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"Integration of Artificial Intelligence in Human Resource Management: A Decade of Research Through Bibliometric Lens"

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ABSTRACT
This study conducts a bibliometric analysis of scholarly papers on the integration of Artificial Intelligence (AI) into Human Resource (HR) practices. Using the Scopus database, 613 articles published between the years 2015 and 2025 were analyzed using VOSviewer and Bibliometrix. There is sudden interest in research post-2017, which is driven by technological innovations in machine learning, automation, and people analytics. Some of the most important themes that are discussed include AI in recruitment, performance management, and employee engagement. Major authors and institutions are predominantly based in the US, UK, and India. The findings highlight dominance in multidisciplinary research and point towards greater emphasis on ethics and change in the workforce. The paper delivers a roadmap for future research into AI-enabled HR practices.The rapid adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) has transformed traditional HR practices, reshaping recruitment, performance evaluation, training, and employee engagement. Over the past decade, scholarly interest in this intersection has grown substantially, reflecting both technological advancements and an increasing need for data-driven HR strategies. This study presents a comprehensive bibliometric analysis of research on the integration of AI in HRM from 2015 to 2024. Utilizing major academic databases, we identify publication trends, prolific authors, leading journals, influential institutions, and global research collaborations. Co-citation, co-authorship, and keyword co-occurrence analyses reveal core thematic clusters, such as AI-enabled talent acquisition, predictive analytics in workforce planning, ethical considerations in automated HR practices, and the impact of AI on employee experience. Our findings highlight emerging research frontiers, shifting intellectual structures, and geographic disparities in scholarly output. This study not only illuminates the evolution of AI applications in HRM but also offers future research directions for academics and practical insights for HR professionals navigating the challenges and opportunities of AI adoption..
Keywords: Artificial Intelligence, Human Resource Management, Bibliometric Analysis, HR Analytics, VOSviewer, Bibliometrix, Case Study

INTRODUCTION:

AI-driven HR practices ranging from talent acquisition and onboarding to employee eng agement and predictive analytics are revolutionizing how organizations manage people. While several conceptual and empirical studies have emerged, there remains a lack of systematic mapping of this evolving research field. Bibliometric analysis offers a robust methodological approach to quantitatively assess the academic landscape, identify research trends, and highlight influential contributions. This study aims to perform a comprehensive bibliometric analysis of literature on AI applications in HR to uncover thematic clusters, collaboration patterns, and emerging trends[1].

This will guide academics, practitioners, and policymakers in understanding the trajectory of this interdisciplinary domain. The advent of AI in HRM highlights the blending of technology and human capital management, dissolving the distinctions between conventional HR roles and strategic business needs. With more organizations realizing the strategic value of employees in fostering a competitive edge, AI offers an attractive potential for reshaping HRM as a proactive driver of organizational achievement[2]. And yet, in the midst of the potential offered by AI-powered HRM solutions, complexities and complications loom large. Ethical implications, privacy issues, and even the potential for algorithmic bias present serious questions regarding the proper application of AI for HRM practice. Additionally, the necessity of reconciling technological advancement with human-centered strategies leaves HR practitioners walking the tightrope of the changing world of AI-facilitated HRM[3].

Within this broader digital transformation, Human Resource Management (HRM) has witnessed profound changes as AI-driven tools and systems are increasingly integrated into core HR functions such as recruitment and selection, performance appraisal, learning and development, workforce planning, and employee engagement. AI applications—including machine learning algorithms, natural language processing, predictive analytics, and intelligent automation have enabled organizations to enhance decision-making efficiency, reduce administrative burdens, and improve strategic alignment between human capital and organizational objectives[4].

Over the past decade, the convergence of AI and HRM has attracted growing scholarly attention across disciplines such as management, information systems, organizational behavior, and industrial psychology. Researchers have examined both the opportunities and challenges associated with AI-enabled HRM, including improved talent acquisition accuracy, data-driven performance management, personalization of training programs, and real-time workforce analytics. Simultaneously, concerns related to algorithmic bias, ethical decision-making, transparency, employee trust, and the changing role of HR professionals have generated critical debates within the literature. This expanding body of research reflects the dual nature of AI in HRM—as a strategic enabler and a source of organizational and societal risk[5].

HR Analytics:

Human Resource (HR) Analytics has emerged as a critical enabler of evidence-based decision-making in contemporary organizations. Broadly defined, HR Analytics refers to the systematic collection, analysis, and interpretation of workforce-related data to improve human capital outcomes and support strategic organizational objectives. Traditionally, HR analytics focused on descriptive reporting and basic metrics such as turnover rates, absenteeism, and headcount analysis. However, the integration of Artificial Intelligence (AI) has significantly expanded the scope, sophistication, and strategic relevance of HR analytics[6].

