in HRM can be understood as a technological mediation of organisational knowing. AI systems decide which employee signals become data, how those data are classified, and which outputs become legitimate evidence for decisions. This directly concerns the knowledge-based view of the firm, in which knowledge is a strategic resource whose integration supports coordination and advantage (Grant, 1996; Spender, 1996).

The distinction between tacit and explicit knowledge is central. AI systems are effective at processing explicit, standardised data but less able to capture tacit expertise, relational context and situated judgement (Polanyi, 1966; Nonaka, 1994). Absorptive capacity explains whether organisations can recognise, assimilate and apply AI-generated insights rather than simply acquiring AI tools (Cohen and Levinthal, 1990). Research on knowledge transfer and knowledge hiding further suggests that algorithmic monitoring may change employees' willingness to share knowledge, especially where data are perceived as instruments of control (Szulanski, 1996; Connelly et al., 2012).

2.3 Science Mapping and Bibliometric Analysis

Bibliometric analysis and science mapping provide systematic methods for examining the structure and evolution of scholarly fields. Co-citation analysis reveals intellectual foundations by identifying works that are frequently cited together, suggesting shared conceptual frameworks (Small, 1973). Bibliographic coupling connects documents that share references, revealing thematic clusters and research fronts (Kessler, 1963). Keyword co-occurrence mapping surfaces the conceptual vocabulary of a field, while performance analysis identifies the most productive and influential contributors (Aria and Cuccurullo, 2017).

These methods have been applied to map a wide range of management and information systems fields, including knowledge management (Zupic and Cater, 2015), digital transformation (Verhoef et al., 2021), and AI ethics (Floridi et al., 2018). However, with some notable exceptions (Vrontis et al., 2022; Malik et al., 2022), comprehensive bibliometric analyses of AI in HRM remain scarce. The present study addresses this gap by providing an extensive science-mapping analysis of the Scopus-indexed field.

3. Methodology

3.1 Data Collection

The study adopted a systematic bibliometric approach following established guidelines for science mapping (Aria and Cuccurullo, 2017). Data were retrieved from Scopus using the following exact string in the Title, Abstract and Keywords fields: ("Artificial Intelligence" OR "AI") AND ("Human Resource*" OR "HRM" OR "Recruitment" OR "Talent Acquisition" OR "Onboarding" OR "Employee Engagement" OR "Employee Performance" OR "Employee Well-being" OR "Employee Training"). The search was conducted in January 2026 and covered publications from 1991 to 2025. Only peer-reviewed English-language journal articles were included.

Scopus was selected because it offers the broadest interdisciplinary coverage of management, information systems and computer science journals among major bibliographic databases, together with consistent citation metadata that supports reproducible science mapping. While Web of Science, Dimensions and regional repositories index partially overlapping collections, the Scopus dataset is sufficiently large and diverse to reveal the field's dominant intellectual clusters and conceptual evolution. The findings should therefore be interpreted as a robust map of the mainstream Scopus-indexed journal literature rather than a complete picture of all AI-HRM scholarship. Cross-database triangulation is identified as an important direction for future research.

Conference papers, book chapters, editorials and review articles were excluded to ensure analytical consistency. The final dataset comprised 693 articles published across 343 sources, with 5,339 cited references. Table 1 summarises the main characteristics of the dataset.

Table 1: Main Information About the Dataset

Description	Results
Timespan	1991:2025
Sources (Journals, Books, etc.)	343
Documents	693
Annual Growth Rate %	17.95
Document Average Age	2.93
Average Citations per Doc	35.67
References	5,339
Authors	1,917
Co-Authors per Doc	3.11
International Co-authorships %	32.32
Single-authored Docs	98

3.2 Analytical Approach

The bibliometric analysis was conducted using R (version 4.3) with the bibliometrix package (Aria and Cuccurullo, 2017). The analysis proceeded in five stages: descriptive performance analysis; document and author bibliographic coupling; keyword co-occurrence mapping; thematic evolution across 1991–2020, 2021–2024 and 2025; and a focused qualitative reading of influential and cluster-central papers. The final stage interpreted the quantitative clusters in relation to knowledge creation, codification, sharing, transfer, validation, use and governance.

