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A bibliometric analysis of intellectual structure and thematic evolution in artificial intelligence enabled green human resource management for environmental sustainability

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Abstract
Artificial Intelligence (AI) and Green Human Resource Management (HRM) are new frontiers in the field of organizational sustainability studies. This study aims to systematically capture the intellectual structure, thematic evolution and network collaboration in the AI-enabled Green HRM domain by using a bibliography data set of 94 publications listed in Scopus index (2019–2026). The articles were further analysed with the help of Biblioshiny package in the R-Studio environment. The data demonstrates an outstanding annual growth rate of 57.46%, and the literature in the field almost quadrupled in 2024/2025, highlighting the field's momentum. Thematic clusters, supported by key research papers relating to AI, sustainable development and Green HRM practices, highlight how AI tools such as machine learning, algorithmic management and digital transformation affect the recruitment, development, retention and motivation of employees who are environmentally responsible. The two research questions are: What are the dominant thematic clusters and evolutionary trajectories in the AI-enabled Green HRM literature 2019–2026? and Who are the countries, institutions and authors that form the core intellectual networks that energize this research field, and what patterns of collaboration are found in their work? The analysis reveals key areas of synergy between AI capabilities and outcomes of Green HRM, such as improved measurement of environmental performance, prediction of employee green behaviours, and sustainability-oriented talent management. In addition to theoretical implications and management considerations, there is a research agenda proposed that focuses on future research directions, especially in emerging economies where the digital transformation and green governance interface have great potential that has yet to be fully explored.

Keywords Green HRM · Artificial intelligence · Environmental sustainability · Bibliometric analysis · Sustainable development · Digital transformation

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1 Introduction

With the drive to reconcile economic growth with ecological preservation, the attention of scholars and practitioners has grown increasingly focused on the role of organizations as key drivers of ecological transformation [16, 36]. In an era of accelerating climate change, resource scarcity and the increasing importance of United Nations 2030 Sustainable Development Goals (SDGs), businesses are increasingly under pressure to integrate sustainability into the processes that shape organizational behaviour (OB), such as human capital systems, not just into the products they produce and supply chains, but into the human systems they rely on [27, 32, 35]. Green Human Resource Management (HRM), as a strategic approach, is one of the institutional responses to this challenge which entails a conscious attempt to integrate Human Resource (HR) practices such as recruitment, training, performance evaluation, and compensation into a strategy to raise employee green behaviour and minimize the organizational ecological footprint [6, 20].

At the same time, the advent of Artificial Intelligence (AI) as a game-changing organizational tool has completely changed the face of HRM. At present, Machine Learning (ML) algorithms, Natural Language Processing (NLP), predictive analytics and intelligent automation are found in talent acquisition, workforce planning, learning and development and performance management systems [13, 41]. With its ability to handle immense amount of behavioural data, tailor learning interventions, and provide insights at scale, AI opens up fresh avenues for boosting the outcome of Green HRM initiatives. The potential of AI to process huge amount of behavioural information, personalize learning experiences, and optimize decisions on a larger scale presents new opportunities to amplify the impact of Green HRM practices. However, the intellectual space in which AI and Green HRM converge remains largely uncharted, and its empirical contributions are rather disjointed, without any systematic bibliometric mapping of its structure, development, or thematic development.

This study is of great significance. Companies that adopt AI to embed Green HRM practices are on the leading edge of a new paradigm in sustainable enterprises, one that merges the power of algorithms with human agency to drive positive environmental impacts on a massive scale. AI-driven recruitment processes can filter for environmental values and competencies; ML algorithms can forecast employees' green behavioural intentions and customize training; sentiment analysis can measure the sustainability climate within the organization; and intelligent systems can integrate carbon literacy metrics into the appraisal systems [12]. If these capabilities are put together in a logical manner and embedded within a Green HRM architecture, they can make a significant contribution to the fast-tracking of the organizations' transition to low carbon and resource efficient organizational culture.

However, this potential is also accompanied by major tensions and unexploited opportunities. The literature has not yet explored and raised the issues of algorithmic bias in the process of green talent selection, data privacy in the process of being monitored by AI for environmental compliance, or employee resistance to AI-driven environmental performance evaluation, and the digital divides in the synergy of AI-Green HRM in developing economies have yet to be raised. Moreover, the theoretical framework that links the capabilities of AI with Green HRM outcomes and further to the measures of environmental sustainability is still not completely developed.

The integration of AI into HR management systems has given rise to ground for innovation in Green HRM, which is evident by the rapid advancement of AI's role in this sector. The faster organizations integrate AI into HRM systems, the greater the potential for fostering and accelerating Green HRM innovations. In recent years, AI has been used in various HR-related tasks, such as evaluating sustainability skills during the application process, and the analysis of employee communication for signals of environmental engagement, which reflects the desire to advance sustainability [13, 42]. The progress of Green HRM scholarship has seen a transformation from descriptive taxonomies of green practices to causal analyses of behavioural outcomes, institutional antecedents and performance consequences [37, 44]. In this context and with the analytical potential offered by bibliometric research, the study is inspired by two main Research Questions (RQs) as follows:

RQ1: What are the dominant thematic clusters and evolutionary trajectories of the AI-enabled Green HRM literature in the period of 2019–2026, and how have these thematic clusters changed over time with the emergence of AI technologies and global sustainability concerns?
RQ2: Who are the key countries, institutions, and authors shaping the AI-enabled Green HRM field; and what patterns of collaboration geographic, institutional, and inter-disciplinary emerge in the development of knowledge in the field?

The RQs are both descriptive and diagnostic. By using RQ1, we are able to map the intellectual content and development of the field in order to identify those theoretical frameworks and empirical issues that have received the most scholarly consideration, and to ascertain the thematic center of gravity of the field as AI capabilities have grown. RQ2 shifts focus to social and institutional frameworks within which knowledge is developed and shared, allowing us to define which actors are key players, where are the underrepresented geographies and where is there a possibility of collaboration that can help to drive the field forward more quickly.

The rest of this study is organized as follows. The theoretical background is presented in Sect. 2, which summarizes key contributions from the literature on Green HRM, and situates the AI-enabled Green HRM domain in the context of sustainability and digital transformation. The literature review is provided in Sect. 3, which provides a collation of significant empirical and conceptual work from the various themes of the subdomains of the field. The material and methods are described in Sect. 4, which covers the data collection protocol, inclusion and exclusion criteria according to PRISMA and bibliometric procedures used. The results are presented and discussed in Sect. 5, along key bibliometric dimensions, including publication trends, the most relevant authors, countries, institutions and sources, author impact metrics, the most-cited documents, keyword frequency and co-occurrence analysis, thematic mapping, and thematic evolution. The findings are summarized and synthesized in relation to the RQs and the general theoretical and management implications in Sect. 6. Section 7 discusses the limitations of the present study and future directions for research, and Sect. 8 presents the main findings and implications for researchers, practitioners, and policy makers involved in achieving AI-driven environmental sustainability.

1.1 Theoretical background

AI-Based Green HRM study lies on the intersection of two traditional theoretical frames, namely, the Ability-Motivation-Opportunity (AMO) theory in HRM and the theory of AI in HRM. These frameworks offer conceptual structure for grasping the environmental outcomes that AI-enhanced HR practices foster in organizations.

By drawing on the AMO framework [5], many HRM studies have shown that the performance outcomes of an organization are dependent on the abilities (competencies) of its employees, their motivation (willingness), and their opportunity (contextual enablers). Green HRM is thus implemented through the development of green skills, through environmental training, the stimulation of green motivation through incentive systems based on the concept of sustainability, and the creation of green opportunities through job redesign and cross-functional sustainability teams [35] (Tang et al. 2018). Each of the dimensions of the AMO is amplified by AI: AI-personalized e-learning boosts ability development with green competency modules tailored to specific skill gaps; AI-driven gamification and real-time environmental performance feedback augment green motivation; and AI-supported collaboration platforms extend green opportunity by connecting sustainability champions across isolated teams.

