Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Artificial Intelligence in Green Human Resource Management: Examining the Mediating Role of Employee Engagement in Attaining Organizational Sustainability

Muhammad Ramzan Ali

Ramzan.ali@ajou.uz

AJOU University in Tashkent https://orcid.org/0000-0002-6510-4877

Tumsela Asghar

Virtual University of Pakistan, Lahore, Pakistan

Zulaykho Kadirova

Tashkent State University of Oriental Studies, Uzbekistan https://orcid.org/0000-0001-8487-3308

Vokhidova Mehri Khasanovna

Tashkent State University of Oriental Studies, Tashkent, Uzbekistan

Muhammad Faheem Akram

Tashkent State University of Oriental Studies, Tashkent, Uzbekistan

Research Article

Keywords: Artificial intelligence, Green human resource management, Employee engagement, Organizational sustainability, Job demands–resources theory, Bibliometric analysis

Posted Date: October 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11412497/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Abstract

Purpose: Artificial intelligence (AI) is entering green human resource management (GHRM), yet the employee-level mechanism through which AI-enabled green HR practices produce organizational sustainability remains unclear. This study maps the field and examines whether employee engagement has been theorized as that mechanism.

Design/methodology/approach: A VOSviewer-based bibliometric analysis was combined with a critical literature analysis. OpenAlex records (2010–2026) were screened using a PRISMA-informed protocol, yielding a core corpus of 206 studies on AI/digital-enabled green or sustainable HRM and a comparison corpus of 579 studies on GHRM and engagement. Performance, co-citation, term co-occurrence, overlay and co-authorship analyses were performed.

Findings: The field is nascent: 77.7% of the core studies appeared in 2025–2026. Of four co-citation clusters, AI and sustainable-HRM scholarship is the least connected to research on how GHRM shapes employee behaviour. Only five core studies (2.4%) model engagement as a mediator, and only 8.3% of GHRM engagement studies mention AI. Capability theories and cross-sectional designs dominate, and emerging evidence shows that AI can also weaken green outcomes.

Originality/value: Integrating job demands–resources theory with ability–motivation–opportunity, social exchange and socio-technical perspectives, the study proposes a dual-pathway framework in which AI-enabled GHRM can build or erode engagement, and derives seven propositions, boundary conditions and a research agenda.

Practical implications: AI should be deployed in GHRM as an engagement-building job resource rather than as a monitoring tool, and the environmental footprint of AI systems should be counted against claimed sustainability gains.

Article classification: Literature review (bibliometric and critical review with conceptual framework)

1. Introduction

Organizations face mounting regulatory, investor and societal pressure to decarbonize operations, reduce waste and demonstrate credible progress towards environmental, social and governance (ESG) objectives. Human resource management is increasingly recognized as a lever for this transition because environmental strategies are ultimately enacted, or neglected, by employees (Jaganjac et al., 2025; Ren et al., 2023). Green human resource management (GHRM) the alignment of recruitment, training, performance management, rewards and involvement with environmental objectives has accordingly become an established research stream (Jackson et al., 2011; Ren et al., 2018; Renwick et al., 2013; Tang et al., 2018a). A substantial body of evidence links GHRM to employee green behaviour and to environmental performance (Dumont et al., 2017; Kim et al., 2019; Ojo et al., 2022; Saeed et al.,

2019; Singh et al., 2020; Yong et al., 2020), including the authors' own work in Pakistan and Uzbekistan (Ali & Iqbal, 2022; Ali et al., 2024, 2026b, 2026c).

In parallel, artificial intelligence (AI) is transforming how HR work is performed. Machine-learning screening, algorithmic performance analytics, adaptive learning platforms and conversational agents now automate or augment many HR decisions (Budhwar et al., 2022; Chowdhury et al., 2023; Gupta, 2024; Tambe et al., 2019). Scholars have begun to ask whether these technologies can make GHRM more precise, personalized and accountable for example, by matching candidates' green competencies, tailoring environmental training or providing real-time eco-feedback (Ajuluchukwu et al., 2026; John & Pramila, 2024; Ogbeibu et al., 2024; Sanwal et al., 2024). Publication activity at this intersection has grown rapidly, and several reviews now map it (Alherimi et al., 2025; Khan et al., 2025; Kumari & Kumar, 2026; Mavunda, 2026; Shetty et al., 2026).

Despite this momentum, the literature has three weaknesses that limit its theoretical and practical value. First, it is predominantly technology- and capability-centric: AI is treated as an organizational capability that improves HR efficiency or firm-level sustainable performance (Al Masud et al., 2024; Imran et al., 2023; Mollah et al., 2024), while the employee-level psychological processes through which AI-enabled practices change behaviour remain a "black box". Second, although employee engagement is one of the best-established mechanisms linking HRM to performance (Albrecht et al., 2015; Christian et al., 2011; Kahn, 1990; Saks, 2006) and has been shown to mediate the GHRM–green behaviour relationship (Ababneh, 2021; Aboramadan, 2022), it is rarely theorized as the mechanism through which AI-enabled GHRM attains organizational sustainability. Third, the literature largely presumes that AI is beneficial. Emerging evidence that algorithmic management can intensify surveillance, opacity and technostress (AlZgool et al., 2025; Kellogg et al., 2020; Shaikh et al., 2026a) and that AI may even weaken green outcomes (Al-Ghalabi et al., 2024; Hoang & Ha, 2025) has not yet been integrated into a coherent explanation. The environmental footprint of AI systems themselves (Dwivedi et al., 2021; Strubell et al., 2019) is likewise rarely considered when claims about "green" AI-enabled HRM are made.

An earlier conference version of this work (Ali et al., 2025b) offered a narrative overview of these ideas. The present article substantially extends that version by replacing narrative assertion with a transparent, reproducible bibliometric evidence base and a critical synthesis, and by developing a theoretically grounded framework with testable propositions. Specifically, the study addresses three research questions (RQs):

- RQ1. How is research on AI-enabled green and sustainable HRM structured in terms of its growth, intellectual base, thematic clusters and evolution?
- RQ2. To what extent, and how, has employee engagement been theorized and tested as the mechanism linking AI-enabled GHRM to organizational sustainability?
- RQ3. What integrative framework, propositions and research agenda can explain when AI-enabled GHRM fosters or undermines employee engagement and organizational sustainability?

To answer these questions, we combine a VOSviewer-based bibliometric analysis of two purposively contrasted corpora one on AI/digital-enabled GHRM and one on GHRM and employee engagement with a critical literature analysis (Donthu et al., 2021; Post et al., 2020; Zupic & Čater, 2015). Comparing the two corpora allows us to show not only what each literature contains but also where they fail to connect. The study makes three contributions. First, it provides the first bibliometric evidence that the AI–GHRM literature and the GHRM–engagement literature have developed largely in parallel, documenting the structural gap that motivates the study. Second, it develops a job demands–resources (JD-R) framework (Bakker & Demerouti, 2017; Demerouti et al., 2001) in which AI-enabled GHRM operates simultaneously as a source of green job resources and of techno-demands, so that employee engagement becomes the pivotal, but contingent, mediator of organizational sustainability. Third, it translates the evidence into seven propositions and a methodological agenda that can guide empirical testing, including in under-represented regions such as Central Asia and the Baltic states.

The remainder of the article is organized as follows. Section 2 clarifies the core constructs and theoretical lenses. Section 3 details the research design, database, search strategy, eligibility criteria, data cleaning and bibliometric techniques. Section 4 reports the bibliometric results, and Section 5 integrates them with a critical literature analysis. Section 6 develops the framework and propositions, Section 7 discusses contributions, implications and the research agenda, and Section 8 states limitations and conclusions.

2. Conceptual and theoretical foundations

2.1 Green HRM and organizational sustainability

GHRM refers to HRM policies and practices that develop employees' ability, motivation and opportunity to contribute to an organization's environmental objectives (Jackson et al., 2011; Renwick et al., 2013). Its practice domains typically include green recruitment and selection, green training and development, green performance management, green rewards and green employee involvement (Molina-Azorin et al., 2021; Ren et al., 2018; Tang et al., 2018a). Practitioner-oriented accounts likewise stress that green recruitment, training and appraisal must be embedded in management philosophy rather than adopted as isolated initiatives (Mehta & Chugan, 2015; Uddin & Islam, 2016), that green skills are increasingly part of employability (Rahmaningtyas et al., 2023), that green rewards must be designed carefully to be effective and equitable (Odhiambo et al., 2023), and that performance evaluation systems themselves need to be sustainable (Ensslin et al., 2022). Early contributions emphasized that environmental management systems succeed only when supported by HR factors (Daily & Huang, 2001; Jabbour & Santos, 2008), and later work theorized GHRM as one element of a broader sustainable HRM agenda that also attends to employee well-being and long-term human capital regeneration (Aust et al., 2020; Ehnert et al., 2016; Kramar, 2014).

Organizational sustainability is understood here in the corporate-sustainability sense of simultaneously sustaining environmental, social and economic capital over time (Dyllick & Hockerts, 2002). Most GHRM

studies, however, operationalize the outcome narrowly as perceived environmental performance or employee green behaviour (Kim et al., 2019; Ojo et al., 2022; Paillé et al., 2014). Employee green behaviour including task-related green behaviours and voluntary or proactive behaviours such as organizational citizenship behaviour for the environment is a proximal outcome that cumulatively contributes to organizational sustainability (Boiral & Paillé, 2012; Norton et al., 2015; Ones & Dilchert, 2012). Distinguishing these levels matters because claims that GHRM "achieves sustainability" are frequently inferred from employee self-reports of behaviour.

2.2 AI-enabled GHRM

Digital HRM encompasses the use of digital technologies to support HR activities (Bondarouk & Brewster, 2016; Strohmeier, 2020). AI-enabled HRM is a narrower subset in which systems learn from data to classify, predict, recommend or act for example, through machine-learning screening, predictive HR analytics, natural-language chatbots or algorithmic scheduling (Budhwar et al., 2022; Pereira et al., 2023; Tambe et al., 2019). Its value depends on an organizational AI capability that combines data, technology, skills and governance (Chowdhury et al., 2023), and on HR analytics practices that have often been promoted more than demonstrated (Marler & Boudreau, 2017). In the green domain, "smart technology, AI, robotics and algorithms" (STARA) capability has been proposed as a complement to GHRM programmes (Ogbeibu et al., 2024), and AI-guided eco-feedback, AI-supported green training and AI-enhanced green recruitment have been examined as distinct practices (Ajuluchukwu et al., 2026).

We define AI-enabled GHRM as the use of AI-based systems to design, deliver or evaluate green HR practices. This definition deliberately separates AI from generic digitalization (for example, paperless HR or e-recruitment), because the two differ in their autonomy, opacity and potential to reshape work. As Section 4 shows, the literature frequently conflates these categories, which obscures the specific consequences of AI.

2.3 Employee engagement and green work engagement

Employee engagement is the harnessing of organization members' selves to their work roles, expressed physically, cognitively and emotionally (Kahn, 1990), and is commonly measured as a positive, fulfilling work-related state characterized by vigour, dedication and absorption (Schaufeli et al., 2002). Meta-analytic evidence shows that engagement is distinct from job satisfaction and organizational commitment and predicts both task and contextual performance (Christian et al., 2011; Rich et al., 2010). Engagement is shaped by HR practices that provide resources, support and meaningful work (Albrecht et al., 2015; Saks, 2006). In the green domain, green work engagement denotes an engaged state directed at environmental tasks and has been shown to mediate the effect of GHRM on employees' green behaviours (Aboramadan, 2022); general employee engagement plays a comparable mediating role (Ababneh, 2021).

The original version of this manuscript treated engagement loosely as encompassing job satisfaction, commitment and well-being. Such conflation is a known source of construct contamination. We therefore adopt the Kahn–Schaufeli definition, treat green work engagement as its domain-specific form,

and distinguish engagement from green commitment, which our earlier empirical and review work identified as a mediator of GHRM effects (Ali et al., 2025c, 2025d, b).

2.4 Theoretical lenses

Four complementary perspectives inform the study. The ability–motivation–opportunity (AMO) framework explains how HR practice bundles raise performance by enhancing employees' abilities, motivation and opportunities to contribute (Appelbaum et al., 2000; Jiang et al., 2012); it is the dominant lens in GHRM research. Social exchange theory (SET) explains why employees reciprocate organizational investment with discretionary effort and engagement (Blau, 1964; Cropanzano & Mitchell, 2005). Self-determination theory (SDT) explains how the satisfaction of autonomy, competence and relatedness needs internalizes motivation (Deci & Ryan, 2000), which is relevant because AI can either support or thwart these needs. The socio-technical systems perspective emphasizes that technical systems and social systems must be jointly optimized (Trist & Bamforth, 1951). At the organizational level, the (natural-)resource-based view and dynamic capabilities explain why hard-to-imitate human and technological resources generate sustainable advantage (Barney, 1991; Hart, 1995; Teece et al., 1997).

We use job demands–resources (JD-R) theory as the integrating lens (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001). JD-R proposes that job resources initiate a motivational process that fosters engagement, whereas job demands initiate a health-impairment process that depletes energy and reduces engagement. This dual-process logic is well suited to AI, which may supply resources (feedback, learning support, autonomy) and impose demands (monitoring, opacity, pace) at the same time. JD-R can incorporate AMO (practices that build ability and opportunity are job resources), SET (resources signal organizational investment that employees reciprocate) and SDT (resources that satisfy basic needs are especially engaging), thereby offering a parsimonious micro-foundation for the macro-level capability claims that dominate the AI–GHRM literature.

3. Methodology

3.1 Research design

The study adopts a hybrid review design that combines science mapping with a critical, theory-building literature analysis. Bibliometric methods reveal the structure of a field objectively and at scale but cannot, on their own, judge the quality or meaning of the work they map; critical reviews provide interpretive depth but risk selective reading (Donthu et al., 2021; Zupic & Čater, 2015). Combining the two follows recommendations for evidence-informed management reviews that are transparent, reproducible and oriented towards theory development (Post et al., 2020; Snyder, 2019; Tranfield et al., 2003). The bibliometric phase answers RQ1 and quantifies the gap addressed by RQ2; the critical phase interprets the clusters, examines the studies that test engagement-based mechanisms and the counter-evidence, and informs the framework developed for RQ3, following a theory-synthesis approach to conceptual articles (Jaakkola, 2020).

Two corpora were constructed. Corpus A (core corpus) contains research on AI- or digitally-enabled green or sustainable HRM and is used to map the field. Corpus B (comparison corpus) contains research on GHRM and employee engagement and is used to assess how far the engagement literature has incorporated AI. The contrast between the two corpora is central to establishing the research gap empirically rather than by assertion.

3.2 Database selection

Data were retrieved from OpenAlex, a large, openly accessible bibliographic database that provides abstracts, author affiliations, cited references and document-type metadata through a documented API (Priem et al., 2022). OpenAlex was chosen for three reasons. First, its coverage of journals from emerging economies where most AI–GHRM studies originate is broader than that of selective indices (Culbert et al., 2025; Visser et al., 2021). Second, its openness allows any reader to reproduce the search exactly, which strengthens methodological transparency. Third, VOSviewer can process the resulting networks directly. We acknowledge that OpenAlex has weaker metadata completeness for references and affiliations than Scopus or Web of Science (Culbert et al., 2025); Section 8 discusses this limitation, and the supplementary materials provide equivalent Scopus and Web of Science search strings to facilitate replication.

3.3 Search strategy

The search was executed on 17 October 2026 against titles and abstracts (OpenAlex field title_and_abstract.search, which applies stemming), for publications dated 2010–2026. The strings, developed iteratively from the vocabulary of seminal GHRM and AI-HRM reviews (Budhwar et al., 2022; Renwick et al., 2013) and tested for recall against known key studies, were as follows (Table 1).