4. Results

4.1 Publication Trends and Performance Analysis

The analysis reveals a field in rapid acceleration. As shown in Figure 1, AI in HRM research experienced modest growth from 1991 through 2018, with an average of fewer than three publications per year. A marked inflection point occurred in 2019, when publications jumped to 19, followed by sustained acceleration: 29 in 2020, 48 in 2021, 49 in 2022, 88 in 2023, 153 in 2024, and 274 in 2025. This trajectory yields an annual growth rate of 17.95%, confirming the field's emergence as a significant area of scholarly activity.

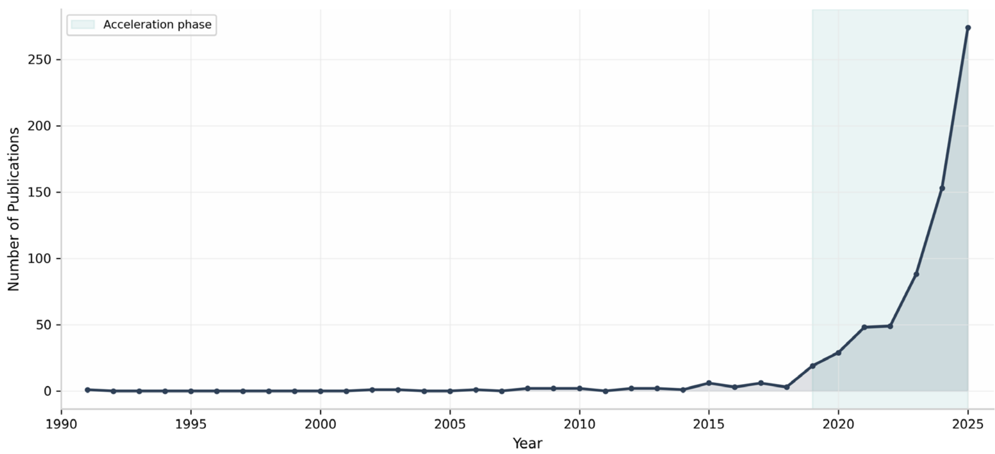


Figure 1: Annual Publication Trend in AI-HRM Research (1991-2025)

The dataset spans 343 sources, reflecting the interdisciplinary nature of the field. Table 2 presents the ten most productive journals. The International Journal of Human Resource Management and International Journal of Organizational Analysis lead with 13 articles each, followed by Technology in Society (12), Administrative Sciences (11), and Technological Forecasting and Social Change (11). The presence of both HRM-specialist journals (Human Resource Management Review, Personnel Review) and technology-focused outlets (Computers in Human Behavior, IEEE Transactions on Engineering Management) confirms the field's bridging function between management and technology scholarship.

Table 2: Top 10 Most Productive Sources

Source	Articles
International Journal of Human Resource Management	13
International Journal of Organizational Analysis	13
Technology in Society	12
Administrative Sciences	11
Technological Forecasting and Social Change	11
Human Resource Management Review	10
Personnel Review	10
Human Resource Development International	9
IEEE Transactions on Engineering Management	9
Cogent Business and Management	8

4.2 Authorship and Collaboration Patterns

The 693 articles were authored by 1,917 researchers, with an average of 3.11 co-authors per document. Single-authored papers constituted 14.1% of the dataset (98 articles), while international co-authorships accounted for 32.32% of publications, indicating a moderate level of global collaboration. Table 3 identifies the most productive authors.

