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The role of artificial intelligence in green human resource management and organizational sustainability: a systematic literature review and bibliometric analysis

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Abstract

Artificial intelligence (AI) is increasingly presented as the technology that will allow green human resource management (GHRM) to deliver organizational sustainability, yet the evidence behind this claim is recent, scattered and largely unexamined. This study combines a PRISMA-guided systematic literature review with a VOSviewer-based bibliometric analysis to establish what is known, how it is known and what remains untested. A Scopus search (12 November 2026) returned 297 records; after document-type filtering and title–abstract–keyword screening, 97 journal articles and reviews formed the mapping corpus, and two further eligible articles were added to the critical synthesis (n = 99). Keyword co-occurrence, overlay, co-citation, bibliographic coupling and country co-authorship maps were produced, and every study was coded for the structural role assigned to AI, theory, method, context and outcome. The field is young (77.3% of the corpus is published from 2025-2026), geographically limited (mostly emerging Asian countries), and methodologically homogeneous, with 44 of 62 quantitative studies using cross-sectional structural equation modelling of self-reported data. Five roles for AI are discussed (enabler, amplifier, mediator, complementary resource and embedded practice), but they are often mixed up, or not well explained theoretically. The conceptual foundations are the resource-based view and the GHRM foundations and the critical literature on algorithmic

management is not present in the co-citation structure. These are flanked by reports in other studies of non-significant and negative effects, as well as no environmental footprint for AI itself, meaning the current optimism is premature. The paper introduces a typology of AI roles and a socio-technical capability-conversion framework that consists of six propositions, and a research agenda.

Keywords Artificial intelligence; Green human resource management; Organizational sustainability; Sustainable HRM; Systematic literature review; Bibliometric analysis; VOSviewer; Socio-technical systems

1 Introduction

Organizational sustainability, understood as the capacity of a firm to maintain economic, environmental and social performance without depleting the capitals on which it depends, has moved from the periphery to the centre of corporate strategy (Dyllick & Hockerts, 2002; Hart, 1995). Human resource management is one of the main channels through which environmental strategy reaches everyday work. Green human resource management (GHRM) comprises the recruitment, training, appraisal, reward and involvement practices that build the abilities, motivation and opportunities employees need to act in environmentally responsible ways (Jackson et al., 2011; Ren et al., 2018; Renwick et al., 2013). A decade of empirical research has associated GHRM with employee green behaviour, environmental performance and broader sustainability outcomes across manufacturing, hospitality, information technology and higher education (Aboramadan, 2022; Dumont et al., 2017; Kim et al., 2019; Ojo et al., 2022; Paillé et al., 2014; Yong et al., 2020).

In parallel, artificial intelligence (AI) is changing how HR work is done. Algorithms screen applicants, personalize learning, monitor performance and generate feedback at a scale that manual HR systems cannot reach (Budhwar et al., 2022; Pan & Froese, 2023; Tambe et al., 2019; Vrontis et al., 2022), and generative AI has widened the range of HR tasks that can be automated or augmented (Budhwar et al., 2023). AI is also promoted as an instrument for sustainability because it can monitor resource use, predict emissions and guide behaviour, although the same technologies may inhibit sustainability targets through their energy use, bias and opacity (Nishant et al., 2020; van Wynsberghe, 2021; Vinuesa et al., 2020). The meeting of these two streams has produced a new literature on AI-enabled, AI-driven or AI-augmented

green and sustainable HRM (Ajuluchukwu et al., 2026; Jia & Hou, 2024; Mollah et al., 2024; Ogbeibu et al., 2024).

This literature has grown faster than it has been examined. Three problems motivate the present study. First, the role that AI plays in relation to GHRM is conceptually unsettled. In some studies AI capability is an antecedent that enables GHRM (Azhar et al., 2025; Ogbeibu et al., 2024); in others it is a moderator that strengthens GHRM effects (Khan et al., 2024; Odugbesan et al., 2023); elsewhere GHRM is the antecedent and AI the mediator (Jahangir et al., 2025; Kayani et al., 2026); and in a further group AI is folded into the HR practice itself (Ajuluchukwu et al., 2026; Jia & Hou, 2024). These specifications imply different causal claims and different managerial advice, yet they are seldom distinguished. Second, the first reviews of the field have largely catalogued the applications of AI across HR functions and reported a positive contribution (Alherimi et al., 2025; Ibrahim & Eitah, 2025; Kapruwan et al., 2026; Singh & Sinha, 2026a). They have not asked how robust the underlying evidence is, which theories it rests on, or which costs of AI it leaves out. Third, management research on AI warns that value depends less on the technology than on how it is combined with human capabilities and organizational context (Chowdhury et al., 2023; Malik et al., 2023; Raisch & Krakowski, 2021), and research on algorithmic management documents control, opacity and fairness problems (Kellogg et al., 2020; Meijerink et al., 2021). Whether the AI–GHRM literature has absorbed these insights is an open empirical question that a bibliometric analysis of its intellectual base can answer.

The study therefore addresses four research questions. RQ1: How has research on AI in green and sustainable HRM developed in terms of volume, sources, countries and influential studies? RQ2: What are the thematic structure, the intellectual foundations and the current research fronts of the field, and how have they shifted over time? RQ3: Which roles are assigned to AI in relation to GHRM and organizational sustainability, and with which theories, methods, contexts and outcomes are these roles studied? RQ4: Which gaps follow from the combined bibliometric and critical evidence, and how can they be organized into an integrative framework and a research agenda?

The paper makes four contributions. First, it offers a typology of five structural roles of AI in GHRM research, derived from coding every included study, and shows that the roles are

distributed almost evenly and are rarely justified, which explains why findings do not accumulate. Second, it highlights three bibliometric structures (co-word, co-citation and bibliographic coupling) calculated on VOSviewer and demonstrates that foundations of GHRM, the resource-based view and measurement literature make up the core of the field's intellectual base, while the critical scholarship on algorithmic HRM is absent in the co-citation core. Third, it offers a critical appraisal that highlights non-significant and negative results, the inclusion of AI as a unified perceptual phenomenon, the location and methodological nature of the evidence, and the lack of the environmental impact of AI. Fourth, it synthesizes and embeds these findings in a socio-technical capability-conversion framework, consisting of six propositions that can be tested and a prioritized research agenda. The contribution is purposefully bounded: the paper does not set out to estimate the size of the effects of the use of AI in GHRM, and it does not assert that GHRM with AI does or does not work; it can only hypothesize what the existing evidence can or cannot support.

The rest of the paper is organized as follows. Section 2 provides an overview of the conceptual underpinning and situates the study in relation to previous studies. The methodology is reported in section 3. The bibliometric results are presented in Section 4, and the critical synthesis in Section 5. The integrative framework, propositions and research agenda are developed in Section 6. Implications, limitations and conclusions are provided in Sections 7 – 9.

2 Conceptual background

2.1 Green HRM and organizational sustainability

GHRM was established as a field by reviews that defined its practice domains and called for multilevel theory and better measurement (Amrutha & Geetha, 2020; Benevene & Buonomo, 2020; Jackson et al., 2011; Ren et al., 2018; Renwick et al., 2013). A validated multidimensional scale covering green recruitment and selection, training, performance management, pay and reward, and involvement made large-scale survey research possible (Tang et al., 2018). The dominant explanation of GHRM effects is the ability–motivation–opportunity (AMO) framework (Appelbaum et al., 2000; Jiang et al., 2012): practices raise environmental competence, reward environmental contributions and create occasions to act. A second explanation works through shared perceptions. HR systems that are distinctive, consistent and consensual create strong climates that signal which behaviours matter (Bowen & Ostroff, 2004;

Schneider et al., 2013), and perceptions of a green work climate transmit the effect of sustainability policies and GHRM to employee behaviour (Dumont et al., 2017; Gupta & Kaur, 2024; Norton et al., 2014). At the organizational level, GHRM has been linked to environmental and sustainable performance, particularly in combination with green supply chain management and green innovation (Jabbour & de Sousa Jabbour, 2016; Roscoe et al., 2019; Singh et al., 2020; Zaid et al., 2018). A related stream, sustainable HRM, broadens the outcome to the long-term regeneration of human resources and to social as well as ecological goals (Aust et al., 2020; Ehnert et al., 2016; Kramar, 2014). In almost all of this work HR practices are assumed to be delivered by people and to be technologically neutral.

2.2 Artificial intelligence in HRM

Reviews of AI in HRM describe adoption across recruitment, learning, performance management and workforce analytics and identify persistent difficulties: HR outcomes are complex and hard to measure, data sets are small, and fairness and explainability concerns are acute (Marler & Boudreau, 2017; Pan & Froese, 2023; Tambe et al., 2019; Vrontis et al., 2022). Three ideas from this literature matter for the present study. First, AI is not one thing. Digital HRM, HR analytics, machine learning, robotics and generative AI differ in what they automate and in the judgement they leave to people (Brougham & Haar, 2018; Budhwar et al., 2023; Strohmeier, 2020). Second, AI creates value only when it is combined with complementary organizational capabilities, and augmentation of human judgement is often more appropriate than automation (Chowdhury et al., 2023; Malik et al., 2023; Mikalef & Gupta, 2021; Raisch & Krakowski, 2021). Third, algorithmic HRM redistributes control and can reduce transparency, autonomy and perceived fairness (Cheng & Hackett, 2021; Kellogg et al., 2020; Köchling & Wehner, 2020; Meijerink et al., 2021). A separate body of work points out that AI has an environmental cost of its own. Training and running large models consume energy and hardware, so that "AI for sustainability" must be distinguished from the "sustainability of AI" (Luccioni et al., 2024; Schwartz et al., 2020; van Wynsberghe, 2021).

2.3 Theoretical lenses

Four lenses are relevant to the intersection of AI, GHRM and organizational sustainability. The natural-resource-based extension of the resource-based view states that what is valuable is the resource and capability that is valuable, rare, and hard to imitate, such as the capability to

prevent pollution and sustainable development (Barney, 1991; Hart, 1995). The argument is stung when applied to AI, however: AI tools are now on the market, and the tool is hence not the unique resource, but rather the combination of that tool, of the skilled people, and of the supportive context (Akter et al., 2016; Mikalef & Gupta, 2021; Wamba et al., 2017). The dynamic capabilities perspective extends this with the requirement that these bundles need to be reconfigurated when technologies and environmental demands shift (Eisenhardt & Martin, 2000; Teece, 2007; Teece et al., 1997). The AMO framework describes the individual-level conditions that trigger the reactions of individual HR practices (Appelbaum et al., 2000; Jiang et al., 2012). Socio-technical systems theory, last but not least, identifies three conditions for the performance enhancement by new technology: 1) the work organization must be redesigned to adapt to the new technology; 2) social relations must also be restructured to fit the new technology; and 3) the two parts of the systems must be optimized together (Appelbaum, 1997; Makarius et al., 2020; Trist & Bamforth, 1951). The four lenses are complementary. The first two explain why combinations matter and must evolve, the third explains what each practice does to people, and the fourth explains why technical and social conditions must be present together. Section 5 examines how far the reviewed studies actually use them.

