Mapping Global Trends in AI and Human Resources Management Based on Bibliometric Analysis: Using Publish or Perish and Vosviewer

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DOI: https://doi.org/10.47772/IJRISS.2026.100700771

Received: 29 July 2026; Accepted: 03 August 2026; Published: 12 August 2026

ABSTRACT

This empirical study aims to analyze the green financial investment disclosure index (GFDI) for the 2020-2025 period for public entities in Indonesia. The unit of analysis is the annual reports of 335 issuers, sourced from the Indonesian Stock Exchange (IDX), which are grouped into real and manufacturing sectors. The data was analyzed descriptively qualitatively and verified using the two independent sample T test. The results of the analysis showed the following: 1) GFDI of annual reports for the 2020-2025 period of companies listed on the JSE averaged 0.50378; 2) The average GFDI of annual reports for the 2020-205 period of manufacturing sector issuers is 0.48426, while the average GFDI of annual reports for the 2020-2025 period of real sector issuers is 0.52204; Furthermore, the results of the verification analysis show that there are differences in the annual reports for the 2020-2025 period between issuers in the manufacturing sector and the real sector.

Keywords: item disclosure, disclosure index, green economic, annual report, public entity, Indonesia stock exchange.

INTRODUCTION

The penetration of artificial intelligence (AI) in Human Resource Management (HRM) has transformed it from mere administrative automation to a strategic decision-making tool. Its applications range from recruitment algorithms and predictive HR analytics to AI-based sentiment analysis, fundamentally changing the HR management landscape [1,2].

In Indonesia, the adoption of digital technology is driven by the need for operational efficiency and organizational well-being post-pandemic, as companies integrate with digital ecosystems to maintain competitiveness [3].

This phenomenon has triggered a redefinition of the role and competencies of HR Managers. On the one hand, HR Managers are challenged by new technical competencies, such as data literacy, an understanding of algorithm ethics, data governance, and the ability to interact with analytical platforms [4,5]. On the other hand, as analytical and routine cognitive tasks are taken over by AI, human interaction becomes a key differentiator. This amplifies the urgency of social competencies, such as empathy, emotional intelligence, ethical and transformational leadership, management, and navigating organizational culture [6].

At the end of 2019 until the semester of 2023 the whole world is facing a multidimensional crisis - the outbreak Covid19, this year is the second year for economic recovery and returning to normal. The Indonesian economy is estimated to achieve chaotic growth after the C10 pandemic and after the direct presidential election on February 14 2024. So the market also hopes that with the election of a new government, economic conditions will move in a better direction. The Indonesian economy in 2025 growth by 5.05 percent, lower than the achievement in 2024 which experienced growth of 5.31 percent. In terms of production, the highest growth occurred in the Transportation and Warehousing Business Field at 13.96 percent. Meanwhile, in terms of expenditure, the highest growth was achieved by the Consumption Expenditure of Nonprofit Institutions Serving Households at 9.83 percent [6].

A paradoxical tension exists in HRM practices: HR managers are required to become increasingly technically proficient to navigate AI-based technologies, yet simultaneously must become increasingly 'human' to maintain inclusive industrial relations and mitigate dehumanization in the workplace ([7].

Although the use of AI in HRM has attracted global academic attention, the majority of existing literature still has significant gaps:

- Fragmented Focus: Most studies focus on the impact of AI on organizational performance at the macro level or the adoption of specific AI tools (e.g., recruitment automation), but rarely evaluate its impact simultaneously on two key competency dimensions (social and technical) at the practitioner/manager level [8].
- Lack of Integrated Systematic Synthesis: Current research at both the global and local levels tends to utilize single case studies or partial qualitative research, resulting in a lack of a comprehensive map that methodologically integrates empirical findings.
- Need for a Future Research Agenda Framework: There is no structured framework that consolidates current empirical evidence to formulate a research agenda that will guide academics and practitioners in the future [9].

The novelty of this research lies in its approach, which uses a literature review to in-depth evaluate the impact of AI on the dual competencies (social vs. technical) of HR Managers, while projecting future research trends based on identified empirical and methodological gaps.

Based on the context and problem formulation above, this article aims to:

1. review the literature on various applications and adoptions of AI in human resource management (HRM);
2. understand the managerial capabilities and competencies that need to be mapped to the various technologies used in AI adoption in HRM.

LITERATURE REVIEW

AI is described as a broad group of technologies in which computers can perform human-like tasks, exhibiting signs of cognition and the ability to make adaptive decisions [4]. The underlying technology of AI is machine learning (ML) approaches, such as deep learning (DL), also known as artificial neural networks. [10], a pioneer of ML, argues that this approach enables computers to learn without having to be specifically programmed to do so. Applications such as spam filtering in email, natural language processing (NLP), translation, audio-to-text transcription, speech recognition, driverless cars, and visual inspection in quality control are some examples of AI-based systems that use machine learning [11]. DL is an advanced form of ML that uses artificial neural networks and processes large amounts of network information from input sources to produce decisions, almost like the way the human brain processes information through billions of interconnected neuron networks [11,12]. DL approaches use complex algorithms that can improve the performance of AI systems for better decision-making ([11] ML and DL enable machines to operate autonomously without significant human intervention. These systems learn from human input data and evolve as they learn from experience [13]. Another ML approach, Natural Language Processing (NLP), involves computer systems that learn from human understanding of natural language so that they can manipulate text or speech that uses natural language. This technology can be used in machine translation, text processing, user interfaces, speech recognition, and so on [14].