Table 1
Search strategy and eligibility criteria

Element	Specification
Database / date	OpenAlex API; retrieved 17 October 2026; publication years 2010–2026 (2026 partial)
Corpus A string	("green human resource" OR "green HRM" OR "green HR" OR "GHRM" OR "sustainable human resource" OR "sustainable HRM" OR "environmental human resource") AND ("artificial intelligence" OR "machine learning" OR "AI-enabled" OR "AI-based" OR "AI-driven" OR "chatbot" OR "HR analytics" OR "people analytics" OR "digital HRM" OR "e-HRM" OR "electronic HRM" OR "digital transformation" OR "digitalization" OR "digitalisation" OR "STARA" OR "robotics" OR "automation" OR "big data")
Corpus B string	("green human resource" OR "green HRM" OR "GHRM" OR "green HR practices") AND ("employee engagement" OR "work engagement" OR "green engagement" OR "engagement")
Inclusion	Journal articles and reviews; English language; abstract available; both constructs present in title or abstract; for Corpus A, both constructs a substantive focus (named in the title or mentioned at least twice in the abstract); organizational/HRM context
Exclusion	Book chapters, conference papers, preprints, editorials and other document types; retracted items; non-English records; records without abstracts; repository-hosted non-peer-reviewed items (e.g., Zenodo); duplicates and near-duplicate versions; records outside the HRM–sustainability–technology domain (e.g., education technology, tax administration, supply-chain studies without an HRM construct)

Broad digital terms were included deliberately because the boundary between AI and other digital HR technologies is contested in the literature; the screening and the subsequent analysis then distinguish AI-specific studies from generic digitalization studies. Book chapters and conference papers were excluded to concentrate on journal-based scholarship, a conventional quality filter in bibliometric reviews (Donthu et al., 2021); the authors' own conference papers are cited where relevant but are not part of the mapped corpus.

3.4 Screening and data cleaning

Screening followed the logic of the PRISMA 2020 statement (Page et al., 2021) (Fig. 1). The Corpus A query returned 1,067 records, of which 819 were journal articles or reviews. Automated eligibility rules removed 109 non-English records, 29 records without abstracts, 2 retracted items, 9 records without a GHRM/sustainable-HRM construct and 142 records without an AI/digital construct in the title or abstract, leaving 528. A focus rule (each construct named in the title or mentioned at least twice in the abstract) removed 266 records in which a construct appeared only in passing, and 4 exact-title duplicates were removed, leaving 258. Title-and-abstract screening by the first author removed 2 near-duplicate versions and 45 off-topic records, leaving 211, and 5 repository-hosted, non-peer-reviewed records were excluded, yielding a final Corpus A of 206 documents (192 articles and 14 reviews). Applying the same language, abstract, retraction, repository and duplicate rules to the 695 Corpus B records yielded 579 documents. The full screening log, with reasons for each exclusion, is provided as supplementary material.

Bibliographic data were cleaned before mapping. Titles and abstracts were stripped of publisher copyright statements. A thesaurus file merged synonyms and spelling variants (for example, “GHRM”, “green human resource management” and “green HRM practices” were merged into green HRM; “e-HRM”, “electronic HRM”, “digital HRM” and “HRIS” into e-HRM; “employee green behaviour”, “pro-environmental behaviour” and “EGB” into employee green behaviour; “engagement” and “work engagement” into employee engagement; “RBV” and “NRBV” into resource-based view) and removed generic terms (e.g., study, research, approach, findings), research-method terms (e.g., PLS-SEM, questionnaire, systematic literature review) and country names. The complete thesaurus (517 entries) is supplied with the supplementary materials. For the co-citation analysis, cited references were identified by persistent OpenAlex identifiers, which avoids the author-name and spelling ambiguities that affect string-matched references; each node label was verified against Crossref and is shown with the year of the issue in which the work appeared.

3.5 Bibliometric techniques and VOSviewer parameters

Analyses were performed in VOSviewer version 1.6.21 (van Eck & Waltman, 2010, 2026), executed through its documented command-line interface so that each map can be regenerated exactly. VOSviewer normalizes co-occurrence data with the association-strength measure, positions items with the VOS mapping technique and assigns them to clusters with a modularity-based clustering technique solved by the smart local moving algorithm (Waltman & van Eck, 2013; Waltman et al., 2010). Four techniques were used (Table 2): (a) performance analysis of output, sources, citations and countries; (b) co-citation analysis of cited references, which reveals the intellectual base a field draws on (Small, 1973); (c) term co-occurrence analysis of titles and abstracts, using VOSviewer’s natural-language-processing term extraction, which reveals the conceptual structure; and (d) overlay visualization of the average publication year of terms, which reveals thematic evolution. Country co-authorship was mapped to describe the social structure of the field.

Table 2
VOSviewer analyses and parameters

Analysis	Unit / counting	Threshold and items	Layout and clustering
Term co-occurrence (Corpus A)	Noun phrases in titles + abstracts; binary counting	≥ 5 occurrences after thesaurus cleaning: 94 terms, 2,726 links	Association strength; resolution 1.0; minimum cluster size 3; small clusters merged
Term co-occurrence (Corpus B)	As above	≥ 15 occurrences: 98 terms, 4,092 links	As above
Overlay (Corpus A)	Average publication year of documents containing a term	Colour scale 2024.5–2026.0	Positions from term map
Co-citation (Corpus A)	Cited references (OpenAlex IDs) in 83 citing documents; full counting of co-cited pairs	≥ 5 citations: 61 of 3,690 references; 1,143 links	Resolution 1.0; minimum cluster size 2
Country co-authorship (Corpus A)	Countries of author affiliations; full counting	≥ 2 documents: 24 of 43 countries; largest connected component of 20 countries mapped	Resolution 1.0; minimum cluster size 2

Two methodological decisions merit explanation. First, by default VOSviewer retains the 60% most "relevant" terms, where relevance penalizes terms that co-occur evenly with all others. In a pilot run this default removed the focal constructs themselves (green HRM, artificial intelligence, employee engagement) because they appear across most of the corpus. Because the purpose of the analysis is precisely to locate these constructs relative to one another, all terms meeting the occurrence threshold after thesaurus cleaning were retained. Second, co-citation analysis was restricted to the 83 Corpus A documents for which OpenAlex holds reference lists (40.3%); this restriction is reported as a limitation, and the clusters were cross-checked qualitatively against the full-text reading.

3.6 Critical literature analysis

The critical phase proceeded in three steps. First, each cluster was interpreted by reading the most-cited and most central documents in it. Second, all Corpus A studies that modelled engagement (n = 58 mentioning engagement; 5 modelling it as a mediator) and all studies reporting null or negative effects of AI or digital HR technologies were read in full or at abstract level and coded for theory, design, sample, construct definition and findings. Third, the coded evidence was compared with established findings from the GHRM and engagement literatures (including the full texts supplied in the authors' article collection) to identify convergences, contradictions and omissions, which were then translated into the propositions in Section 6. Simple keyword indicators computed over all abstracts (for example, the number of abstracts naming a theory or a research design) are reported as descriptive signals of emphasis rather than as precise counts.

4. Bibliometric results

4.1 Performance analysis

Table 3 summarizes the core indicators. The field is young and accelerating: the first study in Corpus A appeared in 2017 (Yusliza et al., 2017), but 160 of the 206 documents (77.7%) were published in 2025–2026, and output in the first ten months of 2026 already exceeds that of 2025 (Fig. 2). The comparison corpus shows the same acceleration. Citation impact is accordingly limited: the 206 documents had received 1,297 citations (h-index 17), and 115 (55.8%) were not yet cited. The most-cited studies are capability-oriented empirical papers, led by work on e-HRM as an antecedent of GHRM (Yusliza et al., 2017), GHRM and big data as antecedents of green innovation (Imran et al., 2023), and STARA capability as a complement to GHRM (Ogbeibu et al., 2024).

Table 3
Performance indicators of the core corpus (Corpus A)

Indicator	Value
Documents (articles / reviews)	206 (192 / 14)
Publication period	2017–2026; 160 documents (77.7%) in 2025–2026
Distinct authors / sources	576 / 167
Total citations; h-index; uncited documents	1,297; 17; 115 (55.8%)
Most productive sources	Discover Sustainability (10); Sustainability (9); Business Strategy and the Environment (3)
Most productive countries (documents)	India (38); Indonesia (33); Pakistan (26); Malaysia (19); China (15); Saudi Arabia (10); United Kingdom (8); United Arab Emirates (8)
International co-authorship	45 documents (21.8%); 48 documents lack affiliation country metadata
Documents naming AI specifically	113 (54.9%); the remainder concern e-HRM, analytics or digitalization
Documents mentioning engagement / modelling it as a mediator	58 (28.2%) / 5 (2.4%)
Research design signals in abstracts	Survey/SEM 100; review 49; conceptual 27; qualitative 23; multi-wave or time-lagged 5

Two further patterns are noteworthy. Publication is dispersed across 167 sources, and the two most productive outlets are broad-scope open-access journals; only a handful of documents appear in leading HRM or management journals. Production is concentrated in South and Southeast Asia and the Gulf region, while European and North American research is sparse and contexts such as Central Asia are

almost absent a notable gap given the rapid digital transformation of HRM in these economies (Ali et al., 2026b, 2026c). The country co-authorship map (supplementary Figure S1) shows small, regionally bounded collaboration clusters (for example, Pakistan–China, Saudi Arabia–United Arab Emirates and Malaysia–United States) rather than an integrated global network.

4.2 Intellectual structure: co-citation analysis

The co-citation map of the 61 most frequently cited references reveals four clusters (Fig. 3; Table 4). Cluster 1 (22 references; red) captures GHRM mechanisms and outcomes: measurement of GHRM (Tang et al., 2018a), its effects on employee green behaviour (Ababneh, 2021; Saeed et al., 2019) and green culture (Roscoe et al., 2019), and its links to green innovation and environmental performance (Aftab et al., 2023; Singh et al., 2020). It also contains the first studies to connect digital technologies with GHRM (Trujillo-Gallego et al., 2022). Cluster 2 (15 references; green) is a capability-and-methods core that pairs the resource-based and dynamic-capabilities views (Barney, 1991; Teece et al., 1997) with influential GHRM studies on employee workplace green behaviour, sustainable performance and the GHRM–green supply chain linkage (Dumont et al., 2017; Jabbour & de Sousa Jabbour, 2016; Mousa & Othman, 2020) and with STARA capability (Ogbeibu et al., 2024); it is reinforced by the PLS-SEM and common-method-bias references (Podsakoff et al., 2003) that pervade the empirical work. Cluster 3 (13 references; blue) contains the foundations of GHRM (Ahmad, 2015; Daily & Huang, 2001; Jabbour & Santos, 2008; Jackson et al., 2011; Pinzone et al., 2016; Renwick et al., 2013). Cluster 4 (11 references; yellow) combines sustainable HRM (Aust et al., 2020; Ehnert et al., 2016; Guerci et al., 2016; Kramar, 2014) with digital and AI-HRM scholarship (Budhwar et al., 2022; Chowdhury et al., 2023; Marler & Boudreau, 2017; Strohmeier, 2020; Tambe et al., 2019).

Table 4
Co-citation clusters of the intellectual base

Cluster	Label and interpretation	Most-cited references (local citations)
1 (22; red)	GHRM mechanisms and outcomes: GHRM → employee green behaviour, green culture, green innovation and environmental performance	Singh et al. (2020) (17); Tang et al. (2018a) (16); Saeed et al. (2019) (13); Ren et al. (2018) (10); Trujillo-Gallego et al. (2022) (9); Roscoe et al. (2019) (9)
2 (15; green)	Capability-and-methods core: RBV/dynamic capabilities, GHRM–performance studies, STARA, PLS-SEM conventions	Dumont et al. (2017) (15); Jabbour & de Sousa Jabbour (2016) (14); Barney (1991) (13); Podsakoff et al. (2003) (12); Mousa & Othman (2020) (10); Ogbeibu et al. (2024) (8)
3 (13; blue)	Foundations of GHRM and environmental HRM	Renwick et al. (2013) (29); Ahmad (2015) (12); Jabbour & Santos (2008) (9); Daily & Huang (2001) (8); Pinzone et al. (2016) (5); Jackson et al. (2011) (5)
4 (11; yellow)	Sustainable HRM and digital/AI HRM	Kramar (2014) (9); Guerci et al. (2016) (9); Ehnert et al. (2016) (9); Strohmeier (2020) (8); Budhwar et al. (2022) (6); Aust et al. (2020) (6); Tambe et al. (2019) (5); Marler & Boudreau (2017) (5); Chowdhury et al. (2023) (5)

The structure of the links between clusters is as informative as the clusters themselves. Dividing the summed co-citation strength between two clusters by the number of possible reference pairs gives a density measure. The density between Cluster 4 (sustainable and digital/AI HRM) and Cluster 1 (GHRM mechanisms) is 0.44, the lowest of all cluster pairs (other between-cluster densities range from 0.71 to 1.27; within-cluster densities from 1.44 to 2.70). In other words, the scholarship that theorizes AI in HRM is rarely cited alongside the scholarship that explains how GHRM changes employee behaviour. Notably, no engagement-theory work (e.g., Kahn, Schaufeli or Saks) reaches the threshold, and job demands–resources theory is cited by only three documents. The intellectual base of the field is therefore anchored in GHRM and capability theory, with the micro-foundations of engagement largely imported only indirectly, through GHRM studies such as Ababneh (2021).

4.3 Conceptual structure: term co-occurrence analysis

The term map of Corpus A contains 94 terms in five clusters (Fig. 4; Table 5). Cluster 1 (29 terms) concerns AI adoption, HR analytics and responsible governance, combining artificial intelligence, e-HRM, HR analytics, decision making, automation and machine learning with governance, ESG, algorithmic bias and ethical concern. Cluster 2 (22 terms) concerns innovation-led sustainable performance and corporate responsibility, including innovation, big data analytics, organizational performance, CSR, transparency, accountability and circular economy. Cluster 3 (18 terms) concerns digital transformation and capability-based GHRM, organized around green HRM, sustainability, digital transformation, digitalization, resource-based view, dynamic capabilities, competitive advantage, SMEs and digital leadership. Cluster 4 (17 terms) represents the GHRM practice bundle and employee green behaviour green recruitment, green training, rewards, compensation, AMO framework, motivation, STARA capability, employee green behaviour and environmental performance. Cluster 5 (8 terms) links sustainable HRM with employee engagement, employee performance, organizational resilience, AI-driven HRM, work–life balance and skill development.

Table 5

Thematic clusters of the core corpus (term co-occurrence)

Cluster (terms)	Theme	Most frequent terms (occurrences)	Mean year*
1 (29)	AI adoption, HR analytics and responsible governance	artificial intelligence (83); organizational sustainability (36); e-HRM (31); adoption (29); HR analytics (25); decision making (23); governance (18); ESG (10); algorithmic bias (5)	2025.16
2 (22)	Innovation-led sustainable performance and CSR	innovation (36); recruitment (22); big data analytics (20); organizational performance (19); transparency (13); CSR (10); accountability (9); circular economy (7)	2025.23
3 (18)	Digital transformation and capability-based GHRM	green HRM (153); sustainability (108); digital transformation (58); digitalization (43); sustainable performance (32); resource-based view (19); dynamic capabilities (12)	2025.19
4 (17)	GHRM practice bundle and employee green behaviour	training (40); environmental sustainability (30); employee green behaviour (24); environmental performance (19); green recruitment (18); green training (16); AMO framework (12); STARA capability (7)	2025.22
5 (8)	Sustainable HRM, engagement and employee outcomes	sustainable HRM (68); employee engagement (41); employee performance (14); organizational resilience (9); AI-driven HRM (8); work–life balance (6)	2025.21

*Note. * Unweighted mean of the average publication years of the terms in each cluster; rounded values are similar because the corpus is concentrated in 2024–2026, so* Fig. 5 *should be used to compare individual terms.*

The position of employee engagement is the central finding for RQ2. Engagement is not located in the cluster that connects GHRM practices to employee green behaviour and environmental performance (Cluster 4), nor in the AI cluster (Cluster 1). Instead, it clusters with sustainable HRM, employee performance and well-being (Cluster 5). Across the 41 documents in which engagement appears, it co-occurs with green HRM in 30 and with artificial intelligence in 19, but with employee green behaviour in only 9, environmental performance in 8, environmental sustainability in 9 and the AMO framework in 4. The literature therefore treats engagement mainly as an outcome of AI-enabled or sustainable HRM an employee-centred benefit rather than as the mechanism through which such HRM achieves environmental and organizational sustainability.