2.4 Earlier reviews and the gap addressed

Several reviews of AI and green or sustainable HRM appeared in 2025 and 2026, which is itself a sign of how quickly the topic has gained attention. Alherimi et al. (2025) reviewed 53 articles and identified five themes centred on the functions that AI supports. Ibrahim and Eitah (2025) summarized studies with both terms in the title and concluded that the role of AI is positive provided that skills and an enabling environment exist. Khan et al. (2025) organized AI applications by sustainability dimension. Singh and Sinha (2026a) and Singh and Sinha (2026b) reviewed 35 and 52 studies in relation to the circular economy and workforce resilience, Kapruwan et al. (2026) mapped AI tools to GHRM functions through a resource-based lens, Mavunda (2026) focused on Sub-Saharan Africa, and Jena et al. (2026) combined a bibliometric overview with a barrier analysis. Related work has reviewed AI in HRM for manufacturing sustainability (Wu et al., 2026) and the interface between HR analytics and sustainable HRM (Yin, 2025).

These reviews establish that the topic exists and describe where AI can be applied. Read together, they leave four matters open. They do not differentiate the structural roles that primary studies assign to AI, so heterogeneous models are summarized as a single positive effect. They rarely examine the intellectual base of the field, so it is unknown whether the critical AI-in-HRM literature informs it. They give little weight to non-significant or negative findings and to the design limits of the primary studies. And they do not treat the environmental footprint of AI as part of the sustainability question. The present study addresses these four matters by combining science mapping, which shows the structure of a field independently of any reviewer's selection (Donthu et al., 2021; Zupic & Čater, 2015), with a critical synthesis that reads the mapped studies for what they assume, measure and omit (Post et al., 2020; Snyder, 2019). Earlier work by the first author on GHRM, green leadership and work commitment, including a first test of AI elements, treated digital technology as peripheral (Ali et al., 2025b; Ali et al., 2026a; Ali et al., 2026b); the present review places it at the centre.

3 Methodology

3.1 Research design

The study follows a sequential mixed review design in which a bibliometric analysis and a systematic literature review are applied to the same corpus (Kraus et al., 2022; Linnenluecke et al., 2020). The systematic review component follows the logic of transparent, replicable evidence synthesis in management (Paul et al., 2021; Snyder, 2019; Tranfield et al., 2003) and is reported according to PRISMA 2020 (Page et al., 2021). The bibliometric component follows established guidance for science mapping in management and organization research (Donthu et al., 2021; Zupic & Čater, 2015). The two components answer different questions. Science mapping reveals structure (themes, foundations, fronts and collaboration) from the aggregated behaviour of many authors, whereas the critical synthesis interprets that structure by reading and coding the studies. Their integration is the basis for the framework and agenda in Section 6. The review protocol was not registered in advance; all search strings, decision rules, data files and scripts are provided as supplementary material so that each number in the paper can be reproduced.

3.2 Database selection

Scopus was used as the data source. It is a curated abstract and citation database whose content selection and author, affiliation and reference metadata are quality-controlled, and it is one of the two standard sources for bibliometric studies (Baas et al., 2020). Its journal coverage in the social sciences is broader than that of the Web of Science Core Collection, which matters for a young topic published to a considerable extent in newer and regional journals (Mongeon & Paul-Hus, 2016). Scopus exports include the cited-reference lists required for co-citation and bibliographic coupling and can be processed by VOSviewer (van Eck & Waltman, 2010). Web of Science could not be accessed through the authors' institutions at the time of the search. Reliance on one database is therefore a limitation, discussed in Section 8; it has the advantage that no cross-database merging and de-duplication of heterogeneous reference formats was required.

3.3 Search strategy

The search combined two blocks of terms in titles, abstracts and keywords. The AI block covered artificial intelligence and its main techniques and HR applications; the HRM block covered green and sustainable HRM and its named practices. Digitalization terms without an AI component (for example "e-HRM" or "digital HRM" alone) were deliberately not used as search terms, because the review concerns AI and not HR digitalization in general (Strohmeier, 2020). The exact query, run on 12 November 2026 without date restriction, was:

```
TITLE-ABS-KEY ( ( "artificial intelligence" OR "AI" OR "machine learning"
OR "deep learning" OR "generative AI" OR "ChatGPT" OR "large language
model*" OR "algorithmic management" OR "algorithmic HR*" OR "intelligent
automation" OR chatbot* OR "HR analytics" OR "people analytics" OR
"workforce analytics" OR "big data analytics" ) AND ( "green human
resource*" OR "green HRM" OR "GHRM" OR "green HR" OR "sustainable human
resource*" OR "sustainable HRM" OR "green recruitment" OR "green
training" OR "green performance management" OR "green talent management"
OR "environmental human resource*" ) )
```

The search returned 297 records published between 2018 and 2026, all in English.

3.4 Inclusion and exclusion criteria

Table 1 lists the eligibility criteria. Two decisions need explanation. First, only journal articles and reviews were retained. Conference papers and book chapters make up 45.1% of the retrieved

records (134 of 297), which shows how much of this young topic is published outside journals, but their peer-review standards are heterogeneous and their reference lists are less consistently indexed. Second, a study was included only if AI was an object of study. Studies in which machine learning or text mining served merely as the authors' own analysis technique were excluded, because they say nothing about AI as part of HR practice.

Table 1 Eligibility criteria

Criterion	Inclusion	Exclusion
Topic	AI or AI-based analytics (AI, machine learning, generative AI, STARA, HR or big data analytics) is an object of study in an HRM context	AI, machine learning or text mining used only as the authors' analysis technique; AI mentioned only in passing (e.g. as future research)
HRM focus	Green HRM or sustainable HRM (or a named practice such as green training, recruitment or talent management) is a substantive construct or topic	Green supply chain, green innovation or general sustainability studies without an HRM construct; generic HRM without a sustainability focus
Document type	Journal article or review (including articles in press)	Conference paper, conference review, book chapter, book, editorial, erratum
Language	English	Other languages
Period	No restriction (earliest record 2018; search date 12 November 2026)	–
Source	Indexed in Scopus; or eligible journal article in the authors' reference collection (critical synthesis only)	Grey literature, theses, reports

3.5 Screening and data cleaning

Figure 1 summarizes the selection process. Document-type filtering removed 159 records (67 conference papers, 67 book chapters, 17 conference reviews and 8 books). The remaining 138 journal records were checked for duplicates by DOI and by normalized title (none were found) and were then screened against the criteria in Table 1 on the basis of title, abstract and author keywords. Forty-one records were excluded: 16 mentioned AI only peripherally, typically in a closing sentence on future research; 9 had no substantive green or sustainable HRM focus; 9 used AI or machine learning only as the analysis technique; and 7 were false positives of the search string. Ninety-seven records (83 articles and 14 reviews) met all criteria and form the bibliometric corpus. A screening log with the decision and reason for every one of the 297 records is provided as supplementary material.

The authors' reference collection was checked against the same criteria. Two eligible journal articles that were not in the Scopus result set were identified: Ajuluchukwu et al. (2026), published in a journal not yet covered by the Scopus search result at the search date, and Mollah

et al. (2024), whose wording ("AI-augmented HRM") does not match the HRM block of the query. Both were added to the critical synthesis (n = 99) but not to the science maps, because the maps require homogeneous Scopus metadata.

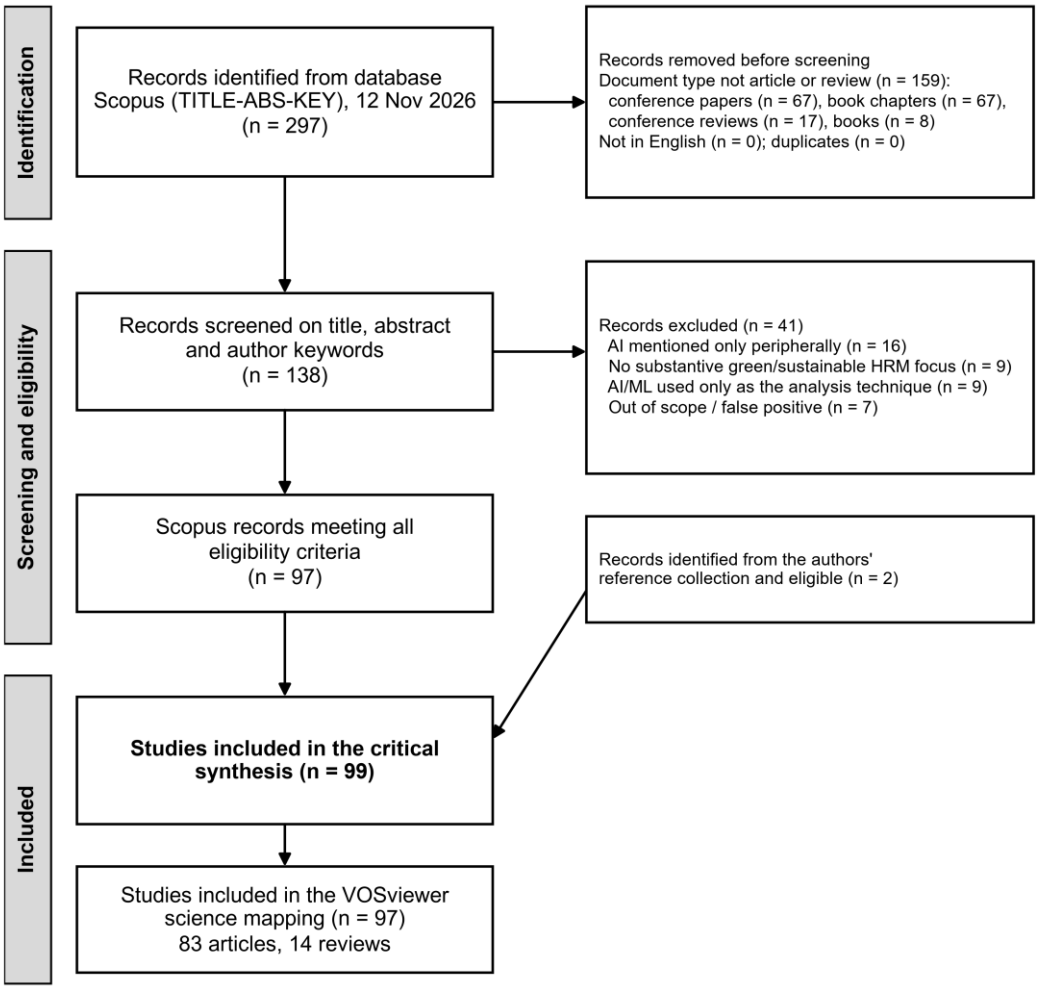


Fig. 1 PRISMA 2020 flow diagram of record identification, screening and inclusion

Before mapping, the bibliographic data were cleaned in three ways. (1) Author keywords were harmonized with a thesaurus that merges spelling variants, abbreviations and near-synonyms (for example "GHRM", "green human resource management practices" and "green HR" into "green HRM"; "AI" and "artificial intelligence (AI)" into "artificial intelligence"; British and American spellings). Journal of Economic Literature codes, country names, method labels and four non-informative single words were removed. This reduced 370 distinct author keywords to 258. (2)

Cited references were parsed from the Scopus reference strings and matched on first-author surname, publication year and the first six words of the title, which merges formatting variants of the same reference; 6,960 cited references reduced to 5,405 unique references. (3) Country names were standardized, and affiliation fragments that were not countries were removed. The thesaurus file and the parsing rules are part of the supplementary material.