This study enriches the theoretical field with the first comprehensive bibliometric mapping on how these theoretical traditions are being applied, integrated and developed in the field of AI-assisted Green HRM scholarship. Notably, the thematic evolution analysis charts a shift from the field's theoretical core of HRM and sustainability constructs (2019–2024) to applied frameworks of AI and digital transformation (2025–2026), highlighting the need for integrative mid-range theories that connect with algorithmic capabilities and human environmental agency.

2 Literature review

2.1 Green HRM: foundations and evolution

From the initial conceptualizations of Green HRM as an add-on peripheral environmental management practice, it has grown to a strategic organizational capability that has measurable connections to environmental performance [20, 35]. The key elements of Green HRM were identified early on in the literature as green recruitment and selection, green training and development, green performance management, green rewards and compensation, and green employee relations, along with their individual and bundled impacts on employee environmental behaviour [6] (Tang et al. 2018). Further research on this topic revealed that Green HRM practices work not just directly on behaviours, but also via. intervening variables such as organizational green culture, employee green psychological capital and green organizational citizenship behaviours [37, 44].

The empirical literature has gradually been growing at an intersectoral and trans geographical level. Initial research focused on the industrial and tourist sectors, where the impact of services on the environment can be better seen and measured. However, more recently, research on Green HRM has been expanded into the fields of healthcare, higher education, finance, and public sector, where the importance of organizational environmental responsibility has been realized as a subject that is not limited to a specific industry.

A major advancement in the scholarship of Green HRM has been the increasingly strategic, organizational-level approach to analysis that is combined with the individual-level behavioural science approach. Few theories have been used to describe the motivations behind, and the reasons for, the decisions that employees make to engage in pro-environmental actions as a result of Green HRM interventions, such as the theories of planned behaviour, conservation of resources, self-determination, and social learning [8, 10].

2.2 AI in HRM: abilities and challenges

One of the most significant technological advancements in the field of HRM in the last decade has been the incorporation of AI. In recruitment, AI can be used to create an applicant tracking system and to analyse data from video interviews for insights into a candidate's personality. In development, ML can be used to assess skills and develop learning paths. In evaluation, Natural Language Processing (NLP) can analyse customer service transcripts and predict employee performance. In rewards, algorithmic compensation models can be used to determine salary and benefits packages [13, 41].

The literature reflects that technology behind the majority of AI-HRM applications we identified is ML (Kumar et al. 2025). HR functions can leverage predictive analytics using ML models to proactively predict employee attrition, predict green skill shortages, identify high-potential employees to become sustainability champions, and optimize the deployment of human resource for environmental outcomes [25]. However, AI in HRM also poses substantial problems, which are starting to be addressed in the literature on AI in HRM. AI systems used in HR-related processes such as green talent management may be prone to reproducing and reinforcing discriminatory patterns as a result of algorithmic bias, whereby AI models trained on past environmental performance data could inadvertently reflect structural inequalities in employees' opportunities to learn and progress in sustainability [19, 41].

2.3 AI and green HRM: a synergy for environmental sustainability

The synergy between AI and Green HRM is unique, and cannot be achieved by either group alone. Green HRM gives the normative and strategic direction (integration of environmental values within HRM systems) while AI offers analytical depth, scalability, and real-time responsiveness to operationalize environmental values across large, complex organizations [30]. Together, they can be said to give you 'precision green people management':

the ability to detect, predict, personalize and optimize individual employee environmental behaviours with unprecedented granularity (Kumar et al. 2025).

Some emerging research areas within this synergistic area are as follows: explainable AI for employee retention in Green HRM contexts [29], AI-IoT integration frameworks for eco-friendly talent management [14], AI-Green HRM integration models for secure workforce analytics in hospitality [11], data-driven optimization of Green HRM practices using explainable AI in manufacturing [40], and AI-mediated moderation of the relationship between green work commitment and environmental sustainability [3]. All such studies suggest that the field is progressing from theoretical discussion of the synergy between AI and HRM to a pragmatic evaluation of particular mechanisms, restrictions, and architectures for implementing AI in HRM.

2.4 Relationship with previous bibliometric reviews

The past literature have been the subject of bibliometric interest independently. The broader cross-section of AI in HRM [42, 43] draws together the use of AI in recruitment, development, and performance management, but does not maintain a consistent focus on environmental outcomes. There are parallels to the scope of bibliometric analysis near Green HRM, such as studies on green entrepreneurship [28], which focuses on mapping the scholarship without involving AI as a technological dimension. The conceptual and framework-building studies related to the AI-Green HRM intersection are also evident in literature [25, 34], but they are more limited in their scope. They tend to suggest a specific model for integration rather than exploring the intellectual landscape of the field as a whole. The study does not claim to be "different" from the three existing research streams in terms of being more or less distinct. Rather, it investigates the AI-Green HRM intersection as a standalone unit of bibliometric analysis, exploring its thematic clusters, evolutionary trajectory, and collaborative geography. By treating the AI-Green HRM intersection as an independent field of analysis rather than as a subset of either parent discipline, the study provides a dedicated understanding of its intellectual structure and development.

3 Material and methods

In this study, a systematic bibliometric method is used to explore the intellectual structure and thematic development on the research field of AI-enabled Green HRM. The bibliometric analysis is chosen as the primary method as it provides quantitative and reproducible mapping of vast amount of scholarly literature based on the analysis of publication patterns, citation networks, keyword co-occurrence analysis and collaborative structures, which are essential for describing an emerging interdisciplinary field [15, 33, 45]. In the study, methodological protocol set by the leading bibliometric reviews [17] and [15] has been used. The study uses the Biblioshiny program in R-Studio for data visualization and analysis.

Scopus is chosen as the main data source because of the breadth of coverage and disciplines, the quality controls, the uniform metadata structure, and the extensive citation tracking capabilities. As it covers more than 25,000 peer-reviewed journals, book series, conference proceedings and trade publications in all fields, Scopus is a suitable source for a bibliometric analysis of a field that spans management science, computer science and environmental studies. The database was searched using the search string TITLE-ABS-KEY(("Green HRM" OR "Green Human Resource Management" OR "GHRM") AND ("Artificial Intelligence" OR "AI" OR "Machine Learning")), which was applied to the title, abstract and keyword fields, and was limited to the 2019 to May 2026 publication timeframe as shown in Fig. 1.

3.1 PRISMA framework

The process of including and excluding was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework applied to bibliometric applications as shown in Fig. 1. We found 312

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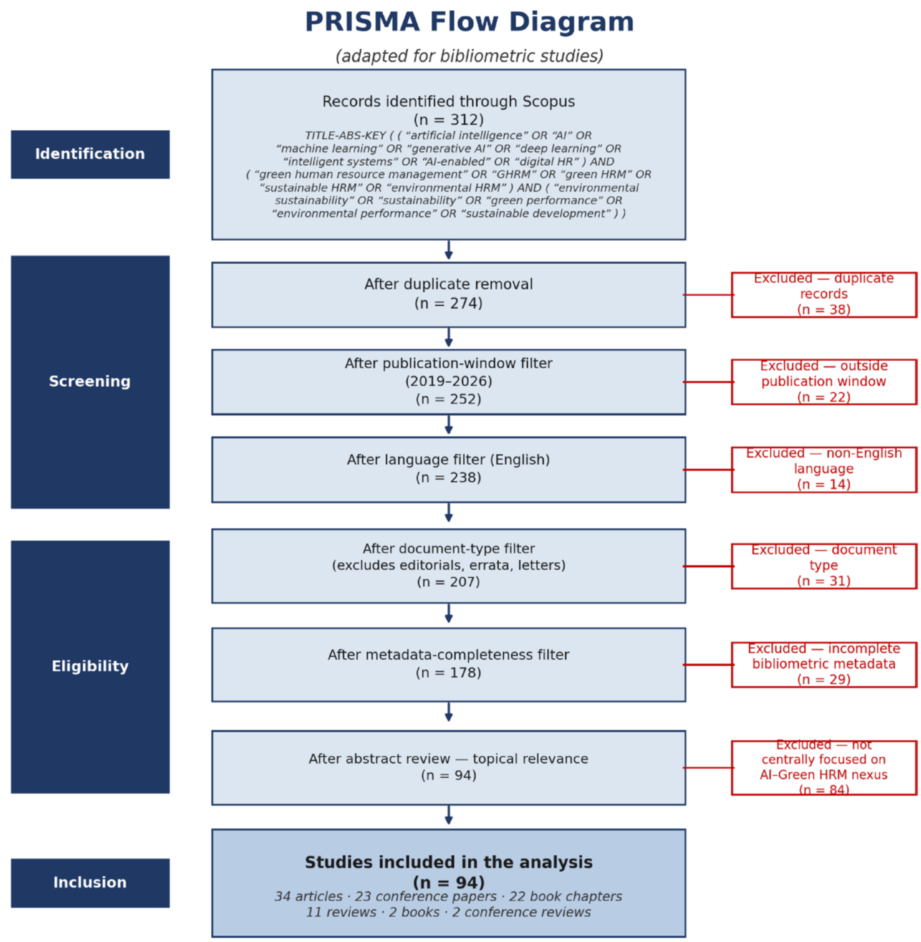