4.4 Thematic evolution: overlay visualization

The overlay map (Fig. 5) shows a shift in emphasis. Terms with the earliest average publication year relate to efficiency and capability: big data analytics (2024.2), automation (2024.4), productivity (2024.5), manufacturing (2024.6), competitive advantage (2024.6), decision making (2024.7) and the resource-

based view (2024.7). The most recent terms relate to accountability and people: environmental responsibility (2025.9), digital literacy (2025.9), governance (2025.8), accountability (2025.8), performance management (2025.8), digital leadership (2025.7), ESG (2025.7), sustainable development goals (2025.7), algorithmic bias (2025.6), the AMO framework (2025.6) and employee green behaviour (2025.5). Employee engagement (2025.3) sits in the middle. The field is thus moving from a technological efficiency logic towards questions of governance, employee capability and behaviour precisely the terrain on which an engagement-based explanation is needed.

4.5 Comparison with the GHRM–engagement literature

The comparison corpus (Fig. 6) shows the mirror image of the gap. Its 98 terms form four clusters: a GHRM practice bundle linked to environmental and sustainable performance through AMO, social exchange theory, rewards, involvement and commitment; a practice-implementation and culture cluster; a GHRM–employee green behaviour–leadership cluster containing green work engagement, organizational citizenship behaviour and green transformational leadership; and an engagement-and-organizational-outcomes cluster that also contains digital transformation and artificial intelligence. Only 48 of the 579 documents (8.3%) mention AI-related terms and 99 (17.1%) mention any digital term. Artificial intelligence occurs in 34 documents and co-occurs with green HRM in 34 and with employee engagement in 27, but the domain-specific construct of green work engagement never co-occurs with AI. Theory use also differs: in Corpus B, AMO (60 abstracts), RBV (45) and SET (45) dominate, whereas in Corpus A RBV (33), AMO (16) and dynamic capabilities (16) dominate, SET appears in only five abstracts and self-determination theory in none.

Taken together, the bibliometric evidence locates the research gap precisely. The AI GHRM literature is dominated by capability and performance logics and treats engagement as a peripheral outcome; the GHRM–engagement literature has well-developed micro-level mechanisms but has barely engaged with AI. The intellectual bases of the two literatures AI and sustainable HRM on one side, GHRM–behaviour mechanisms on the other are the least connected parts of the co-citation network. This is the space in which the present study is positioned.

5. Critical literature analysis

This section interprets the bibliometric clusters by examining what the key studies actually claim, how they test their claims and where they disagree. Five themes emerge.

5.1 From digitized to intelligent GHRM: what AI is expected to do

The first theme concerns the functions that AI is expected to perform in GHRM. Conceptual and practitioner-oriented contributions propose that AI can screen applicants for environmental values and green competencies, personalize environmental training, monitor energy use or waste at the level of

teams, and deliver real-time feedback and recognition for green actions (Gupta, 2024; John & Pramila, 2024; Olazo & Evaristo, 2025; Sanwal et al., 2024; Singh et al., 2025). Empirical studies lend partial support. In a large cross-sectional survey, AI-guided eco-feedback and AI-supported green training were positively associated with sustainability outcomes, whereas AI-enhanced green recruitment and AI-managed green performance appraisal were related to sustainability mainly indirectly, through digital literacy and green organizational climate (Ajuluchukwu et al., 2026). STARA capability has been shown to strengthen GHRM programmes and environmental sustainability in manufacturing firms using a time-lagged design (Ogbeibu et al., 2024), and to support GHRM, green supply chain management and sustainable performance (Al Masud et al., 2024) and green performance in hospitality via GHRM and employee green commitment (Hossain et al., 2025). Related work finds that big data analytics strengthens the effects of GHRM on green innovation and organizational performance (Alshuaibi et al., 2024; Imran et al., 2023; Mahmood et al., 2023; Shaikh et al., 2026b) and that HR analytics capability supports supply-chain sustainability through data-informed GHRM strategy (Ali et al., 2025a; Mensah et al., 2026).

Three critical observations qualify this evidence. First, the label “AI” is applied loosely: only 54.9% of Corpus A abstracts refer to AI specifically, and many studies use AI, big data, e-HRM and digital transformation interchangeably. Effects of paperless HR or e-recruitment (Yusliza et al., 2017) cannot be generalized to learning systems whose recommendations are opaque to employees. Second, AI is typically measured as a perceived organizational capability or adoption level rather than as specific AI applications experienced by employees, so it is unclear which AI functions produce which effects. Third, most designs are single-source and cross-sectional, which limits causal inference (Podsakoff et al., 2003); the few time-lagged or multi-wave studies (Meher et al., 2026; Nazir et al., 2026; Ogbeibu et al., 2024; Yousaf et al., 2026) are exceptions rather than the norm, as is a three-wave study showing that digital transformation promotes sustainable HRM through HRM strength (Li & Fan, 2025).

5.2 Capability and performance logics dominate

The second theme is the dominance of organizational-level capability explanations. The resource-based view, dynamic capabilities and, less often, institutional and stakeholder theories frame AI and GHRM as complementary resources that jointly produce sustainable performance or competitive advantage (De et al., 2024; Fiorini et al., 2024; Ma et al., 2023; Mollah et al., 2024; Trujillo-Gallego et al., 2022), echoing earlier firm-level work on green innovation, environmental management and performance (Buffa et al., 2018; Ma et al., 2020; Tang et al., 2018b). For instance, organizational strategy rather than digital culture predicted AI-augmented HRM, which in turn predicted sustainable organizational performance (Mollah et al., 2024), and digital transformation affected sustainable development performance partly through GHRM and green supply chain management (Ma et al., 2023). These studies establish associations at the level of the firm, but they rarely theorize how employees perceive, accept or resist AI-enabled green practices. Because environmental performance ultimately depends on day-to-day employee behaviour (Norton et al., 2015; Ones & Dilchert, 2012), capability explanations leave the micro-foundations of the effect unexplained. This omission is consequential: recent reviews of GHRM and digital HRM conclude

that reliance on a narrow set of macro theories and cross-sectional self-reports constrains theoretical progress (Kumari & Kumar, 2026; Paulet et al., 2021).

5.3 The engagement mechanism: established in GHRM, underdeveloped in AI–GHRM

The third theme concerns employee engagement. In the GHRM literature, the case for engagement-type mechanisms is strong. GHRM fosters green work engagement, which in turn promotes in-role and extra-role green behaviours (Aboramadan, 2022); employee engagement mediates the effect of GHRM on green behaviour, with personality attributes conditioning the relationships (Ababneh, 2021). Related mediators include psychological green climate (Dumont et al., 2017), pro-environmental psychological capital (Saeed et al., 2019), organizational and green commitment (Ali et al., 2025c, 2026b; Kim et al., 2019; Nurul Alam et al., 2025), green self-efficacy and environmental knowledge (Miah et al., 2026), employee well-being (Gyensare et al., 2024) and pro-environmental behaviour as the bridge to environmental performance (Ali & Iqbal, 2022; Ansari et al., 2021; Ojo et al., 2022). Leadership and climate condition these mechanisms (Agrawal & Pradhan, 2023; Gupta & Kaur, 2024; Shi & Liang, 2025; Singh et al., 2020; Tuan, 2022; Yang et al., 2024), and a rapidly growing literature identifies further antecedents of employee green behaviour, including corporate social responsibility (Aukhoon et al., 2024; Zhang et al., 2024), green culture and identity (Mirhadian et al., 2024), generativity (Luo et al., 2024), green interpersonal citizenship (Kaur & Gupta, 2024) and GHRM itself (Yadate, 2025), studied with attitude–behaviour models (Wang, 2016) and, less often, qualitative designs (Ali & Juan, 2024; Fareed El-Tony & Choo, 2025).

Within the AI–GHRM literature, by contrast, only five studies model engagement as a mediator (Table 6). AI-driven sustainable HRM increased employee engagement, which improved performance, with conscientiousness strengthening the first link (Jia & Hou, 2024); AI-driven sustainable HRM increased job engagement and resilience through relational contracts, with perceived AI decision-making amplifying the effect in a three-wave design (Mehmood et al., 2026); AI-enabled and gamified GHRM improved environmental literacy through sustainable learning engagement and green knowledge internalization (Saiyed et al., 2026); GHRM improved individual green performance through creative process engagement, while digital transformation had no direct effect (Istanti et al., 2025); and AI adoption in HR processes improved sustainable organizational performance through green organizational learning and green employee engagement (Ahmed et al., 2025). Related studies treat engagement as an outcome of digital GHRM (Meher et al., 2026; Sharma & Dhamija, 2026) or theorize it conceptually (Ali et al., 2026a; Rasheed & Rida, 2024).

Table 6

Corpus A studies that model engagement as a mediator

Study	Theory	Design and sample	Engagement construct	Key finding
Jia & Hou (2024)	AMO; person–organization fit	Survey; 470 employees, China	Employee engagement	AI-driven sustainable HRM → engagement → performance; conscientiousness moderates
Mehmood et al. (2026)	Social exchange	Three-wave survey; 481 respondents, China	Job engagement (outcome via relational contracts)	AI-driven sustainable HRM → relational contracts → engagement and resilience; perceived AI decision-making moderates
Saiyed et al. (2026)	Organizational learning	Survey of HR managers in MNCs; PLS-SEM plus machine learning	Sustainable learning engagement	AI-enabled/gamified GHRM → learning engagement → knowledge internalization → environmental literacy
Istanti et al. (2025)	AMO; social exchange	Cross-sectional survey; public-hospital professionals	Creative process engagement	GHRM → engagement → individual green performance; digital transformation has no direct effect
Ahmed et al. (2025)	Not specified in abstract	Cross-sectional survey; employees of AI-adopting organizations	Green employee engagement	AI adoption in HR and AI-enabled HR planning → green learning and engagement → sustainable performance; environmental uncertainty moderates

Four weaknesses limit this evidence. First, the engagement construct is heterogeneous employee, job, green, learning and creative-process engagement are used interchangeably so findings cannot be accumulated. Second, mediation is mostly inferred from cross-sectional data, which can severely bias estimates of indirect effects (Maxwell & Cole, 2007; Preacher & Hayes, 2008; Zhao et al., 2010). Third, outcomes are predominantly self-reported employee or firm performance rather than objective environmental indicators such as energy use, waste or emissions (Sahan et al., 2025). Fourth, none of the studies theorizes why AI should engage rather than disengage employees, beyond assuming that AI improves the quality of HR practices. The contrast with the GHRM literature, where engagement is grounded in social exchange and resource-based motivational processes (Aboramadan, 2022; Albrecht et al., 2015), is clear.

5.4 The ambivalent side of AI-enabled GHRM

The fourth theme, largely absent from the earlier version of this manuscript, is counter-evidence that AI and digital HR technologies can undermine green outcomes. Digital HR technology was found to have a

negative relationship with the environmental performance of Jordanian banks (Al-Ghalabi et al., 2024). In Vietnamese IT firms, AI reduced green structural capital, an effect that was weaker where GHRM was stronger (Hoang & Ha, 2025). Over-reliance on digital technologies reduced employees' environmental participation even though digital transformation strengthened GHRM and green behaviour overall (Shaikh et al., 2026a). GHRM practices increased technostress among banking employees, and technostress reduced engagement (AlZgool et al., 2025). These findings are consistent with research on algorithmic management, which shows that algorithms can restrict, record, rate and replace workers and thereby provoke resistance (Kellogg et al., 2020), and with work on algorithmic discrimination and the governance of HR analytics (Kapoor et al., 2026; Tambe et al., 2019; Wójcik, 2024). They also echo evidence that employees' resistance to change can weaken the effects of GHRM (Nejati et al., 2017).

A further omission is the environmental cost of AI itself. Training and operating large models consumes substantial energy (Strubell et al., 2019), and the sustainability implications of AI are increasingly debated (Dwivedi et al., 2021). Yet the AI–GHRM literature almost never nets this footprint against the gains it attributes to AI-enabled HR practices. A credible claim that AI-enabled GHRM attains organizational sustainability must therefore treat AI as both a potential resource and a potential burden for employees and for the environment.

5.5 Towards responsible, human-centred AI governance

The fifth theme, visible as the most recent cluster in the overlay map, concerns governance, transparency, accountability and ESG alignment. Studies in this stream emphasize ethical considerations and AI readiness as moderators (Mahade et al., 2025), call for robust ethical frameworks (Alherimi et al., 2025; Khan et al., 2025), and propose human-centred governance of HR analytics built on transparency, employee voice and well-being (Kapoor et al., 2026). Organizational culture and structure shape whether sustainability initiatives are implemented as intended (Jaganjac et al., 2025; Shaikh et al., 2025), and sustainable HRM scholarship stresses the long-term regeneration of human resources rather than short-term efficiency (Aust et al., 2020; Kramar, 2014; Wikhamn, 2019). This emerging governance theme provides the boundary conditions that an engagement-based explanation requires. Table 7 summarizes how the bibliometric and critical findings jointly define the research gaps addressed in the next section.

Table 7
Integration of bibliometric and critical findings into research gaps

Gap	Bibliometric evidence	Critical-review evidence	Addressed by
G1. Missing micro-foundations	Capability terms (RBV, dynamic capabilities, competitive advantage) dominate Corpus A; SET in 5 and SDT in 0 abstracts	AI–GHRM effects explained at firm level; employee experience of AI rarely theorized	JD-R framework; P1–P2
G2. Engagement disconnected from environmental outcomes	Engagement in the SHRM/well-being cluster; co-occurs with environmental performance in 8 of 41 documents; 5 mediation studies	Heterogeneous engagement constructs; cross-sectional mediation	P2, P4, P7
G3. Two literatures developing in parallel	Lowest co-citation density between AI/SHRM and GHRM-mechanism clusters (0.44); AI in 8.3% of Corpus B	GHRM–engagement mechanisms not transferred to AI contexts	Integrative framework
G4. Presumed benevolence of AI	Governance, accountability and algorithmic bias are the newest terms	Negative or mixed effects of AI/digital HR technologies; technostress lowers engagement	P3, P5
G5. AI footprint ignored	Energy and AI system footprint rarely co-occur with GHRM terms	Energy costs of AI documented outside HRM	P6
G6. Methodological and contextual narrowness	Survey/SEM signals in 100 abstracts vs. 5 multi-wave designs; production concentrated in a few countries	Self-reported outcomes; little multilevel or objective data	Research agenda (Table 9)

6. An integrative framework: AI-enabled GHRM, employee engagement and organizational sustainability

Building on the evidence above, we propose a dual-pathway framework (Fig. 7). Its core logic is derived from JD-R theory (Bakker & Demerouti, 2017): AI-enabled GHRM practices change the job resources and job demands that employees experience in relation to environmental work, these changes shape employees' (green) engagement, and engagement converts organizational green intentions into the discretionary and task behaviours from which organizational sustainability emerges. AMO, SET, SDT and socio-technical systems theory specify the content of the resources, the conditions under which they are reciprocated, and the design choices that determine whether AI acts as a resource or a demand.