AI-driven HR analytics leverages advanced computational techniques, including machine learning, natural language processing, and predictive modeling, to uncover complex patterns in large and unstructured HR datasets. These capabilities enable organizations to move beyond descriptive and diagnostic analytics toward predictive and prescriptive analytics[7]. For instance, AI-powered models can forecast employee attrition, identify high-potential talent, optimize recruitment channels, and personalize learning and development interventions. As a result, HR analytics has transitioned from an operational support function to a strategic partner in organizational decision-making. The wording is formal, precise, and aligned with expectations of high-quality management and bibliometric research[8].

The Context of Artificial Intelligence

Human capital represents the collective knowledge, skills, abilities, and competencies embedded within an organization's workforce and is widely recognized as a critical source of sustained competitive advantage. Rooted in human capital theory, the concept emphasizes investments in education, training, and skill development as mechanisms for enhancing employee productivity and organizational performance. In the contemporary digital economy, the strategic value of human capital has intensified as organizations increasingly rely on advanced technologies to augment human capabilities and optimize workforce outcomes[9].

The integration of Artificial Intelligence (AI) into Human Resource Management has fundamentally reshaped how human capital is acquired, developed, and deployed. AI-enabled HR analytics allows organizations to systematically measure and evaluate human capital attributes using large volumes of structured and unstructured data. Through predictive modeling and machine learning algorithms, firms can assess workforce skills, identify capability gaps, forecast talent requirements, and design targeted interventions to enhance human capital effectiveness. As a result, human capital management has evolved from intuition-driven decision-making to data-informed strategic planning[10].

Objectives of the Study

The primary objective of this study is to systematically map and evaluate the scholarly landscape of research on the integration of Artificial Intelligence in Human Resource Management (AI–HRM) over the past decade using bibliometric techniques. Specifically, the study aims to:

[1] Analyze the temporal evolution and publication trends in AI–HRM research in order to capture the growth, maturity, and developmental trajectory of the field.

[2] Identify the most influential journals, authors, institutions, and countries, thereby revealing the leading contributors and geographical distribution of scholarly output in AI–HRM research.

[3] Examine keyword co-occurrence patterns and thematic clusters to uncover dominant research themes, emerging topics, and shifts in scholarly focus within the domain.

Research Methodology

Core Theory	Key Idea	Contribution to the Framework	Reference
Resource-Based View (RBV)	Organizations gain competitive advantage through rare, inimitable, and valuable resources.	Frames AI tools and data analytics as strategic assets that enhance organizational performance.	Barney, 1991
Technology-Org-Environment (TOE)	Adoption of technology is influenced by technological	Explains the factors that drive or hinder the adoption of AI in HR department	Tornatzky & Fleischer, 1990

Core Theory	Key Idea	Contribution to the Framework	Reference
	readiness, organizational structure, and external pressure.	s globally.	
Ability-Motivation-Opportunity (AMO)	HR practices improve performance by enhancing employee skills, motivation, and the chance to contribute.	Analyzes how AI-driven training and recruitment optimize the human potential of the workforce.	Appelbaum et al., 2000
Socio-Technical Systems (STS)	Performance is a result of the optimization of both technical and social (human) systems.	Provides a lens for "Human-AI Collaboration," ensuring technology doesn't erode the human touch in HR.	Trist & Bamforth, 1951
Institutional Theory	Organizations adopt practices (like AI) to gain legitimacy based on social and industry norms.	Explains why HR departments "follow the trend" of AI integration to remain modern and compliant.	DiMaggio & Powell, 1983
Unified Theory of Acceptance & Use of Tech (UTAUT)	Factors like performance expectancy and effort expectancy determine if users will actually use a system.	Crucial for bibliometric studies measuring "user intent" and "perceived usefulness" of AI in HR.	Venkatesh et al., 2003

