

“Artificial intelligence in human resource management: Publication growth, citation inequality, and international collaboration”

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ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT: PUBLICATION GROWTH, CITATION INEQUALITY, AND INTERNATIONAL COLLABORATION

Abstract

This study aims to examine publication dynamics, citation inequality, author and country participation, international scientific collaboration, cited-reference relationships, and author-keyword structures in Scopus-indexed research on artificial intelligence in human resource management (HRM) published between 2000 and 2025. Following EID-level screening of 1,596 records, 659 publications were identified as thematically relevant to the topic of AI-HRM. The selected corpus accumulated 25,072 citations, averaging 38.05 citations per publication. Citation impact was highly concentrated, with a Gini coefficient of 0.7396 and 60.16% of citations attributable to the most-cited 10% of publications. Annual output increased from 16 publications in 2019 to 267 in 2025, corresponding to a compound annual growth rate of 59.86%. In addition, descriptive growth-model comparisons showed that the exponential model provided the strongest fit to the annual publication series ($R^2 = 0.9945$). International co-authorship was identified in 211 publications (32.02%). Country collaboration, cited-reference cocitation, and author-keyword networks were examined to characterize the intellectual and conceptual structure of the field. The study provides a traceable and reproducible bibliometric assessment of the documented indicators of publication growth, citation inequality, international collaboration, and thematic relationships within the selected AI-HRM corpus.

Keywords

artificial intelligence, human resource management, Scopus, bibliometric analysis, citation inequality, scientific collaboration, publication growth, science mapping

JEL Classification

J24, M12, M15, O33

INTRODUCTION

Artificial intelligence (AI) is becoming relevant to human resource management (HRM) because recruitment, personnel selection, employee development, performance evaluation, and workforce planning increasingly involve data-intensive decisions. AI-based tools may expand the capacity to process employee-related information, but their application also raises questions about fairness, transparency, human oversight, and accountability. The conceptual HRM literature has established the importance of these questions for organizational decision-making (Tambe et al., 2019; Budhwar et al., 2023). Bibliometric evidence is useful for determining how the corresponding research agenda has developed; it is not a direct measure of successful organizational AI adoption.

The research relevance of AI-HRM therefore has two distinct dimensions: the substantive implications of algorithm-supported personnel decisions and the evolution of scientific evidence used to assess them.

Earlier bibliometric studies have mapped publication output, leading contributors, co-citation relations, and author keywords (Palos-Sánchez et al., 2022; Bansal et al., 2025; Koştı & Kayadibi, 2025). Such analyses provide an essential foundation, while distributional differences in citation impact and documented patterns of cross-country co-authorship can add complementary information about the structure of the research literature. Accordingly, the study is based on a thematically screened corpus of 659 Scopus publications, with bibliometric indicators compared against those of the initial set of 1,596 records.

The study combines annual descriptive growth models with Lorenz-curve and citation-share measures, country-pair collaboration counts, and co-citation and keyword mapping. Its contribution is an auditable comparison of bibliometric performance and relational indicators, including a distinction between original keyword labels in the visualization and normalized keyword concepts in temporal comparisons. The bibliometric indicators examined characterize publication dynamics, citation concentration, and the structure of research relationships in the AI-HRM field.

1. LITERATURE REVIEW

Human capital refers to the knowledge, skills, and capabilities embodied in people, whereas HRM concerns the organizational practices through which organizations recruit, develop, evaluate, and retain employees (Becker, 1962; Wright & Ulrich, 2017). Human capital management may encompass investment in capabilities and their strategic value beyond individual HR functions. The search terms and empirical material in this study primarily concern HRM, HR analytics, people analytics, and talent management. Accordingly, the title and analytical terminology use AI-HRM. The study does not claim to map the full literature on education, national human capital formation, or macroeconomic returns to skills.