AI-powered technologies are revolutionizing HR-related practices such as recruitment, training, and competency mapping, resulting in improved organizational performance [1,6]. The adoption of AI in HR helps create new knowledge-sharing configurations in decision-making support and problem-solving of existing HR processes, such as recruiting, performance management, internal mobility, learning, employee self-service automation, diversity management, employee well-being, and more [6, 15, 16]. AI-powered tools lead to organizational learning that helps recalibrate or reorient business models [17]. Studies show that the function of HRM can leverage AI to benefit both employees and employers by processing vast amounts of data across multiple platforms (including job portals, social media, etc.). Some other applications include suggesting learning programs based on employee skill gaps and assessing employee performance by reducing bias [6, 9].

Current AI systems can augment human decision-making, helping managers override decision-making when necessary. At the next level, AI systems possess autonomous problem-solving and decision-making capabilities, and can surpass human intelligence and decision-making abilities [18]. Therefore, while the adoption of AI in HRM shows promising benefits, its effectiveness hinges on the successful adoption of AI in HRM, which relies not on technological infrastructure but on adequate managerial capabilities.

This study uses PKD as a theoretical framework to support the claim that the application of AI in human resource management (HRM) requires a network of capabilities [19]. Consequently, business processes interact with and utilize various levels of managerial capabilities, learning capabilities, absorptive capacities, and knowledge management, while also leveraging capabilities provided by AI devices and technologies—such as predictive capabilities, pattern and speech recognition, and natural language processing, among other examples [20].

While the Resource-based View (RBV) [21] focuses on gaining competitive advantage in a stable environment, its limitations lie in its static nature and inability to respond to environmental changes. Therefore, our focus on the dynamic capabilities perspective (DCV) as a response to survive in a rapidly changing external environment is a timely step [22]. Dynamic capabilities include three key elements: resources, strategy, and capabilities [22]. "Resources are firm-specific assets such as employees, equipment, buildings, and intangible assets that are difficult—if not impossible—to imitate." Strategy at the highest level involves scanning the external environment to obtain unstructured data that must be organized and interpreted at the managerial capability level. The seizing stage involves rapid response mechanisms, such as investing in modern technology or new business models for products or processes. The transformation stage involves aligning current technologies and business models with the organization, which often clashes with existing business models. The strength of a firm's capabilities determines the degree and speed of alignment and realignment of firm resources by organizational strategy [21].

Based on the PKD perspective, a crucial role that managers play is asset orchestration, which is defined as “Assembling and orchestrating a configuration of jointly specialized assets in a dynamic environment” [23]. Thus, dynamic HR managerial capabilities will play a crucial role in orchestrating jointly specialized assets, such as implementing AI into HR systems and coordinating joint specializations between HR departments, employees, and implementations [24]. Through this, managers play the role of entrepreneurs and require competencies to assess the external environment to utilize the required market and technology capabilities [25]. They organize and interpret information obtained from customers, new discoveries in the market, and competitor information, while applying inductive and deductive reasoning [22]. Since leaders and managers are directly involved in making crucial decisions regarding AI implementation and hold control over AI-enabled processes, this managerial capability is referred to as meta-dynamism capability [26].

Regarding managerial capabilities, three main foundations have been identified in the literature on dynamic capabilities:

1. Managerial cognition, or cognitive capability, broadly defined as the 'capacity to perform a function' [27]. This aids in strategic decision-making by detecting market opportunities using heuristics, mental models, and interpretations in decision-making [22,27].

2. Managerial human capital encompasses managerial knowledge and skills formed through professional experiencemand personal. Their educational level, functional area, and industry experience and heterogeneity play a crucial role in detecting, capturing, and reconfiguring their resource base (25,27).

3. Managerial social capital – managers' external relationships help them acquire the resources necessary for the company and understand competitive practices. They play a role in detecting and seizing opportunities [27]. The ability to build relationships and acquire resources through these relationships is also referred to as relational capabilities [19].

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

Some managerial decision-making scenarios require AI- and cloud-based solutions. AI-based systems are black-box in nature because their decision-making algorithms and DL capabilities are not transparent. From the end-user perspective, this raises explainability issues [4]. Thus, it also requires managerial capabilities that can override AI-assisted decision-making to have control and final say over the decision-making process [13,16]. Even a fully autonomous system, if implemented, would require overriding decisions by HR managers [13].

Recognizing the importance of managerial capabilities, this study critically assesses and identifies the managerial capabilities required for adopting AI in HR through SLR, content analysis, and text.

METHODOLOGY

While there are several excellent examples of bibliometric analysis and reviews in emerging fields of study—such as online learning, telemedicine, sustainable tourism, big data analytics, blockchain applications, and bitcoin [28,29,30], similar efforts are still limited in the field of Human Resource Management (HRM), particularly those that examine the topic using SLR methods. content analysis, and bibliometric analysis. Therefore, this study applies a methodology that includes SLR and bibliometric analysis to address the first objective, and content analysis to address the second objective.

The bibliometric approach was chosen because it can map intellectual structures, identify relationships between research topics, and systematically analyze research development trends based on scientific publication data [31]. In recent studies from 2020 to 2026, bibliometric analysis has been increasingly used because it is considered effective in identifying collaboration patterns, the evolution of research themes, and research gaps within a scientific field [31].

The data collection process was carried out by searching articles were published International journal indexed by the Google Scholar, CrossRef, Scopus and WOS/Clarivate through dbase using Publish or Perish (PoP) software. All those chosen because it offers broad and inclusive literature coverage, including articles from leading international journals, conference proceedings, books, and other academic publications, thus providing a more comprehensive representation of research [32]. Meanwhile, the Publish or Perish application is used to facilitate the process of searching, filtering, and managing publication metadata in a systematic and measurable manner.