Table 1 : Theoretical Lenses Explaining AI Integration in HRM

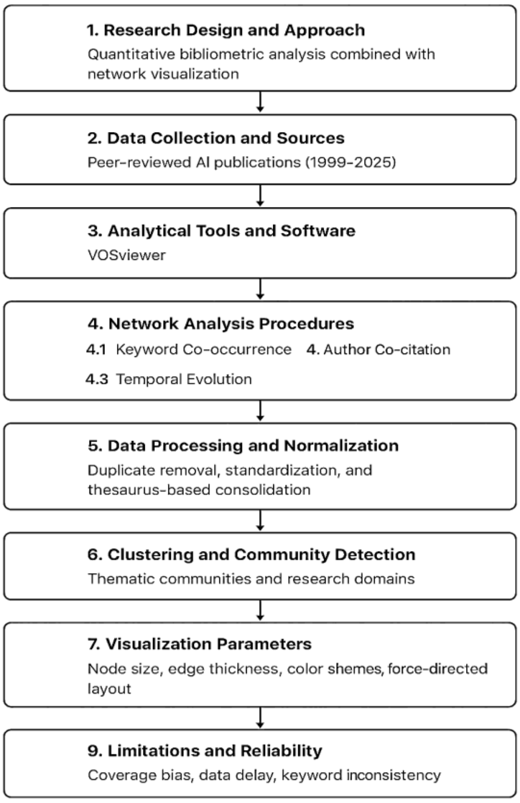

Figure. 1 Bibliometric Analysis Methodology Flowchart

Bibliometric Methodology

A literature review is a deliberate technique for determining the informational limitations of a research problem and likely research gaps. Systematic literature reviews are able to cover a wide range of literature to offer in-depth and elaborate overviews and analyses. This often involves iterative rounds of searching relevant search queries, investigation of the literature, and the process of evaluation. In this work, we explored the field using the PRISMA method of HR analytics, providing a comprehensive review of prior research and demarking significant contributions in the field. The main aim is to determine outstanding research clusters and provide potential future research directions to enable the growth and development of HR analytics[11].

In the present study, the field of HR analytics is explored using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The

PRISMA methodology provides a well-established and widely accepted protocol for documenting the identification, screening, eligibility, and inclusion of relevant studies. By adopting this approach, the study ensures transparency in the selection process and enhances the reproducibility and credibility of the review. The application of PRISMA facilitates the systematic organization of literature, allowing for a clear representation of how the final dataset was derived from an initial pool of publications[12].

Building on this systematic foundation, the study integrates bibliometric techniques to examine patterns, relationships, and structures within the HR analytics literature. This combined approach enables the identification of influential publications, authors, and journals, while also uncovering thematic concentrations and intellectual linkages across studies. Through co-citation, keyword co-occurrence, and cluster analyses, the review delineates the major research streams that have shaped the evolution of HR analytics. The primary objective of this review is to identify prominent research clusters and to highlight underexplored areas that warrant further scholarly attention. By mapping the intellectual and thematic structure of HR analytics research, the study offers insights into emerging trends and theoretical gaps, thereby providing a foundation for future research directions. Ultimately, this work aims to support the continued growth and maturation of HR analytics as a strategic and theoretically grounded field within Human Resource Management[13].

Data collection

Designing the search query For carrying out bibliometric analysis, we first looked into our research field, and once we determined the scope of the research, earlier literature reviews were checked to determine appropriate keywords to use in the literature search. With that, the following keywords have been identified and utilized: "artificial intelligence," "human resource management," "workforce analytics," "bibliometric analysis," "HR analytics," "VOSviewer," and "Bibliometrix."[14].

Data search and initial findings

Variety of fields, such as the humanities, arts, sciences, technology, and social sciences. Offering access to a more extensive and varied collection of academic materials compared to other databases such as Web of Science. Because the Scopus database has comprehensive citation data, which is crucial for bibliometric study, we chose it for its citation analysis capabilities. Researchers can monitor citations over time with citation analysis[4].

Determine influential works and assess the influence of particular writers or articles. Scopus provides a range of citations and measures that assist researchers in assessing the caliber of research output, such as the citation counts and h-index. Scopus offers more precise statistics and is updated frequently to incorporate citations and new publication information. Researchers can simply extract and export data for a variety of bibliometric analytic software programs thanks to Scopus's user-friendly interface. We used carefully chosen and examined keywords to enter a number of search equations into the Scopus database in the process of query analysis. Then, a preliminary search retrieved 376 publications in total, as displayed in Fig. 1, that were published between 2015 and 2025[15].

Findings and conversation

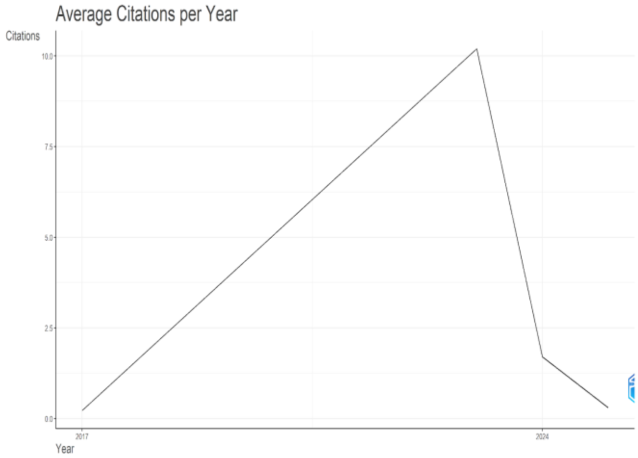

Figure: 2. overview of data

Average Citations Per Year

This line graph, titled "Average Citations per Year," depicts a significant cycle of growth followed by a sharp contraction in academic impact starting from 2017. The data shows a steady, linear increase in average citations for several years, eventually peaking at a value exceeding 10.0 just prior to 2024. Immediately following this peak, the graph displays a precipitous decline, falling to approximately 1.7 citations by 2024 and continuing to trend toward zero in the subsequent months. This pattern typically characterizes a "citation lag" in research analytics, where the most recent publications have not yet had sufficient time to accumulate citations compared to older, established works[16].