3.6 Bibliometric techniques

Five analyses were carried out (Table 2). Keyword co-occurrence (co-word) analysis maps the conceptual structure of a field from the terms authors use together (Callon et al., 1983). An overlay of the same map by average publication year shows how attention has shifted. Co-citation analysis treats two references as related when they are cited together and reveals the intellectual base on which a field builds (Small, 1973). Bibliographic coupling treats two documents as related when they share references; because it does not depend on citations received, it is better suited than co-citation to recent literature and to identifying current research fronts (Boyack & Klavans, 2010; Kessler, 1963). Country co-authorship describes the social structure of the field. Using co-citation and coupling together separates what the field draws on from what it currently does (Zupic & Čater, 2015).

The network files were generated from the cleaned Scopus export with documented Python scripts using full counting, and were then analysed in VOSviewer 1.6.21 (van Eck & Waltman, 2010). VOSviewer normalized link strengths with the association-strength measure (van Eck & Waltman, 2009) and applied its layout and clustering techniques, which rest on the same underlying principle (Waltman et al., 2010), with the default clustering resolution of 1.00. Small clusters were merged with a minimum cluster size of five items, except in the small country network. Thresholds were set low because the corpus is small: a keyword had to occur in at least two documents, a reference had to be cited by at least six of the 97 documents, and a country needed at least two documents. Because low thresholds admit items supported by few documents, the interpretation in Section 4 rests on the high-occurrence items of each cluster. Clusters were labelled by the authors after reading the items in each cluster, and, for the coupling clusters, the abstracts of the member studies.

Table 2 Bibliometric analyses and settings

Analysis	Unit and purpose	Inclusion threshold	Items / links	VOSviewer settings

Keyword co-occurrence	Author keywords after thesaurus; thematic structure	≥ 2 occurrences	41 keywords / 199 links	Full counting; association strength; resolution 1.00; min. cluster size 5
Overlay	Same network coloured by average publication year; emerging topics	as above	as above	Score: average publication year
Co-citation	Cited references; intellectual base	≥ 6 citing documents	54 references / 856 links	Full counting; association strength; resolution 1.00; min. cluster size 5
Bibliographic coupling	Included documents; research fronts	all documents	97 documents / 1,954 links	Full counting; association strength; resolution 1.00; min. cluster size 5
Co-authorship	Countries; collaboration structure	≥ 2 documents	23 countries / 54 links	Full counting; association strength; resolution 1.00

3.7 Coding and critical synthesis

Each included study was coded on eight attributes: (1) the structural role assigned to AI in relation to green or sustainable HRM; (2) framing as green or sustainable HRM; (3) the AI technology named; (4) the theories named; (5) research design and analysis method; (6) country of data collection; (7) sector; and (8) outcome type. The role of AI was coded by reading the abstract of every study, using eight mutually exclusive categories that emerged inductively from the first reading and were then applied to all studies: AI as antecedent or enabler of GHRM; AI as moderator; AI as mediator between GHRM and outcomes; AI and GHRM as parallel, complementary resources; AI embedded in the HR practice construct; technical artefacts and decision models; qualitative and case evidence; and reviews or conceptual papers. Attributes 2 to 8 were coded with documented keyword rules applied to the title, abstract and author keywords, and the results were checked against the abstracts.

Three features of this procedure limit what can be claimed and are stated here rather than only in the limitations section. Coding relied on the bibliographic record (title, abstract, keywords and reference list) and not on a full-text reading of all 99 studies; an attribute is therefore recorded only when the abstract states it, and counts of theories, countries and designs are lower bounds. Screening and coding were carried out by one coder with the support of an AI-based assistant and documented rules, so inter-coder reliability could not be computed. And no formal quality appraisal score was assigned to individual studies; instead, design features that bear on the strength of inference (cross-sectional self-report designs, sampling, construct specification) were recorded and are discussed as properties of the evidence base. The critical synthesis then proceeded in three steps: comparing the model specifications within and across AI roles; identifying results that contradict the dominant positive narrative; and comparing what the field

cites and studies with what the wider AI-in-HRM and sustainable-AI literatures identify as central.

4 Bibliometric results

4.1 Growth and document profile

Research at the intersection of AI and green or sustainable HRM is very recent. The earliest of the 297 retrieved records date from 2018, annual output remained in single digits until 2022, and it then rose from 23 records in 2023 to 89 in 2025 and 129 in the incomplete year 2026 (Fig. 2). The journal corpus shows the same pattern: 75 of the 97 included studies (77.3%) were published in 2025 or 2026, and only eight before 2023. Two consequences follow. Citation-based indicators favour the few early studies, and the field has had little time for replication, critique or consolidation. Table 3 summarizes the corpus.

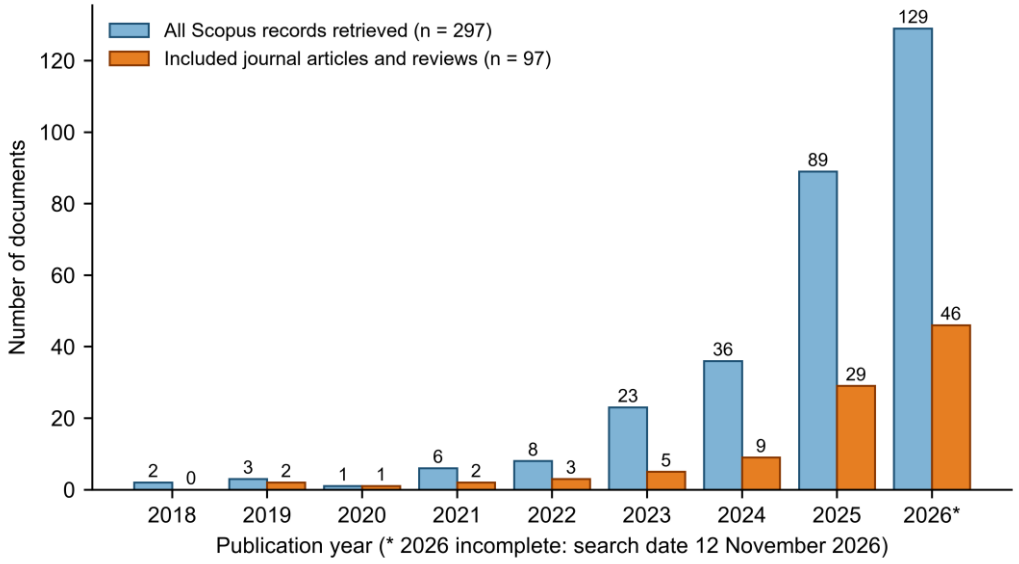


Fig. 2 Annual number of Scopus records retrieved and of journal articles and reviews included (2018–2026)

Table 3 Main characteristics of the bibliometric corpus

Characteristic	Value
Records retrieved from Scopus (all document types)	297
Journal articles and reviews screened	138
Studies included in the science mapping	97 (83 articles, 14 reviews)
Publication years	2019–2026 (2026 incomplete)
Share published in 2025–2026	77.3%
Journals	70
Authors	353
Countries of author affiliation	52

Studies with authors from more than one country	46 (47.4%)
Open-access studies	60 (61.9%)
Citations received (Scopus, 12 November 2026)	2,273; mean 23.4; median 4
Cited references (total / unique after matching)	6,960 / 5,405
Author keywords (raw / after thesaurus)	370 / 258

4.2 Sources, countries and influential studies

The 97 studies are spread over 70 journals, which is typical of a topic without an established home. Sustainability (10 studies) and Discover Sustainability (6) are the most frequent outlets, followed by Sustainable Futures (4) and Business Strategy and the Environment, Journal of Cleaner Production and Journal of Hospitality and Tourism Insights (3 each) (Table 4). Sixty studies (61.9%) are open access. Journals from the core of the HRM discipline are rare: Human Resource Management Review, Personnel Review, Employee Relations and the International Journal of Hospitality Management each contribute one study. The topic is being developed mainly in sustainability and environmental management journals and not in the HRM journals in which the critical AI-in-HRM debate takes place.

Authors from 52 countries contributed. India (23 studies), China (22), Pakistan (19) and Malaysia (13) lead, followed by Saudi Arabia (9), the United Arab Emirates (8), and the United Kingdom, the United States and Vietnam (7 each). Productivity and impact diverge: studies with authors in the United Arab Emirates, China and Pakistan have accumulated the most citations, whereas the Indian output, much of it published in 2025–2026, has so far attracted few. Authorship is also concentrated in a small number of teams. One group of co-authors contributes five studies on Pakistani manufacturing and service SMEs, and another contributes five studies on Vietnamese hotels, so the number of independent research programmes is smaller than the number of papers suggests.

Table 4 Most productive journals and countries

Rank	Journal	Studies	Citations	Country	Studies	Citations
1	Sustainability	10	182	India	23	222
2	Discover Sustainability	6	186	China	22	579
3	Sustainable Futures	4	1	Pakistan	19	501
4	Business Strategy and the Environment	3	198	Malaysia	13	377
5	Journal of Cleaner Production	3	682	Saudi Arabia	9	239
6	Journal of Hospitality and Tourism Insights	3	36	United Arab Emirates	8	661
7	Corporate Social Responsibility and Environmental Management	2	1	United Kingdom	7	310
8	Systems	2	7	United States	7	349

Note: countries counted once per study (full counting); a study with authors from several countries is counted for each.

Citations are highly skewed (mean 23.4, median 4). The five most-cited studies account for 48.9% of the 2,273 citations received by the corpus (Table 5). The most-cited study, Singh and El-Kassar (2019), examined how the integration of big data technologies with green supply chain and green HR practices builds sustainable capabilities; it predates the AI label and has become the anchor of the analytics stream. Waqas et al. (2021) likewise treated big data analytics as a route to green innovation and environmental performance. The most-cited studies that use the term AI are Odugbesan et al. (2023), in which AI moderates the effect of green talent management on innovative work behaviour, and Ogbeibu et al. (2024) and Ogbeibu et al. (2022), which introduced the capability construct covering smart technology, AI, robotics and algorithms (STARA) into GHRM research. Jia and Hou (2024) is the most-cited study of AI-driven sustainable HRM at the employee level.

Table 5 Ten most-cited studies in the corpus

Rank	Study	Journal	Citations	Role of AI / analytics	Front
1	Singh and El-Kassar (2019)	Journal of Cleaner Production	474	Complementary resource	5
2	Waqas et al. (2021)	Journal of Cleaner Production	206	Complementary resource	5
3	Odugbesan et al. (2023)	Journal of Knowledge Management	200	Amplifier (moderator)	7
4	Ogbeibu et al. (2024)	Business Strategy and the Environment	129	Enabler	7
5	Ogbeibu et al. (2022)	Journal of Intellectual Capital	102	Amplifier (moderator)	7
6	Khan et al. (2024)	Journal of Environmental Planning and Management	86	Amplifier (moderator)	5
7	Jia and Hou (2024)	Discover Sustainability	73	Embedded practice	1
8	Feng and Sheng (2023)	Business Strategy and the Environment	69	Complementary resource	5
9	Singh et al. (2025b)	Sustainability	66	Review / conceptual	1
10	Ali et al. (2020)	Journal of Asian Finance, Economics and Business	65	Complementary resource	5

Note: citation counts from Scopus on 12 November 2026. Front = bibliographic coupling cluster (Table 8).

4.3 Thematic structure: keyword co-occurrence

Forty-one harmonized author keywords occur in at least two studies; they are connected by 199 links with a total link strength of 483 and form four clusters (Fig. 3, Table 6). "Green HRM" (62 occurrences) and "artificial intelligence" (50) are the two hubs, followed by "sustainable performance" (21), "big data analytics" (18) and "sustainable HRM" (17).