Table 3: Top 10 Most Productive Authors

Author	Articles	Articles Fractionalized
Malik A	10	3.23
Budhwar P	6	1.53
Dutta D	6	2.83
Wang J	6	1.95
Wang X	6	1.67
Bhattacharya S	5	1.51
Nawaz N	5	3.58
Stone DL	5	1.92
Black JS	4	1.83
Kim S	4	1.50

4.3 Country Analysis

The analysis of country-level contributions reveals a field dominated by the United States, China, and European research systems. Table 4 presents the top ten countries by total citations. The United States leads decisively with 4,629 total citations and an average of 64.3 citations per article, reflecting both the volume and impact of American scholarship. China follows with 1,835 citations, while France (1,695), Australia (1,458), and India (1,398) round out the top five.

Table 4: Top 10 Countries by Citation Impact

Country	Total Citations	Avg. Citations/Article
USA	4,629	64.3
China	1,835	28.2
France	1,695	113.0
Australia	1,458	60.8
India	1,398	18.9
Germany	1,197	39.9
Cyprus	1,111	555.5
United Kingdom	1,065	31.3
Italy	738	36.9
Finland	702	100.3

4.4 Most Cited Documents

Table 5 presents the fifteen most globally cited documents in the dataset. Huang and Rust (2018) in the Journal of Service Research, examining artificial intelligence and service delivery, dominates with 2,503 total citations and an average of 278.1 citations per year. Vrontis et al (2022) and Chowdhury et al (2023), both published in Human Resource Management Review, follow with 767 and 631 citations respectively. These three works collectively provide the intellectual foundations for much subsequent research in the field.

Table 5: Top 15 Most Globally Cited Documents

Paper	Total Citations	TC per Year
Huang M-H, 2018, J Serv Res	2,503	278.1
Vrontis D, 2022, Int J Hum Resour Manag	767	153.4
Chowdhury S, 2023, Hum Resour Manag Rev	631	157.8
Huang M-H, 2019, Calif Manage Rev	426	53.3
Pereira V, 2023, Hum Resour Manag Rev	344	86.0
Mercado JE, 2016, Hum Factors	329	29.9
Tong S, 2021, Strateg Manage J	310	51.7
Pillai R, 2020, Benchmarking	307	43.9
Kong H, 2021, Int J Contemp Hosp Manag	304	50.7
Van den Broek E, 2021, MIS Quart	293	48.8
Van Esch P, 2019, Comput Hum Behav	291	36.4
Black JS, 2020, Bus Horiz	284	40.6
Malik N, 2022, Int J Manpow	283	56.6
Braganza A, 2021, J Bus Res	282	47.0
Korzynski P, 2023, Cent Europ Manag J	266	66.5

4.5 Keyword and Conceptual Analysis

Keyword frequency analysis reveals the conceptual landscape of the field. Figure 4 shows that the ten most frequent author keywords include “artificial intelligence” (625 occurrences) and “human resource management” (227), which dominate as expected given the search strategy. More revealing are the secondary terms: “recruitment” (101), “HR analytics” (58), “ethics” (39), and “employee engagement” (33). These keywords identify the primary application domains and concern areas that organise the field’s research activity.