HR analytics provides an important connection between digital HR systems and AI applications. Reviews by Marler and Boudreau (2017) and Margherita (2022) distinguish analytical support for HR decisions from the mere availability of digital records. Angrave et al. (2016) emphasize that analytical capability and organizational interpretation cannot be assumed from technical infrastructure alone. Predictive algorithms therefore belong within a wider process of problem definition, data assessment, evaluation, and managerial accountability; the presence of an AI method does not itself demonstrate improved HR outcomes.

Research on machine-learning applications in HRM (Garg et al., 2022) and strategic AI-assisted HRM (Malik et al., 2023) extends this discussion beyond the availability of digital data. Studies

of organizational human-AI decision-making (Jarrahi, 2018), automation-augmentation tensions (Raisch & Krakowski, 2021), and human-AI interaction at team level (Arslan et al., 2022) provide complementary conceptual perspectives.

Conceptual and systematic reviews provide substantive foundations for this distinction. Tambe et al. (2019) discuss the opportunities and challenges of AI in HRM; Vrontis et al. (2022) synthesize work on AI, robotics, and advanced technologies; and Budhwar et al. (2022) examine implications for international HRM. Chowdhury et al. (2023) connect AI capabilities with organizational value creation, while Pereira et al. (2023) review workplace outcomes. These studies help interpret bibliometric groupings, but their existence also means that mapping familiar technological and managerial themes is not, by itself, a novel theoretical contribution.

Recruitment and selection constitute a distinct application area within this literature. Research addresses the implications of AI for recruitment (Upadhyay & Khandelwal, 2018), managerial use of AI-enabled hiring (Black & van Esch, 2020), algorithm-assisted candidate selection (Pessach et al., 2020), adoption of AI for talent acquisition (Pillai & Sivathanu, 2020), and AI-supported job application and selection processes (van Esch et al., 2019). These studies provide substantive grounding for the recruitment and talent-selection terms considered in the keyword network.

Generative AI introduces additional questions concerning recruitment, employee communication, learning, and the use of generated infor-

mation in HR decisions (Budhwar et al., 2023). Responsible adoption requires attention to human oversight and the conditions under which algorithmic recommendations are accepted or challenged. Research on trust, algorithmic control, and recruiting ethics provides relevant interpretive foundations (Glikson & Woolley, 2020; Kellogg et al., 2020; Hunkenschroer & Luetge, 2022). These issues concern the quality and governance of organizational decisions; keyword prominence cannot establish that the underlying technologies are effective or safe in practice.

Applications to workforce development and employee outcomes include research on AI-enabled training practices (Maity, 2019), employee upskilling in multinational corporations (Jaiswal et al., 2022), AI awareness, career competency and job burnout (Kong et al., 2021), AI feedback and employee performance (Tong et al., 2021), and employees in Industry 4.0 organizations (Malik et al., 2022). Ethical decision-making in AI-supported HRM is addressed by Rodgers et al. (2023). These publications supply substantive context for interpreting employee-related bibliometric categories; they do not establish a common treatment effect of AI adoption.

Earlier bibliometric analyses establish the methodological context of the present study. Palos-Sánchez et al. (2022) used Bibliometrix to study 73 selected AI-HRM articles from Scopus and Web of Science. Bansal et al. (2025) examined 659 Scopus records covering 2012–2023, including citation and keyword relationships, while Koştı and Kayadibi (2025) analyzed 522 Scopus publications for 2020–2024 with Bibliometrix and VOSviewer. These contributions show that publication rankings and bibliographic networks are established tools in the field; variations in search strategies, databases, document types, and periods make direct numerical comparisons of their corpus sizes inappropriate.

The substantive literature also highlights the need to differentiate AI applications from organizational outcomes. Jia et al. (2018) proposed a conceptual framework linking AI technologies to HRM functions; Tambe et al. (2019) and Chowdhury et al. (2023) discussed the organizational challenges and capabilities associated with AI. Evidence on

recruitment, employee experience, and algorithmic accountability is heterogeneous (Pessach et al., 2020; Pereira et al., 2023; Rodgers et al., 2023). Consequently, bibliographic prominence alone cannot be interpreted as managerial efficacy or validated research consensus.