Cluster 1, capability foundations of green HRM and environmental performance, links green HRM to environmental performance, organizational sustainability and the sustainable development goals, and contains the field's two main theories as keywords (resource-based view and dynamic capabilities) together with STARA capability and AI adoption. Cluster 2, AI-driven sustainable HRM and the digital workplace, groups sustainable HRM with digital transformation, HR analytics, algorithmic management, generative AI, employee engagement

and employee performance. It is the only cluster in which the social dimension of sustainability and the risks of algorithmic work appear. Cluster 3, analytics capability and firm-level sustainable performance, combines big data analytics with sustainable and financial performance, green innovation, circular economy and data-driven culture. Cluster 4, AI and employee-level green outcomes, connects artificial intelligence with employee green behaviour, green talent management, innovative work behaviour, transformational leadership and green competitive advantage.

The map shows a split that recurs throughout the analysis. Green HRM is connected to firm-level performance, capabilities and analytics (Clusters 1 and 3), whereas sustainable HRM is connected to the digital workplace and employee outcomes (Cluster 2). The environmental and the social readings of "sustainability" are thus pursued by partly separate communities with different vocabularies. Notably absent as keywords with two or more occurrences are terms for ethics, fairness, trust, transparency or privacy, and any term for the energy or carbon footprint of AI.

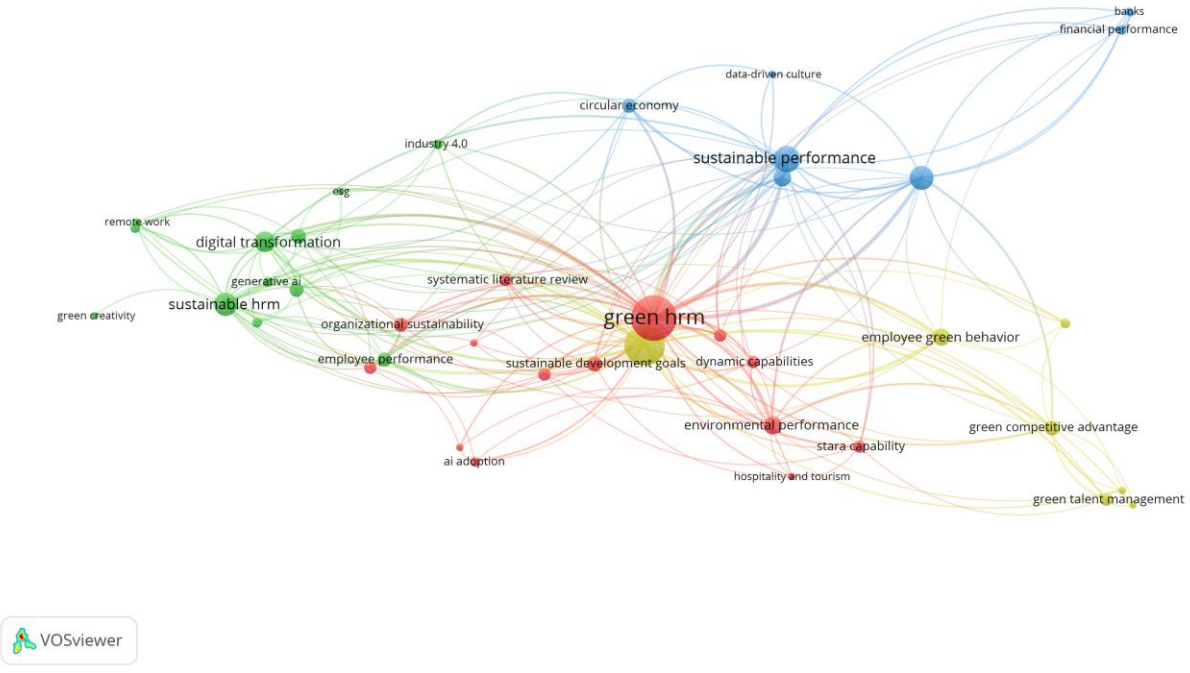


Fig. 3 Keyword co-occurrence network of the 41 author keywords occurring in at least two studies (VOSviewer 1.6.21; association-strength normalization; node size = occurrences; colours = clusters)

Table 6 Keyword co-occurrence clusters

Cluster	Label	Keyword	Keywords (occurrences)

		s	
1	Capability foundations of green HRM and environmental performance	14	green hrm (62); environmental performance (10); sustainable development goals (7); organizational sustainability (6); environmental sustainability (5); resource-based view (5); stara capability (5); dynamic capabilities (5); systematic literature review (5); machine learning (5); ai adoption (3); organizational performance (2); hospitality and tourism (2); employee retention (2)
2	AI-driven sustainable HRM and the digital workplace	12	sustainable hrm (17); digital transformation (13); human resource management (7); hr analytics (6); employee performance (6); generative ai (3); algorithmic management (3); industry 4.0 (3); employee engagement (3); green creativity (2); remote work (2); esg (2)
3	Analytics capability and firm-level sustainable performance	8	sustainable performance (21); big data analytics (18); green innovation (9); circular economy (6); financial performance (3); green management (2); data-driven culture (2); banks (2)
4	AI and employee-level green outcomes	7	artificial intelligence (50); employee green behavior (9); green competitive advantage (7); green talent management (5); green supply chain management (3); transformational leadership (2); innovative work behavior (2)

Note: clusters from VOSviewer 1.6.21; keywords harmonized with the thesaurus described in Section 3.5.

4.4 Emerging trends: overlay analysis

The overlay map (Fig. 4) colours each keyword by the average publication year of the studies that use it. The oldest vocabulary belongs to the analytics stream: "green management", "banks" and "financial performance" (average 2020.5 to 2022.3), "big data analytics" (2023.6), "green supply chain management" (2023.7) and "green talent management" (2023.8). The label "artificial intelligence" is more recent (2025.3), and the most recent terms are "generative AI" (2025.7), "employee green behavior" (2025.9), "algorithmic management", "ESG" and "remote work" (all 2026.0), together with "HR analytics" (2025.5) and "organizational sustainability" (2025.7). Three shifts can be read from this pattern: from big data analytics to AI as the technological referent; from firm-level performance to employee-level behaviour and experience; and, at the youngest edge, from AI as a capability to AI as a way of managing people. The older keywords also carry far more citations per study (for example 67.2 for big data analytics against 15.0 for artificial intelligence), which is a function of age and should not be read as greater influence of the ideas.

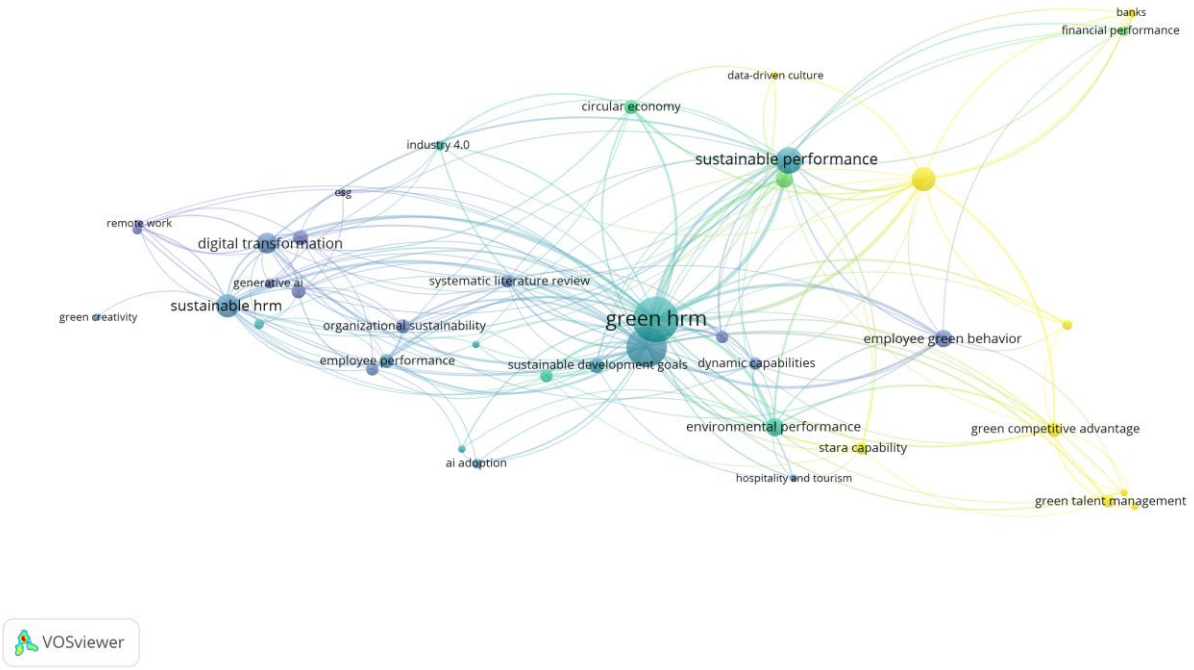


Fig. 4 Overlay visualization of the keyword network (colour = average publication year of the studies using the keyword)

4.5 Intellectual base: co-citation analysis

Fifty-four references are cited by at least six of the 97 studies; they are connected by 856 co-citation links and form four clusters (Fig. 5, Table 7). The most-cited references are Renwick et al. (2013) and the discriminant-validity criterion of Henseler et al. (2015) (21 citing studies each), followed by the common method bias test of Kock (2015) (20), Dumont et al. (2017) (16), and Barney (1991), Fornell and Larcker (1981) and Hair et al. (2019) (14 each).

Cluster A (17 references) joins the emerging AI–GHRM empirical core, led by Ogbeibu et al. (2024) and including Azhar et al. (2025), Al Masud et al. (2024) and Najam Shaikh et al. (2025), with employee-level GHRM research (Dumont et al., 2017), dynamic capabilities (Teece et al., 1997), the AMO framework (Appelbaum et al., 2000) and measurement references (Fornell & Larcker, 1981; Henseler et al., 2015; Podsakoff et al., 2003). Cluster B (17 references) contains the GHRM foundations (Jabbour & de Sousa Jabbour, 2016; Jackson et al., 2011; Ren et al., 2018; Renwick et al., 2013; Tang et al., 2018), the resource-based and natural-resource-based views (Barney, 1991; Hart, 1995) and the big data analytics capability literature (Akter et al., 2016; Gunasekaran et al., 2017; Singh & El-Kassar, 2019). Cluster C (11 references) is the bridge to AI in HRM and sustainable HRM: Tambe et al. (2019), Budhwar et al. (2023), Marler

and Boudreau (2017) and Chowdhury et al. (2023) sit beside Aust et al. (2020) and Ehnert et al. (2016) and the PRISMA statement (Page et al., 2021), which reflects the reviews in the corpus. Cluster D (9 references) combines partial least squares methodology (Hair et al., 2019; Kock, 2015) with the origins of the STARA construct (Brougham & Haar, 2018; Ogbeibu et al., 2021; Ogbeibu et al., 2022).

Three observations follow. First, the field has a recognizable base, but AI enters it through a narrow door: a small set of AI-in-HRM overviews and the STARA and big data capability constructs. None of the 54 core references comes from the literatures on algorithmic management and control, automation versus augmentation, algorithmic fairness or socio-technical systems, and none concerns the environmental cost of AI. Second, at least ten of the 54 core references are methodological (structural equation modelling, common method bias, statistical power), and two of the three most-cited references are measurement criteria. A field whose most shared references are tests for survey models is a field whose common ground is a research design more than a theory. Third, the AI-in-HRM cluster is tied to sustainable HRM and to the reviews, whereas the empirical green HRM studies draw mainly on Clusters A, B and D. The critical AI literature that does reach the field therefore reaches its reviews more than its empirical models.