Fig. 1 PRISMA framework. *Source*: Biblioshiny

results in the first database search. There were 274 documents which went on to screening after 38 duplicates were removed. A total of 178 documents were excluded due to the following reasons: outside publication window (2019–May 2026) ($n = 22$); published in languages other than English ($n = 14$); document type excluded based on the defined criteria (editorials, errata, letters) ($n = 31$); incomplete bibliometric metadata ($n = 29$); and records not centrally focused on the AI-Green HRM nexus after abstract review ($n = 84$). The remaining 94 documents were evaluated for eligibility and approved for inclusion which included 34 articles, 23 conference papers, 22 book chapters, 11 reviews, 2 books, and 2 conference reviews.

Since journal articles constitute only 36% of the final corpus, the citation-based performance metrics presented in the following section should be interpreted with caution. Specifically, the findings distinguish citation patterns observed within the journal article subset from those influenced by the inclusion of conference papers and book chapters, which generally accumulate citations more slowly and less consistently than journal articles.

3.2 Research framework design

This research framework uses five complementary bibliometric methods to achieve a multidimensional view of the AI-enabled Green HRM domain. The quantitative foundation is given in the first step, where the publication output, source distribution, types of documents and metrics of collaboration among the authors are described. Second, analysis of performance elucidates the most productive authors, the most cited documents, the most relevant sources, and the most active institutional affiliations, which allows an intellectual centre to be defined for the field as shown in Table 1. Third, co-word analysis of author keywords and Keywords Plus assesses the co-occurrence patterns of terms to determine thematic clusters and the field's conceptual structure. Fourth, thematical

Table 1 Main information about data

Description	Results
Timespan	2019:2026
Sources (Journals, Books, etc.)	72
Documents	94
Annual Growth Rate %	57.46
Document Average Age	1.22
Average citations per doc	7.16
References	5180
Document contents	
Keywords Plus (ID)	435
Author's Keywords (DE)	284
Authors	
Authors	300
Authors of single-authored docs	2
Authors collaboration	
Single-authored docs	2
Co-Authors per Doc	3.49
I nternational co-authorships %	31.91
Document types	
Article	34
Book	2
Book chapter	22
Conference paper	23
Conference review	2
Review	11

mapping uses the centrality-density framework of Callon to differentiate themes into motifs and basic/declining themes, and those emerging/transversal, according to the degree of cohesion in the internal structure of the theme and its external links with the rest of the network of keywords. Fifth, thematic evolution analysis compares the evolution of the keyword clusters in two time periods: 2019–2024 and 2025–May 2026. Fifth, thematic evolution analysis, which compares the evolution of the keyword clusters in the two chronological periods 2019–2024 and 2025–2026, shows how the intellectual concerns of the field have changed over time.

The Louvain community detection algorithm is used to find thematic clusters in the keyword co-occurrence network by setting the minimum frequency of keywords to two occurrences. The visualization parameters of the network were n = 250 keywords, ngrams = 1, community repulsion = 0.5. Using logistic growth modelling on the number of annual publications, characterised the lifecycle stage of the field, with R-squared value of 0.970 and strong fit with the observed publication trajectory. All analyses were performed using the R-Studio interface, Biblioshiny, and additional data analysis was performed in MS Excel. Both RQs are addressed in the research framework, with the thematic mapping and evolution analyses addressing RQ1 and the performance analysis and collaboration network examination addressing RQ2.

4 Results

4.1 Annual scientific production and field lifecycle

The trend of publication per year for the AI field of Green HRM shows a steep rise which resembles the publication trend of an emerging scientific field in its growth stage. The production since 2019 was negligible, as the first steps of AI's potential intersections with Green HRM practice began. There was an increase in the number of documents in 2022 (3 documents) and 2023 (8 documents), but the rise was small and not statistically significant, indicating a growing scholarly momentum. This period was then followed by a period of explosive growth: 14

publications were released in 2024, and 44 publications in 2025, the largest increase for this particular field in any single year in its short history, representing an increase of 214% over the previous year. However, the May, 2026 data (24 publications at analysis time, with the year still running) is nearing the 2024 level, indicating a high level of productivity as shown in Fig. 2.

This overall growth rate of 57.46% is outstanding even in the context of rapidly developing interdisciplinary fields. As a comparison, Nandhini and Sowmya [28] conducted bibliometric analysis of green entrepreneurship over a decade and identified the growth rates to be significantly lower. The logistic growth model is fitted to the publication series Green HRM and has a very satisfactory fit ($R^2 = 0.970$, RMSE = 2.56), with the inflection point (tm) calculated as 2025.15, which indicates that the year 2025 is the most productive year in the field and the rate of growth is currently transitioning from the rapid growth phase to the consolidation phase. Near saturation of the existing research population is predicted by 2028 (cumulative predicted: 94.49 documents out of an estimated 95 documents of capacity), but this projection can only capture the current wave of literature, and does not rule out other waves coming as a result of new technological developments or policy concerns, like generative AI or agentic AI systems, may trigger another surge of publications that this model cannot predict.

4.2 Most relevant sources

Interdisciplinary in nature, the 94 documents in the dataset have been spread across 72 sources, and there is no single dominant publishing outlet. Sustainability (Switzerland) has the highest number of articles per year, with 9 articles in 2026 and 7 articles in 2025, and is the most prolific individual journal source, with a total of ~20 articles over the 12-year study period as shown in Table 2. This is because of its wide sustainability scope and open access publication system so that new studies can be disseminated quickly. However, there is a more specific sustainability outlet that has emerged as an important platform for AI-Green HRM research Discover Sustainability (4 articles 2025 and 2026).

Lecture Notes in Networks and Systems (5 articles in 2026), E3S Web of Conferences (2 articles in 2025 and in 2026), International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT 2023, 2 articles), and Smart Innovation, Systems and Technologies (2 articles in 2026) are especially notable for their conference proceedings. This conference-proceedings weight is comparable to the engineering and computer science contributions to the field, and is similar to the more rapid publication process of technical fields in conference proceedings. This interdisciplinary breadth of the publishing landscape is also reflected in