The article selection process involved screening based on inclusion and exclusion criteria. Inclusion criteria included articles directly related to the research topic, available as full-text scientific articles, published between 2020 and 2026, and possessing clear and accessible metadata. Meanwhile, articles that are duplicates, irrelevant to the research topic, or lack complete bibliographic information are excluded from the analysis. Based on these steps, a number of articles were identified and subsequently used as a sample for the bibliometric study.

Data analysis was conducted in two main stages: descriptive analysis and bibliometric visualization using VOSviewer software. Descriptive analysis was used to describe the distribution of publications based on year, number of citations, authors, publication sources, and the evolution of research themes. Subsequently, VOSviewer was used to visualize relationships among bibliographic data, thereby facilitating the interpretation of research patterns in the fields of AI and HRM [33,34].

The Methodological Process Model

Before generating network graphics, your paper's framework relies on a data collection and filtration loop. This workflow handles database querying, duplicate exclusion, and file conversions.

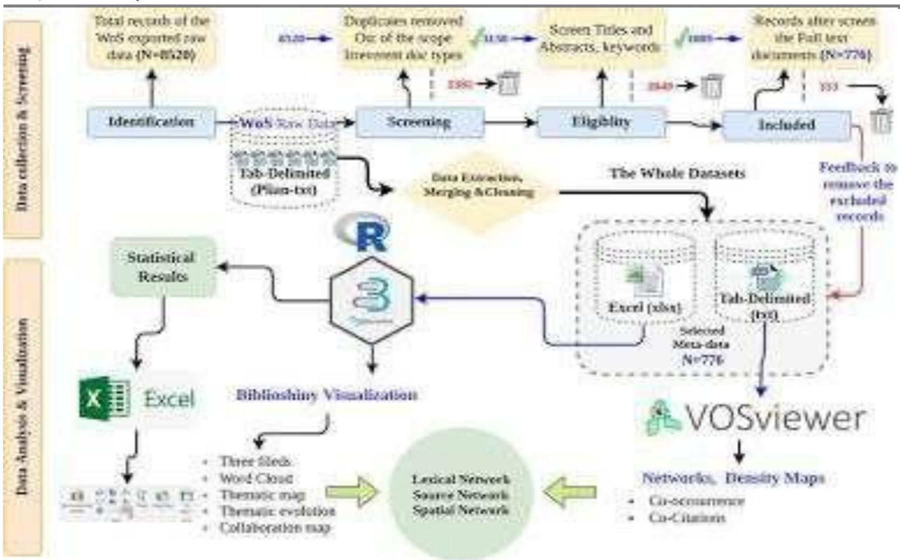

Figure 1. Bibliometric Data Collection & Processing Model. Source: ResearchGate

The following **Research Model** maps the standard step-by-step pipeline used for this specific type of bibliometric analysis:

1. Step1 - Define Research Scope & Query Formulation:

Identify primary research questions regarding Global Trends in EMA. Formulate exact search strings and keywords such as "Environmental Management Accounting", "Green Accounting", and "Sustainability Accounting".

2. Sep 2 - Data Retrieval via Harzing's Publish or Perish:

Input the chosen keywords into **Publish or Perish (PoP)** software. Select target databases (such as *Google Scholar*, *Scopus*, *Crossref*, or *Web of Science*) and set the chronological filter boundaries (e.g., 2015–2025 or 2021–2026) to collect raw metadata

3. Step 3 - Data Cleaning & Reference Management:.

Export the collected metadata from PoP in standard formats like .ris, .csv, or .bib. Import these files into a reference manager (such as *Mendeley* or *Zotero*) to remove duplicates, eliminate incomplete entries, and filter out irrelevant papers through title and abstract screening.

4. Step 4 - Bibliometric Analysis & Network Visualization in VOSviewer:

Load the cleaned dataset into **VOSviewer** to construct distance-based bibliometric maps. Run specific analytical configurations:

- **Co-occurrence Analysis:** For mapping clusters of prominent keywords.
- **Co-authorship Analysis:** For identifying prominent authors, institutions, and countries.
- **Citation/Co-citation Analysis:** For establishing the structural foundation of the literature.

5. Step 5-Thematic Interpretation & Trend Synthesis:S

Analyze the generated visual charts (Network, Overlay, and Density visualizations). Group overlapping items into distinct thematic clusters (e.g., linking AI to HRM, Manager's Competences) to point out current research gaps and forecast future global trends.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

FINDINGS AND DISCUSSION

The research data was obtained through a search using the Publish or Perish application on the Google Scholar database, then further analyzed quantitatively using Microsoft Excel and visualized using VOSviewer. The results of the analysis are presented in the form of tables and visual maps to provide an overview of research developments and the structure of relationships between topics in the fields of AI and HRM.

Table 1. Citation Metrics

Publication years:	2000-2026
Citation years:	26 (2000-2026)
Papers:	1000
Citations:	8492
Cites/year:	326.62
Cites/paper:	8.49
Authors/paper:	2.00
h-index:	45
g-index:	86
hI,norm:	30
hI,annual:	1.15
hA-index:	18
Papers with ACC ≥ 1,2,5,10,20: 234,138,74,40,18	

The initial metadata retrieval executed via Publish or Perish produced a comprehensive, high-volume dataset spanning a 26-year publication window from **2000 to 2026**. This core dataset comprises **1,000 papers**, establishing a broad and statistically robust foundation for evaluating scientific output and impact within the domain.