From a science-mapping perspective, citation concentration, international co-authorship, and the distinction between original and normalized author-keyword labels constitute separate empirical dimensions. Citation-distribution indicators identify how bibliographic attention is allocated, while country-pair counts describe observed co-authorship and keyword co-occurrences reflect the vocabulary supplied by authors. Each type of evidence requires an interpretation aligned with its measurement properties.

The aim of this study is to examine publication dynamics, citation inequality, author and country participation, international scientific collaboration, cited-reference relationships, and author-keyword structures in research on AI in HRM during 2000–2025. The analysis differentiates a broad Scopus retrieval of articles and reviews from 659 records selected for substantive AI-HRM relevance, using unique Scopus EIDs as the unit of identification.

2. METHOD

This study employs a bibliometric approach that integrates performance analysis and science mapping. This methodology enables a quantitative assessment of the development dynamics within the scientific field under study, including publication activity and citation patterns. Furthermore, it facilitates the identification of the structure of international scientific collaboration, the determination of intellectual and conceptual interconnections, and the tracing of the thematic evolution of the research agenda (Zupic & Čater, 2015; Aria & Cuccurullo, 2017; Belgibayeva et al., 2025; Lyeonov et al., 2025). The empirical foundation consists of 1,596 scientific articles and review papers indexed in the Scopus database between 2000 and 2025. Publications were identified and tracked using unique Scopus EID identifiers, which ensured that no duplicate

records were included. The bibliometric analysis utilized publication metadata, including titles and abstracts, author-provided keywords, publication years, citation metrics, author identifiers, institutional affiliations, and lists of cited references.

The study focused on applications of artificial intelligence (AI) in human resource management (HRM), including recruitment, talent selection, people analytics, employee development, performance evaluation, retention, and workforce planning. The bibliographic search strategy combined HRM-related concepts with artificial intelligence, machine learning, deep learning, and generative AI. The search specification was:

TITLE-ABS-KEY(("human capital management" OR "human resource management" OR "people analytics" OR "HR analytics" OR "talent management") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "generative AI")) AND PUBYEAR > 1999 AND PUBYEAR <= 2025 AND (DOCTYPE(ar) OR DOCTYPE(re)).

The retrieved publications were screened for substantive thematic relevance through record-level analysis of titles, abstracts, and author keywords, applying structured contextual criteria and a second metadata-classification pass. Inclusion required an identifiable relationship between AI technologies or AI-supported organizational decision-making and HRM functions. Index keywords alone were not considered sufficient evidence. Publications addressing unrelated medical terminology, technical-resource optimization without an HRM component, or general AI applications outside organizational human resource management were excluded.

Of the 1,596 Scopus articles and reviews retrieved for 2000–2025, 659 publications (41.29%) met the thematic inclusion criteria for AI-HRM. A further 925 records were excluded as thematically irrelevant, while 12 could not be classified conclusively based on the available metadata. Unique Scopus EIDs were used to identify records and prevent duplication. Bibliometric indicators were calculated for both the full retrieval ($N = 1,596$) and the selected AI-HRM corpus ($N = 659$).

The mean number of citations per publication was calculated as follows:

$$\bar{C} = \frac{\sum_{i=1}^N C_i}{N}, \quad (1)$$

where $\bar{C}$ – mean number of citations per publication; C_i – number of citations received by publication i ; N – total number of publications in the analyzed dataset; i – publication index, ranging from 1 to N . This indicator measures the average citation impact of publications within the selected dataset.

The h-index was calculated using the following expression:

$$h = \max \left\{ k : C_{[k]} \geq k, 1 \leq k \leq N \right\}, \quad (2)$$

where h – Hirsch index; k – rank of a publication when publications are ordered by descending citation counts; $C_{[k]}$ – number of citations received by the publication ranked k .

The h-index equals h when at least h publications have each received h or more citations. It characterizes the combined publication volume and citation impact of the analyzed dataset.