Fig. 2 Annual scientific production and field lifecycle. *Source*: Scopus

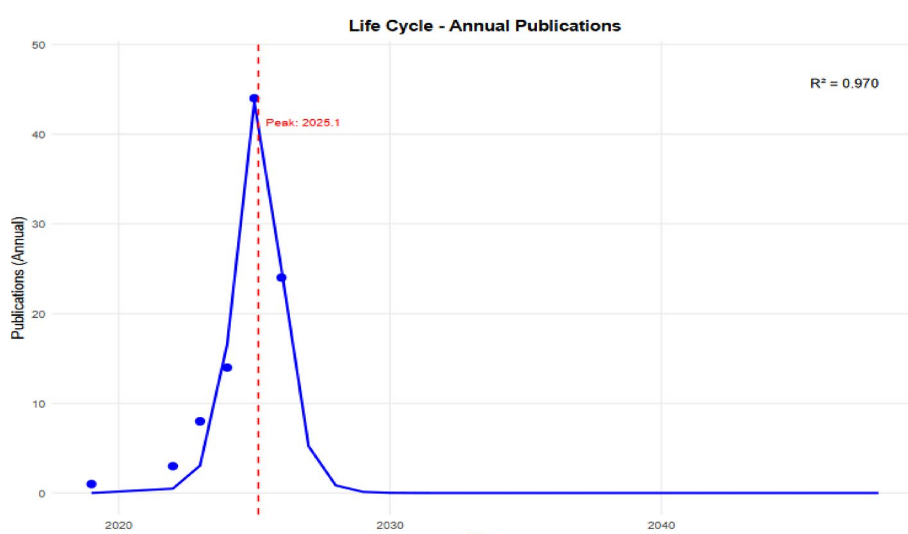


Table 2 Most relevant sources in AI-enabled green HRM research

Source	Articles	Type
Sustainability (Switzerland)	20	Journal
Discover Sustainability	8	Journal
Lecture Notes in Networks and Systems	7	Conference Proceeding
E3S Web of Conferences	4	Conference Proceeding
Smart Innovation, Systems and Technologies	2	Conference Proceeding
Springer Proceedings in Business and Economics	2	Conference Proceeding
Green Engineering for Optimizing Firm Performance	2	Book
ICAICCIT 2023	2	Conference
Business Strategy and the Environment	1	Journal
International Journal of Hospitality Management	1	Journal

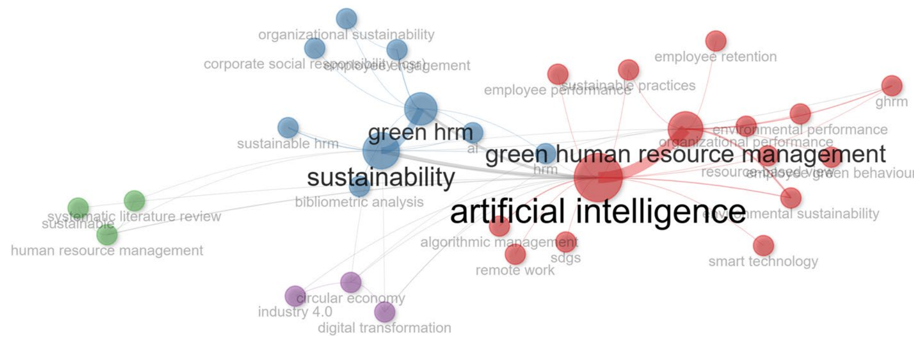


Fig. 3 Keyword co-occurrences. *Source*: Biblioshiny

Springer Proceedings in Business and Economics (2 articles each), Green Engineering for Optimizing Firm Performance: AI and Automation for Sustainable Technologies and in discipline-specific edited volumes.

4.3 Most relevant authors

The contributor profile of AI-enabled Green HRM research is somewhat distributed, unlike the fields where the authors are more consolidated, where one author is generally dominant. This distribution is typical of the field's nascent status and the formation of the new centre of gravity that characterize the field of authorship as seen in Fig. 3. However, there are a few authors who are prominent in both quantity and effect. S. Ogbeibu, from Business Strategy and the Environment, leads in citations with the most cited document in the dataset (98 citations), which explores the capabilities of STARA as drivers of Green HRM and environmental sustainability. Jia and Hou The study on AI in HRM and employee engagement by (Discover Sustainability, 2024) receives 51 citations, whereas the study on AI for green organizational performance in hospitality by Azhar et al. (International Journal of Hospitality Management, 2025) has 15 citations.

John J.E. and Pramila S. are repeated authors appearing in various publications across the years (2024 in Lecture Notes in Networks and Systems; 2025 in Studies in Systems, Decision and Control), and Ali M.R., Peiseniece L., and Mikelsone E. are repeated authors appearing in various publications across the years. The 31.91% of international co-authorship and an average of 3.49 co-authors per document suggest that cooperation is a meaningful aspect of knowledge production in this field, whereby multi-institutional and multi-national research partnerships are gaining in importance for the publications published in 2025–2026.

4.4 Most cited documents

A citation analysis of this field, although young, has identified some documents that have become paradigm documents in AI-enhanced Green HRM. The top ten most cited documents worldwide are listed in Table 3 where citations, citations per year and normalized total citations.

Table 3 Most globally cited documents in AI-enabled green HRM research

Authors (Year), Source	Title (abbreviated)	TC	TC/Year	NTC
Ogbeibu et al. [30], Business Strategy Environment	STARA capability, Green HRM & Environmental Sustainability	98	32.67	13.69
Ogbeibu et al. [31], Journal Intellectual Capital	Green Talent Management & Turnover Intention: STARA Competence	97	19.40	13.55
Jia and Hou [21], Discover Sustainability	AI-driven Sustainable HRM, Conscientiousness & Employee Engagement	51	17.00	7.12
Sova et al. [39], E3S Web of Conferences	AI & Digital HRM on Resource Consumption: Sustainable Development	20	5.00	2.79
Anshima and Bhardwaj [4], Advances in Logistics, Operations, and Management Science (book series)	Leveraging AI for Reinforcement of GHRM	17	4.25	2.37
Shayegan et al. [38], Foresight & STI Governance	Sustainable Org. Performance via New Technologies & Green HRM	24	6.00	3.35
Al-Ghalabi et al. [2], Heritage & Sustainable Dev	Digital HR Technology, Green HRM & Environmental Performance	15	5.00	2.10
Azhar et al. [7], International Journal Hospitality Management	AI Adoption for Green Performance: Moderated Mediation	15	7.50	2.10
Abid et al. [1], Polish Journal Management Studies	Moderating Role of Tech. Competence & AI in Green HRM	14	4.67	1.96
Ali et al. [3], International Journal Information Management	AI-driven Capabilities, Green HRM & Organizational Sustainability	9	4.50	1.26

Table 4 Most frequent keywords in AI-enabled green HRM research

Keyword term	Frequency	Thematic significance
Artificial Intelligence	41	Primary technological driver; anchors Cluster 1
Sustainable Development	40	Core normative framework; anchors Cluster 2
Human Resource Management	33	Foundational disciplinary anchor
Human Resources Management	28	Variant form; confirms HRM centrality
Sustainability	26	Overarching performance objective
Green Human Resource Management	24	Field-defining construct; anchors Cluster 3
Environmental Management	18	Operational environmental focus
Green HRM	17	Abbreviated field-defining construct
Green Development	15	Developmental policy orientation
Human Resource	13	Individual HR capability focus

The landscape of citations has several patterns. First, the two publications by Ogbeibu et al. [31] and Ogbeibu et al. [30] respectively in Journal of Intellectual Capital and Business Strategy and the Environment provide the intellectual backbone of the field, identified as strategic HR capability bundles of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA). Not only does the 2024 paper have a higher Normalized Total Citations (NTC) of 13.69, but also a higher Total Citation(TC)/Year of 32.67, which is much higher than any other paper in the data set, further confirming the paper's paradigmatic status. Second, the Jia and Hou [21] article published in Discover Sustainability has quickly garnered citations because of its approach to examining the use of AI in HRM, which is relevant for a wide range of management disciplines, and its discussion of employee conscientiousness and engagement. Third, a noteworthy TC is the publication of 2023 paper titled foresight and STI governance by [38] with a TC of 24, which indicates its great acceptance by the Russian-language scientific community.

4.5 Most frequent keywords

The 284 author assigned keywords and 435 Keywords Plus terms are co-word analysed to create the semantic landscape of AI-enabled Green HRM research. Table 4 shows the 10 most common words and the number of times they were used, as well as the thematic significance of the field.