1. Overall Volume and Citation Impact

- Total Citation Yield: The retrieved corpus accumulated a total of 8,492 citations across the 26-year period, demonstrating considerable academic interest and scholarly resonance.

- Annual and Per-Paper Citation Velocity: The dataset exhibits a citation velocity of 326.62 citations per year (Cites/year), reflecting steady knowledge consumption and ongoing integration into active literature. On an individual level, articles averaged 8.49 citations per paper (Cites/paper).

- Co-Authorship Dynamics: The average authorship rate stands at 2.00 authors per paper, indicating a balanced collaborative pattern—typically reflecting co-authored empirical and theoretical research between academic peers or mentor-mentee partnerships.

2. Core Bibliometric Impact Indices

To assess scientific performance beyond raw citation counts, several normalized citation indices were evaluated:

- h-index (45): At least 45 papers in the dataset have received 45 or more citations each. This high h-index confirms a strong core group of influential publications driving the intellectual growth of the field.

- g-index (86): The g-index reaches 86, signifying that the top 86 papers cumulatively account for a substantial concentration of total citations. The high g-index relative to the h-index indicates the presence of several highly cited benchmark studies pulling up the overall distribution.

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ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

- Individual-Level & Normalized Indices hI, norm = 30, hI, annual = 1.15, hA-index = 18:

The normalized individual h-index (hI,norm) of **30** adjusts for multi-authorship, confirming that individual contribution credit remains substantial. The annual individual growth (hI,annual) of **1.15** indicates a steady year-over-year accumulation of impactful papers, while the hA-index of **18** highlights active, highly cited contemporary contributions from key authors.

3. Annual Citation Thresholds (ACC)

An analysis of papers meeting specific Annual Citation Count thresholds 1, 2, 5, 10, 20 provides deeper insight into the distribution of paper impact:

- 234 papers achieve an 1 (receiving at least 1 citation per year).
- 138 papers achieve an 2 (receiving at least 2 citation per year).
- 74 papers achieve an 5 (receiving at least 5 citation per year).
- 40 papers achieve an 10 (receiving at least 10 citation per year).
- **18 papers** achieve an 20 1 (receiving at least 20 citation per year), representing the elite, highly cited landmark articles that form the foundational theoretical pillars of the literature corpus.

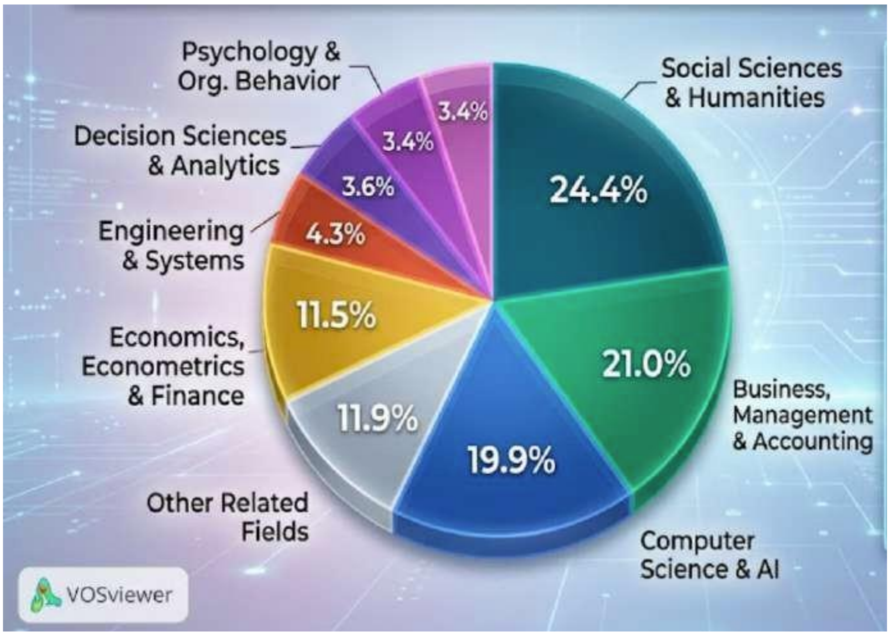

Figure 2. Percentage (%) of various Disciplinary Categories

Source: data is processed, 2026

The systematic selection process guided by the PRISMA 2020 framework resulted in a highly interdisciplinary corpus of articles examining Artificial Intelligence (AI) and Human Resource Management (HRM) competencies. Analysis of the subject areas indexed across Scopus, Web of Science, Google Scholar, and Crossref reveals that research in this domain is distributed across eight distinct academic disciplines.

1. Dominant Theoretical Pillars

- Social Sciences & Humanities (24.4%): Representing the single largest share of the dataset, this discipline focuses on the broader socio-technical implications of AI adoption. Scholars in this field examine labor market transformations, workplace power dynamics, legal policy frameworks, and ethical governance structures required to safeguard human dignity in automated environments.

- Business, Management & Accounting (21.0%): Serving as the primary organizational lens, this segment addresses the operational and strategic integration of AI within human capital management. Literature here focuses on modernizing talent acquisition, optimizing performance management systems, and defining the evolving strategic role of HR leaders.

- Computer Science & Artificial Intelligence (19.9%): Constituting the technical foundation of the corpus, this discipline provides insight into algorithm design, machine learning architectures, Natural Language Processing (NLP) models, and automated platform engines that power contemporary HR tech tools.