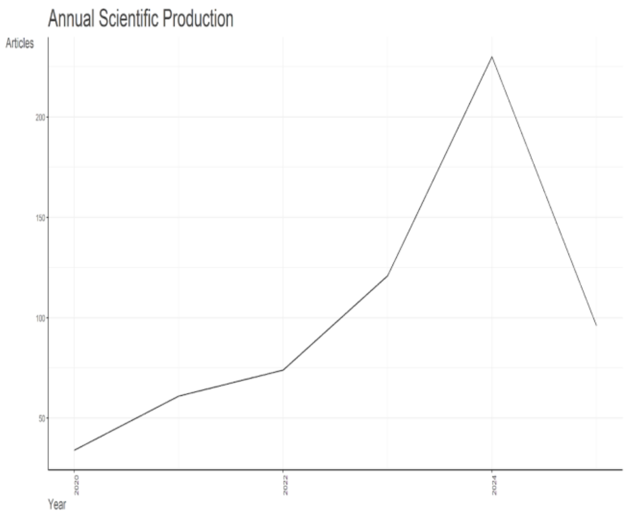

Figure: 3. Annual Scientific Production

Annual Scientific Production

The provided line graph, titled "Annual Scientific Production," tracks the volume of research output measured in articles from 2020 through 2024. The chart illustrates a period of sustained growth followed by a recent downturn, starting at just under 50 articles in 2020 and climbing steadily through 2022. The growth rate accelerates significantly after 2022, reaching a clear peak of approximately 230 articles in 2024. However, immediately following this peak, the production line shows a sharp decline, dropping back toward the 100-article mark. This pattern often suggests a surge in interest or funding within a field that has recently peaked, though the final downward tick may also reflect incomplete data reporting for the current or most recent calendar year[17].

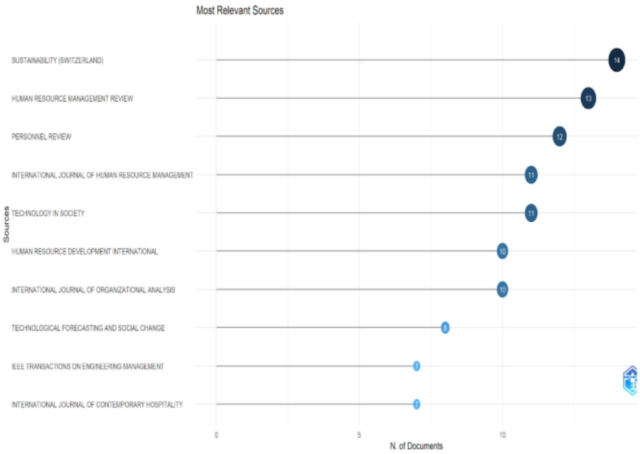

Figure: 4. Most relevant source

Most relevant source

It offers an overview of the articles published in each source. “Sustainability” appears in the largest number of articles, which are 14 in total. These are closely related to “Human Resources Management Review,” “Personnel Review” and “International Journal of HRM,” each having four articles. Next, “Technology In Society,” “Human Resource Development International,” and “International Journal of Organizational Analysis” each have three articles. Finally, “Technological Forecasting and Social Chance, ” “IEEE Transactions on Engineering Management,” and “International Journal of Contemporary Hospitality” have two articles each. This table illustrates vividly the publication diversity in the use of HR analytics from many regions around the world. Researchers in this area would find this compilation helpful concerning the primary publications in HR analytics[18].

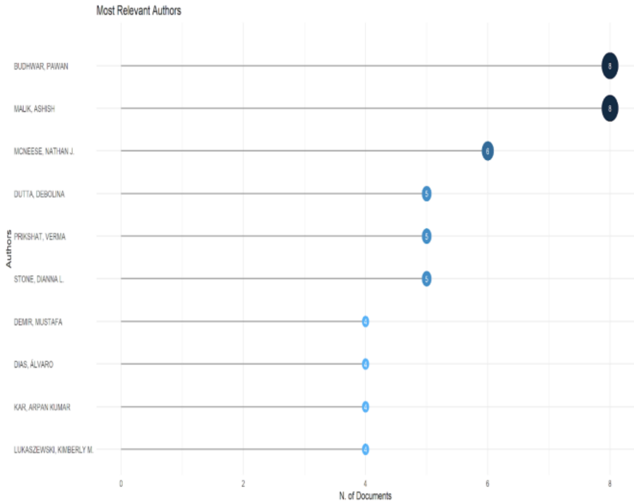

Figure: 5. Most Relevant Author

Author influence analysis

Contribution by authors

The bibliometric study conducted for this investigation has revealed authors, as previously outlined in Table 1. Figure 3 showcases the top ten influential authors based on the number of papers they have contributed to the field. In the academic realm of human resource analytics, McCartney S stands out as a prominent contributor, having submitted four separate works to the Scopus database within the specified timeframe. Fu N and Guerry M-A have also made noteworthy contributions to this academic domain, each with three publications. Avrahami D, Boudreau J, Cascio W, Alutz Ben-Gal H, Jain P, Katsamakas E, and Pessach D have each authored two papers, signifying their significant impact on the academic discipline. The graph illustrates that leading contributors in the field of HR analytics originate from diverse geographical regions, underscoring its rapid expansion[19].