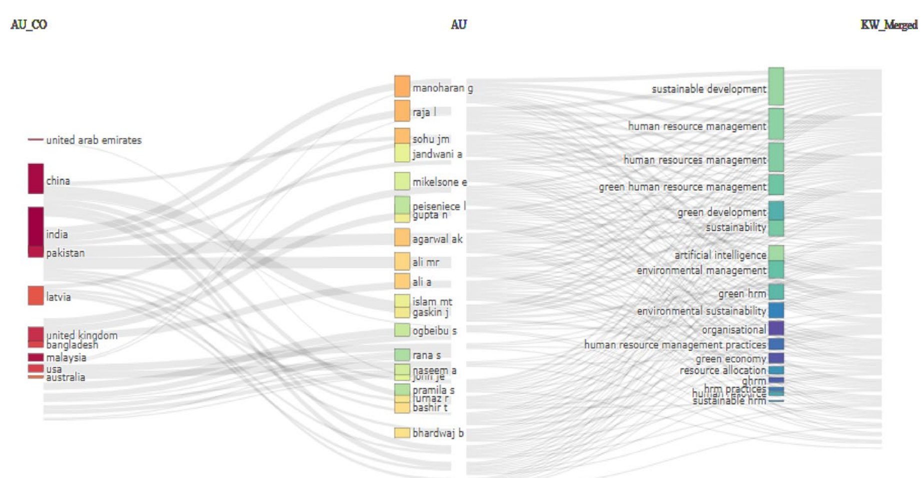
The fact that the two most common keywords were 'artificial intelligence' (41) and 'sustainable development' (40) is notable enough in its own right: 'sustainable development' is even more frequent than 'artificial intelligence', indicating that the field has reached a certain state of 'conceptual balance' between the technological and normative poles of its concepts. The term 'human resource management' (33) is the third most common and highlights the continued importance of the HRM disciplinary perspective despite the rising importance of AI and sustainability discourses. The use of both the terms 'green human resource management' (24) and 'green HRM' (17) over the same frequency of 'GHRM' (7) indicates terminological fragmentation which is typical in emerging areas in which consensus in the definition is still to be established. These variant forms could be combined in future bibliometric analyses to obtain "cleaner" estimates of the core construct of the field.

4.6 Most relevant affiliations and countries

The institutional affiliation landscape of AI-enabled Green HRM research reflects a globally distributed but regionally concentrated production pattern. In keeping with India's technology-adjacent management research, and sizable engineering conference ecosystem, Indian institutions feature prominently in the conference proceedings literature. The study "Discover Sustainability: AI in HRM in the UAE higher education sector", authored by Mahade et al. [26], represents UAE institutions. Al-Ghalabi et al. [2] and Freihat et al. [18] are Jordanian institutions, with the first contributing a chapter on digital HR technology and environmental performance in banking in Jordan, and the second on green supply chain management in the Jordanian industrial sector. The increasing involvement of scholars from Pakistan in addressing the intersections of AI and HRM in the field of HRM is reflected in the multiple publication mentions and the presence of Pakistan as a specific country keyword (3 mentions) as shown in Fig. 4.

International co-authorship at a 31.91% of documents is most prevalent between teams from South Asia (India, Pakistan, Bangladesh), from Southeast Asia (Indonesia, Malaysia) and from the Gulf Cooperation Council (UAE, Jordan), with European and North American authors being most numerous in higher-cited journal publications. The geographic distribution is also very different from that of green entrepreneurship bibliometric research found by Nandhini and Sowmya [28], who found that the UK, Italy, China and the USA accounted for the majority of the research output. The lack of major traditional research institutions in the AI-Green HRM dataset could be attributed to the novelty of the field and the specificity of the cases of the emerging economy and the intersections with AI-Sustainability in rapidly expanding industrial settings.

Fig. 4 Three fields plot. *Source*: Biblioshiny



4.7 Thematic map and cluster analysis

The Louvain community detection algorithm is employed to identify the six different thematic clusters in the AI-enabled Green HRM keyword co-occurrence network. Described below are the four clusters, with each cluster discussed in relation to the keywords that make it up, the callon centrality and density scores, and the thematic substance of the cluster as shown in Fig. 5.

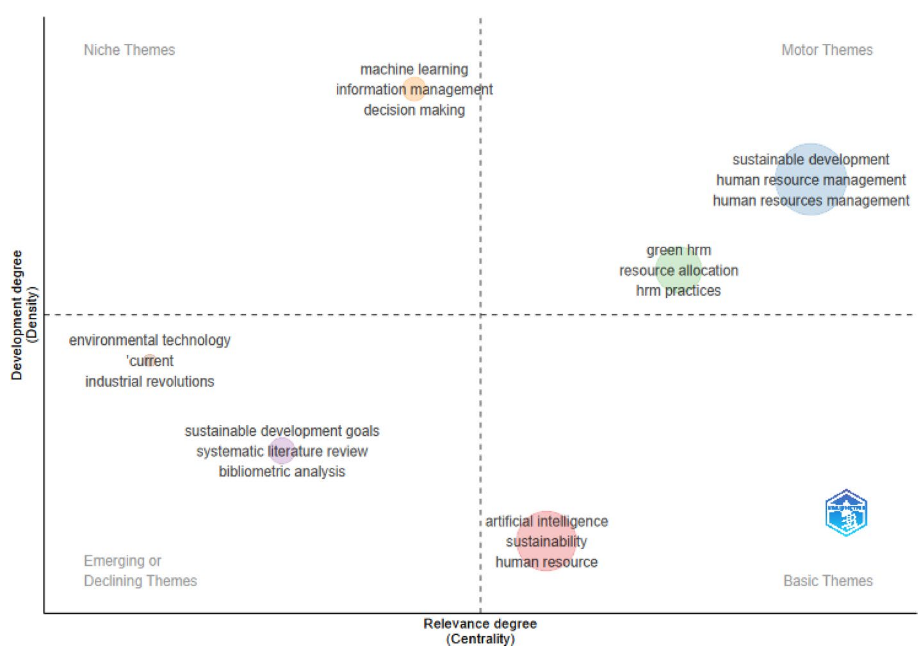
4.7.1 Cluster 1: Artificial intelligence (Centrality: 10.44, Density: 70.77, Freq: 176)

The main technological pole of the field is centred on the term 'artificial intelligence' (41) and 'sustainability' (26) with secondary terms being: 'human resource' (13), 'sustainable HRM' (10), 'resource management' (8), 'circular economy' (5), 'digital transformation' (4), 'environmental performance' (4), 'industry 4.0' (4), and 'organizational performance' (4). The lower centrality score of the cluster compared to Cluster 2 hints at a slightly less interconnected nature within the cluster, which may be attributed to the technical specificity of AI-related terms, but the high density within the cluster points to a high internal cohesion. This cluster falls in the category of a niche (or motor theme) as described by Callon et al. [9] because of its trajectory towards centrality.

4.7.2 Cluster 2: Sustainable development (Centrality: 19.03, Density: 101.36, Freq: 287)

This is the largest and most central cluster in the field, containing the terms 'sustainable development' (40), 'human resource management' (33), 'human resources management' (28), 'green HRM' (24), 'environmental management' (18), 'green development' (15) and 'environmental sustainability' (9). This cluster's high centrality (19.03) and high density (101.36) shows that it is the main motor theme within the field, research well developed and located at the heart of the field, thus giving it a significant drive in the intellectual field. Several of the keywords of the HRM practice cluster appear together with the keywords of the SDG cluster, which is an indication of the normative nature of the field to link HRM practice with the broader societal sustainability agenda.

Fig. 5 Thematic map. *Source*: Biblioshiny



4.7.3 Cluster 3: Green HRM (Centrality: 14.50, Density: 95.82, Freq: 100)

This cluster has 'green HRM' (17) and 'resource allocation' (11) as its central concepts, and further comprises 'HRM practices' (8), 'organisational' (7), 'eco-friendly' (6), 'employee engagement' (6), 'well-being' (5), 'empowerment of personnel' (4), 'corporate social responsibility' (3), 'recruitment training' (3), 'talent management' (3). The cluster depicts the architecture of the implementation of Green HRM, namely the practices, tools and conditions of the organization in which environmental sustainability goals are integrated into HRM. It is dense and highly central, which still further identifies it as a well-developed motor theme in the field.