2. Analytical & Economic Extensions

- Economics, Econometrics & Finance (11.5%): This body of literature evaluates the macro- and micro-economic drivers of enterprise AI adoption. It investigates return on investment (ROI) for HR analytics infrastructure, labor displacement metrics, productivity gains, and cost-benefit ratios.

- Engineering & Systems (4.3%): Studies within this field examine workflow automation, human-system interaction design, industrial engineering efficiency, and systemic process optimization.

- Decision Sciences & Analytics (3.6%): This sector contributes quantitative methodology, focusing on predictive people analytics, multi-criteria decision frameworks, and mathematical risk modeling in talent selection.

3. Behavioral & Emerging Interdisciplinary Frontiers

Psychology & Organizational Behavior (3.4%): Though smaller in volume, this critical discipline addresses the human psychological response to automated workplace systems. Key research threads center on trust building, mitigation of algorithmic bias perception, employee technological anxiety, and psychological safety.

- Other Interdisciplinary Fields (11.9%): The remaining portion captures cross-cutting insights from niche domains, including healthcare management (employee well-being tracking), environmental sustainability (green HRM practices), and public administration law.

Table 2. Distribution of Publications

Publish a journal	**Number of Journals**	**Number of Citations**
emerald.com	225	9.460
mdpi.com	83	4.519
Wiley Online Library	47	6.126
Springer	279	3.788
Elsevier	145	4.672
researchgate.net	54	1.260
academia.edu	37	2.534
Taylor & Francis	40	1.159
journals.sagepub.com	10	841
pdfs.semanticscholar.org	10	445

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

hrcak.srce.hr	10	330
aimspress.com	10	204
cell.com	10	181
jssm.umt.edu.my	10	123
repository.unair.ac.id	5	55
papers.ssrn.com	5	108
repository.pnb.ac.id	5	72
repository.unar.ac.id	5	8
ojs.journalsdg.org	5	30
research reposiory.r,it.edu.au	5	102

Table 2. above presents the bibliometric dataset was analyzed to evaluate the contribution and citation impact of various academic publishers, digital libraries, and institutional repositories. The table presents a comparative overview of the total number of indexed journals and their cumulative citation counts, revealing a distinct distribution pattern in research influence within the domain of AI and Human Resource Management (HRM).

1. Dominance of Major Academic Publishers

The findings demonstrate that established, peer-reviewed commercial publishers serve as the primary knowledge hubs for research on AI in HRM:

- Emerald Publishing (emerald.com): Emerges as the undisputed leader in thematic impact, generating the highest total citation count at 9,460 citations across 225 journals. This highlights Emerald's role as the primary outlet for highly cited, foundational management and HR technology literature.

- Springer (Springer): Represents the largest total volume of venues with 279 journals, producing 3,788 citations. This indicates a broad dissemination strategy spanning interdisciplinary computer science, systems engineering, and business management journals.

 Elsevier (Elsevier): Holds a substantial footprint with 145 journals and 4,672 citations, reflecting strong academic engagement in high-impact organizational and technological journals.

- Wiley Online Library (Wiley Online Library): Exhibits an exceptional citation-to-journal ratio, producing 6,126 citations across just 47 journals. This demonstrates a high concentration of influential, highly cited studies in top-tier business journals.

- MDPI (mdpi.com): Captures significant open-access volume with 83 journals yielding 4,519 citations, reflecting rapid publication growth and high visibility in contemporary research.

- Taylor & Francis (Taylor & Francis) & SAGE (journals.sagepub.com): Contribute specialized management perspectives, with Taylor & Francis accounting for 40 journals (1,159 citations) and SAGE contributing 10 journals (841 citations).

2. Preprints, Open Repositories, and Scientific Networks

In addition to traditional publishers, open-access databases and academic social networks play a notable secondary role in research dissemination:

- ResearchGate (researchgate.net) & Academia.edu (academia.edu): Accounted for 54 journals (1,260 citations) and 37 journals (2,534 citations) respectively, serving as early-access and self-archiving channels for global scholars.

- Preprint & Aggregator Platforms: Networks like SSRN (papers.ssrn.com) (5 journals / 108 citations) and Semantic Scholar (pdfs.semanticscholar.org) (10 journals / 445 citations) facilitate early dissemination of emerging working papers on rapid AI developments prior to formal peer review.

3. Regional and Institutional Repositories

Regional portals and university institutional repositories (e.g., *HRCAK*, *AIMS Press*, *Cell Press*, *UMT*, *UNAIR*, *PNB*, and *RMIT*) represent smaller niche outlets (ranging between 5 to 10 journals each). While their individual citation counts remain modest (ranging from **8 to 330 citations**), they provide localized empirical insights and regional case studies that enrich the global discourse on localized AI adoption and competency gaps.

This publication and citation mapping confirms that while research dissemination is distributed across various open-access and institutional platforms, **the core intellectual influence is heavily concentrated within premier management publishers (Emerald, Wiley, Elsevier, and Springer)**. This distribution reinforces the high reputability and rigor of the underlying dataset utilized for this bibliometric review.