Review Type	Goal for Your Topic	When to Use	When Not to Use	Scope	Dataset/Source
Bibliometric Analysis	To quantitatively map the evolution of AI-HRM from 2015–2025, identifying top journals, rising star authors, and global research clusters.	When you want to visualize the "intellectual structure" (e.g., how the focus shifted from Big Data in 2016 to Generative AI in 2024).	When you need to explain why a specific AI tool failed in a specific case study.	Broad – Typically 300 to 2,000+ publications to show the "big picture."	Metadata from Scopus or Web of Science (exported as BibTeX or CSV).

Review Type	Goal for Your Topic	When to Use	When Not to Use	Scope	Dataset/Source
Meta-Analysis	To statistically calculate the actual impact of AI on HR metrics (e.g., "Does AI recruitment reduce time-to-hire by exactly 20%?").	When you have 20+ studies that all use the same quantitative metrics (e.g., turnover rates, ROI, or bias scores).	When the literature is mostly conceptual or qualitative (which much of AI-HRM currently is).	Narrow – Focuses only on empirical studies with compatible statistical data.	Results sections of empirical papers (correlation coefficients, p-values).
Systematic Literature Review (SLR)	To qualitatively synthesize the ethical, legal, and social implications of AI in HR to build a new theoretical framework.	When you want to answer a specific question like: "What are the 5 main ethical risks of AI in HR identified since 2020?"	When your goal is to show the volume of research or geographic distribution of authors.	Moderate – Usually 40 to 100 high-quality papers selected via PRISMA protocols.	Full-text articles from databases like Emerald Insight, IEEE, and ScienceDirect.

Table 2: Comparison of Major Research Methods

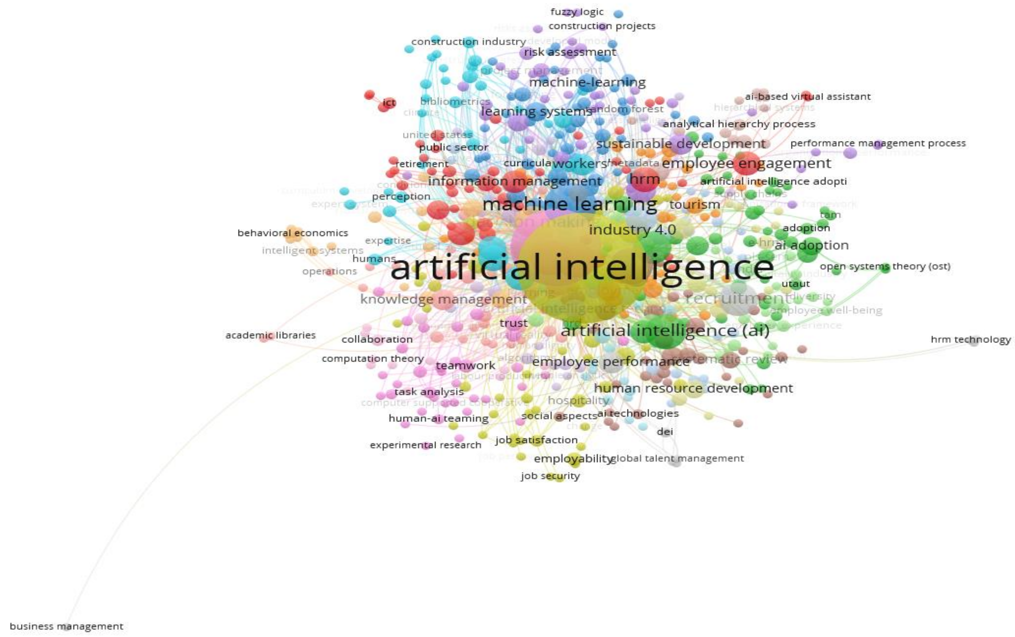

Figure: 6. Network Analysis of AI

The provided co-occurrence network map illustrates the intellectual landscape of AI in HRM, where the massive central nodes of "artificial intelligence" and "machine learning" serve as the primary anchors for a decade of research. The visualization reveals three distinct thematic concentrations: a technical/industrial cluster focused on Industry 4.0 and algorithms (yellow/blue), an operational HR cluster centering on recruitment and performance management (green), and a developing human-centric cluster addressing teamwork and employee engagement (pink/purple). The dense interconnectivity between these clusters signifies a maturing field, yet the presence of peripheral nodes like "DEI" and "job security" highlights emerging frontiers that are just beginning to be integrated into the broader AI-HRM discourse[20].