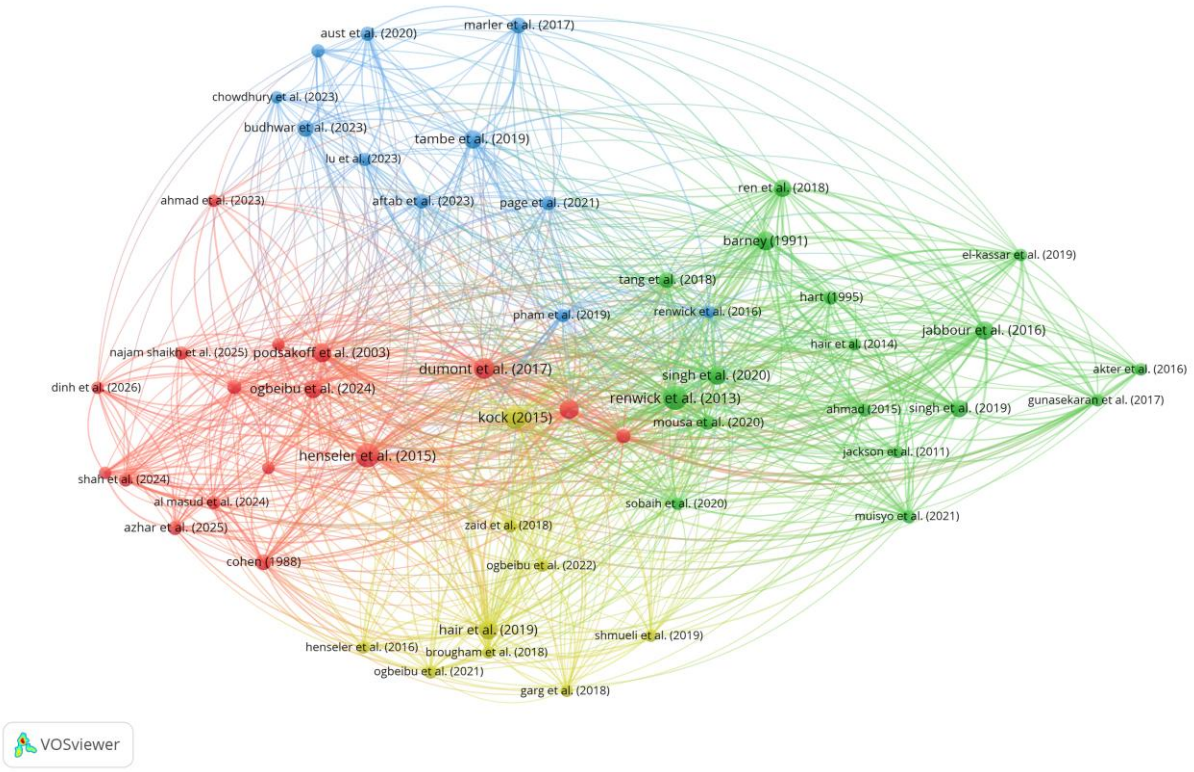


Fig. 5 Co-citation network of the 54 references cited by at least six of the 97 studies (VOSviewer 1.6.21; node size = number of citing studies in the corpus; colours = clusters)

Table 7 Co-citation clusters (intellectual base)

Cluster	Label	References	Most-cited references [number of citing studies in the corpus]
A	Emerging AI–GHRM empirical core, employee-level GHRM, dynamic capabilities and measurement	17	Henseler et al. (2015) [21]; Dumont et al. (2017) [16]; Fornell and Larcker (1981) [14]; Ogbeibu et al. (2024) [13]; Podsakoff et al. (2003) [13]; Azhar et al. (2025) [8]; Teece et al. (1997) [8]; Al Masud et al. (2024) [7]; Najam Shaikh et al. (2025) [7]; Appelbaum et al. (2000) [6]
B	GHRM foundations, resource-based views and big data analytics capability	17	Renwick et al. (2013) [21]; Barney (1991) [14]; Jabbour and de Sousa Jabbour (2016) [13]; Singh et al. (2020) [12]; Singh and El-Kassar (2019) [11]; Ren et al. (2018) [11]; Tang et al. (2018) [9]; Mousa and Othman (2020) [8]; Hart (1995) [8]; Akter et al. (2016) [6]; Jackson et al. (2011) [6]; Gunasekaran et al. (2017) [6]
C	AI in HRM, HR analytics and sustainable HRM	11	Tambe et al. (2019) [12]; Budhwar et al. (2023) [10]; Marler and Boudreau (2017) [9]; Aust et al. (2020) [8]; Page et al. (2021) [8]; Ehnert et al. (2016) [7]; Chowdhury et al. (2023) [6]
D	Partial least squares methodology and the STARA construct	9	Kock (2015) [20]; Hair et al. (2019) [14]; Zaid et al. (2018) [7]; Ogbeibu et al. (2021) [7]; Ogbeibu et al. (2022) [6]; Brougham and Haar (2018) [6]

Note: only references that are also discussed in the text are listed; the full list of the 54 co-cited references is given in the supplementary material.

4.6 Research fronts: bibliographic coupling

All 97 studies are connected by bibliographic coupling (1,954 links; total link strength 4,034). VOSviewer grouped them into seven clusters, interpreted here as research fronts (Fig. 6, Table

8). Cross-tabulating the clusters with the coded role of AI shows that the fronts differ in how they position AI, which is evidence that the role typology captures real divisions in the literature.

Front 1 (29 studies), AI-driven sustainable HRM, reviews and the social dimension, is the largest. It contains 13 of the 23 reviews and conceptual papers, all five qualitative studies and five of the ten studies in which AI is embedded in the HR practice construct. Its studies address engagement, performance, resilience, fairness and dignity (Calabrese et al., 2026; Huang et al., 2026; Jia & Hou, 2024; Mehmood et al., 2026; Virgillito & Ledda, 2026). Front 2 (19 studies), AI and STARA capability in green HRM models, consists mainly of survey studies in Asian manufacturing, hospitality and logistics in which AI is an antecedent, moderator or mediator (Al Masud et al., 2024; Azhar et al., 2025; Hoang & Ha, 2025; Hossain et al., 2025; Kayani et al., 2026). Front 3 (17 studies), AI-enabled green HRM, leadership and employee green behaviour in hospitality, is the youngest (mean publication year 2025.9) and includes the series of Vietnamese hotel studies (Dinh et al., 2026a; Dinh et al., 2026b) and studies of green creativity, training and task–technology fit (Hao et al., 2025; Wang et al., 2026; Yousaf et al., 2026). Front 4 (12 studies), systematizing reviews and contextual readiness, groups reviews of AI-enabled GHRM (Alherimi et al., 2025; Jena et al., 2026; Kapruwan et al., 2026; Mavunda, 2026) with studies of readiness and governance (Islam et al., 2026; Kapoor et al., 2026).

Front 5 (10 studies), big data analytics and green capabilities, is the oldest (mean year 2022.2) and by far the most cited (1,066 citations). Analytics is treated either as a resource alongside GHRM or as a moderator of its effects (Feng & Sheng, 2023; Jaaron et al., 2025; Khan et al., 2024; Singh & El-Kassar, 2019; Waqas et al., 2021). Front 6 (5 studies) continues this logic for SMEs and adds ethical AI as a capability (Shaikh et al., 2026; Tedjakusuma et al., 2026). Front 7 (5 studies), green talent management and STARA competence, contains the highly cited studies in which AI moderates talent management effects (Odugbesan et al., 2023; Ogbeibu et al., 2022; Ogbeibu et al., 2024).

The coupling structure confirms and sharpens the co-word result. The analytics front (Front 5) is intellectually distinct from the AI fronts although it studies similar relationships, so its well-cited findings on big data capabilities are being carried over to "AI" by analogy more than by evidence. The social-sustainability front (Front 1) and the environmental-performance fronts

(Fronts 2, 3, 5, 6 and 7) share few references. And the reviews are concentrated in Fronts 1 and 4, apart from the empirical fronts whose results they summarize.

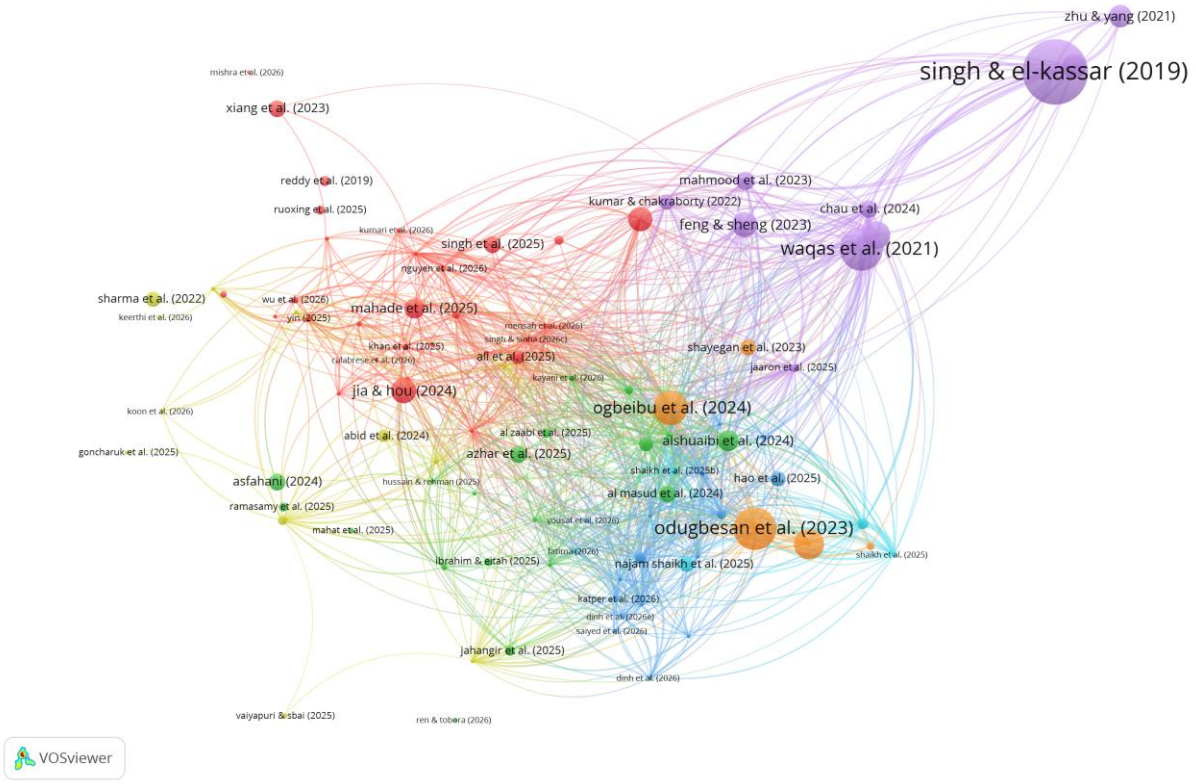


Fig. 6 Bibliographic coupling network of the 97 included studies (VOSviewer 1.6.21; node size = citations received; colours = clusters)

Table 8 Bibliographic coupling clusters (research fronts)