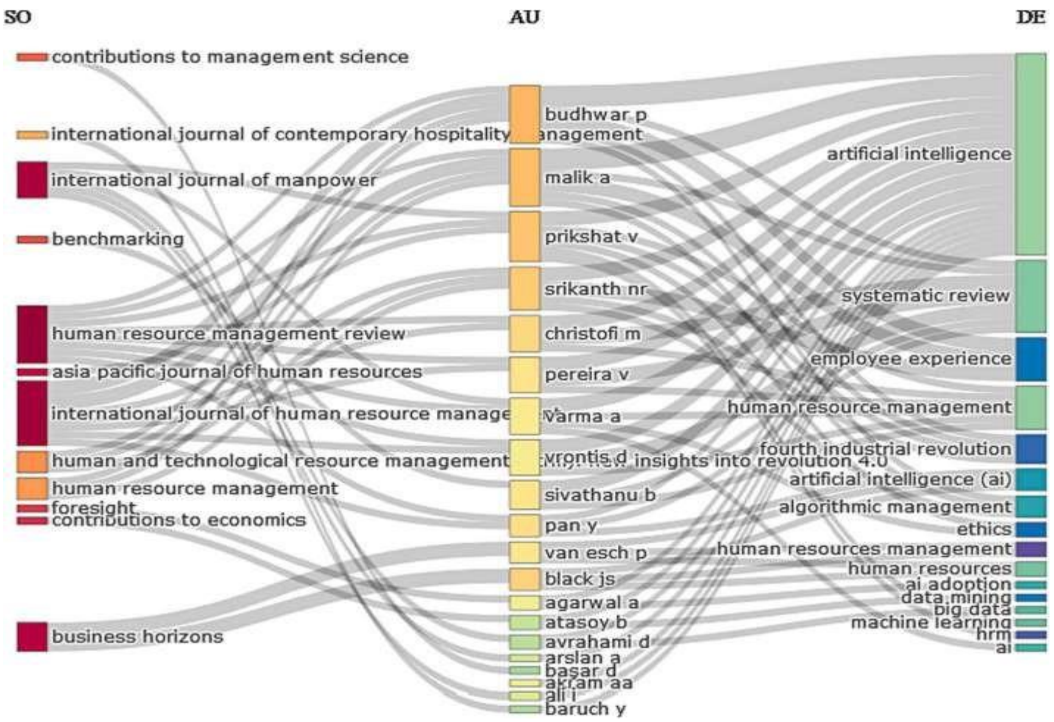

Figure. 3. Three fields plot: source-author-keywords plot.

The three fields plot, which maps the sources to authors to keywords, reiterated the fact that research of AI in HRM predominantly focussed on a systematic review of literature on the adoption of AI, machine learning, and the fourth industrial revolution in HRM with employee experience as an outcome (See Fig. 5). In addition, the ethics of AI ap-plications in HRM was another important topic for research [35, 36, 37, 38]. Similarly, the most frequently occurring research words, as given in Table 3, and the co-occurrence network that examines the potential relationship of two bibliometric items in the same record [39], as given in Fig. 4, helped identify the underlying themes of AI in HRM literature. They predominantly focussed on recruitment, personnel selection, employee experience, and job design. Specific other word frequencies like automation, augmentation, future of work, robotics, and the Technology-Organization-Environment (TOE) model are also mentioned in the co-occurrence network analysis and thematic maps, as given in Figs. 3 and 4.

Table 3 Frequently occurring words.

Terms	Frequency
Artificial Intelligence	37
Human Resource Management	6
Systematic Review	6
Human Resources	4
Machine Learning	4
Big Data	3
AI	2
AI Adoption	2
Algorithmic Management	2
Artificial Intelligence (AI)	2
Augmentation	2
Automation	2
Data Mining	2
Employee Experience	2
Ethics	2
Fourth Industrial Revolution	2
Future of Work	2
HRM	2
Human Capital	2
Human Resources Management	2
India	2
Job Design	2
Personnel Selection	2
Recruitment	2
Robotics	2
Talent Acquisition	2
Talent Management	2

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

Technology	2
Toe Model	2
Adoption	1
Advanced Technologies	1
Age	1
AI-Adoption in HRM	1
AI-Augmented HRM	1
AI-Enabled Chatbots	1
AI-Enabled Recruiting	1
AI Anxiety	1
AI Awareness	1
AI Ethics	1
AI Recruitment	1
AI Transparency	1
Algorithm-based Surveillance	1
Algorithms	1
Artificial Intelligence-Human Resource1 Management Interface	
Artificial Intelligence and Hiring	1
Artificial Intelligence Applications	1
Artificial Intelligence Evaluation	1
Attitudes	1
Augmented Intelligence	1
Automated Decisions	1

The keyword profile in Table 3 demonstrates that while the literature has firmly established the **technical mechanics of AI in recruitment and talent management**, it is only beginning to explore the **socio-psychological, ethical, and governance challenges** (e.g., *AI Anxiety*, *Algorithmic Surveillance*, *Transparency*). These low-frequency, emerging constructs confirm the necessity for future research to focus on building managerial competencies in ethical oversight and human-AI collaboration.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
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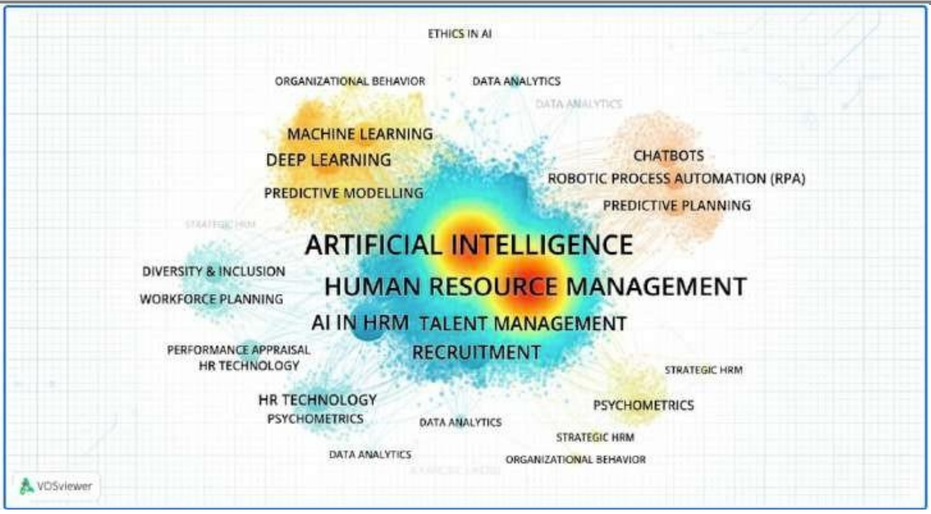

Figure 4. Co-occurrence network analysis.