6.1 The resource pathway

AI-enabled GHRM can enlarge the green job resources available to employees. Personalized green training tailored to individual skill gaps strengthens competence; AI-generated eco-feedback makes the environmental consequences of work visible and timely; recommendation systems can connect employees with green projects and communities of practice; and analytics can make environmental contributions recognizable in performance management and rewards. In AMO terms, these practices raise ability and opportunity (Appelbaum et al., 2000; Jiang et al., 2012); in SDT terms, informative feedback and competence support satisfy basic needs and support internalized motivation (Deci & Ryan, 2000). Evidence that AI-guided eco-feedback and AI-supported training are those most directly associated with sustainability outcomes (Ajuluchukwu et al., 2026), and that green training is a particularly powerful GHRM practice (Ali et al., 2026c; Pham et al., 2020), is consistent with this reasoning.

Proposition 1

AI-enabled GHRM practices that provide personalized learning, timely environmental feedback and visible recognition increase employees' green job resources.

JD-R theory predicts that job resources foster engagement, and SET adds that employees reciprocate organizational investment that they perceive as supportive (Cropanzano & Mitchell, 2005). Resources that are directed at environmental tasks should therefore foster green work engagement in particular (Aboramadan, 2022).

Proposition 2

Green job resources generated by AI-enabled GHRM are positively related to employees' (green) work engagement.

6.2 The demand pathway

The same technologies can impose techno-demands. Continuous monitoring of environmental behaviour may be experienced as surveillance; opaque algorithmic evaluations can undermine perceived fairness and autonomy; rapid changes to tools and processes generate technostress; and automation may raise job-insecurity concerns (Kellogg et al., 2020; Tambe et al., 2019). Such demands initiate a depletion process that lowers engagement (Demerouti et al., 2001), as observed when GHRM-related technostress reduced engagement (AlZgool et al., 2025), and may explain the negative or mixed effects of digital HR technologies on green outcomes (Al-Ghalabi et al., 2024; Hoang & Ha, 2025; Shaikh et al., 2026a).

Proposition 3

AI-enabled GHRM practices that rely on intensive monitoring, opaque evaluation or rapid technological change increase techno-demands, which are negatively related to employees' (green) work engagement.

6.3 From engagement to organizational sustainability

Engaged employees invest physical, cognitive and emotional energy in their roles (Kahn, 1990) and display higher task and contextual performance (Christian et al., 2011; Rich et al., 2010). Applied to environmental work, engagement should increase both required green behaviours and voluntary behaviours such as eco-initiatives and environmental citizenship (Boiral & Paillé, 2012; Norton et al., 2015), which aggregate into environmental performance and, through cost, reputation and human-capital effects, into the social and economic pillars of organizational sustainability (Dyllick & Hockerts, 2002; Kim et al., 2019; Paillé et al., 2014); employee engagement in innovation has, for example, been associated with sustainable performance excellence (Shah et al., 2025). Because AI-enabled GHRM may also influence sustainability directly for example, through process optimization we expect engagement to transmit part, not all, of its effect.

Proposition 4

Employees' (green) work engagement is positively related to employee green behaviour, which in turn is positively related to organizational sustainability; engagement partially mediates the relationship between AI-enabled GHRM and organizational sustainability.

6.4 Boundary conditions

Whether AI-enabled GHRM operates primarily through the resource or the demand pathway depends on how it is designed and governed. Socio-technical theory suggests that outcomes improve when technical and social systems are jointly optimized (Trist & Bamforth, 1951). Four conditions are especially relevant: perceived algorithmic fairness and transparency, which shape whether AI decisions are interpreted as supportive (Kapoor et al., 2026; Mehmood et al., 2026); human-in-the-loop design and employee voice, which preserve autonomy; employees' digital literacy, which determines whether AI tools can be used as resources (Ajuluchukwu et al., 2026); and green organizational climate and leadership, which signal that environmental goals are genuine (Dumont et al., 2017; Shi & Liang, 2025; Singh et al., 2020).

Proposition 5

Perceived algorithmic fairness and transparency, human-in-the-loop design with employee voice, employees' digital literacy, and a supportive green climate and leadership strengthen the resource pathway and weaken the demand pathway.

Finally, organizational sustainability is a net outcome. Gains from AI-enabled GHRM must be evaluated against the energy, hardware and data footprint of the AI systems that deliver them (Strubell et al., 2019). Moreover, engagement develops and decays over time, so the strength of the mediated effect should depend on how long employees have experienced the system and on whether early demands are resolved.

Proposition 6

The contribution of AI-enabled GHRM to organizational sustainability is smaller when the environmental footprint of the AI systems involved is large and is not offset or governed.

Proposition 7

The mediating role of engagement is time-dependent: techno-demands are most salient in early implementation, whereas resource-based engagement effects accumulate as employees gain experience and trust in the system.

7. Discussion

7.1 Theoretical contributions

Judged against established criteria for theoretical contribution what new relationships are proposed, why they hold and where they apply (Corley & Gioia, 2011; Whetten, 1989) the study makes four contributions. First, it provides a reproducible map of an emerging field and, by contrasting two corpora, offers bibliometric evidence of a structural disconnect between research on AI in HRM and research on GHRM–engagement mechanisms. Prior reviews have described the AI–GHRM field's growth, themes and challenges (Alherimi et al., 2025; Khan et al., 2025; Shetty et al., 2026) or have combined green and digital HRM at the level of the SDGs (Kumari & Kumar, 2026), but none has examined where the mechanism-level literature on engagement is and is not connected to it. Second, it relocates the explanation of AI–GHRM effects from the organizational to the employee level by specifying engagement as the mediating mechanism, responding to calls for micro-foundational theorizing in GHRM (Kumari & Kumar, 2026; Ren et al., 2018). Third, by adopting JD-R theory, it replaces the implicit assumption that AI is beneficial with a dual-pathway logic that accommodates both the positive findings that dominate the field and the negative findings that the field has so far treated as anomalies. Fourth, it extends the boundaries of "green" HRM to include the environmental footprint of the HR technology itself, aligning AI–GHRM research with sustainable HRM's concern for long-term, system-level consequences (Aust et al., 2020; Ehnert et al., 2016).

Table 8

Positioning of the study relative to recent reviews of AI/digital and green HRM

Review	Method and scope	Focus	Difference from the present study
Alherimi et al. (2025)	SLR with bibliometric elements; 53 articles, 2018–2025	AI applications across GHRM functions; ethics and readiness	No engagement mechanism; no comparison with the engagement literature
Khan et al. (2025)	SLR; 25 Scopus articles, 2015–2025	AI and sustainable HRM themes	Thematic synthesis without science mapping
Shetty et al. (2026)	Bibliometric (Biblioshiny); 94 Scopus records, 2019–2026	Intellectual structure and collaboration in AI-enabled GHRM	Descriptive mapping; no mechanism-level theorizing
Kumari & Kumar (2026)	SPAR-4-SLR + bibliometrics; 436 Scopus/WoS articles, 2016–2025	Green and digital HRM and the SDGs	Proposes S-O-R lens; does not isolate AI or engagement
Mavunda (2026)	SLR; 58 articles, 2018–2025	AI, digital transformation and GHRM in Sub-Saharan Africa	Regional focus; no bibliometric mapping
Present study	VOSviewer bibliometrics on two contrasted corpora (206 + 579) + critical analysis	AI-enabled GHRM → engagement → organizational sustainability	Quantifies the disconnect; dual-pathway JD-R framework; seven propositions; AI footprint

7.2 Practical implications

For HR leaders, the findings caution against treating AI as a self-evidently green investment. AI should be deployed in GHRM primarily as an engagement-building resource: personalized learning, developmental eco-feedback and recognition are more likely to engage employees than fine-grained monitoring of individual behaviour. Organizations should involve employees in the design of AI-enabled green practices, explain how algorithmic assessments are produced, keep humans accountable for consequential decisions, and invest in digital literacy before or alongside deployment. They should track engagement and techno-stress indicators during implementation rather than assuming that adoption equals success. Finally, sustainability reporting on AI-enabled HR should account for the energy and hardware footprint of the systems used, so that claimed environmental gains are net rather than gross. For policymakers and professional bodies, the results support guidance on transparent and fair use of AI in HR, aligned with ESG disclosure frameworks.

7.3 Research agenda

Table 9 translates the gaps into an agenda. The highest priority is methodological: testing the mediating role of engagement requires designs that separate the measurement of antecedent, mediator and outcome in time and source, together with objective environmental indicators. Multilevel designs are

needed because AI-enabled GHRM is an organizational or unit-level practice, whereas engagement is an individual state. Contextual diversification is also needed, including under-studied regions such as Central Asia and the Baltic states, where our own comparative work suggests that the salience of specific GHRM practices differs across countries (Ali et al., 2026c).

Table 9
Research agenda

Domain	Priority questions	Suggested designs and measures
Theory	When does AI act as a job resource versus a demand in green work? Which basic needs (autonomy, competence, relatedness) does each AI application support or thwart?	JD-R and SDT-based models; comparison of AI applications (eco-feedback, training, appraisal, recruitment)
Mechanism	Does green work engagement mediate AI-enabled GHRM effects beyond green commitment, climate and self-efficacy?	Three-wave or longitudinal panel designs; competing-mediator models; latent change models
Measurement	How should AI-enabled GHRM be measured as employee-experienced practices rather than perceived capability?	Scale development and validation; multi-source data (HR records, supervisors, system logs)
Outcomes	Do engagement effects translate into objective environmental outcomes?	Energy, waste and emissions data (e.g., Scope 1–2 indicators); multilevel models linking individuals to units
Dark side and governance	Under what governance conditions do surveillance, opacity and technostress outweigh resource effects?	Field experiments and quasi-experiments around AI roll-outs; qualitative process studies
AI footprint	What is the net environmental contribution of AI-enabled GHRM?	Life-cycle or energy accounting of HR systems combined with outcome data
Context	How do institutional, cultural and sectoral contexts shape the framework?	Cross-country designs including Central Asia and Europe; SMEs and public sector; measurement invariance testing

8. Limitations and conclusion

8.1 Limitations

Several limitations should be noted. First, the bibliometric analysis relies on a single database. OpenAlex offers broad and open coverage but has less complete reference and affiliation metadata than Scopus or Web of Science (Culbert et al., 2025); reference lists were available for 40.3% of the core documents and affiliation countries were missing for 48 documents, so co-citation and country results should be read as indicative. Second, because 2026 is a partial year and most documents are recent, citation-based

indicators understate the influence of new work; the field's structure is likely to change quickly. Third, term maps are derived from titles and abstracts and depend on thesaurus decisions, which we have documented in full to allow sensitivity checks. Fourth, screening was conducted by a single researcher using transparent rules; independent double screening would further strengthen reliability. Fifth, the framework is conceptual; its propositions require empirical testing, ideally with the designs set out in Table 9. Finally, restricting the corpora to English-language journal articles may under-represent relevant work published in other languages or outlets.

8.2 Conclusion

AI is being promoted as a means of making GHRM more effective, but the evidence base has advanced faster in volume than in explanatory depth. This study shows, through a reproducible bibliometric analysis of two contrasted literatures and a critical reading of the key studies, that the AI–GHRM field explains its effects mainly through organizational capabilities, that employee engagement the best-established mechanism through which HR practices shape behaviour has rarely been modelled as the link to organizational sustainability, and that evidence of AI's potential to undermine green outcomes has not been integrated. The proposed dual-pathway framework positions engagement as the pivotal but contingent mediator: AI-enabled GHRM attains organizational sustainability when it is designed and governed to expand employees' green job resources rather than their techno-demands, and when its own environmental footprint is taken into account. Testing this framework with longitudinal, multilevel and multi-source designs offers a clear path for the next phase of research.

Declarations

Prior dissemination. An earlier, substantially shorter narrative version of this work was presented at the International Scientific and Practical Conference "Sustainable Economic Growth: Integrating Green Economy Principles and Practices" (12 April 2025) and deposited at https://doi.org/10.5281/zenodo.15193336 (Ali et al., 2025b). The present manuscript contains new data, analyses, framework and text.

Data availability. The search strings, screening log, cleaned corpora identifiers, VOSviewer thesaurus, map and network files and analysis scripts are provided as supplementary material and allow full reproduction of the analyses.

Funding. Not Applicable

Conflict of interest. The authors declare no conflict of interest.

Author contributions. Muhammad Ramzan Ali: Conceptualization, Methodology, Investigation, Writing – original draft. Tumsela Asghar: Formal analysis, Software. Zulaykho Kadirova: Validation, Writing – review & editing, Project administration. Muhammad Faheem Akram: Validation, Writing – review & editing, Project administration. Vokhidova Mehri Khasanovna: Validation, Writing – review & editing, Project administration

References

1. Ababneh, O. M. A. (2021). How do green HRM practices affect employees' green behaviors? The role of employee engagement and personality attributes. *Journal of Environmental Planning and Management*, *64*(7), 1204–1226. https://doi.org/10.1080/09640568.2020.1814708
2. Aboramadan, M. (2022). The effect of green HRM on employee green behaviors in higher education: The mediating mechanism of green work engagement. *International Journal of Organizational Analysis*, *30*(1), 7–23. https://doi.org/10.1108/ijoa-05-2020-2190
3. Aftab, J., Abid, N., Cucari, N., & Savastano, M. (2023). Green human resource management and environmental performance: The role of green innovation and environmental strategy in a developing country. *Business Strategy and the Environment*, *32*(4), 1782–1798. https://doi.org/10.1002/bse.3219
4. Agrawal, S., & Pradhan, S. (2023). Employee green behavior in hotels: The role of green human resource management, green transformational leadership and value congruence. *Consumer Behavior in Tourism and Hospitality*, *18*(2), 241–255. https://doi.org/10.1108/cbth-11-2022-0191
5. Ahmad, S. (2015). Green human resource management: Policies and practices. *Cogent Business & Management*, *2*(1), 1030817. https://doi.org/10.1080/23311975.2015.1030817
6. Ahmed, O., Saqib, A., Salman, S., Siddiqui, E. A., & Ali, O. (2025). AI-powered HRM and sustainable organizational performance: The mediating roles of green learning and engagement under environmental uncertainty. *Research Journal for Social Affairs*, *3*(6), 1383–1399. https://doi.org/10.71317/rjsa.003.06.0617
7. Ajuluchukwu, E. N., Ofem, U. J., Undie, S., Akeke, M., Elogbo, E. E., Udida, F. U., Olom, P. A., Eze, M. R., & Bessong, B. (2026). Exploring the impact of green human resource management practices enabled by artificial intelligence on organizational sustainability: The mediating roles of digital literacy and green organizational climate. *Journal of Sustainable Business*, *11*(1), 8. https://doi.org/10.1186/s40991-026-00138-5
8. Al Masud, A., Islam, M. T., Rahman, M. K. H., Or Rosid, M. H., Rahman, M. J., Akter, T., & Szabó, K. (2024). Fostering sustainability through technological brilliance: A study on the nexus of organizational STARA capability, GHRM, GSCM, and sustainable performance. *Discover Sustainability*, *5*(1), 325. https://doi.org/10.1007/s43621-024-00495-w
9. Al-Ghalabi, R. R., Alsheikh, G. A. A., Al-Shamaileh, L. R., & Altarawneh, A. (2024). Impact of digital HR technology between green human resources and environmental performance in Jordanian banks. *Heritage and Sustainable Development*, *6*(1), 267–286. https://doi.org/10.37868/hsd.v6i1.512
10. Albrecht, S. L., Bakker, A. B., Gruman, J. A., Macey, W. H., & Saks, A. M. (2015). Employee engagement, human resource management practices and competitive advantage. *Journal of Organizational Effectiveness: People and Performance*, *2*(1), 7–35. https://doi.org/10.1108/joepp-08-2014-0042