4.7.4 Cluster 4: Sustainable development goals (Centrality: 6.20, Density: 78.90, Freq: 43)

This connects the concepts of Green HRM and AI practices to the wider SDG governance framework, and is composed of the following constituent keywords: sustainable development goals (7), bibliometric analysis (5), systematic literature review (5), algorithmic management (3), artificial intelligence technologies (3), information systems (3), fintech (2), and remote work (2). The cluster highlights the rising research field of AI-based Green HRM in the normative framework of global governance for sustainability as well as methodological keywords that indicate self-reflective research work (bibliometric analysis, systematic literature review).

4.7.5 Cluster 5: Machine learning (Centrality: 6.61, Density: 150.50, Freq: 39)

Despite its smaller size, this cluster has the highest density score (150.50) of any cluster in the analysis indicating exceptionally strong internal keyword co-occurrence and a highly coherent specialist research niche. It is built around 'machine learning' (5) and 'decision making' (4) with 'information management' (4), 'predictive analytics' (3), 'industrial economics' (3), 'diversity, equity and inclusion' (2), 'economic and social effects' (2) and 'sustainable HR practices' (2) all playing a role. This high density and medium centrality indicate this is a cluster transforming from niche specialty to emerging theme/motor due to the growing number of machine learning applications within Green HRM.

4.7.6 Cluster 6: Environmental technology (Centrality: 5.33, Density: 93.06, Freq: 24)

It is the smallest cluster, which includes 'environmental technology' (3), 'HRM' (3), 'industrial revolutions' (3), 'data analytics' (2), 'environmental responsibility' (2), 'industrial relations' (2), and 'AI' (2). It brings together engineering and industrial ecology aspects of the field, linking AI-driven HR activities with physical environmental technology deployment and industrial transformation processes. Being one of the least central and most frequent domains, it has a relatively weak position in the wider domain, but could become more prominent as Operational Technology is increasingly linked to Human Capital Management in research streams in the fields of Industry 4.0 and Industry 5.0.

4.8 Thematic evolution

Thematic evolution analysis of the two periods (2019–2024 and 2025–2026) shows a striking shift in the focus of the intellectual center of gravity within the field. In the previous period (2019–2024), the keyword clusters were focused on 'sustainable development,' 'human resource,' 'human resource management practices,' 'sustainability' and 'green development,' which contained conceptual foundational discussions that defined the conceptual and normative scope on the domain of AI for HRM. There are a few patterns of key thematic transition from this earlier period to 2025–2026 to note.

The transition terms within the 'sustainable development' cluster remained fairly consistent; the term 'sustainable development' was one of the most stable, and one of the most common across both periods (Stability Index:

0.0217 for the change in 'sustainable development'). The inclusion index was highest in the transition phase from 'sustainable development' (2019–2024) to the sustainability governance cluster 'sustainable development' (2025–2026) with 0.643, which reaffirms the continued importance of sustainable development governance frameworks as shown in Fig. 6. Transition flows to the 'artificial intelligence' cluster (Inclusion Index: 0.333) and to the 'sustainable HRM' cluster (Inclusion Index: 0.333) for the 'sustainability' cluster in 2019–2024 were both high, highlighting a division of the sustainability field: a technologically oriented subfield, and a practice-oriented subfield.

The most impactful evolutionary change will be the emergence of the cluster 'artificial intelligence' as an influential one in 2025–2026, based on various keyword streams from 2019–2024. The transition from 'sustainable development' (2019–2024) to 'artificial intelligence' (2025–2026) has an inclusion index (I) of 0.091, which covers the transition: 'artificial intelligence,' 'green human resource management,' 'green HRM,' 'resource allocation,' and 'environmental management' all of which indicate that AI is being integrated within the previously established areas of research for sustainable development and HRM, and not as an independent research field. At the same time, the specific technical applications of ML in HR analytics and green performance measurement gave rise to a 'machine learning' cluster, which comes from the earlier period's cluster 'human resource management practices' (inclusion index: 0.200).

While the bibliometric data alone cannot distinguish, two forces could plausibly account for this transition: the maturing technical capability of generative and applied AI systems gaining widespread use in HR practice in 2024–2025, and the growing emphasis on sustainability-governance and reporting requirements, forcing organizations to put their Green HRM commitments into practice with measurable tools as opposed to declarative policy. The emerging streams of keywords from 2025–2026 indicate specific future research avenues; sustainable workforce analytics and financial mechanisms, governance of remote and hybrid green-work, and explainable AI and human-AI co-governance models for contestable environmental-performance decisions, as highlighted in the broader AI-HRM literature [29]. These directions are expanded upon as an explicit research agenda in Sect. 6.2.

4.9 Word cloud analysis

The merged keyword dataset can be visualized as a word cloud, which gives a quick overview on the conceptual priorities of the field. The visualization mainly focusses on the term 'artificial intelligence' (41 occurrences), followed by the term 'sustainable development' (40), 'human resource management' (33), 'human resources management' (28) and 'sustainability' (26). There is also a second tier of results such as 'green human resource management' (24), 'environmental management' (18), 'green HRM' (17), 'green development' (15) and 'human resource' (13). Some examples of tertiary tier include 'resource allocation' (11), 'sustainable HRM' (10), 'environmental sustainability' (9), 'eco-friendly' (6), 'employee engagement' (6), and 'green manufacturing' (6) as shown in Fig. 7.

Fig. 6 Thematic evolution.*Source*: Biblioshiny

Fig. 7 Word cloud.*Source*: Biblioshiny

As a technological area (AI-focused) and a normative area (sustainability and SDG-focused), the field's visual hierarchy is captured in the word cloud, and HRM practices are located in the conceptual space between these two areas. Interestingly, the terms that appear in the top frequencies that are related to HRM are not the traditional HRM terms: 'turnover,' 'motivation,' 'leadership,' or 'organizational commitment' that the AI-based Green HRM field has its own special lexicon that incorporates but does not directly match the HRM mainstream's lexicon.

4.10 Source production over time

The analysis on the number of publications produced at the source shows that the spectrum of venues publishing research on AI for Green HRM has diversified over time. In 2022, there was one high output journal, Sustainability (Switzerland), and a low output contribution from ICAICCIT 2023 (1 article) in 2023. By 2024, Discover Sustainability (2 articles), ICAICCIT (2 articles), Lecture Notes in Networks and Systems (1) and E3S Web of Conferences (1) came into existence as new publications. There was a significant boost in the publications in this period, Sustainability (7), Discover Sustainability (4), Lecture Notes in Networks and Systems (2), E3S Web of Conferences (2), Environment Technology Resource Proceedings (2), Green Engineering for Optimizing Firm Performance (2), and Springer Proceedings in Business and Economics (2). By 2026 Sustainability (9), Lecture Notes in Networks and Systems (5), Discover Sustainability (4), Smart Innovation Systems and Technologies (2) and some other sources became regular sources of publications as portrait in Fig. 8.

The trajectory of this source growth suggests that AI-driven Green HRM research is not being concentrated in a single prominent journal or conference series, but instead is spread out across a wide variety of journals, conference series, and edited volumes. This spread is indicative of the field's good interdisciplinary vitality and is a challenge for systematic monitoring and accumulation of citations. The growth of targeted edited volumes, such as Green HRM: A View from Global South Countries (2024), AI-Enabled Workforce Management for Hybrid Workplaces (2026), and Eco-HR: Integrating Sustainability into Workforce Management (2026), indicates that the study of HRM and sustainability has reached a stage of intellectual maturity where it is no longer feasible to be satisfied with the scholarly work of individual authors.