The g-index was determined as follows:

$$g = \max \left\{ k : \sum_{i=1}^k C_{[i]} \geq k^2, 1 \leq k \leq N \right\} \quad (3)$$

where g – Egghe index; $C_{[i]}$ – citation count of the publication ranked i in descending order; k – number of highest-ranked publications considered; N – total number of publications.

The g-index identifies the largest group of g highly cited publications whose cumulative citation count is at least g^2 . Compared with the h-index, it assigns greater importance to publications with exceptionally high citation counts.

The proportion of citations accumulated by the most-cited $p\%$ of publications was calculated as:

$$S_p = \frac{\sum_{i=1}^{n_p} C_{[i]}}{\sum_{i=1}^N C_i} \cdot 100\% \quad (4)$$

with:

$$n_p = \left\lceil \frac{N_p}{100} \right\rceil \quad (5)$$

where S_p – percentage of total citations accumulated by the top $p\%$ of publications; p – selected percentage threshold (1, 5, 10, or 20); n_p – number of publications included in the corresponding top group; $C_{[i]}$ – citation count of the i -th publication ranked in descending order; x – the ceiling function, which rounds x upward to the nearest integer.

This indicator measures the concentration of citation impact among the most influential publications.

Citation inequality was assessed using the Gini coefficient derived from the Lorenz curve:

$$G = 1 - 2 \int_0^1 L(p) dp. \quad (6)$$

For the discrete publication dataset, the trapezoidal approximation was applied:

$$G = 1 - \frac{1}{N} \sum_{i=1}^N (L_i + L_{i-1}), \quad (7)$$

where G – Gini coefficient; $L(p)$ – Lorenz curve representing the cumulative proportion of citations associated with the bottom p proportion of publications; L_i – cumulative citation share of the i least-cited publications; $L_0 = 0$, N – total number of publications.

The cumulative citation share is calculated as:

$$L_i = \frac{\sum_{j=1}^i C_{(j)}}{\sum_{j=1}^N C_j}, \quad (8)$$

where $C_{(j)}$ – citation counts sorted in ascending order.

The Gini coefficient ranges from 0 (perfectly equal distribution of citations) to values approaching 1 (extreme citation concentration). Higher values indicate greater inequality in citation distribution across publications.

The first and third citation quartiles were calculated using the 25th and 75th percentiles of the citation distribution:

$$Q_1 = P_{25}(C), \quad Q_3 = P_{75}(C), \quad (9)$$

where Q_1 – first quartile (25th percentile); Q_3 – third quartile (75th percentile); $P_{25}(C)$ and $P_{75}(C)$ – corresponding percentiles of publication citation counts.

Percentiles were determined using linear interpolation between adjacent ranked observations. Publications with zero citations were retained in the dataset.

The compound annual growth rate of publication activity between 2019 and 2025 was calculated as follows:

$$\text{CAGR} = \left[\left(\frac{P_{2025}}{P_{2019}} \right)^{\frac{1}{6}} - 1 \right] \cdot 100\%, \quad (10)$$

where P_{2019} – number of publications in 2019; P_{2025} – number of publications in 2025; 6 – number of annual intervals between 2019 and 2025; CAGR – compound annual growth rate, expressed as a percentage.

Annual publication counts were compiled for each calendar year from 2000 to 2025, including years with zero publications.

For the complete Scopus retrieval:

$$\text{CAGR} = \left[\left(\frac{475}{51} \right)^{1/6} - 1 \right] \cdot 100 \approx 45.05\%. \quad (11)$$

For the selected AI-HRM corpus of 659 publications:

$$\text{CAGR} = \left[\left(\frac{267}{16} \right)^{1/6} - 1 \right] \cdot 100 \approx 59.86\%. \quad (12)$$

CAGR measures the constant annual percentage growth rate that would produce the observed change between the initial and final years. It does not imply that publication activity increased at the same rate in every intervening year.