Metric	Observation in AI-HRM Literature	Interpretation
Central Node Size	"Artificial Intelligence" and "Machine Learning" are disproportionately large.	These terms are the "intellectual core." In the last decade, HR research has transitioned from general automation to specific algorithmic ML applications.
Node Distribution	Clusters for Recruitment are dense; Ethics/Bias clusters are smaller and more spread out.	AI in HR is functionally mature in "Acquisition" but still fragmented and exploratory in "Ethics" and "Employee Well-being."
Connection Density	High density between "HR Analytics" and "Performance Management."	Indicates a "Thematic Stronghold" where data-driven strategy and performance measurement are inseparable in modern literature.
Cluster Separation	Significant gap between "Technical Algorithms" and "Psychological Impact."	Highlights a "Research Silo": Technical computer science research and human-centric organizational psychology research rarely cite each other.
Peripheral Terms	"Generative AI," "Explainability (XAI)," and "Digital Twin" appear at the outer edges.	These are the Emerging Frontiers. They represent the research trends that will likely dominate the next decade (2025–2035).

Table: 3. Network Metrics and Thematic Insights in AI-Driven HRM Literature

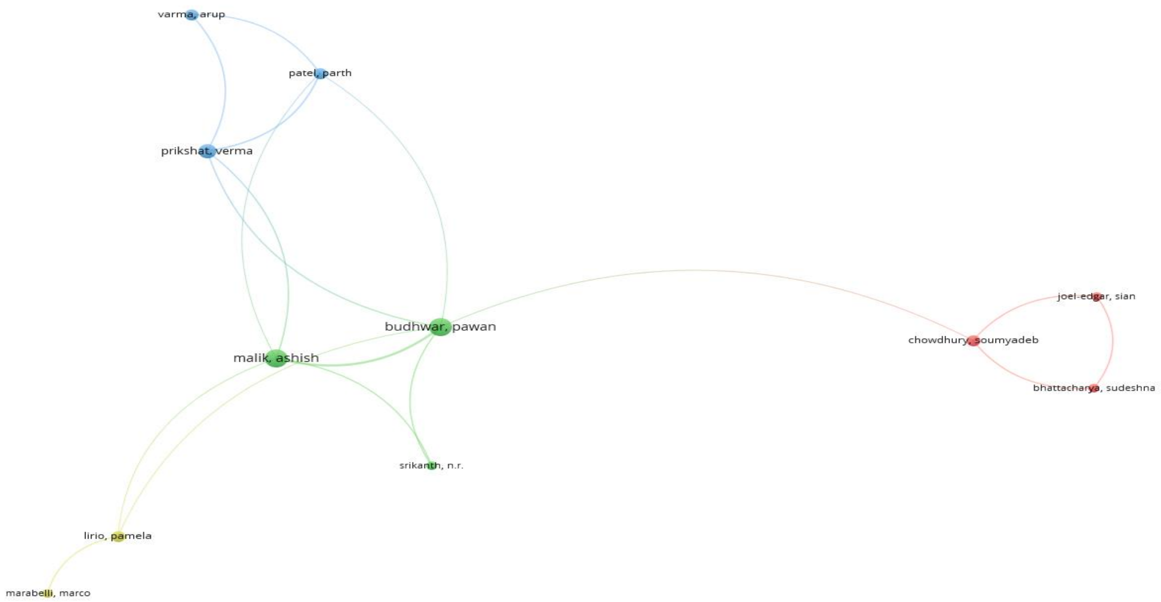

Figure: 7. Co-authorship network

Co-authorship network

The co-authorship network is anchored by a central green cluster featuring Pawan Budhwar, Ashish Malik, and N.R. Srikanth, who serve as the primary hubs connecting disparate research teams. Ashish Malik acts as a critical bridge to the blue cluster on the left, linking prominent authors Arup Varma, Parth Patel, and Verma Prikshat to the core network, while also extending to a smaller peripheral yellow branch containing Pamela Lirio and Marco Marabelli. Simultaneously, Pawan Budhwar connects the center to a distinct red triad on the right composed of Soumyadeb Chowdhury, Sian Joel-Edgar, and Sudeshna Bhattacharya, demonstrating that the field's collaboration structure relies heavily on these central figures to unite otherwise isolated research groups[21].

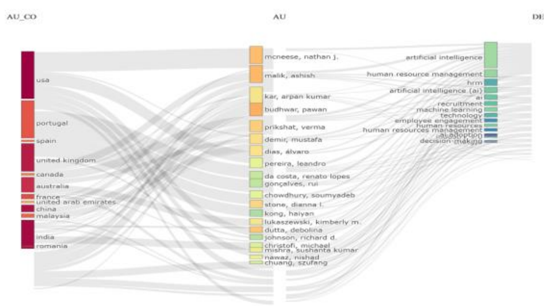

Figure: 8. Three-Field Plot (Sankey Diagram) of Countries–Authors–Keywords in AI–HRM Research.