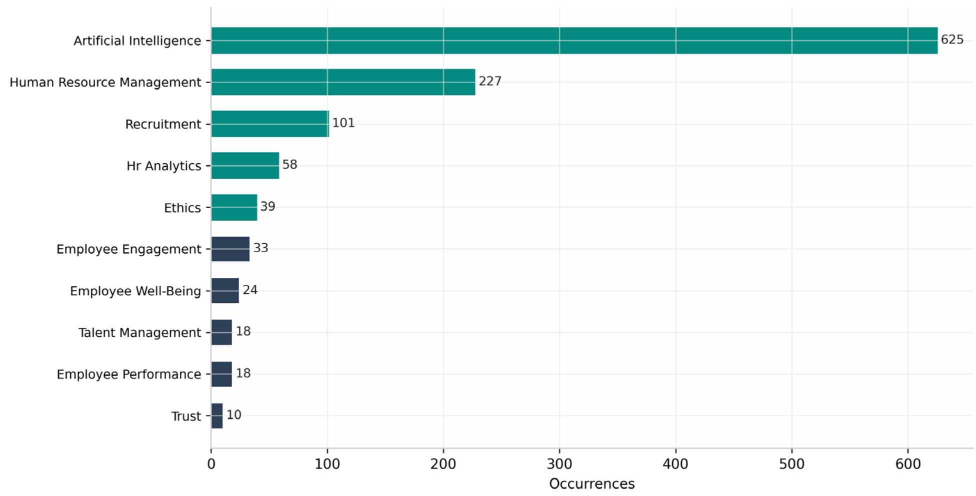


Figure 4: Top 10 Most Frequent Keywords in AI-HRM Research

As shown in Figure 5, keyword frequency trends from 2015 to 2025 reveal important shifts in research attention. The frequency of "artificial intelligence" as a keyword grew exponentially, from near-zero in 2015 to over 500 occurrences in 2025. "Human resource management" shows a parallel but more moderate trajectory. Notably, "ethics" and "employee engagement" show accelerating growth from 2022 onwards, suggesting that normative and employee-centric concerns are gaining prominence as the field matures.

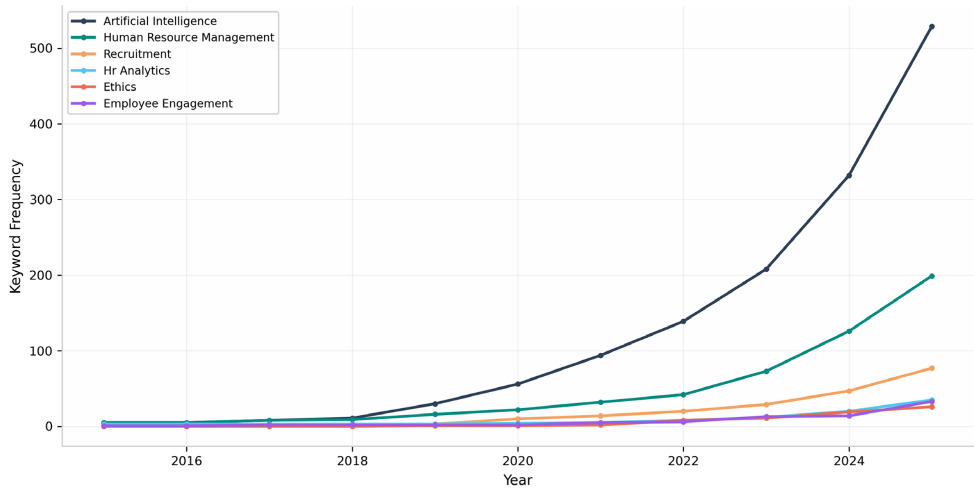
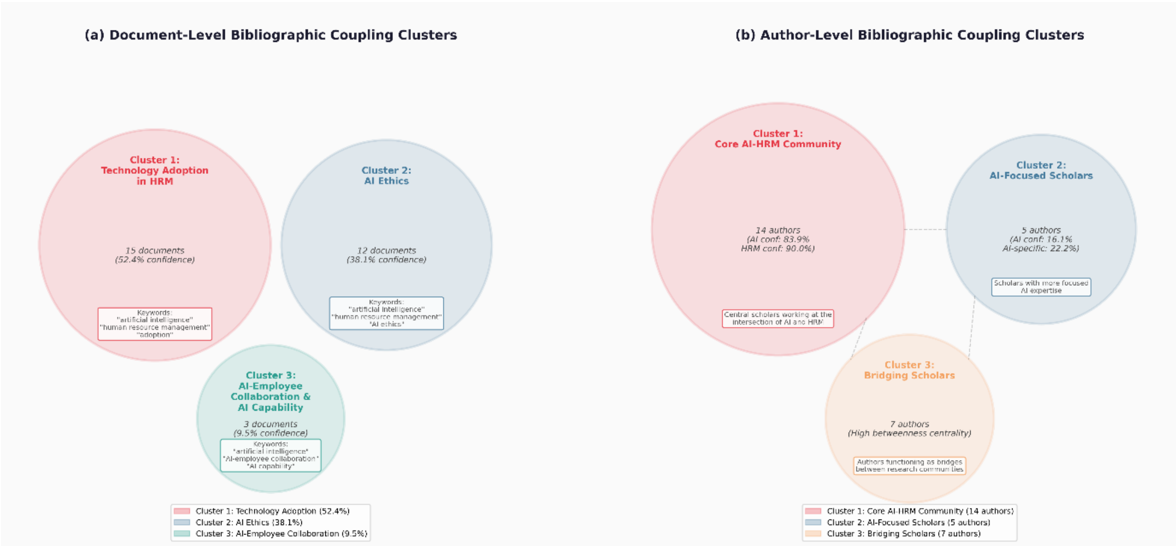