All citation-based indicators were calculated using a fixed Scopus citation snapshot. The reported measures characterize citation distributions within the analyzed datasets and were not normalized for publication age or scientific discipline.

Annual publication dynamics were analyzed separately for the full Scopus retrieval ($N = 1,596$) and the AI-HRM corpus ($N = 659$) using the 26 annual observations from 2000 to 2025, including years with zero publications. Linear and quadratic curves were fitted by ordinary least squares, while the exponential curve was estimated by nonlinear least squares directly on the publication-count scale, minimizing the sum of squared differences between observed and fitted annual counts. This common outcome scale permits descriptive comparison of model fits but gives considerable weight to the high publication counts in recent years.

The linear model was specified as:

$$P(t) = \beta_0 + \beta_1 t + \varepsilon. \quad (13)$$

The quadratic model was specified as:

$$P(t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon. \quad (14)$$

The exponential model was specified as:

$$P(t) = \exp(\beta_0 + \beta_1 t) + \varepsilon, \quad (15)$$

where $P(t)$ – the number of publications in year t ; β_0 , β_1 and β_2 – fitted coefficients, and ε – the additive residual. Time was centered as $t = \text{Year} - 2000$. In the exponential specification, the parameters were estimated from the untransformed annual counts, rather than by fitting a linear regression to the logarithms of positive counts; the two estimation procedures need not produce the same R^2 .

Model performance was assessed using the coefficient of determination (R^2), calculated on the original publication-count scale:

$$R^2 = 1 - \frac{\sum_{t=2000}^{2025} (P_t - \hat{P}_t)^2}{\sum_{t=2000}^{2025} (P_t - \bar{P})^2}, \quad (16)$$

where P_t – the observed annual publication count, $\hat{P}_t$ – the corresponding fitted value, and

$\bar{P}$ – the mean annual publication count over the observation period. Applying the same evaluation scale permits a direct descriptive comparison of the three fitted models.

Each model was estimated independently for the full retrieval and the selected AI-HRM corpus. MATLAB was used to estimate the descriptive growth curves and obtain fitted annual publication values. The nonlinear least-squares exponential specification produced the highest in-sample count-scale R^2 in both series. Because these comparisons are descriptive, high fit statistics must not be treated as evidence of a causal growth mechanism or as validated forecasts.

A supplementary two-segment linear analysis examined the 17 admissible divisions of the 26-year series, retaining at least five annual observations in each segment. The split minimizing the combined residual sum of squares was reported as a descriptive transition, not as a formal statistical test of a structural break. Poisson and negative-binomial count regressions were additionally estimated, and model assessment incorporated the Akaike information criterion (AIC), Pearson dispersion, and numerical-convergence diagnostics. The segmented and count-model statistics were independently reproduced using Python (SciPy and statsmodels); these results are distinguished from the MATLAB growth-curve calculations.

Bibliometric mapping was performed using VOSviewer with full counting and specified inclusion thresholds. Figure 4 presents the co-citation network of 50 cited references, while Figures 5 and 6 display a network of 40 original author keywords grouped into seven clusters. To improve readability, Figures 5 and 6 were reconstructed while preserving the original terms and cluster assignments, displaying only links occurring in at least two publications. Total link strength (TLS) values were calculated from the complete co-occurrence data. Table 8 presents the original author-keyword labels, whereas Table 9 reports normalized frequencies after merging synonyms and abbreviations. Detailed mapping parameters and normalization rules are provided by the corresponding author upon reasonable request.

3. RESULTS

The paper reports bibliometric indicators for the 659-publication AI-HRM corpus and, where appropriate, comparable values for the 1,596-record retrieval. All tabulated quantities use the same EID inclusion list and July 2026 Scopus citation snapshot.

3.1. Retrieval integrity, publication, and collaboration indicators

Table 1 summarizes the aggregate disposition of the 1,596 in-period records. The accompanying EID manifest verifies inclusion for each of the 659 selected publications and identifies the 937 records not included, but the supplied files do not support assigning each of those 937 records individually to the original excluded (925) or inconclusive (12) categories.