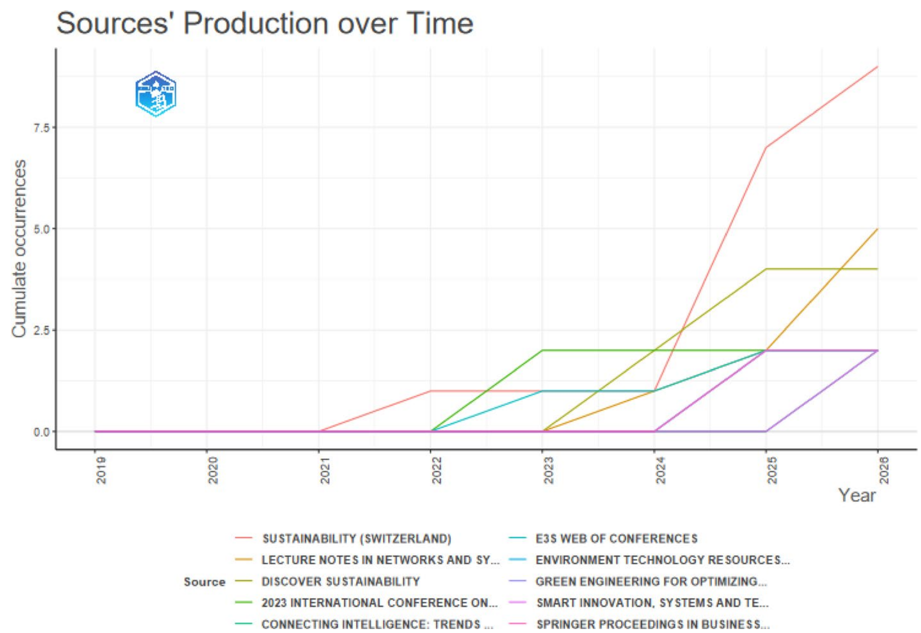


Fig. 8 Sources production over time.*Source*: Biblioshiny

5 Discussion

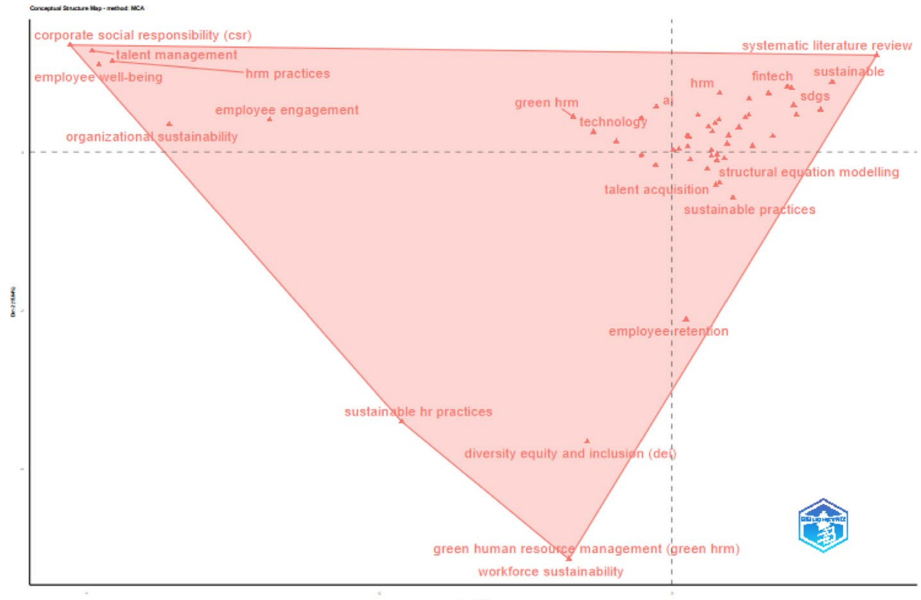
The bibliometric findings presented in Sect. 5 collectively render a portrait of an emerging scientific field that is rapidly establishing its intellectual identity at the convergence of AI and green HRM. There are four broad themes which emerge from the data.

The growth rate is exceptional (57.46% annually) and the logistic growth curve with an inflection point in 2025, confirms that AI-based Green HRM is not an intellectual curiosity but a true answer to the urgent needs of the organization and society. Three drivers, which all happened in parallel, are conducive to the rapid production of AI knowledge in organizational management: First, the mainstreaming of AI in organizational management, second, the regulatory and stakeholder pressure to make companies more environmentally accountable, and third, the empirical evidence base supporting the effectiveness of AI in the domain of Green HRM. In this study, we suggest that foundational theoretical works can have an immediate, strong and cascading impact in young interdisciplinary disciplines like Automated Applicant Screening (AAS), evidenced by the steep number of publications that explicitly reference STARA (e.g., [30, 31]). Figure 9 shows the factor analysis.

Second, the co-word analysis shows that there is a real conceptual integration of the two discourses in the field of Green HRM, and not a mere comparison. The thematic clusters obtained by the Louvain community detection have high intra-cluster cohesion and meaningful inter-cluster cohesions, indicating that researchers are actively building new hybrid conceptual frameworks, rather than just transferring existing concepts from AI to Green HRM or the other way around. High-density Machine Learning cluster (density: 150.50) and the high-centrality Sustainable Development cluster (centrality: 19.03) characterize, respectively, the specialist technical centre and a centre of the field's norms and integrative values. Six clusters fall between these two extremes: the Green HRM cluster (centrality: 14.50, density: 95.82), which plays the role of the operational translation layer between AI capabilities and environmental HR practices and outcomes.

Third, the thematic evolution analysis shows the evolution of the theme between the two periods, 2019–2024 and 2025–2026, which reflects the general trends in AI technologies and sustainability governance. The first period focused more on the definition of HRM and sustainability concepts, which was essential to lay the groundwork for the introduction of AI-Green HRM as a new research field. The shift towards ML, algorithmic management, predictive analytics, and AI technologies in this later phase indicates the growth of AI in the organizational context and the presence of empirical testing environments in real-world organizational environments [22]. The

Fig. 9 Factor analysis.*Source*: Biblioshiny



field is now expanding its normative and contextual dimensions, with the keywords 2025–2026 being SDGs, fintech, remote work, and algorithmic management, representing new arenas of AI-powered Green HRM practice and their implications for regulation, the transformation of work in a digital age, and the design of financial mechanisms [23].

Fourth, the geographical and institutional distribution of research output reveals substantial structural disparities in the global knowledge production landscape. The relative concentration of high-citation outputs amongst a handful of authors in the West and the Gulf region, but also a large number of authors from South Asia, who provide conference-proceedings papers, demonstrates both a differential hierarchy of authors' prestige and a differential availability of research infrastructure and journals access across world regions. Developing economy contexts where industrial growth puts pressure on the environment, environmental governance is less robust, and there are large informal job markets which pose unique sustainability challenges have historically been of particular interest to Green HRM scholarship. A more systematic way of engaging with these contexts beyond the focus on high-visibility publications that are accessible to researchers working in institutionally well-resourced contexts would be very useful in the AI-enabled field of Green HRM.

Several theoretical dilemmas also emerge in the discussion, which need to be examined in future studies. The two lines of development of 'algorithmic management' and 'employee empowerment' within the intersecting thematic clusters reveal the underlying normative tension in the use of AI in Green HRM: the use of AI systems to enforce and monitor environmental compliance (algorithmic management logic), as well as to enable and personalize employees' environmental agency (empowerment logic) [43]. These are two distinct conceptions of organization change of human behaviour and therefore have different implications for employee well-being, organizational justice, and sustainability of environmental behaviour change. The stress is not solvable in the bibliometric data, but is highlighted as one of the paradigmatic stress in the field that empirical and conceptual studies need to tackle systematically.

5.1 Evidence boundaries and the governance of AI in green HRM

The co-word data show that 'algorithmic management' and 'employee empowerment' are neighbouring and crossing themes in the literature for 2025–2026, but do not reveal the way in which this stress is addressed in organizational practice. The stress is interpreted as a non-resolved governance issue, not as a fixed finding: AI systems for the monitoring of environmental compliance and AI systems for the personalization of employees' environmental agency share the same technical infrastructure but have different distributions of organizational control [43]. The two conceptions of change in human behaviour have different implications for employee well-being, organizational justice and sustainability of environmental behaviours, and the bibliometric data does not resolve them, but can help identify them as a paradigmatic concern that should be addressed systematically in future conceptual and empirical work.