11. Alherimi, N., Abdulmaksoud, S., Ahmed, V., & Bahroun, Z. (2025). A systematic literature review of artificial intelligence advancements in green human resource management. *Sustainability*, *17*(22), 10283. https://doi.org/10.3390/su172210283
12. Ali, M. R., & Iqbal, S. M. J. (2022). Examining the mediating influence of green behavior on the impact of green HR practices on environmental sustainability. *iRASD Journal of Management*, *4*(3), 479–494. https://doi.org/10.52131/jom.2022.0403.0093
13. Ali, A., & Juan, H. (2024). Trends and trajectories in employee green behavior research. *Frontiers in Sociology*, *9*, 1486377. https://doi.org/10.3389/fsoc.2024.1486377
14. Ali, M. R., Aziz, M. S., & Younis, M. (2026a). Fostering environmental sustainability through green human resource management, green leadership, and work engagement: Examining the emerging role of artificial intelligence. In *Proceedings of the Republican Scientific-Practical Conference "Human and Artificial Intelligence Collaboration in Higher Education: The Future of Education"* (pp. 388–410). Zenodo. https://doi.org/10.5281/zenodo.22897287
15. Ali, M. R., Kadirova, Z., & Ismoyilov, B. (2024). Practicing green HRM to achieve environmental sustainability. *Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference*, *1*, 24–33. https://doi.org/10.17770/etr2024vol1.7961
16. Ali, N., Milang, S. W., Sagaf, F. F. A., & Ladjin, N. (2025a). Digital transformation in green HRM: Implementation of HR analytics to improve HR sustainability in manufacturing companies in Bandung City. *Journal of Management*, *4*(1), 52–64.
17. Ali, M. R., Peiseniece, L., & Mikelsone, E. (2025b). Artificial intelligence in green human resource management: Understanding the mediating role of employee engagement in achieving environmental sustainability. In *Proceedings of the International Scientific and Practical Conference "Sustainable Economic Growth: Integrating Green Economy Principles and Practices"* (pp. 51–63). Zenodo. https://doi.org/10.5281/zenodo.15193336
18. Ali, M. R., Peiseniece, L., & Mikelsone, E. (2025c). The mediating role of green work commitment in the relationship between green HR practices, AI elements, and environmental sustainability: A quantitative analysis. *Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference*, *2*, 15–22. https://doi.org/10.17770/etr2025vol2.8578
19. Ali, M. R., Peiseniece, L., & Mikelsone, E. (2025d). Through the green work commitment, a literature review examines the relationship between green HRM and environmental sustainability. *Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference*, *1*, 31–43. https://doi.org/10.17770/etr2025vol1.8635
20. Ali, M. R., Peiseniece, L., & Mikelsone, E. (2026b). Fostering environmental sustainability through green HRM green leadership and work commitment. *Discover Sustainability*. Advance online publication. https://doi.org/10.1007/s43621-026-04468-z
21. Ali, M. R., Peiseniece, L., Mikelsone, E., Shah, A. S. A., & Kadirova, Z. (2026c). Co-creating sustainable innovation from within: Green HRM practices enabling employee green behavior in KIBS ecosystems

across Pakistan, China, and Uzbekistan. *Journal of Management Practices, Humanities and Social Sciences*, *10*(2). https://doi.org/10.33152/jmphss-10.2.7

22. Alshuaibi, M. S. I., Alhebri, A., Khan, S. N., & Sheikh, A. A. (2024). Big data analytics, GHRM practices, and green digital learning paving the way towards green innovation and sustainable firm performance. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(4), 100396. https://doi.org/10.1016/j.joitmc.2024.100396
23. AlZgool, M. R. H., Abbas, S. I., Al-Omari, M. A., Haji-Othman, Y., & Kzar, M. H. (2025). The impact of green HRM on employee technostress: The moderating role of emotional intelligence in digital leadership in the banking sector. *International Journal of Innovative Research and Scientific Studies*, *8*(3), 4035–4045. https://doi.org/10.53894/ijirss.v8i3.7429
24. Ansari, N. Y., Farrukh, M., & Raza, A. (2021). Green human resource management and employees pro-environmental behaviours: Examining the underlying mechanism. *Corporate Social Responsibility and Environmental Management*, *28*(1), 229–238. https://doi.org/10.1002/csr.2044
25. Appelbaum, E., Bailey, T., Berg, P., & Kalleberg, A. L. (2000). *Manufacturing advantage: Why high-performance work systems pay off*. Cornell University Press.
26. Aukhoon, M. A., Iqbal, J., & Parray, Z. A. (2024). Impact of corporate social responsibility on employee green behavior: Role of green human resource management practices and employee green culture. *Corporate Social Responsibility and Environmental Management*, *31*(5), 3768–3778. https://doi.org/10.1002/csr.2773
27. Aust, I., Matthews, B., & Muller-Camen, M. (2020). Common good HRM: A paradigm shift in sustainable HRM? *Human Resource Management Review*, *30*(3), 100705. https://doi.org/10.1016/j.hrmr.2019.100705
28. Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, *22*(3), 309–328. https://doi.org/10.1108/02683940710733115
29. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, *22*(3), 273–285. https://doi.org/10.1037/ocp0000056
30. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108
31. Blau, P. M. (1964). *Exchange and power in social life*. John Wiley & Sons.
32. Boiral, O., & Paillé, P. (2012). Organizational citizenship behaviour for the environment: Measurement and validation. *Journal of Business Ethics*, *109*(4), 431–445. https://doi.org/10.1007/s10551-011-1138-9
33. Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. *The International Journal of Human Resource Management*, *27*(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296
34. Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda. *The International Journal of*

Human Resource Management, *33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

35. Buffa, F., Franch, M., & Rizio, D. (2018). Environmental management practices for sustainable business models in small and medium sized hotel enterprises. *Journal of Cleaner Production*, *194*, 656–664. https://doi.org/10.1016/j.jclepro.2018.05.143
36. Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899
37. Christian, M. S., Garza, A. S., & Slaughter, J. E. (2011). Work engagement: A quantitative review and test of its relations with task and contextual performance. *Personnel Psychology*, *64*(1), 89–136. https://doi.org/10.1111/j.1744-6570.2010.01203.x
38. Corley, K. G., & Gioia, D. A. (2011). Building theory about theory building: What constitutes a theoretical contribution? *Academy of Management Review*, *36*(1), 12–32. https://doi.org/10.5465/amr.2009.0486
39. Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of Management*, *31*(6), 874–900. https://doi.org/10.1177/0149206305279602
40. Culbert, J. H., Hobert, A., Jahn, N., Haupka, N., Schmidt, M., Donner, P., & Mayr, P. (2025). Reference coverage analysis of OpenAlex compared to Web of Science and Scopus. *Scientometrics*, *130*(4), 2475–2492. https://doi.org/10.1007/s11192-025-05293-3
41. Daily, B. F., & Huang, S. (2001). Achieving sustainability through attention to human resource factors in environmental management. *International Journal of Operations & Production Management*, *21*(12), 1539–1552. https://doi.org/10.1108/01443570110410892
42. De, T., Verma, P., Gangaraju, P. K., Nibhanupudi Siva Bhaskar, A., Mahlawat, S., Kumar, V., & Singh, S. (2024). Exploring the synergistic effects of circular economy, Industry 4.0 technology, and green human resource management practices on sustainable performance: Empirical evidence from Indian companies. *Business Strategy & Development*, *7*(3), e70002. https://doi.org/10.1002/bsd2.70002
43. Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/s15327965pli1104_01
44. Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology*, *86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499
45. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070
46. Dumont, J., Shen, J., & Deng, X. (2017). Effects of green HRM practices on employee workplace green behavior: The role of psychological green climate and employee green values. *Human*

Resource Management, *56*(4), 613–627. https://doi.org/10.1002/hrm.21792

47. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
48. Dyllick, T., & Hockerts, K. (2002). Beyond the business case for corporate sustainability. *Business Strategy and the Environment*, *11*(2), 130–141. https://doi.org/10.1002/bse.323
49. Ehnert, I., Parsa, S., Roper, I., Wagner, M., & Muller-Camen, M. (2016). Reporting on sustainability and HRM: A comparative study of sustainability reporting practices by the world's largest companies. *The International Journal of Human Resource Management*, *27*(1), 88–108. https://doi.org/10.1080/09585192.2015.1024157
50. Ensslin, S. R., Rodrigues, K. T., Yoshiura, L. J. M., da Silva, J. C., & Longaray, A. A. (2022). Organizational performance management and the 'sustainability' of the performance evaluation system: A view guided by the integrative review perspective. *Sustainability*, *14*(17), 11005. https://doi.org/10.3390/su141711005
51. Fareed El-Tony, Y., & Choo, L. S. (2025). Employee green behavior in laboratories of higher education institutions: A qualitative study. *International Journal of Sustainability in Higher Education*, *26*(3), 697–715. https://doi.org/10.1108/ijshe-03-2024-0168
52. Fiorini, P. C., Jabbour, C. J. C., Latan, H., de Sousa Jabbour, A. B. L., & Mariano, E. B. (2024). Green emerging digital technologies, green supply chains, and the performance of environmentally friendly firms: The underpinning role of human resources. *IEEE Transactions on Engineering Management*, *71*, 13134–13148. https://doi.org/10.1109/tem.2022.3210470
53. Guerci, M., Longoni, A., & Luzzini, D. (2016). Translating stakeholder pressures into environmental performance – the mediating role of green HRM practices. *The International Journal of Human Resource Management*, *27*(2), 262–289. https://doi.org/10.1080/09585192.2015.1065431
54. Gupta, R. (2024). Impact of artificial intelligence (AI) on human resource management (HRM). *International Journal For Multidisciplinary Research*, *6*(3), 21444. https://doi.org/10.36948/ijfmr.2024.v06i03.21444
55. Gupta, R., & Kaur, S. (2024). A 2-1-1 multi-level perspective of understanding the relationship between green human resource management practices, green psychological climate, and green employee behavior. *Corporate Social Responsibility and Environmental Management*, *31*(5), 4068–4084. https://doi.org/10.1002/csr.2778
56. Gyensare, M. A., Adomako, S., & Amankwah-Amoah, J. (2024). Green HRM practices, employee well-being, and sustainable work behavior: Examining the moderating role of resource commitment. *Business Strategy and the Environment*, *33*(4), 3129–3141. https://doi.org/10.1002/bse.3642

57. Hart, S. L. (1995). A natural-resource-based view of the firm. *The Academy of Management Review*, *20*(4), 986–1014. https://doi.org/10.2307/258963
58. Hoang, S. D., & Ha, M.-T. (2025). Can AI truly drive sustainability, or is green intellectual capital the key? Investigating their two-way relationship in the GHRM–performance link. *Journal of Intellectual Capital*, *26*(5), 1122–1145. https://doi.org/10.1108/jic-10-2024-0321
59. Hossain, M. I., Islam, M. T., Kumar, J., & Jamadar, Y. (2025). Harnessing STARA for enhancing green performance of hospitality industry: Green HRM, employees commitment as mediators and psychological climate as moderator. *Journal of Hospitality and Tourism Insights*, *8*(8), 2837–2859. https://doi.org/10.1108/jhti-09-2024-1041
60. Imran, R., Alraja, M. N., & Khashab, B. (2023). Sustainable performance and green innovation: Green human resources management and big data as antecedents. *IEEE Transactions on Engineering Management*, *70*(12), 4191–4206. https://doi.org/10.1109/tem.2021.3114256
61. Istanti, E., Mujanah, S., & Sumiati, S. (2025). From human resources to sustainable outcomes: A moderated mediation analysis of creative engagement and digital transformation in hospitals. *Edelweiss Applied Science and Technology*, *9*(12), 182–196. https://doi.org/10.55214/2576-8484.v9i12.11308
62. Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review*, *10*(1-2), 18–26. https://doi.org/10.1007/s13162-020-00161-0
63. Jabbour, C. J. C., & de Sousa Jabbour, A. B. L. (2016). Green human resource management and green supply chain management: Linking two emerging agendas. *Journal of Cleaner Production*, *112*, 1824–1833. https://doi.org/10.1016/j.jclepro.2015.01.052
64. Jabbour, C. J. C., & Santos, F. C. A. (2008). The central role of human resource management in the search for sustainable organizations. *The International Journal of Human Resource Management*, *19*(12), 2133–2154. https://doi.org/10.1080/09585190802479389
65. Jackson, S. E., Renwick, D. W. S., Jabbour, C. J. C., & Muller-Camen, M. (2011). State-of-the-art and future directions for green human resource management: Introduction to the special issue. *German Journal of Human Resource Management: Zeitschrift für Personalforschung*, *25*(2), 99–116. https://doi.org/10.1177/239700221102500203
66. Jaganjac, B., Hansen, K. W., Lunde, H., & Hunnes, J. A. (2025). The role of organizational culture and structure in implementing sustainability initiatives. *Business Ethics, the Environment & Responsibility*, *34*(4), 1239–1254. https://doi.org/10.1111/beer.12710
67. Jia, X., & Hou, Y. (2024). Architecting the future: Exploring the synergy of AI-driven sustainable HRM, conscientiousness, and employee engagement. *Discover Sustainability*, *5*(1), 30. https://doi.org/10.1007/s43621-024-00214-5
68. Jiang, K., Lepak, D. P., Hu, J., & Baer, J. C. (2012). How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal*, *55*(6), 1264–1294. https://doi.org/10.5465/amj.2011.0088

69. John, J. E., & Pramila, S. (2024). Integrating AI tools into HRM to promote green HRM practices. In *ICT: Smart systems and technologies (lecture notes in networks and systems)* (pp. 249–259). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-9489-2_22
70. Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Academy of Management Journal*, *33*(4), 692–724. https://doi.org/10.2307/256287
71. Kapoor, M. A., Vikas, S., & Sharma, S. (2026). From algorithmic engagement to sustainable work: A TRUST-AI framework for human-centered HR analytics in emerging economy workplaces. *Frontiers in Human Dynamics*, *8*, 1883258. https://doi.org/10.3389/fhumd.2026.1883258
72. Kaur, H., & Gupta, R. (2024). Analysing green interpersonal citizenship behaviour as a mediator between green HRM and green outcomes: A study of manufacturing units. *Corporate Social Responsibility and Environmental Management*, *31*(6), 5155–5173. https://doi.org/10.1002/csr.2856
73. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174
74. Khan, A. J., Chaudhry, I. S., Iqbal, J., & El Refae, G. A. (2025). Automation to sustainability: A systematic review of artificial intelligence applications in human resource management. *Human Behavior and Emerging Technologies*, *2025*(1), 7021656. https://doi.org/10.1155/hbe2/7021656
75. Kim, Y. J., Kim, W. G., Choi, H.-M., & Phetvaroon, K. (2019). The effect of green human resource management on hotel employees' eco-friendly behavior and environmental performance. *International Journal of Hospitality Management*, *76*, 83–93. https://doi.org/10.1016/j.ijhm.2018.04.007
76. Kramar, R. (2014). Beyond strategic human resource management: Is sustainable human resource management the next approach? *The International Journal of Human Resource Management*, *25*(8), 1069–1089. https://doi.org/10.1080/09585192.2013.816863
77. Kumari, P., & Kumar, S. (2026). Mapping the intellectual structure of green and digital human resource management in advancing the UN Sustainable Development Goals (SDGs): A SPAR-4-SLR and bibliometric analysis of emerging research trends. *Sustainable Development*. Advance online publication. https://doi.org/10.1002/sd.71476
78. Li, Z., & Fan, W. (2025). How digital transformation promotes sustainable human resource management: Evidence from China. *Asia Pacific Business Review*, 1–24. Advance online publication. https://doi.org/10.1080/13602381.2025.2596664
79. Luo, J. M., Shang, Z., & Wu, S. I. (2024). Impact of employees' generativity on green policy attitude, environmental commitment, and green behaviour. *Journal of Environmental Planning and Management*, *67*(14), 3645–3668. https://doi.org/10.1080/09640568.2023.2232103
80. Ma, L., Zhang, X., & Dong, L. (2023). Enhancing sustainable performance: The innovative strategy of digital transformation leading green collaborative management. *Sustainability*, *15*(17), 13085. https://doi.org/10.3390/su151713085