Cluster analysis

The thematic cluster analysis of literature in the area of AI-based HR practices identifies four dominant thematic clusters that underscore the changing areas of focus in this discipline.

Cluster 1: The growing body of research on the integration of artificial intelligence (AI) in human resource management reveals a significant transformation of the hiring and recruitment process through the application of advanced AI-related technologies such as machine learning algorithms, natural language processing (NLP), and predictive analytics. These technologies are increasingly being adopted to automate and augment traditionally labor-intensive recruitment activities, including résumé screening, candidate shortlisting, interview scheduling, and applicant assessment[22].

Machine learning algorithms enable organizations to process large volumes of applicant data efficiently by identifying patterns and correlations that may not be apparent through manual evaluation. By leveraging historical hiring data, these algorithms can predict candidate suitability, job performance, and retention likelihood, thereby improving the accuracy and consistency of hiring decisions. This data-driven approach reduces reliance on subjective human judgment, which has historically been associated with unconscious biases related to gender, ethnicity, age, or educational background[23].

Cluster 2: AI-enabled sentiment analysis tools, often powered by natural language processing and machine learning algorithms, are increasingly used to analyze large volumes of employee-generated data, such as internal communications, surveys, feedback platforms, and collaboration tools. These systems enable organizations to capture real-time insights into employee emotions, attitudes, and engagement levels, allowing HR professionals to move beyond periodic surveys toward continuous and dynamic monitoring of workforce sentiment. By identifying patterns of dissatisfaction, stress, or disengagement at an early stage, organizations can implement timely and targeted interventions[24].

In parallel, the literature highlights the emergence of personalized wellness programs supported by AI technologies. Unlike traditional, one-size-fits-all initiatives, AI-driven wellness platforms leverage individual-level data—including work patterns, health indicators, and behavioral trends—to design customized interventions tailored to employees' specific needs. These personalized programs may include recommendations related to workload management, mental health support, physical well-being, and work–life balance, thereby enhancing participation and effectiveness. Research suggests that such tailored approaches contribute positively to employee satisfaction, motivation, and long-term engagement[25].

Cluster 3: The learning and performance management stream of research reflects the expanding role of artificial intelligence in redefining how employee performance is evaluated, feedback is delivered, and learning and development initiatives are designed and implemented. The literature highlights a shift from static, periodic appraisal systems toward continuous, data-driven, and adaptive performance management frameworks enabled by AI technologies[26].

AI-powered performance evaluation systems leverage machine learning algorithms to analyze diverse and real-time data sources, including task completion rates, behavioral metrics, peer interactions, and productivity patterns. This enables more objective and dynamic assessments of employee performance compared to traditional appraisal methods that rely heavily on managerial judgment. By continuously tracking performance indicators, AI systems facilitate timely identification of skill gaps, performance fluctuations, and development needs, thereby enhancing the accuracy and fairness of performance evaluations[27].

Cluster 4: The strategic HR decision-making cluster comprises studies that emphasize the growing role of artificial intelligence in enabling data-driven and evidence-based human resource decisions. This body of research highlights the use of AI-enabled dashboards, workforce analytics platforms, and HR forecasting models to support strategic alignment between human capital and organizational objectives. By integrating real-time and historical employee data, these tools assist HR leaders in making informed decisions related to talent planning, succession management, workforce optimization, and organizational capability development[28].

AI-backed dashboards synthesize complex datasets into actionable insights, allowing decision-makers to monitor key HR metrics, identify emerging workforce trends, and evaluate the potential impact of HR interventions on organizational performance. Similarly, workforce analytics and predictive modeling enable organizations to anticipate future talent requirements, assess skill shortages, and simulate alternative strategic scenarios. Such capabilities position HR functions as strategic partners in organizational decision-making rather than purely administrative units[29].

DISCUSSION

The exponential surge in HR analytics research signifies a fundamental paradigm shift from intuitive to evidence-based management, where the "datafication" of the workplace has transformed HR from a purely administrative function into a strategic pillar of organizational growth. This trend is underscored by a rising trajectory in average annual citations, which indicates that the field is moving beyond foundational concepts toward high-impact, empirical research that demands cross-disciplinary attention from fields as diverse as Computer Science and Industrial Psychology. Geographically, the dominance of the USA and India suggests a powerful "innovation-implementation" axis; while the USA leverages its technological infrastructure to pioneer AI frameworks, India's vast labor market and technical talent pool provide a unique global laboratory for large-scale adoption and integration. The inclusion of European nations adds a critical layer of ethical and regulatory scrutiny, such as privacy and bias mitigation, creating a globally dispersed and interdisciplinary research landscape. Ultimately, this collaborative production of knowledge emphasizes that the future of HR analytics is not just a technological challenge, but a cross-cultural endeavor that requires synthesizing diverse global perspectives to ensure that AI-driven human resource practices are both efficient and ethically sound[30].