Front	Label	Studies	Mean year	Citations	Main roles of AI (studies)	Representative studies
1	AI-driven sustainable HRM, reviews and the social dimension	29	2025.2	346	Review / conceptual (13); Embedded practice (5); Qualitative (5); Technical artefact (3); Enabler (2)	Jia and Hou (2024); Mehmood et al. (2026); Huang et al. (2026); Virgillito and Ledda (2026); Calabrese et al. (2026); Yin (2025); Singh et al. (2025a)
2	AI and STARA capability in green HRM models	19	2025.2	227	Enabler (5); Amplifier (moderator) (4); Mediator (3); Technical artefact (3); Review / conceptual (2); Complementary resource (2)	Hossain et al. (2025); Al Masud et al. (2024); Azhar et al. (2025); Hoang and Ha (2025); Kayani et al. (2026); Alshuaibi et al. (2024)
3	AI-enabled green HRM, leadership and employee green behaviour in hospitality	17	2025.9	59	Enabler (8); Embedded practice (4); Amplifier (moderator) (4)	Dinh et al. (2026a); Dinh et al. (2026b); Wang et al. (2026); Hao et al. (2025); Yousaf et al. (2026); Han et al. (2026)
4	Systematizing reviews and contextual readiness	12	2025.2	64	Review / conceptual (8)	Alherimi et al. (2025); Jena et al. (2026); Kapruwan et al. (2026); Mavunda (2026); Islam et al. (2026); Kapoor et al. (2026)

5	Big data analytics and green capabilities	10	2022.2	1,066	Complementary resource (6); Amplifier (moderator) (4)	Singh and El-Kassar (2019); Waqas et al. (2021); Feng and Sheng (2023); Khan et al. (2024); Jaaron et al. (2025); Mahmood et al. (2023)
6	Analytics and ethical AI capability in SMEs and manufacturing	5	2025.4	44	Complementary resource (2); Mediator (2)	Shaikh et al. (2026); Shaikh et al. (2025); Tedjakusuma et al. (2026); Najam Shaikh et al. (2025)
7	Green talent management and STARA competence	5	2023.2	467	Amplifier (moderator) (4)	Odugbesan et al. (2023); Ogbeibu et al. (2022); Ogbeibu et al. (2024); Hu et al. (2024)

Note: mean year = mean publication year of the studies in the front; roles as defined in Table 9 (roles with at least two studies shown).

4.7 Collaboration structure

Forty-six of the 97 studies (47.4%) have authors from more than one country. The co-authorship network of the 23 countries with at least two studies has 54 links and no single centre (Fig. 7). The strongest structures are a Pakistan–Malaysia axis, a China-centred group, an India–United Arab Emirates group, a Saudi Arabia–Jordan group, and a group around the United Kingdom and Australia that links several Asian and Middle Eastern countries. Vietnam, despite seven studies, has no co-authorship link with any other country in the network. Collaboration is thus mainly South–South and intra-regional. Researchers from the countries where the critical AI-in-HRM literature is mostly produced participate as occasional partners and not as a hub.

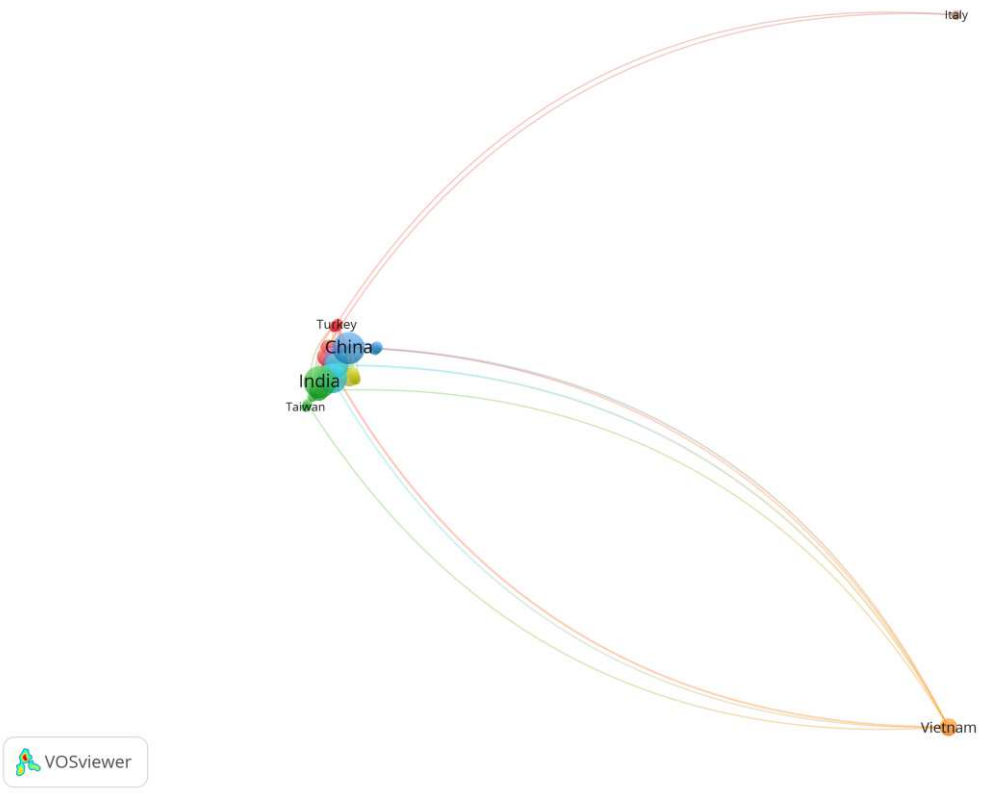


Fig. 7 Country co-authorship network (23 countries with at least two studies; node size = number of studies; colours = clusters)

5 Critical synthesis of the literature

5.1 Five structural roles of AI

The coding of all 97 Scopus studies shows that 62 report quantitative models of relationships among AI, green or sustainable HRM and outcomes, 23 are reviews or conceptual papers, 7 present technical artefacts or decision models and 5 offer qualitative or case evidence. Among the 62 quantitative studies, AI occupies five different structural positions (Table 9). The two additional studies in the synthesis, Ajuluchukwu et al. (2026) and Mollah et al. (2024), both treat AI as part of the HR practice construct and belong to the embedded-practice group.

In the enabler role (18 studies), AI capability or adoption is an antecedent and GHRM transmits its effect to performance. Ogbeibu et al. (2024) found that organizational STARA capability predicts GHRM programmes and environmental sustainability, and similar chains run from AI to GHRM to green or sustainable performance in manufacturing (Al Masud et al., 2024; Najam Shaikh et al., 2025), hospitality (Azhar et al., 2025; Dinh et al., 2026a; Hossain et al., 2025),

other firm samples (Ali et al., 2025a; Katper et al., 2026) and supply chains (Mensah et al., 2026). In the amplifier role (18 studies), GHRM is the antecedent and AI or analytics moderates its effect on innovation, circular-economy or environmental outcomes (Abid et al., 2024; Alshuaibi et al., 2024; Din et al., 2026; Housheya & Atikbay, 2025; Khan et al., 2024; Odugbesan et al., 2023). In the mediator role (6 studies), the direction is reversed: GHRM is assumed to foster the use of AI, analytics or chatbots, which then carries the effect on performance (Jahangir et al., 2025; Kayani et al., 2026; Mahat et al., 2025; Shaikh et al., 2026; Zhen et al., 2026). In the complementary-resource role (10 studies), AI or analytics and GHRM are parallel antecedents of capabilities or performance (Feng & Sheng, 2023; Nazir et al., 2026; Singh & El-Kassar, 2019; Tedjakusuma et al., 2026; Waqas et al., 2021). In the embedded-practice role (10 studies), there is a single construct, "AI-driven" or "AI-enabled" sustainable or green HRM, whose consequences for employees are examined (Ajuluchukwu et al., 2026; Hao et al., 2025; Jia & Hou, 2024; Mehmood et al., 2026; Thangaraju & Palani, 2025).

Three points deserve emphasis. First, the roles are almost evenly distributed, and no role has become the standard. Second, the roles are not interchangeable. The enabler model claims that AI changes what HR does; the amplifier model claims that AI changes how well a given HR system works; the mediator model claims that HR drives technology use; the embedded model claims that the practice and the technology cannot be separated. Third, and most important, the choice of role is seldom derived from theory or from the nature of the technology. Studies with near-identical constructs, samples and analysis techniques place AI before, beside, between or after GHRM. With cross-sectional data all of these models can fit, so the accumulation of "supported" models adds little knowledge about which specification is correct. The literature has shown repeatedly that perceptions of AI and perceptions of GHRM are correlated; it has not yet shown the ordering among them.

Table 9 Typology of the roles assigned to AI in green and sustainable HRM research (97 Scopus studies)

Role of AI	Underlying claim	Typical model	Studies	Representative studies
Enabler (antecedent)	AI changes what HR does: AI capability makes green HR practices possible or better	AI → GHRM → outcome	18	Ogbeibu et al. (2024); Azhar et al. (2025); Al Masud et al. (2024); Ali et al. (2025a); Mensah et al. (2026)
Amplifier (moderator)	AI changes how well a given HR system works	GHRM × AI → outcome	18	Odugbesan et al. (2023); Khan et al. (2024); Alshuaibi et al. (2024); Jaaron et al. (2025); Han et al. (2026)
Mediator	HR practices drive the use of AI, which carries their effect	GHRM → AI → outcome	6	Jahangir et al. (2025); Kayani et al. (2026); Zhen et al. (2026);

				Shaikh et al. (2026)
Complementary resource	AI or analytics and GHRM are parallel resources or capabilities	AI + GHRM → capability → outcome	10	Singh and El-Kassar (2019); Waqas et al. (2021); Feng and Sheng (2023); Nazir et al. (2026); Tedjakusuma et al. (2026)
Embedded practice	Technology and practice form one construct (AI-driven sustainable or green HRM)	AI-enabled HRM → employee outcome	10	Jia and Hou (2024); Mehmood et al. (2026); Thangaraju and Palani (2025); Hao et al. (2025); Yousaf et al. (2026)
Technical artefact	An AI model or platform is built for an HR sustainability task	Design and evaluation of a model	7	Nguyen et al. (2026); Ramasamy et al. (2025); Mishra et al. (2026)
Qualitative / case	AI in HR practice is observed in context	Interviews, focus groups, cases	5	Virgillito and Ledda (2026); Ramgolam et al. (2026); Xiang et al. (2023)
Review / conceptual	Synthesis or framework	–	23	Alherimi et al. (2025); Singh et al. (2025a); Huang et al. (2026); Yin (2025)

Note: roles coded from the abstract of each study; the 62 quantitative model studies are those in the first five rows.

5.2 Theoretical foundations

Fewer than half of the abstracts name a theory (46 of 97; 36 of the 62 quantitative studies). Where theories are named, the resource-based and natural-resource-based views dominate (19 studies), followed by dynamic capabilities (13) and the AMO framework (10). Socio-technical systems theory appears in five studies: three reviews or conceptual papers (Kumari et al., 2026; Mavunda, 2026; Singh et al., 2025a), one qualitative case (Virgillito & Ledda, 2026) and, among the quantitative studies, only Mensah et al. (2026). Technology-fit and acceptance models, social cognitive theory and social exchange theory each appear in three or four studies. These counts are lower bounds because they rest on abstracts, but the ranking agrees with the co-citation map, in which Barney (1991), Hart (1995) and Teece et al. (1997) are core references and no socio-technical or algorithmic-management source is.