The generated Density Visualization map illustrates the concentration and item density of keywords across the analyzed scholarly literature (2020–2026). In VOSviewer's density view, the color spectrum indicates research focus intensity: bright red and warm yellow regions signal dense clusters of frequently co-occurring terms (established research hotspots), while cool blue and transparent peripheral areas represent lower keyword concentration and emerging or under-researched domains.

1. Saturated Hotspots: The Epistemological Core

The visual center of the density map is dominated by a major double-core thermal hotspot centered on ARTIFICIAL INTELLIGENCE and HUMAN RESOURCE MANAGEMENT, closely surrounded by AI IN HRM, RECRUITMENT, and TALENT MANAGEMENT.

- Operational Focus: The high density around *Recruitment* and *Talent Management* demonstrates that the majority of scholarly effort over the 2020–2026 timeframe has concentrated on talent acquisition, automated candidate evaluation, and operational screening systems.
- Technological Drivers: Adjacent warm zones for MACHINE LEARNING, DEEP LEARNING, and PREDICTIVE MODELLING emphasize the methodological reliance on predictive algorithms to drive transactional efficiency in workforce selection.

2. Transition Zones: Functional Applications

Surrounding the saturated core are mid-density clusters representing established application areas within the HR lifecycle:

- Automation & Process Optimisation: A distinct mid-density branch links ROBOTIC PROCESS AUTOMATION (RPA), CHATBOTS, and PREDICTIVE PLANNING. This cluster reflects the maturity of conversational AI and workflow automation in handling routine HR queries and administrative processes.
- Performance & Analytics: Another active zone encompasses DATA ANALYTICS, HR TECHNOLOGY, and PERFORMANCE APPRAISAL, showing the ongoing shift toward continuous data-driven employee evaluation.

3. Sparse Peripheral Horizons: Research Gaps and Emerging Frontiers

At the outer edges of the density visualization, the color fades into cool blue hues with low node concentration. These sparse regions identify critical frontiers where academic research remains limited despite growing industry importance:

- Ethics and Governance: Terms such as ETHICS IN AI appear at the upper periphery with noticeably low density. This confirms that while technical implementation has been thoroughly researched, the operational governance, algorithmic fairness, and regulatory compliance (e.g., ISO 42001, EU AI Act) of AI systems in HR remain under-explored.

- Socio-Behavioral Constructs: Peripheral placements of ORGANIZATIONAL BEHAVIOR, PSYCHOMETRICS, WORKFORCE PLANNING, and DIVERSITY & INCLUSION reveal a significant gap in evaluating the long-term socio-technical impact of AI deployment on organizational culture, employee trust, and psychological safety.

Contemporary literature underscores that technological advancements are increasingly transforming core Human Resource Management (HRM) practices—most notably recruitment, performance appraisal, onboarding, engagement, and employee self-service—through the integration of Artificial Intelligence (AI). Despite this growing adoption, recent bibliometric and systematic literature reviews reveal that AI-HRM research remains in its infancy, characterized by a fragmented scholarly landscape [40]. Nevertheless, academic interest expanded significantly after 2022, when annual publication volume reached 30 papers—a marked increase compared to the modest outputs of 2019 (6), 2020 (7), and 2021 (12). This momentum highlights both the rising importance and contemporary relevance of AI within HRM.

Thematic mapping further confirms that AI in HRM is an evolving domain requiring deeper empirical exploration, aligning with calls from [6, 38,41]. These gaps justify the primary objective of this study: delineating the managerial capabilities necessary for effective AI adoption. Scholars like [1,9] similarly emphasize the need to uncover the specific competencies driving sustained AI implementation. Accordingly, while our first research question explores the AI tools and techniques that augment managerial functions, the second question maps the exact managerial capabilities required for seamless AI integration.

Grounded in the Dynamic Capabilities View (DCV), a directed content analysis of the systematic literature identified three core dimensions of managerial capability: cognitive capability, human capital, and social capital:

- **Managerial Cognitive Capability**: Encompasses competencies such as ethical decision-making, complex problem-solving, and AI tool validation. These skills are vital for mitigating algorithmic bias, upholding ethical standards, applying design thinking, and ensuring technological reliability across HR operations.

- **Managerial Human Capital**: Involves technical proficiency, strategic leadership, institutional alignment, training capacity, agility, and job design. These competencies enable managers to incorporate emerging technologies, lead digital transitions, align AI with broader organizational architecture, and reconfigure job roles.

- **Managerial Social Capital**: Focuses on technology sourcing, social justice, employee experience enhancement, mentorship, and cross-functional collaboration. These abilities address key challenges surrounding data privacy, algorithmic surveillance fears, and human-AI interaction.