Figure 5: Keyword Frequency Trends in AI-HRM Research (2015-2025)

4.6 Thematic Clustering and Intellectual Structure

Bibliographic coupling analysis of documents identified three clusters, as illustrated in Figure 6. Cluster 1 (15 documents, 52.4%) centres on AI adoption and HR analytics. Cluster 2 (12 documents, 38.1%) focuses on AI ethics and algorithmic governance. Cluster 3 (3 documents, 9.5%) addresses human-AI collaboration and AI capability. The concentration in the first two clusters shows that implementation and normative concerns dominate the field, while collaboration remains an emerging research front.

Author-level bibliographic coupling reveals a complementary social structure. The largest cluster contains 14 authors working across AI and HRM, while a smaller group of five authors represents more focused AI expertise. A third group of seven authors displays high betweenness centrality, indicating that they connect otherwise separate research communities. This structure supports the finding that the field is coherent but still weakly integrated.



4.7 Qualitative Interpretation of the Major Research Streams

The adoption and HR analytics cluster treats workforce knowledge primarily as data that can be codified, aggregated and used for prediction. Studies associated with this stream examine AI capability, organisational readiness, analytics maturity and implementation outcomes (Marler and Boudreau, 2017; Chowdhury et al., 2023). Its underlying assumption is that better data and analytical capability improve HR decision-making. However, the knowledge management lens makes a tension visible: codified indicators can support evidence-based HRM, but they may also oversimplify tacit and context-dependent employee knowledge.

The ethics and algorithmic governance cluster treats algorithmic outputs as knowledge claims that require justification. Research in this stream examines fairness, transparency, accountability, privacy and the risks of people analytics (Floridi et al., 2018; Gal et al., 2020; Rodgers et al., 2023; Tursunbayeva et al., 2022). It therefore shifts attention from whether AI works to whether its knowledge is legitimate, contestable and equitable. This stream also reveals a tension between organisational efficiency and employee voice, because the same data infrastructures that support prediction can intensify surveillance and discourage knowledge sharing.

The human-AI collaboration cluster treats workforce knowledge as distributed across people and machines. Contributions on automation and augmentation emphasise that AI may replace some analytical tasks while complementing human judgement in others (Huang and Rust, 2018; Raisch and Krakowski, 2021). Studies of AI feedback and HR service delivery similarly show that outcomes depend on how employees interpret, trust and respond to algorithmic input (Tong et al., 2021; Van den Broek et al., 2021). The central issue is therefore not substitution alone, but how tacit human knowledge and codified machine knowledge are combined.

Read together, the three clusters represent different positions on workforce knowledge: optimisation, governance and augmentation. Their limited integration helps explain why the field appears fragmented. A stronger knowledge management contribution requires connecting these positions through research on knowledge governance, employee participation and the organisational consequences of AI-mediated knowing.