81. Ma, Y., Zhang, Q., & Yin, H. (2020). Environmental management and labor productivity: The moderating role of quality management. *Journal of Environmental Management*, *255*, 109795. https://doi.org/10.1016/j.jenvman.2019.109795
82. Mahade, A., Elmahi, A., Alomari, K. M., & Abdalla, A. A. (2025). Leveraging AI-driven insights to enhance sustainable human resource management performance: Moderated mediation model: Evidence from UAE higher education. *Discover Sustainability*, *6*(1), 267. https://doi.org/10.1007/s43621-025-01114-y
83. Mahmood, Q.-U.-A., Ahmed, R., & Philbin, S. P. (2023). The moderating effect of big data analytics on green human resource management and organizational performance. *International Journal of Management Science and Engineering Management*, *18*(3), 177–189. https://doi.org/10.1080/17509653.2022.2043197
84. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *The International Journal of Human Resource Management*, *28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699
85. Mavunda, N. A. (2026). Artificial intelligence, digital transformation and green human resource management in Sub-Saharan Africa: A systematic literature review. *International Journal of Organizational Analysis*, 1–16. Advance online publication. https://doi.org/10.1108/ijoa-05-2026-7105
86. Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23–44. https://doi.org/10.1037/1082-989x.12.1.23
87. Meher, J. R., Mishra, S., & Das, A. (2026). Influence of digital transformation on green human resource management, flexibility in remote work and work engagement. *Journal of Organizational Effectiveness: People and Performance*, *13*(6), 1318–1335. https://doi.org/10.1108/joepp-04-2025-0276
88. Mehmood, K., Hakeem, M. M., Han, S., Yang, G. Y., Alshaghdali, N. O., & Rácz, I. P. (2026). Designing human–AI synergy systems: The influence of AI-driven sustainable HRM and AI-based decision-making on employee engagement and resilience. *Systems*, *14*(5), 522. https://doi.org/10.3390/systems14050522
89. Mehta, K., & Chugan, P. K. (2015). Green HRM in pursuit of environmentally sustainable business. *Universal Journal of Industrial and Business Management*, *3*(3), 74–81. https://doi.org/10.13189/ujibm.2015.030302
90. Mensah, P. O., Kparl, E. M., Suleman, A., Kyei-Frimpong, M., Mumin, A. A., Appiah-Kubi, E., & Adjanor-Doku, C. (2026). Leveraging HR analytics capability for sustainable supply chains: The roles of green HRM, AI-driven capabilities and resource commitment. *Business Strategy and the Environment*, e71599. Advance online publication. https://doi.org/10.1002/bse.71599
91. Miah, M., Rahman, S. M. M., Biswas, S., Szabó-Szentgróti, G., & Walter, V. (2026). Effects of green human resource management practices on employee green behavior: The role of employee's

environmental knowledge management and green self-efficacy for greening workplace. *International Journal of Organizational Analysis*, *34*(4), 1174–1208. https://doi.org/10.1108/ijoa-04-2024-4462

92. Mirhadian, N., Azizan, O., & Shahriari, M. (2024). The impact of green culture on employee organizational commitment: The mediating role of green identity. *Journal of Human Behavior in the Social Environment*, *34*(6), 906–925. https://doi.org/10.1080/10911359.2023.2222292
93. Molina-Azorin, J. F., López-Gamero, M. D., Tarí, J. J., Pereira-Moliner, J., & Pertusa-Ortega, E. M. (2021). Environmental management, human resource management and green human resource management: A literature review. *Administrative Sciences*, *11*(2), 48. https://doi.org/10.3390/admsci11020048
94. Mollah, M. A., Rana, M., Amin, M. B., Sony, M. M. A. A. M., Rahaman, M. A., & Fenyves, V. (2024). Examining the role of AI-augmented HRM for sustainable performance: Key determinants for digital culture and organizational strategy. *Sustainability*, *16*(24), 10843. https://doi.org/10.3390/su162410843
95. Mousa, S. K., & Othman, M. (2020). The impact of green human resource management practices on sustainable performance in healthcare organisations: A conceptual framework. *Journal of Cleaner Production*, *243*, 118595. https://doi.org/10.1016/j.jclepro.2019.118595
96. Nazir, M. W., Shen, Z., Rahoo, L. A., & Khan, M. F. (2026). Green HRM and STARA capabilities in higher education: The mediating roles of green innovation and green passion in sustainable performance. *International Journal of Sustainability in Higher Education*, 1–35. Advance online publication. https://doi.org/10.1108/ijshe-01-2026-0113
97. Nejati, M., Rabiei, S., & Chiappetta Jabbour, C. J. (2017). Envisioning the invisible: Understanding the synergy between green human resource management and green supply chain management in manufacturing firms in Iran in light of the moderating effect of employees' resistance to change. *Journal of Cleaner Production*, *168*, 163–172. https://doi.org/10.1016/j.jclepro.2017.08.213
98. Norton, T. A., Parker, S. L., Zacher, H., & Ashkanasy, N. M. (2015). Employee green behavior. *Organization & Environment*, *28*(1), 103–125. https://doi.org/10.1177/1086026615575773
99. Nurul Alam, M., Mashi, M. S., Azizan, N. A., Alotaibi, M., & Hashim, F. (2025). When and how green human resource management practices turn to employees' pro-environmental behavior of hotel employees in Nigeria: The role of employee green commitment and green self-efficacy. *Journal of Quality Assurance in Hospitality & Tourism*, *26*(3), 383–410. https://doi.org/10.1080/1528008x.2023.2249233
100. Odhiambo, G. M., Waiganjo, E., & Simiyu, A. N. (2023). Incentivizing employee pro-environmental behaviour: Harnessing the potential of green rewards. *African Journal of Empirical Research*, *4*(2), 601–611. https://doi.org/10.51867/ajernet.4.2.60
101. Ogbeibu, S., Emelifeonwu, J., Pereira, V., Oseghale, R., Gaskin, J., Sivarajah, U., & Gunasekaran, A. (2024). Demystifying the roles of organisational smart technology, artificial intelligence, robotics and algorithms capability: A strategy for green human resource management and environmental

sustainability. *Business Strategy and the Environment*, *33*(2), 369–388. https://doi.org/10.1002/bse.3495

102. Ojo, A. O., Tan, C. N.-L., & Alias, M. (2022). Linking green HRM practices to environmental performance through pro-environment behaviour in the information technology sector. *Social Responsibility Journal*, *18*(1), 1–18. https://doi.org/10.1108/srj-12-2019-0403
103. Olazo, D., & Evaristo, J. A. (2025). The role of artificial intelligence in promoting employee workplace green behaviors: A systematic analysis. *SEISENSE Business Review*, *5*(1), 15–28. https://doi.org/10.33215/2hddey70
104. Ones, D. S., & Dilchert, S. (2012). Environmental sustainability at work: A call to action. *Industrial and Organizational Psychology*, *5*(4), 444–466. https://doi.org/10.1111/j.1754-9434.2012.01478.x
105. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71
106. Paillé, P., Chen, Y., Boiral, O., & Jin, J. (2014). The impact of human resource management on environmental performance: An employee-level study. *Journal of Business Ethics*, *121*(3), 451–466. https://doi.org/10.1007/s10551-013-1732-0
107. Paulet, R., Holland, P., & Morgan, D. (2021). A meta-review of 10 years of green human resource management: Is green HRM headed towards a roadblock or a revitalisation? *Asia Pacific Journal of Human Resources*, *59*(2), 159–183. https://doi.org/10.1111/1744-7941.12285
108. Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1), 100857. https://doi.org/10.1016/j.hrmr.2021.100857
109. Pham, N. T., Vo-Thanh, T., Shahbaz, M., Duc Huynh, T. L., & Usman, M. (2020). Managing environmental challenges: Training as a solution to improve employee green performance. *Journal of Environmental Management*, *269*, 110781. https://doi.org/10.1016/j.jenvman.2020.110781
110. Pinzone, M., Guerci, M., Lettieri, E., & Redman, T. (2016). Progressing in the change journey towards sustainability in healthcare: The role of 'green' HRM. *Journal of Cleaner Production*, *122*, 201–211. https://doi.org/10.1016/j.jclepro.2016.02.031
111. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
112. Post, C., Sarala, R., Gatrell, C., & Prescott, J. E. (2020). Advancing theory with review articles. *Journal of Management Studies*, *57*(2), 351–376. https://doi.org/10.1111/joms.12549
113. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/brm.40.3.879

114. Priem, J., Piwowar, H., & Orr, R. (2022). OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. *arXiv*, 2205.01833. https://doi.org/10.48550/arXiv.2205.01833

115. Rahmaningtyas, W., Joyoatmojo, S., Kristiani, K., & Murwaningsih, T. (2023). Building a sustainable future: Unraveling the link between environmental awareness and the cultivation of employability and green skills—a literature review. *IOP Conference Series: Earth and Environmental Science*, *1248*(1), 012021. https://doi.org/10.1088/1755-1315/1248/1/012021

116. Rasheed, M., & Rida. (2024). Green at work: Fostering employee engagement in sustainability. In *Government influences on eco-friendly practices in business* (pp. 87–118). IGI Global. https://doi.org/10.4018/979-8-3693-6265-5.ch005

117. Ren, S., Cooke, F. L., Stahl, G. K., Fan, D., & Timming, A. R. (2023). Advancing the sustainability agenda through strategic human resource management: Insights and suggestions for future research. *Human Resource Management*, *62*(3), 251–265. https://doi.org/10.1002/hrm.22169

118. Ren, S., Tang, G., & Jackson, S. E. (2018). Green human resource management research in emergence: A review and future directions. *Asia Pacific Journal of Management*, *35*(3), 769–803. https://doi.org/10.1007/s10490-017-9532-1

119. Renwick, D. W. S., Redman, T., & Maguire, S. (2013). Green human resource management: A review and research agenda. *International Journal of Management Reviews*, *15*(1), 1–14. https://doi.org/10.1111/j.1468-2370.2011.00328.x

120. Rich, B. L., Lepine, J. A., & Crawford, E. R. (2010). Job engagement: Antecedents and effects on job performance. *Academy of Management Journal*, *53*(3), 617–635. https://doi.org/10.5465/amj.2010.51468988

121. Roscoe, S., Subramanian, N., Jabbour, C. J. C., & Chong, T. (2019). Green human resource management and the enablers of green organisational culture: Enhancing a firm's environmental performance for sustainable development. *Business Strategy and the Environment*, *28*(5), 737–749. https://doi.org/10.1002/bse.2277

122. Saeed, B. B., Afsar, B., Hafeez, S., Khan, I., Tahir, M., & Afridi, M. A. (2019). Promoting employee's proenvironmental behavior through green human resource management practices. *Corporate Social Responsibility and Environmental Management*, *26*(2), 424–438. https://doi.org/10.1002/csr.1694

123. Sahan, U. M. H., Jaaffar, A. H. H., & Osabohien, R. (2025). Green human resource management, energy saving behavior and environmental performance: A systematic literature review. *International Journal of Energy Sector Management*, *19*(1), 220–237. https://doi.org/10.1108/ijesm-01-2024-0013

124. Saiyed, S., Nimo J. R., A., Kumar, V., & Hasan, M. (2026). AI-enabled and gamified green HRM practices: Impacts on employee environmental engagement. *Oeconomia Copernicana*, *17*(1), 181–224. https://doi.org/10.24136/oc.3979

125. Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology*, *21*(7), 600–619. https://doi.org/10.1108/02683940610690169

126. Sanwal, T., Rajput, J., Tyagi, M., Yadav, S., Avasthi, S., & Sareen, P. (2024). The application of AI to the adoption of green HRM practices. In *Green HRM awareness and training in higher education*

institutions (pp. 241–268). IGI Global. https://doi.org/10.4018/979-8-3693-2956-6.ch010

127. Schaufeli, W. B., Salanova, M., González-romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71–92. https://doi.org/10.1023/a:1015630930326
128. Shah, A. S. A., Ali, M. R., Vokhidova, M., Xusanov, C., & Musaeva, R. (2025). Charting the future: Analyzing innovative strategies in strategic management for sustainable performance excellence and business leadership in the telecom industry. *Business Ethics and Leadership*, *9*(4), 195–208. https://doi.org/10.61093/bel.9(4).195-208.2025
129. Shaikh, H. U. R., Kamara, A., Mirza, M., & Shah, K. A. (2026a). When digital transformation helps and hurts: Balancing technological innovation, green HRM, and employee green behaviour for sustainable workplace development. *Periodicals of Management Studies*, *6*(1), 203–222. https://doi.org/10.65181/poms.06.01.0110
130. Shaikh, S. N., Sohu, J. M., Shaikh, S., Kherazi, F. Z., & Soomro, S. (2025). Artificial intelligence adoption, green HRM, and employee behavior: Driving environmental sustainability in SMEs with organizational culture as a moderator. *Sage Open*, *15*(4), 21582440251392673. https://doi.org/10.1177/21582440251392673
131. Shaikh, S. N., Zhen, L., Sohu, J. M., Soomro, S., Akhtar, S., Kherazi, F. Z., & Najam, S. (2026b). How green HRM practices foster green competitive advantage through big data analytics capability and are amplified by managerial environmental concern. *Kybernetes*, *55*(1), 422–448. https://doi.org/10.1108/k-06-2024-1433
132. Sharma, D., & Dhamija, A. (2026). Digital green HRM and its effect on employee engagement in the era of sustainable workplace. *International Research Journal of Multidisciplinary Scope*, *07*(03), 335–346. https://doi.org/10.47857/irjms.2026.v07i03.011265
133. Shetty, L., Dwivedi, A., Srivastava, S., Dubey, S., & Rizvi, N. U. (2026). A bibliometric analysis of intellectual structure and thematic evolution in artificial intelligence enabled green human resource management for environmental sustainability. *Discover Sustainability*. Advance online publication. https://doi.org/10.1007/s43621-026-04611-w
134. Shi, C., & Liang, H. (2025). Linking green transformational leadership to employee green behavior: The moderating role of green psychological climate. *Social Behavior and Personality: an international journal*, *53*(1), 1–9. https://doi.org/10.2224/sbp.14009
135. Singh, S. K., Giudice, M. D., Chierici, R., & Graziano, D. (2020). Green innovation and environmental performance: The role of green transformational leadership and green human resource management. *Technological Forecasting and Social Change*, *150*, 119762. https://doi.org/10.1016/j.techfore.2019.119762
136. Singh, R., Joshi, A., Dissanayake, H., Iddagoda, A., Khan, S., Félix, M. J., & Santos, G. (2025). Integrating Industry 4.0, circular economy, and green HRM: A framework for sustainable transformation. *Sustainability*, *17*(7), 3082. https://doi.org/10.3390/su17073082

137. Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the American Society for Information Science*, *24*(4), 265–269. https://doi.org/10.1002/asi.4630240406

138. Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

139. Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management: Zeitschrift für Personalforschung*, *34*(3), 345–365. https://doi.org/10.1177/2397002220921131

140. Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 3645–3650). https://doi.org/10.18653/v1/p19-1355

141. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

142. Tang, G., Chen, Y., Jiang, Y., Paillé, P., & Jia, J. (2018a). Green human resource management practices: Scale development and validity. *Asia Pacific Journal of Human Resources*, *56*(1), 31–55. https://doi.org/10.1111/1744-7941.12147

143. Tang, M., Walsh, G., Lerner, D., Fitza, M. A., & Li, Q. (2018b). Green innovation, managerial concern and firm performance: An empirical study. *Business Strategy and the Environment*, *27*(1), 39–51. https://doi.org/10.1002/bse.1981

144. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

145. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

146. Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations*, *4*(1), 3–38. https://doi.org/10.1177/001872675100400101

147. Trujillo-Gallego, M., Sarache, W., & Sousa Jabbour, A. B. L. D. (2022). Digital technologies and green human resource management: Capabilities for GSCM adoption and enhanced performance. *International Journal of Production Economics*, *249*, 108531. https://doi.org/10.1016/j.ijpe.2022.108531

148. Tuan, L. T. (2022). Promoting employee green behavior in the Chinese and Vietnamese hospitality contexts: The roles of green human resource management practices and responsible leadership. *International Journal of Hospitality Management*, *105*, 103253. https://doi.org/10.1016/j.ijhm.2022.103253

149. Uddin, M. M., & Islam, R. (2016). Green HRM: Goal attainment through environmental sustainability. *Journal of Nepalese Business Studies*, *9*(1), 14–19. https://doi.org/10.3126/jnbs.v9i1.14590

150. van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

151. van Eck, N. J., & Waltman, L. (2026). *VOSviewer manual: Manual for VOSviewer version 1.6.21*. Centre for Science and Technology Studies, Leiden University. https://www.vosviewer.com

152. Visser, M., van Eck, N. J., & Waltman, L. (2021). Large-scale comparison of bibliographic data sources: Scopus, Web of Science, Dimensions, Crossref, and Microsoft Academic. *Quantitative Science Studies*, *2*(1), 20–41. https://doi.org/10.1162/qss_a_00112

153. Waltman, L., & van Eck, N. J. (2013). A smart local moving algorithm for large-scale modularity-based community detection. *The European Physical Journal B*, *86*(11), 471. https://doi.org/10.1140/epjb/e2013-40829-0

154. Waltman, L., van Eck, N. J., & Noyons, E. C. M. (2010). A unified approach to mapping and clustering of bibliometric networks. *Journal of Informetrics*, *4*(4), 629–635. https://doi.org/10.1016/j.joi.2010.07.002

155. Wang, Y.-F. (2016). Modeling predictors of restaurant employees' green behavior: Comparison of six attitude-behavior models. *International Journal of Hospitality Management*, *58*, 66–81. https://doi.org/10.1016/j.ijhm.2016.07.007

156. Whetten, D. A. (1989). What constitutes a theoretical contribution? *The Academy of Management Review*, *14*(4), 490–495. https://doi.org/10.2307/258554

157. Wikhamn, W. (2019). Innovation, sustainable HRM and customer satisfaction. *International Journal of Hospitality Management*, *76*, 102–110. https://doi.org/10.1016/j.ijhm.2018.04.009

158. Wójcik, M. (2024). Algorithmic discrimination in the era of artificial intelligence: Challenges of sustainable human resource management. *Edukacja Ekonomistów i Menedżerów*, *69*(3). https://doi.org/10.33119/eeim.2024.69.6

159. Yadate, D. A. (2025). The effect of green human resource management on employee green behavior. *Corporate Social Responsibility and Environmental Management*, *32*(1), 404–418. https://doi.org/10.1002/csr.2956

160. Yang, J., Yu, T., & Li, A. (2024). How does mindful leadership promote employee green behavior? The moderating role of green human resource management. *Corporate Social Responsibility and Environmental Management*, *31*(6), 5296–5310. https://doi.org/10.1002/csr.2870

161. Yong, J. Y., Yusliza, M., Ramayah, T., Chiappetta Jabbour, C. J., Sehnem, S., & Mani, V. (2020). Pathways towards sustainability in manufacturing organizations: Empirical evidence on the role of green human resource management. *Business Strategy and the Environment*, *29*(1), 212–228. https://doi.org/10.1002/bse.2359

162. Yousaf, M. I., Lyu, B., & Dangwal, A. (2026). Green HRM, AI adoption, and organizational agility: A strategic approach to enhancing sustainability performance of tourism and hospitality firms. *Journal*

of Chinese Human Resources Management, *17*(2). https://doi.org/10.47297/wspchrmwsp2040-800503.20261702

163. Yusliza, M.-Y., Othman, N. Z., & Jabbour, C. J. C. (2017). Deciphering the implementation of green human resource management in an emerging economy. *Journal of Management Development*, *36*(10), 1230–1246. https://doi.org/10.1108/jmd-01-2017-0027
164. Zhang, N., Ren, X., Sun, X., & Jin, C. (2024). The effect of corporate social responsibility characteristics on employee green behavior: A moral emotions perspective. *Behavioral Sciences*, *14*(11), 1045. https://doi.org/10.3390/bs14111045
165. Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257
166. Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods*, *18*(3), 429–472. https://doi.org/10.1177/1094428114562629

Figures

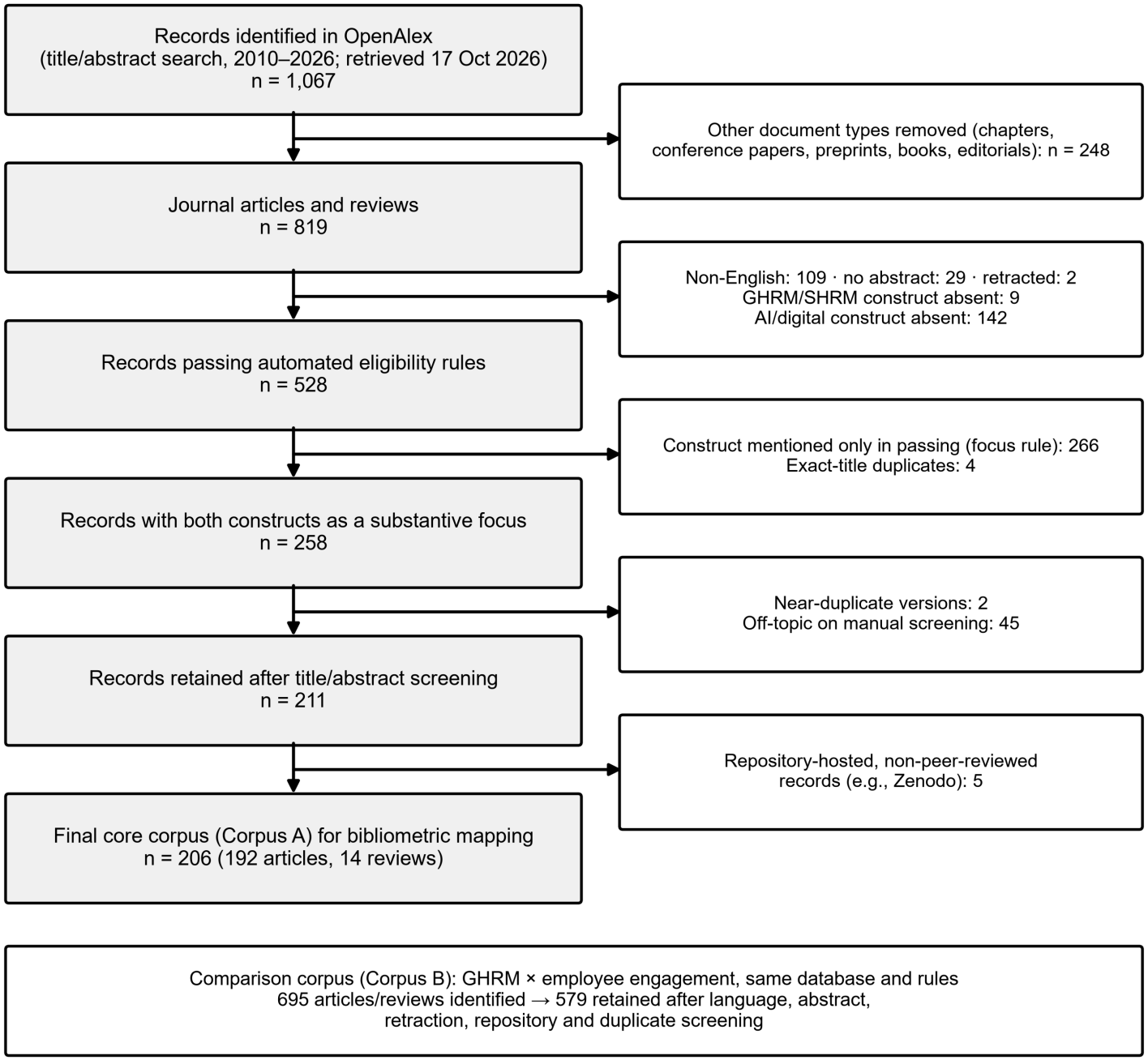
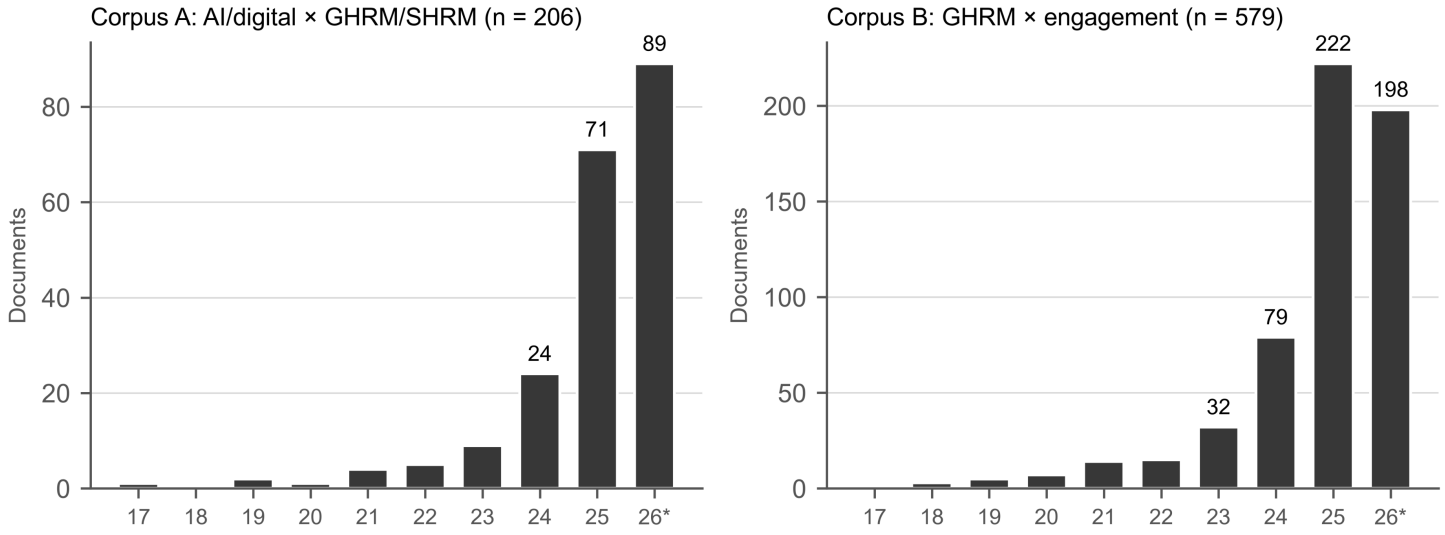


Figure 1

Identification and screening of records (PRISMA 2020-informed flow).



* 2026 is a partial year (records to 17 October 2026). Corpus B years before 2017 (n = 3) omitted from the axis.

Figure 2

Annual number of documents in the core corpus (A) and the comparison corpus (B).

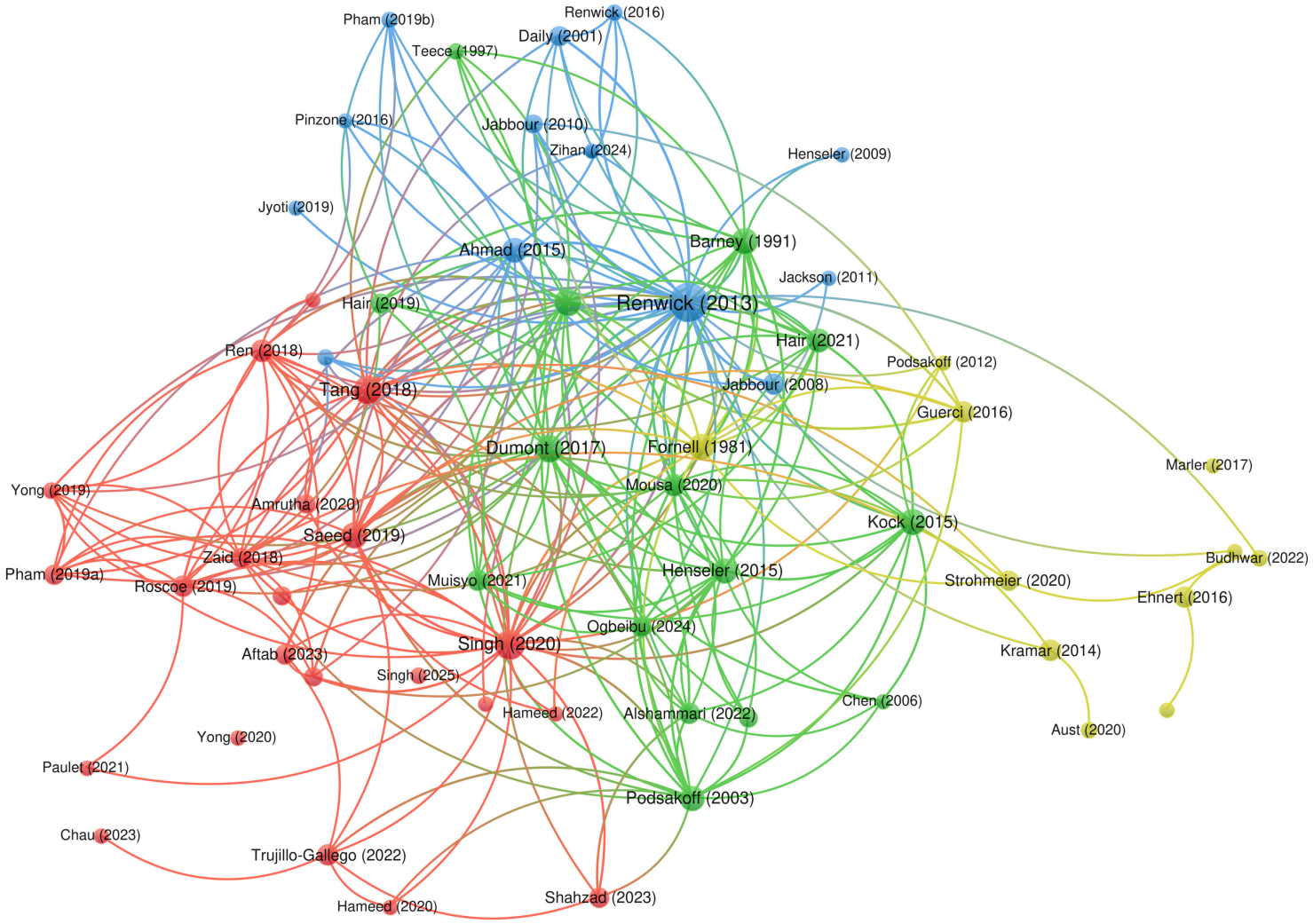


Figure 3

Co-citation network of cited references (VOSviewer; 61 references cited ≥ 5 times; node size = citations within the corpus; colours = clusters; the 250 strongest links are drawn).