This study offers substantial theoretical contributions to the literature on AI adoption within Human Resource Management (HRM) by mapping thematic research gaps, formulating future research questions, and advancing testable propositions. As [41] observe, AI-HRM research remains nascent, underscoring the need for frameworks that explain and accelerate technology integration. While conventional adoption studies rely heavily on frameworks like the Technology Acceptance Model [42] and the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) [43, 44] these models largely overlook the specialized managerial capabilities necessary for successful implementation. Responding to calls from [1,9] to uncover the managerial competencies driving AI performance, as well as recommendations by [2, 6] to invest in HR digital literacy, data savviness, and change leadership, this study adopts the Dynamic Capabilities View [22]. We identify three pivotal dimensions—managerial cognitive capability, managerial human capital, and managerial social capital—as essential drivers of AI adoption, extending [45] work on managerial adaptation and resource reconfiguration during digital transformations.

Furthermore, through systematic content analysis, this study extends DCV by identifying 13 unique competencies nested within these three capability dimensions. This responds directly to [46] by looking beyond classical adoption models and aligns with [47] regarding the need for technology-specific skill mapping. To guide future empirical research across diverse contexts, this study proposes a conceptual framework alongside three core research questions and corresponding propositions:

- **RQ1 & P1 (Managerial Cognition)**: *What specific competencies build cognitive capability?* **P1**: Competencies in ethical decision-making, problem-solving, technical data science expertise, digital savviness, and AI tool validation build managerial cognition, directly influencing AI adoption and enhancing HR functional effectiveness.

- **RQ2 & P2 (Managerial Human Capital)**: *What specific competencies build human capital?* **P2**: Competencies encompassing leadership, institutional change implementation, change coping, organizational agility, and job redesign build managerial human capital, facilitating AI adoption and boosting HR performance.

- **RQ3 & P3 (Managerial Social Capital)**: *What specific competencies build social capital?* **P3**: Competencies in AI technology sourcing, social justice maintenance, employee experience enhancement, mentorship, and human-AI collaboration build managerial social capital, driving AI integration and optimizing HR outcomes.

From a practical perspective, this study demonstrates that effective AI integration in HRM requires organizations to look beyond basic infrastructure and system usability, focusing instead on developing **managerial dynamic capabilities**. To ensure successful AI deployment, organizations must invest in targeted training across three core dimensions:

- **Cognitive Capabilities** (*ethical decision-making, problem-solving, algorithmic validation*) to ensure human oversight and mitigate algorithmic bias in HR decision-making.

- **Human Capital** (*technical expertise, strategic leadership, agility, job redesign*) to effectively lead digital transitions and restructure workflows.

- **Social Capital** (*technology sourcing, social justice, mentoring, human-AI collaboration*) to build trust, protect data privacy, and foster seamless human-agent interaction.

By mapping these 13 core competencies to real-world HR workflows—such as recruitment screening, personalized learning, workforce forecasting, and performance tracking—organizations can build actionable capability frameworks that safeguard fairness, uphold data security [48], and unlock the full strategic potential of AI across the human resource function.

This study acknowledges key limitations while establishing a roadmap for future research. Geographically and structurally, alternative literature sources outside our initial search boundaries should be explored in future reviews. Theoretically, while this study applied the Dynamic Capabilities View (DCV) to categorize managerial cognitive, human, and social capital, future studies should test complementary theoretical models and validate our proposed propositions through empirical testing and meta-analyses.

Bibliometrically, our network and thematic maps reveal that while research on AI in recruitment, selection, and employee experience exhibits "progressive coherence" [49, 51, 52, 53, 54] several underdeveloped clusters require "synthesized coherence." Future scholars should focus on peripheral intersections such as AI ethics, managerial decision-making, machine learning in Industry 4.0, and resource allocation.

Moving forward, the strategic research agenda should prioritize:

- **Human Outcomes**: Assessing the long-term effects of HR automation on employee morale, job security, and psychological well-being.

- **Skill Development & Capability Building**: Mapping competency gaps from entry-level talent to executive leadership, including university curriculum redesign.

- **Ethics & Explainable AI (XAI)**: Investigating managerial competencies necessary to ensure ethical compliance, mitigate algorithmic bias, and deploy explainable AI systems.
- **Organizational Performance**: Testing how AI-aligned managerial capabilities directly impact firm-level productivity, innovation, and competitive advantage across diverse industry contexts.

CONCLUSION

Based on the results of the bibliometric analysis, it can be concluded that HRM based AI has "The disciplinary breakdown confirms that research on AI in HRM has crossed the threshold from a purely technical domain into a complex, multi-faceted field of organizational study. The strong representation of Social Sciences (24.4%) alongside Business Management (21.0%) and Computer Science (19.9%) highlights an urgent academic movement toward balancing algorithmic capability with socio-ethical stewardship."

In addition, recent research trends indicate a shift in focus toward the integration of digital technology and green human resource management. This suggests that sustainability today requires a more integrated approach that combines technology, innovation, and the management of a company's internal resources. Nevertheless, the results of the research mapping still show a concentration of studies on certain topics, while research in specific sectors, such as the service and hospitality industries, remains relatively limited.

While the identified managerial competencies primarily support AI-driven decision augmentation, emerging workforce dynamics require managers to navigate full task automation. To maintain strategic alignment, leaders must agilely differentiate between HR functions that benefit from AI augmentation—where human judgment remains sovereign—and routine tasks that can be fully automated to optimize strategic focus. Selecting between augmentation and automation represents a core managerial dynamic capability. To support this transition, organizations must provide continuous learning opportunities and foster a collaborative environment where managers, employees, and AI applications function in a mutually enabling ecosystem.

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