5. Discussion

5.1 A Critical Reading of the Field's Development

The bibliometric results show a field expanding rapidly but still developing its theoretical centre. The growth of publications after 2019 confirms the organisational salience of AI-HRM, while the young average document age indicates that many ideas have not yet stabilised. More importantly, the three clusters are not merely separate topics. They embody competing assumptions about how workforce knowledge should be produced and used: through data-driven optimisation, ethical governance or human-machine complementarity.

5.2 Theoretical Tensions for Knowledge Management

The first theoretical tension concerns codification versus tacit knowledge. AI-HRM systems make employee attributes visible and comparable, supporting knowledge formalisation and transfer (Grant, 1996). Yet this visibility is partial: contextual expertise, informal relationships and situated judgement remain difficult to codify (Polanyi, 1966; Nonaka, 1994). The second tension concerns augmentation versus automation. An augmentation perspective treats AI as a means of extending HR expertise, whereas automation risks displacing professional judgement and weakening opportunities for learning (Raisch and Krakowski, 2021). The third tension concerns organisational control versus employee knowledge agency. Algorithmic monitoring can improve coordination, but it may also generate distrust, self-protection and knowledge hiding (Connelly et al., 2012; Gal et al., 2020).

5.3 Contribution, Limitations and Future Research

This interpretation clarifies the study's contribution to knowledge management. Rather than only identifying publication patterns, the analysis shows that AI-HRM research is structured around knowledge processes and knowledge politics. The adoption cluster foregrounds knowledge codification and use; the ethics cluster foregrounds validation and governance; and the collaboration cluster foregrounds the integration of human and machine knowledge. Knowledge management theory offers a bridge among these streams by asking who creates workforce knowledge, whose knowledge becomes authoritative, and how AI systems redistribute the capacity to know and decide.

For practice, the findings suggest that successful AI-HRM implementation requires more than technical adoption. Organisations need data-quality controls, transparent decision rules, opportunities for employee contestation, and mechanisms for preserving tacit knowledge alongside algorithmic outputs. For research, the results point to the need for qualitative and employee-centred studies of how AI changes knowledge sharing, learning and professional identity. Future bibliometric work should also compare Scopus with Web of Science and open databases to test whether the intellectual structure identified here is stable across data sources.

6. Conclusion and Research Agenda

This study has mapped the intellectual structure of Scopus-indexed AI-HRM research and interpreted its major clusters through a knowledge management lens. The findings confirm rapid growth and identify three connected but weakly integrated streams concerned with adoption and analytics, ethics and governance, and human-AI collaboration. The central contribution is to show that these streams are also debates about workforce knowledge: how it is codified, validated, shared, used and governed.

The research agenda follows directly from this interpretation. First, future studies should integrate the adoption, ethics and collaboration streams rather than treating them as separate conversations. Second, employee-centred research should examine how AI-mediated HR affects trust, voice, learning, knowledge sharing and perceptions of fairness. Third, knowledge management scholars should investigate how AI reshapes tacit expertise, organisational memory and the authority of HR professionals.

The study is limited by its reliance on Scopus and on formal bibliometric indicators. Although Scopus provides consistent metadata and broad multidisciplinary coverage, relevant work indexed elsewhere may have been omitted. Future research should triangulate multiple databases, include conference and practitioner literature where appropriate, and combine science mapping with systematic qualitative reviews. Even within these limits, the study demonstrates the value of treating AI-HRM literature as a knowledge domain whose structure reveals how organisations are learning to know and govern their workforce through intelligent systems.

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Ethics Declaration: This study is based entirely on secondary analysis of published bibliometric data. No human participants were involved, and no primary data were collected. Therefore, ethical clearance was not required for this research.

AI Declaration: The authors confirm that AI tools were used in the creation of this paper. Specifically, AI-assisted tools were employed for data visualisation and manuscript formatting. All analytical decisions, interpretations, and conclusions were made by the authors.

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