The use of the resource-based view is often nominal. The theory predicts advantage from resources that are rare and hard to imitate, but the studies generally measure whether respondents agree that their organization uses AI, which says nothing about rarity or inimitability, and purchasable AI tools are a doubtful candidate for either (Barney, 1991; Mikalef & Gupta, 2021). The more defensible resource-based argument, that the hard-to-imitate resource is the combination of technology, skills and context, is stated by several authors (Nazir et al., 2026; Singh & El-Kassar, 2019; Tedjakusuma et al., 2026) but is tested as two additive main effects more often than as complementarity. Dynamic capability arguments about sensing and reconfiguring over time are tested with single-wave data. AMO is used to classify practices, but the ability to work with AI is seldom measured. The theories that could explain when AI-enabled

HR practices help or harm, namely socio-technical joint optimization (Makarius et al., 2020; Trist & Bamforth, 1951), HRM system strength (Bowen & Ostroff, 2004) and the automation–augmentation distinction (Raisch & Krakowski, 2021), are close to absent from the empirical models.

5.3 Methods, measures and contexts

The evidence base is methodologically homogeneous. At least 44 of the 62 quantitative studies (71.0%) use structural equation modelling, 35 of them partial least squares, and the abstracts of only seven refer to time-lagged, multi-wave or longitudinal data (Katper et al., 2026; Mehmood et al., 2026; Yousaf et al., 2026). Where sample sizes are reported in the abstract (29 studies), the median is 400 respondents. Data are almost always perceptions reported by employees or managers, usually from a single source and collected through purposive or convenience sampling. Common method variance is acknowledged in the usual way, which is why Podsakoff et al. (2003) and Kock (2015) are among the most co-cited references, but statistical tests do not remove the problem that predictor, mechanism and outcome are opinions of the same person at the same moment (Podsakoff et al., 2003; Rindfleisch et al., 2008). Objective environmental indicators such as energy use, emissions or waste are rare.

The measurement of AI is the weakest link. In most models "AI", "AI adoption", "AI capability" or "STARA capability" is a short perceptual scale that does not identify which system is used, in which HR function, for what decision or with how much autonomy. Screening algorithms, learning recommender systems, chatbots, sensor-based eco-feedback and generative assistants are thereby treated as one variable. Only a few studies examine a specific application, for example avatar-led green training (Hao et al., 2025), chatbot usability (Kayani et al., 2026), AI-based scheduling (Virgillito & Ledda, 2026), explainable attrition models (Nguyen et al., 2026), a generative tool for screening job advertisements (Calabrese et al., 2026) or a multi-agent HR platform (Mishra et al., 2026). The construct label has also shifted from big data analytics to AI without a corresponding change in what is measured, as the overlay map indicates.

The contexts are narrow. Of the 48 quantitative studies whose abstract states where the data were collected, 12 use data from Pakistan, 7 from China, 7 from Vietnam and 4 from India; the remainder come from other Asian, Middle Eastern and African economies. None of these 48 studies reports survey data from Europe or North America; European primary evidence in the

corpus is limited to a qualitative hospital case and a design study of a recruitment tool (Calabrese et al., 2026; Virgillito & Ledda, 2026). Manufacturing (17 studies) and hospitality and tourism (13) account for almost half of the quantitative studies, followed by logistics and supply chains (7), higher education (6) and banking (4). The concentration is not a weakness in itself, since emerging economies are where much industrial growth and environmental pressure are located, and Mavunda (2026) rightly argues for attention to infrastructural constraints in Sub-Saharan Africa. It does mean that the evidence comes from settings with comparatively low AI maturity in HR, where respondents may be rating expectations more than experience, and from regulatory environments that differ from those in which AI in employment is now tightly regulated.

5.4 Outcomes

Outcomes are dominated by environmental and green performance (33 of the 62 quantitative studies) and by sustainable, organizational or financial performance (28). Employee well-being and other social outcomes, such as engagement, retention, resilience and job satisfaction, are examined in 14 studies, and employee green behaviour, creativity or commitment in 10. Although "organizational sustainability" implies economic, environmental and social performance together, few studies measure more than one dimension separately (Ali et al., 2025a; Tedjakusuma et al., 2026), so trade-offs among them cannot be observed. The framing of the field matters here. Seventy-five of the 97 studies are framed as green HRM and 22 as sustainable HRM, and it is in the latter, smaller group that social outcomes and employee experience are studied. The environmental consequences of AI-enabled HR for the organization and its human consequences for employees are therefore examined in different studies, and almost never in the same model.

5.5 Contradictory evidence and blind spots

The dominant narrative of the abstracts, and of several earlier reviews, is that AI strengthens GHRM and sustainability. A closer reading shows results that do not fit this narrative, and they are among the most informative in the corpus. Ogbeibu et al. (2024) found that STARA capability, while positively related to GHRM and environmental sustainability, dampens the positive relationship between green training, involvement and development and environmental sustainability. Hossain et al. (2025) found no direct effect of STARA on green performance; the effect ran only through GHRM and employee green commitment. Hoang and Ha (2025) reported

that AI is negatively related to green structural capital, an effect that weakens at higher levels of GHRM. Jaaron et al. (2025) found that only the assimilation of big data analytics moderated the effect of GHRM, whereas acceptance and adoption did not. Han et al. (2026) found one of three hypothesized moderation effects of AI adoption. Tedjakusuma et al. (2026) found no direct association between GHRM practices and environmental or economic performance; the association ran through ethical AI and green innovation. Kayani et al. (2026) showed that technostress weakens the link between chatbot usability and sustainable employee performance, Ogbeibu et al. (2022) that leader STARA competence is related to turnover intention in complex ways, and Keerthi et al. (2026) that HR sustainability practices were unrelated to sustainability reporting in algorithm-driven quick commerce.

Read together, these results suggest a consistent pattern that the literature has not yet named: technology has little or no direct effect, deeper forms of use matter more than adoption, and AI can substitute for or crowd out the human and structural elements of GHRM as well as complement them. This is what socio-technical theory and the augmentation literature would predict (Raisch & Krakowski, 2021; Trist & Bamforth, 1951). The qualitative evidence points the same way. Virgillito and Ledda (2026) found that an AI scheduling system supported people sustainability because it was embedded in participatory structures, and Ramgolam et al. (2026) found that the use of AI in Mauritian hotels remains limited.

Four blind spots are visible. (1) Ethics, fairness, trust and transparency are mentioned in 21 of the 97 abstracts but are variables in only a handful of models (Mahade et al., 2025; Mehmood et al., 2026; Tedjakusuma et al., 2026; Wang et al., 2026); conceptual papers carry the argument (Huang et al., 2026; Kapoor et al., 2026; Yin, 2025). (2) Readiness and skills, such as digital literacy, AI literacy and technological readiness, appear in few studies even though those that include them find that they matter (Abid et al., 2024; Ajuluchukwu et al., 2026; Ali et al., 2025a; Azhar et al., 2025; Islam et al., 2026). (3) Not one of the 97 abstracts refers to the energy use, carbon emissions or hardware footprint of the AI systems whose environmental benefits are being claimed, although this cost is well documented (Luccioni et al., 2024; Schwartz et al., 2020; van Wynsberghe, 2021). (4) The possibility of symbolic adoption, in which AI-enabled GHRM is announced but loosely coupled to practice, is not examined, even though perceptual measures cannot tell substantive from symbolic adoption and research on decoupling and

greenwashing shows that the gap is common (Bromley & Powell, 2012; Delmas & Burbano, 2011).

6 Discussion: an integrative framework and research agenda

6.1 What the combined evidence shows

The bibliometric and critical results converge on four conclusions. First, the field is a research front without a consolidated core: young, fast-growing, dispersed across outlets and dependent on a few early, highly cited studies from the big data analytics stream. Second, its thematic and intellectual structures are divided between an environmental, firm-level, capability-oriented stream framed as green HRM and a social, employee-level stream framed as sustainable HRM; the two share few keywords and few references. Third, its theoretical base was inherited from GHRM research and strategic management and has not integrated the literatures that explain how algorithmic technologies change HR work. Fourth, the evidence consists overwhelmingly of cross-sectional associations among perceptions, obtained in a limited set of national and sectoral contexts, with AI specified in five different structural positions.

It follows that the frequently repeated statement that "AI enhances GHRM and sustainability" is better understood as a hypothesis that is plausible, repeatedly found to be consistent with survey data and not yet tested in ways that could refute it. The role of AI in GHRM and organizational sustainability is conditional. The more informative findings in the corpus indicate that effects are indirect, depend on depth of use and on human and social conditions, and can be negative.

6.2 A socio-technical capability-conversion framework

Figure 8 integrates the evidence into a framework built on one idea: AI resources do not produce sustainability outcomes; they are converted into outcomes through HR practices and through technical and social conditions, and the conversion can fail or generate costs. The framework assigns each of the four lenses in Section 2.3 a specific task instead of invoking them side by side. The resource-based view explains the first link, AMO the content of the practices, socio-technical theory the conversion conditions and dynamic capabilities the feedback over time. It also locates the five AI roles found in the literature as parts of a single process: AI as enabler (the link from AI resources to practices), AI embedded in practices (the content of the practice box), AI as amplifier (the dashed moderating path), AI as complementary resource (the joint presence

of the first two boxes) and AI as mediator (the feedback through which HR practices increase the use of AI). Six propositions summarize the framework.

Proposition 1 (enablement). AI resources improve organizational sustainability mainly by changing the content and reach of green HR practices (who is selected, what is learned, what is measured and fed back), and their direct effect on sustainability outcomes, net of these practices, is small. This reflects the mediated effects reported by Al Masud et al. (2024) and Azhar et al. (2025) and the absence of a direct effect in Hossain et al. (2025), and it follows from the resource-based argument that the tool alone is not a source of advantage.

Proposition 2 (conditional amplification). AI strengthens the effect of green HR practices on outcomes only at deeper levels of use, such as assimilation into routines and decisions, and can weaken it where AI substitutes for the participatory elements of GHRM. The proposition accounts both for the positive moderation effects (Khan et al., 2024; Odugbesan et al., 2023) and for the results of Jaaron et al. (2025) and Ogbeibu et al. (2024).

Proposition 3 (dual conversion). AI-enabled green HR practices affect employee-level and organizational outcomes through two mechanisms: a technical one, comprising digital and AI literacy, technological readiness and explainability, and a social one, comprising green climate, leadership, trust and perceived fairness. Evidence for each mechanism exists separately (Ajuluchukwu et al., 2026; Ali et al., 2025a; Islam et al., 2026; Mehmood et al., 2026; Wang et al., 2026); the proposition calls for testing them in the same model.

Proposition 4 (joint optimization). The technical and social mechanisms are complementary: the effect of each on sustainability outcomes is stronger when the other is high. This is the central prediction of socio-technical systems theory (Appelbaum, 1997; Trist & Bamforth, 1951). It is consistent with the finding that a pro-environmental culture conditions the effect of AI adoption (Najam Shaikh et al., 2025) and with the participatory case described by Virgillito and Ledda (2026), and it has not been tested as an interaction.

Proposition 5 (countervailing effects). AI-enabled GHRM also generates costs that reduce its net contribution to organizational sustainability: erosion of trust and fairness through opaque or biased algorithms, technostress and insecurity, the energy and material footprint of AI systems, and symbolic adoption. The net effect on the three sustainability dimensions can therefore differ

in sign, and environmental gains may coincide with social losses (Hoang & Ha, 2025; Kayani et al., 2026; Kellogg et al., 2020; Köchling & Wehner, 2020; van Wynsberghe, 2021).