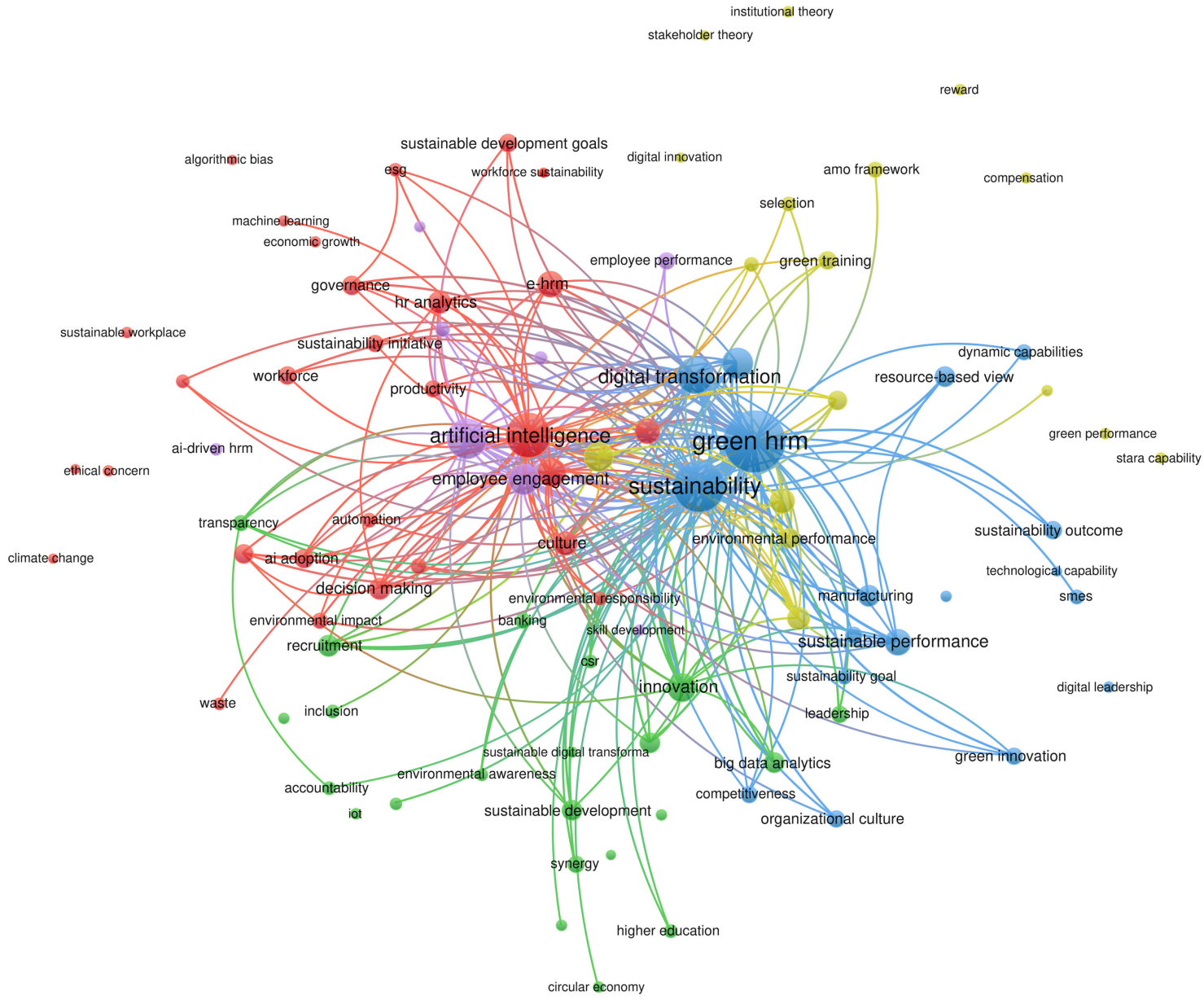


Figure 4

Term co-occurrence network of the core corpus (VOSviewer; 94 terms with ≥ 5 occurrences; node size = occurrences; colours = clusters; the 250 strongest links are drawn).

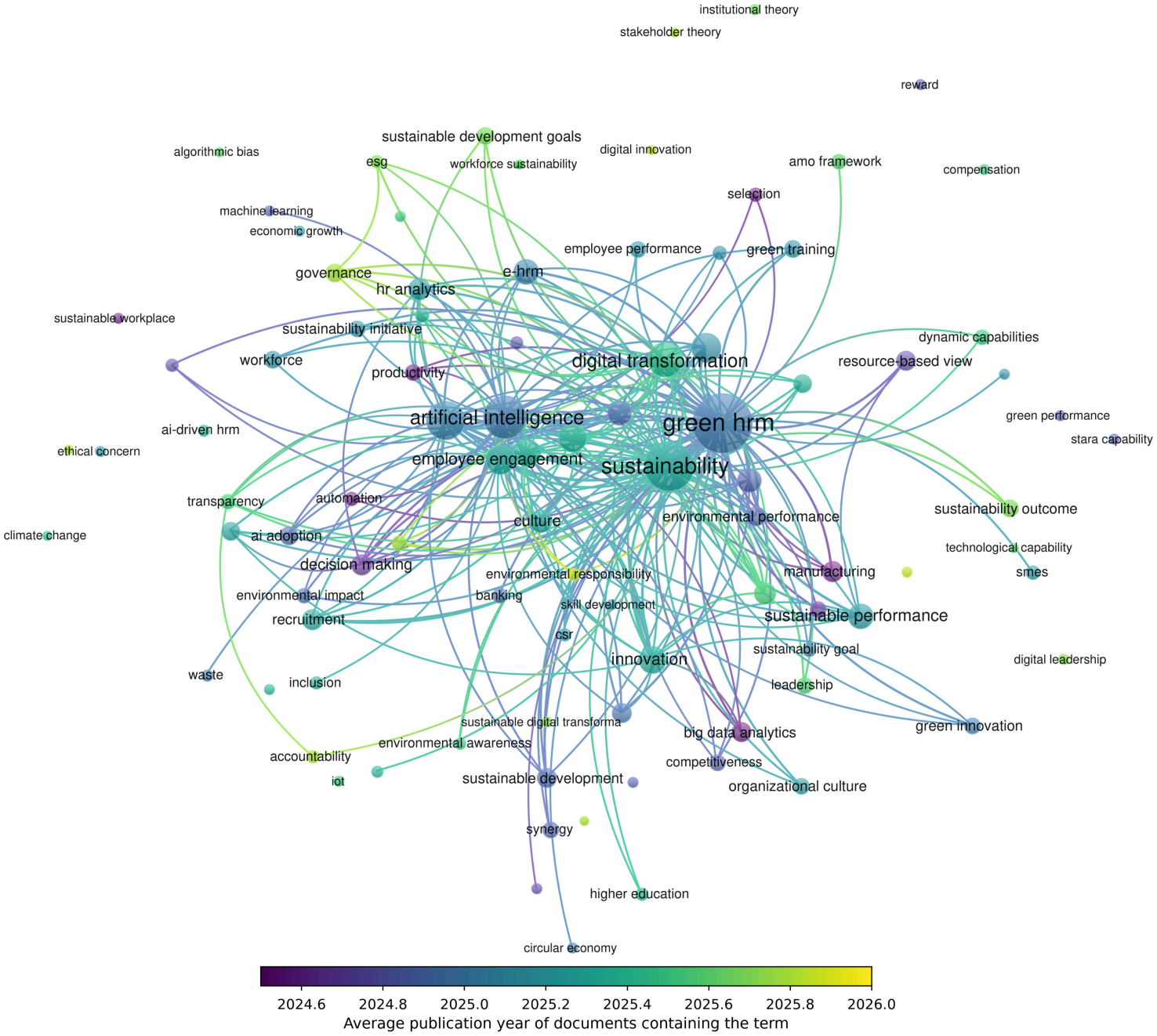


Figure 5

Overlay visualization of the core corpus (VOSviewer). Node colour shows the average publication year of the documents containing each term, from 2024.5 (dark purple) to 2026.0 (yellow).

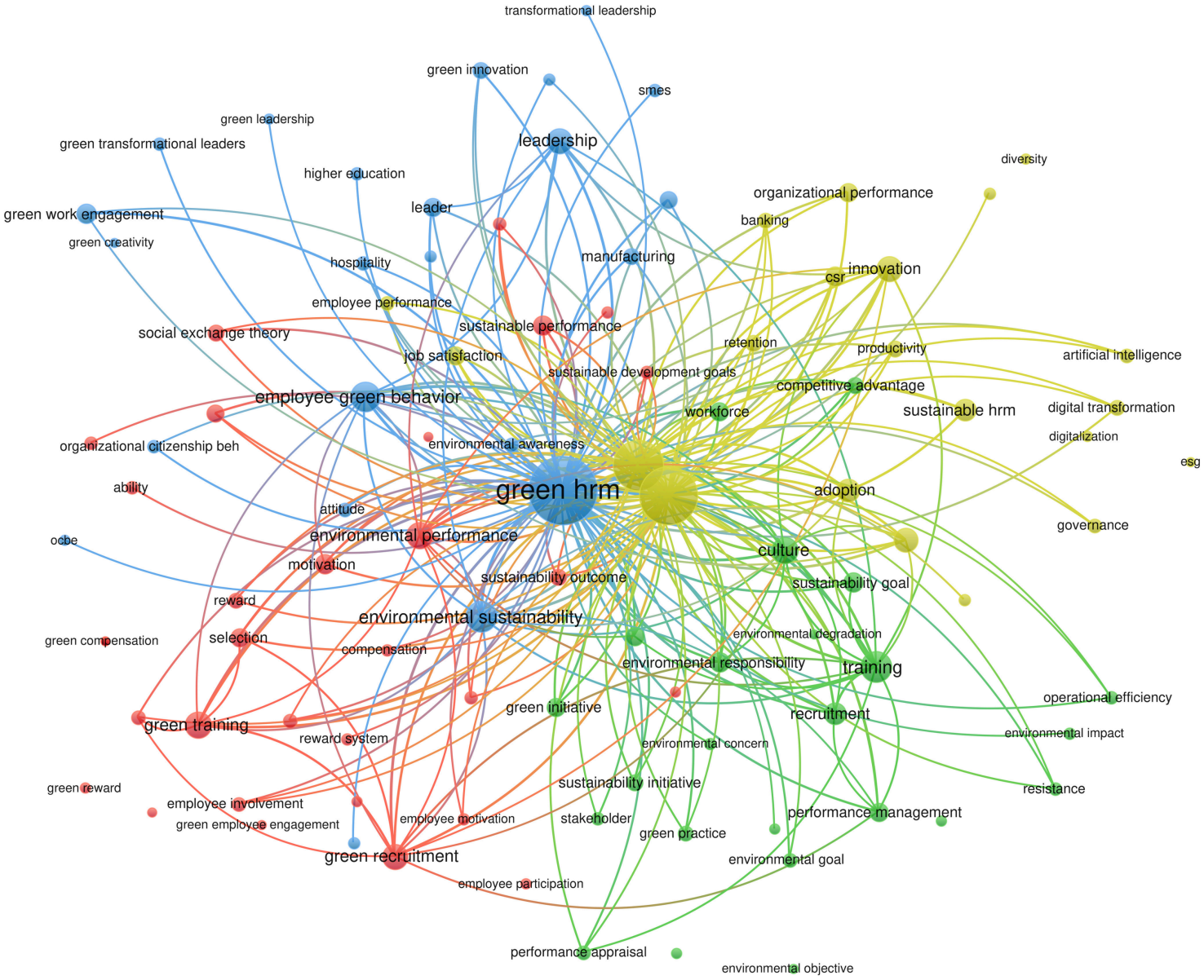


Figure 6

Term co-occurrence network of the GHRM–engagement comparison corpus (VOSviewer; 98 terms with ≥ 15 occurrences; the 250 strongest links are drawn).

P7: engagement is a partial, time-dependent mediator

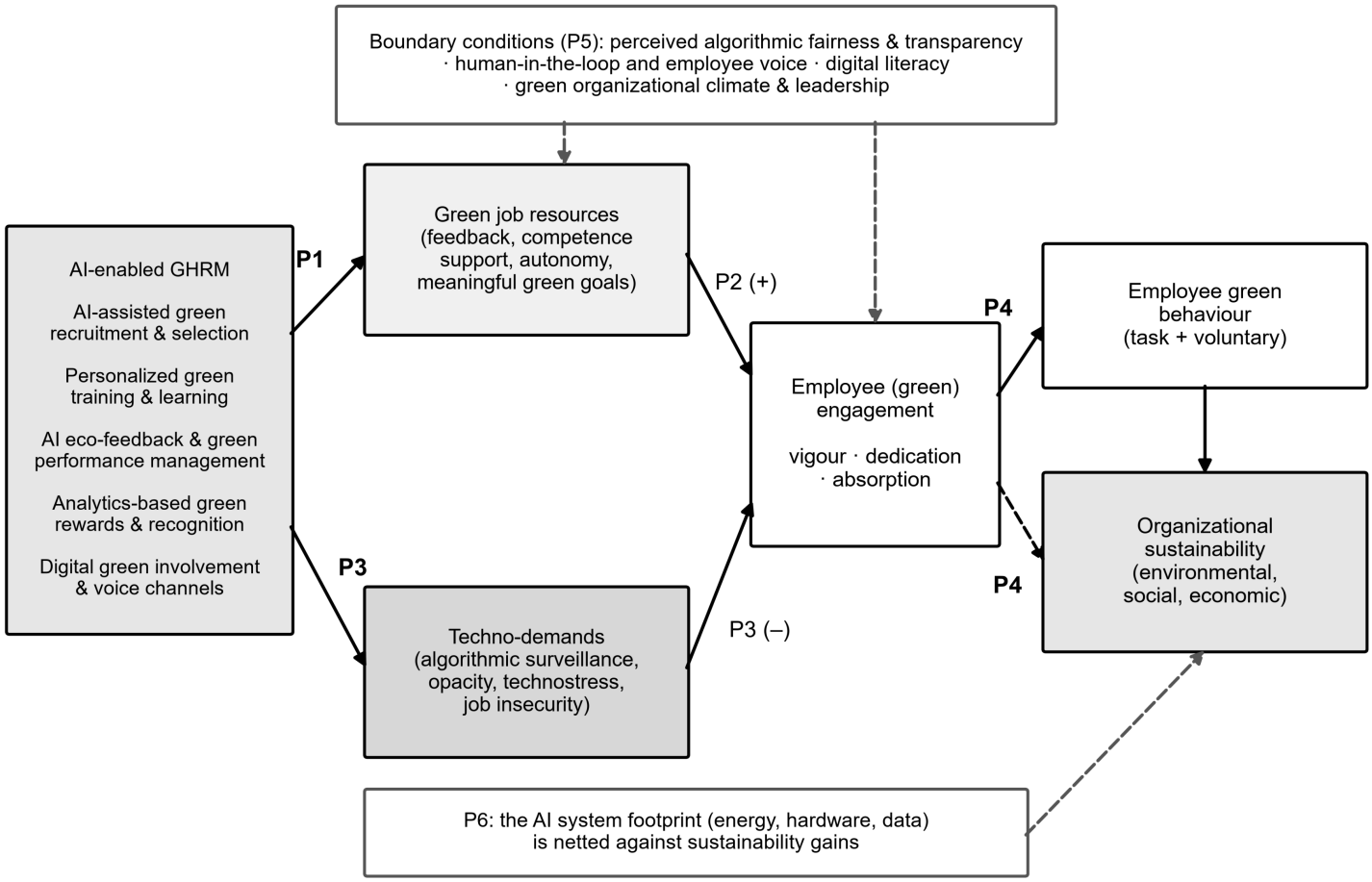


Figure 7

Dual-pathway framework of AI-enabled GHRM, employee engagement and organizational sustainability (P = proposition).