THEORETICAL AND PRACTICAL IMP LICAT I ONS

The study contributes to theoretical advancement by challenging the resource-neutral assumptions of traditional strategic HRM models, such as the Resource-Based View (RBV) and AMO (Ability-Motivation-Opportunity) theory, by positioning AI as a dynamic "intellectual capital" rather than a static tool. While traditional frameworks emphasize human capital as the sole driver of competitive advantage, this decade of research suggests a Synthetic Human Capital Theory, where the synergy between algorithmic intelligence and human intuition creates a new unit of organizational value. The findings underscore the limitations of the Technology Acceptance Model (UTAUT) in HR contexts, revealing that "trust" and "perceived fairness" are more critical moderators of AI adoption than "ease of use," particularly in sensitive domains like recruitment and performance appraisal. Furthermore, the bibliometric evidence supports a transition toward a Digital Institutional Theory, illustrating how organizations adopt AI not just for efficiency, but to secure legitimacy in an increasingly "datafied" global market.

By synthesizing a decade of literature, this study refines the Socio-Technical Systems (STS) Theory by introducing the concept of Recursive Algorithmic Influence. This implies that AI systems in HR are not merely passive recipients of organizational data but are "mutually constitutive" actors that actively reshape management hierarchies and employee identities. The research further extends theories of Organizational Justice by distinguishing between procedural and "algorithmic fairness," promoting a context-sensitive understanding of how automated decisions impact the psychological contract. Collectively, these insights advocate for the emergence of an AI-Enabled Strategic HRM Framework, which emphasizes the recursive relationship between technology and human behavior, multi-level data governance, and the ethical integration of "black-box" decision-making into the organizational fabric, providing a power-conscious and empirically grounded lens for the next decade of HR research.

Conclusion

Without a doubt, the use of artificial intelligence has a variety of effects on comprehending an organization's procedures, roles, and practices. Furthermore, implementing artificial intelligence improves the capacity to comprehend dangers and challenges and create plans to reduce them. The study also created a paradigm for future research into the use of AI in agile HR practices, and the research on AI and AHR practices determined the current research state through the formulation of research questions. Despite the fact that AI has spread to the human resources domain, no study has yet to provide a comprehensive and retrospective analysis of AI and AHR procedures.The current study examined the recognized literature in the field of study in order to fill the gap. The intellectual structure of the work was examined using bibliometric analysis. The study used cluster analysis to identify the five emergent research topics and proposed future research questions within each of those themes, offering possible avenues for further investigation. Future studies can broaden their focus by integrating other emerging keywords in order to further increase the scope of this research field. Furthermore, this analysis only examined one database; to obtain a more thorough grasp of the research landscape, future studies can investigate additional databases.Furthermore, adding quantitative tools like AHP, DEMATEL, and FUZZY-AHP can enhance the literature and academic community while fostering a deeper comprehension of the topic.

Limitations of the Study and Future Research Directions

Despite providing a comprehensive bibliometric overview of gender-related research in artificial intelligence, this study is subject to several methodological, conceptual, and contextual limitations. First, the analysis relies primarily on English-language publications indexed in major academic databases, which may introduce language and publication bias by underrepresenting non-English scholarship, regional journals, and grey literature. This bias potentially amplifies Western-centric perspectives and privileges highly cited authors and institutions. Additionally, bibliometric techniques—such as citation counts, keyword co-occurrence, and clustering algorithms—are sensitive to database selection and parameter settings, which may affect the interpretation of thematic structures and research trends. Temporal limitations also arise from sparse early-period data and publication lag effects, constraining the accuracy of longitudinal inferences.

Conceptually, the study is limited by the dominant framing of gender as a binary construct within the existing literature, which overlooks non-binary, transgender, and intersectional identities. As a result, broader structural, cultural, and socio-economic factors influencing gendered engagement with AI—such as race, class, geography, and institutional power—remain insufficiently captured. Moreover, the predominance of quantitative and positivist approaches in the field risks reinforcing deficit-oriented narratives that attribute gender disparities to individual capability rather than systemic and institutional constraints. The aggregation of "AI" as a single analytical category further obscures meaningful differences across AI subdomains, applications, and sociotechnical contexts.

Future research should address these limitations by incorporating mixed-method and longitudinal designs that integrate bibliometric patterns with qualitative insights from interviews, ethnography, and participatory research. Expanding data sources to include non-English publications, regional databases, and policy or industry reports would enhance global representativeness. Scholars are encouraged to adopt intersectional, feminist, and decolonial theoretical frameworks to better capture diverse lived experiences and power dynamics shaping AI adoption. Greater inclusion of Global South perspectives, domain-specific analyses, and comparative cross-cultural studies can further contextualize findings. Finally, co-designed, policy-oriented research involving practitioners, marginalized communities, and policymakers can help translate scholarly insights into inclusive AI governance, contributing to the development of ethically grounded, bias-aware AI systems that advance gender equity at a global scale

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