The set of literature that is mapped here is only beginning to address the process by which this governance question manifests itself. The transparency side of the stress has been tackled by explainable AI for contestable retention and performance decisions [29], while the equity side has been addressed by algorithmic bias, which occurs when environmental-performance training data was a result of the historical structural inequality in employees' opportunities to acquire sustainability skills [19, 41]. The least developed area, as compared to the technical sophistication of the field, is employee-surveillance concerns, where most of this corpus comes from, and where there is a near absence of any regulatory or governance framework specific to contexts of emerging economies. An agenda that considers responsible AI governance, explainable AI, algorithmic-bias auditing, and regulatory architectures designed for institutional settings in emerging economies as fundamental, not secondary, aspects of the field, would help bridge this divide between this field's booming technical development and its relatively undeveloped ethical foundations.

6 Conclusion

This bibliometric study offers the first systematic, comprehensive map of the research field on AI-enabled Green HRM based on a collection of 94 publications published between 2019 and till May 2026, available in the Scopus database. The analysis has several theoretical, methodological and practical implications. In theory it defines AI for Green HRM as an identifiable research area with thematic clusters, networks of citations, and trajectories. Conceptually, it shows the utility of using co-word analysis, thematic mapping, thematic evolution analysis and logistic growth modelling together in the characterisation of newly developing interdisciplinary fields with high growth rates and still evolving conceptual boundaries in a methodological way. In this respect, it offers scholars, practitioners and policy makers a data-driven map for the intellectual landscape of this field and a research agenda that focuses on the most important gaps.

The two main RQs outlined in the introduction have been answered using the empirical results. Regarding RQ1, the dominant thematic clusters are: AI (technological pole), Sustainable Development (normative integrative hub), Green HRM (operational practice layer), Sustainable Development Goals (governance alignment dimension), Machine Learning (specialist technical application stream), and Environmental Technology (engineering-industrial nexus). Based on the thematic evolution analysis, the conceptualization of HRM-sustainability has moved from fundamentals of an HRM-sustainability concept (2019–2024) to applied research into HRM-sustainability implementation research (2025–2026) as a result of the evolution of the AI technologies and the increased intensity of the sustainability governance demands. To address RQ2, the field's knowledge production can be described as broadly distributed geographically, emerging in institutions in South Asia and the Gulf region; distributed in authorship with the most influential scholarly lineage being the [30], STARA framework,and distributed in publication ecology, appearing in journals on sustainability, engineering conference proceedings, and edited volumes on management.

Its interdisciplinary nature and the presence of truly integrated concepts of AI and Green HRM make the field one of the most vibrant areas of current sustainability management research. The book's emphasis on the human capital mechanisms by which organizations can transform digital technological capabilities into environmental behavioural change fills a key gap in the AI-HRM literature, which has been predominantly concerned with the role of AI in HRM, and the Green HRM literature, which has been predominantly concerned with the role of HRM in environmental sustainability [24]. Theoretically robust and practically impactful, AI-powered Green HRM provides a framework to address the challenge of demonstrating measurable progress toward environmental sustainability in organizations around the world, not just with tons of carbon avoided, but with cultural and behavioural shifts that make it sustainable.

6.1 Policy and managerial implications

The analyses highlight the importance for organizational leaders and HR strategists to invest in AI tools that are designed to boost the effectiveness of Green HRM initiatives, instead of approaching AI adoption and green HR practice as two distinct organizational efforts. The most cited documents in the field consistently show that environmental performance improvements are realised when the application of AI abilities STARA, ML and predictive analytics are intentionally designed to support the goals of Green HRM screening for environmental values, personalization of sustainability training, predicting sustainable behavioural intentions, and incorporating carbon literacy as a factor in performance management. AI-driven Green HRM initiatives that are thought of as interdependent rather than separate programs will deliver better environmental results. In practice, the organizations that wish to implement AI in a Green HRM system can benefit from a framework for implementing AI suggested by the thematic structure of the field:

6.1.1 Governance mechanisms

Design cross functional governance (HR, sustainability and data-governance functions working together) for any AI system used in environmental-performance evaluation with clear escalation procedures for any algorithmic decisions which cause conflict algorithmic-management/empowerment tension addressed prior to deployment, not after.

6.1.2 Explainability and contestability

Focus on AI instruments that enable explainable outputs for decisions related to retention, training allocation, and performance evaluation with environmental implications [29] and that allow affected employees to understand and contest outcomes instead of receive them as a hidden form of surveillance.

6.1.3 Bias auditing

Mandate regular algorithmic-bias audits for any AI system trained on historical environmental performance or green skills data, as history shows that this type of data can contain structural inequality in the prior opportunities that employees have had to work in sustainability [19, 41].

6.1.4 AI deployment and employee training/change management

Pair AI deployment with explicit training on how AI-generated sustainability metrics will be used; this literature suggests that this is the important thing to do, but has not been shown empirically to prevent employee resistance.

6.1.5 Sustainability metrics

Use AI-generated environmental-performance metrics that are consistent with an organization's current sustainability reporting framework instead of creating parallel AI-specific metrics that dilute accountability.

The analysis identifies two policy priorities for policymakers, especially in the emerging-economy settings in which the knowledge base of this field is focused. Firstly, capacity building support such as grants, shared infrastructure or advisory programs for small and medium enterprises that lack in-house AI and sustainability reporting expertise that is typically found in large organizations; the institutional concentration pattern of AI (Sect. 4.6) indicates that the knowledge gap is not necessarily between large and small organizations, but also by location.

Second, the keyword “fintech” and “green-finance” appear in the literature in the period 2025–2026 (Sect. 4.8), suggesting a potential policy tool in the form of financial instruments based on workforce-sustainability metrics, the latter of which is a literature-suggested policy outcome, but not one that has been tested. For academics, the thematic evolution data identifies several high-priority research directions for the near term. The high density and low centrality of the ML cluster indicate that applied ML research is still in early stages of development in the context of Green HRM, but is growing rapidly and has not yet fully become part of the broader Sustainable Development cluster constituencies. Research which explicitly connects ML methodologies with SDG aligned measurement frameworks would help fill this gap in integration. As algorithmic management and Diversity, Equity, and Inclusion emerge as keywords alongside ML, there is a pressing need to study the equity and justice aspects on the implementation of AI-Green HRM, such as the questions of who benefits, who suffers and how algorithmic bias in green talent management can be identified and addressed.

6.2 Limitations and future research directions

This study has a number of limitations that restrict the applicability of the results and indicate areas for further bibliometric and primary research. First, the reliance on a single database is defensible if the oracular corpus of which Scopus's conference-proceedings and engineering venues are a part is substantially more complete, but a Web of Science cross validation pass would be useful in future bibliometric studies to compare this six-cluster solution with another one; and because this field's own thematic content suggests particular relevance, the coverage of conference-proceedings and engineering venues in the South and East Asian research community might be somewhat underrepresented in the current study. Second, because the year was incomplete as of the search date, the 57.46% annual growth rate, the inflection points of the logistic model, and the 2028 saturation estimate should be considered provisional estimates that will likely change when the 2026 indexing is finished, not fixed numbers. Third, the current state of the art for bibliometrics, which is to perform searches with terms as keywords, is sensitive to this degree of fragmentation of the terminological landscape, since it can miss documents found in studies using other retrieval techniques, such as semantic or embedding-based search.

The following are some priority areas for primary research based on this mapping. The equity implications of the AI-based Green HRM algorithmic bias in evaluating environmental-performances, inequal access to the development of green-skill and power imbalance in the AI-mediated environmental compliance monitoring are theoretically and practically significant gaps that this literature has only started to name. Beyond conceptual and cross-sectional studies, there is a scarcity of definitive evidence to support the field of Green HRM because of the lack of any longitudinal studies that follow the changes in the impacts of AI-based interventions on employee environmental behaviours, organizational environmental culture, and tangible environmental metrics (e.g., carbon emissions, energy consumption, waste disposal). The research would investigate the relationship between the effectiveness of AI-Green HRM and the characteristics of the sector, culture and attitude towards AI and environmental responsibility, and the regulatory framework. Lastly, investigations into the dynamics of introducing AI into HRM, such as the change-management and organizational-learning issues involved, could fill this gap between the conceptual depth of the field and the operational guidance that practitioners currently do not have.

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Declarations

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