Proposition 6 (dynamic feedback). The relationship is recursive. Sustainability data and experience recalibrate AI resources and HR practices over time, so that GHRM also shapes AI use, as the mediator-role studies assume (Jahangir et al., 2025; Zhen et al., 2026). The different causal orderings in the literature may therefore describe different moments of one process, which cross-sectional designs cannot separate (Teece, 2007).

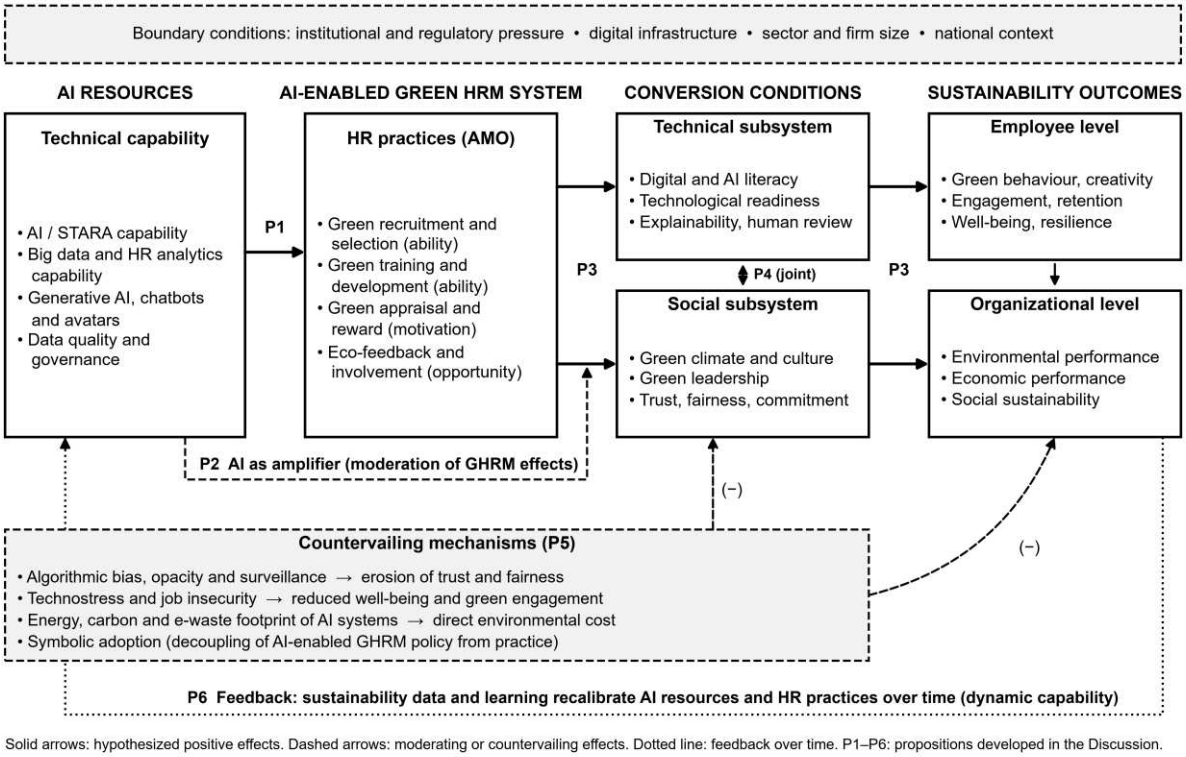


Fig. 8 Socio-technical capability-conversion framework of AI-enabled green HRM and organizational sustainability (P1–P6 = propositions)

6.3 Research agenda

Table 10 turns the gaps into research questions and design recommendations. Four priorities stand out. The first is construct clarity. Future studies should specify the AI system (function, task, degree of autonomy and data used) and distinguish adoption from assimilation, in place of generic perceptual scales (Mikalef & Gupta, 2021; Strohmeier, 2020). The second is causal design: Multi-wave, multi-source and quasi-experimental studies of actual implementations with

objective environmental indicators are required to help differentiate between the five role specifications (Rindfleisch et al., 2008). The third is 'net sustainability accounting' which involves quantifying environmental, social and economic results in the same research and accounting for the environmental impact of the AI systems themselves (Luccioni et al., 2024; Schwartz et al., 2020). The fourth is contextual breadth comparative studies of regulatory regimes and levels of digital maturity (Europe vs North America) and multilevel designs linking employee experiences to organizational outcomes (Budhwar et al., 2022; Ren et al., 2018).

Table 10 Research agenda derived from the bibliometric and critical evidence

Gap (evidence in this review)	Research questions	Recommended designs
Role ambiguity: five structural roles of AI, almost evenly distributed and rarely justified (Table 9)	Under which conditions does AI enable, amplify, substitute for or follow from green HR practices? Do the roles describe phases of one process (P1, P2, P6)?	Multi-wave panel and cross-lagged models; comparison of competing specifications on the same data; implementation studies
Construct opacity: AI measured as a generic perception; label shift from big data analytics to AI (Sections 4.4, 5.3)	Which AI applications (screening, adaptive training, eco-feedback, generative assistants) affect which HR practices and outcomes? Does assimilation matter more than adoption?	Application-specific measures; system-log and usage data; scale development separating adoption, assimilation and autonomy
Missing conversion conditions: readiness, literacy, climate and trust studied rarely and separately (Section 5.5)	Do the technical and social mechanisms jointly determine outcomes (P3, P4)?	Parallel mediation with latent interaction; multilevel models with climate aggregated to the unit; qualitative comparative analysis
One-sided outcomes: environmental and social outcomes in separate studies; AI footprint absent from all abstracts (Sections 5.4, 5.5)	What is the net effect of AI-enabled GHRM on environmental, social and economic performance once fairness, well-being and the energy use of AI are counted (P5)?	Triple-bottom-line outcome sets; objective energy, emissions and waste indicators; life-cycle estimates of AI systems
Narrow intellectual base: algorithmic-management, augmentation and socio-technical literatures outside the co-citation core (Section 4.5)	How do control, transparency and augmentation choices in AI-enabled HR shape green climate and behaviour?	Theory-driven models using socio-technical systems and HRM system strength; qualitative process studies
Contextual concentration: quantitative evidence from emerging Asian, Middle Eastern and African economies; manufacturing and hospitality dominate (Section 5.3)	Do the relationships hold under different regulatory regimes and levels of digital maturity?	Cross-national designs with measurement-invariance testing; studies in Europe and North America; under-studied sectors (public sector, healthcare, SMEs)
Design monoculture: cross-sectional, single-source survey models (Sections 4.5, 5.3)	Are the reported associations causal, and how large are they?	Field and quasi-experiments around roll-outs; multi-source data; meta-analysis once constructs converge; pre-registered replications

7 Implications

7.1 Theoretical implications

The study has three implications for theory. First, it changes the question from whether AI improves GHRM to which role AI plays, under which conditions and at what cost. The five-role typology provides a language for describing a model's claim and its justification, while Proposition 6 puts forward a proposal for the roles as phases of one process. Second, it suggests

that the resource-based reasoning which is predominant in the field should be finished. Socio-technical systems theory is also a specification of the conditions for conversion that the resource-based view leaves open, and its introduction into GHRM research bridges the gap between this field and the broader discussion on augmentation and algorithmic management (Makarius et al., 2020; Meijerink et al., 2021; Raisch & Krakowski, 2021). Third, it takes the concept of organizational sustainability used in this literature further, requiring that the technology be part of the organization being studied: the environmental and social costs of AI are part of the result and not externalities (van Wynsberghe, 2021).

7.2 Practical implications

The review will help HR managers and sustainability managers take action, but with a degree of caution and specificity. There is no evidence that having AI tools on hand will necessarily lead to better environmental outcomes; the benefits, if they are found, come with a redesigned HR process and through employees who are able and willing to engage with the tools. Investment in AI for green recruitment, training, appraisal or eco-feedback should thus be matched by investment in digital and AI literacy, by visible leadership commitment and recognition that sustains a green climate, and by explanation and human review of the decisions made by AI (Köchling & Wehner, 2020; Tambe et al., 2019). What the tools change should be measurable, whether that's energy, waste or emissions, and it should include the energy use of the systems of AI. To vendors and consultants, the findings warn against the “green HR is AI-enabled” marketing strategies based on perception surveys. For policy makers, especially in the emerging economies, where most of the evidence is drawn from, the outcomes indicate that digital-skills programmes are needed to be tied in with green-transition programmes and that transparency of algorithmic systems utilized in employment decisions is needed.

8 Limitations

The study has some limitations that restrict the conclusions that can be drawn. It is based on a single database. Scopus is very broad, but journals with coverage somewhere else are not covered, and one of the studies identified was in a journal not covered by the Scopus result set, so it had to be added by hand; to test the stability of the maps, the Scopus data could be replicated with Web of Science data. Secondly, the corpus is limited to journal articles and reviews, and not all activity is described in the maps, as 45.1% of the records retrieved are

conference papers and book chapters. Thirdly, it is a small and very young corpus (97 documents). The maps need to have low thresholds, solutions to small networks are sensitive to individual documents, and citation counts are mostly about age. Fourth, screening and coding were based on titles, abstracts, keywords, and reference lists, rather than on full texts, and were performed by one coder assisted by AI-based, rule-based coding, which lacked inter-coder reliability or was not evaluated. The next most critical step for the review itself is an entire text recoding by two independent coders. Fifth, there must be an explicit AI or analytics term in the search string and an explicit green or sustainability term in the HRM term, with studies of digital HRM with no AI wording, or of sustainability-related HR practices with other words, not covered. Sixth, no meta-analysis was attempted, because constructs and model specifications are too heterogeneous; statements about the direction of findings are narrative. Finally, the search reflects the state of Scopus on 12 November 2026, and records for 2026 are incomplete.

9 Conclusion

This study set out to establish what research has shown about the role of AI in green HRM and organizational sustainability. Combining a PRISMA-guided review with VOSviewer science mapping of 97 Scopus-indexed journal studies, and a critical synthesis of 99, it found a field that has expanded very rapidly since 2023, that is carried mainly by researchers in emerging Asian and Middle Eastern economies, and that is organized around green HRM, AI capability, big data analytics and sustainable performance. The field's shared foundations are GHRM research, the resource-based view and survey methodology; the critical literature on algorithmic HRM and on the environmental cost of AI is outside its core. AI appears in five structural roles that are used without clear theoretical justification, and the evidence consists predominantly of cross-sectional associations among perceptions. The findings that depart from the optimistic narrative, including absent direct effects, effects that depend on depth of use and occasional negative effects, are the ones that point most clearly to how AI-enabled GHRM works.

The main message is that AI in green HRM serves as a conditional resource. Its role in organizational sustainability is tied to its transformation via technology redesign and via co-produced technical and social conditions and should be measured against the costs imposed by the technology on humans and the environment. The typology, framework, proposals and agenda

presented here are designed to assist the next generation of studies to test this claim with designs that can challenge it.

Declarations

Ethics approval: The study analyses published literature and involved no human participants, so this study does not require ethical approval

Consent for publication. Not applicable.

Availability of data and materials. The Scopus search string, the screening log for all 297 records, the coding sheet, the VOSviewer map and network files, the keyword thesaurus and the Python scripts used to prepare the data and figures are provided as supplementary material. The raw Scopus export is subject to the database licence and can be regenerated with the search string reported in Section 3.3.

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