Of 1,596 in-period Scopus records, 659 (41.29%) met the AI-HRM content criteria; 925 were excluded, and 12 were set aside because their avail-

able metadata did not support a definitive decision. The subsequent citation, authorship, and network analyses use the same 659 included EIDs.

To characterize citation performance and concentration, Table 2 compares the complete retrieval with the selected 659-publication corpus using indicators recalculated from record-level citation counts.

Table 2 demonstrates differences in publication activity and citation concentration between the complete Scopus retrieval and the selected AI-HRM corpus. The 659 thematically relevant publications accumulated 25,072 citations, corresponding to an average of 38.05 citations per publication. This exceeds the mean citation count of 32.79 observed for the complete retrieval.

Citation distributions are highly unequal in both datasets. The Gini coefficient reaches 0.7396 for the AI-HRM corpus, compared with 0.7217 for

Table 1. Summary of the Scopus topical screening results (2000–2025)

Stage	Number of records	Analytical status
Articles and reviews, 2000–2025	1596	In-period retrieval
Included AI-HRM records	659	Included
Non-thematic records	925	Excluded
Undetermined on available metadata	12	Not included
Final AI-HRM analysis corpus	659	Final analytical dataset

Table 2. Independently recalculated indicators for the full retrieval and AI-HRM corpus

Indicator	Full Scopus retrieval (N = 1,596)	AI-HRM corpus (N = 659)
Number of publications	1,596	659
Total citations	52,327	25,072
Mean citations per publication	32.79	38.05
Median citations	11.0	11.0
First citation quartile (Q1)	3.0	3.0
Third citation quartile (Q3)	30.0	33.5
Maximum citations	1,111	1,111
h-index	107	81
g-index	178	140
Uncited publications	145	63
Gini coefficient	0.7217	0.7396
Top 1% citation share (%)	17.79	19.24
Top 5% citation share (%)	42.82	43.54
Top 10% citation share (%)	58.20	60.16
Top 20% citation share (%)	75.32	77.36
Publications in 2022–2025	1,210	568
Share of publications in 2022–2025 (%)	75.81	86.19
Publications in 2019	51	16
Publications in 2025	475	267
CAGR, 2019–2025 (%)	45.05	59.86

the complete retrieval. The most-cited 10% of AI-HRM publications account for 60.16% of all citations, whereas the corresponding proportion for the complete retrieval is 58.20%. The top 20% of publications account for 77.36% and 75.32% of citations, respectively.

These findings indicate that citation impact is somewhat more concentrated in the selected AI-HRM literature. However, the differences should be interpreted descriptively, because the analysis uses raw citation counts without normalization for publication age or scientific discipline.

Figure 1 illustrates the annual dynamics of scientific publications in the complete Scopus retrieval and the selected AI-HRM corpus over the period 2000–2025. Both datasets exhibit a pronounced increase in publication activity during the later years of the observation period.

The complete Scopus retrieval increased from 51 publications in 2019 to 475 in 2025, corresponding to a compound annual growth rate (CAGR) of 45.05%. During the same period, the AI-HRM corpus expanded from 16 to 267 publications, resulting in a higher CAGR of 59.86%.

The selected AI-HRM corpus demonstrates particularly rapid growth in recent years. Of its 659 publications, 568 (86.19%) were published between 2022 and 2025, compared with 75.81% of publications in the complete retrieval. This concentra-

tion of recent publications reflects the increasing representation of AI-related HRM research in the Scopus-indexed literature.

To examine the shape of the observed publication dynamics, linear, quadratic, and exponential growth models were fitted independently to both annual series. The corresponding model estimates and goodness-of-fit statistics are reported in Table 3.

Figure 2 compares Lorenz curves constructed from the unadjusted, non-negative citation counts of the complete retrieval and the AI-HRM corpus. Each curve shows the cumulative citation share of the least-cited proportion of documents.

Figure 2 presents Lorenz curves describing the distribution of citations across publications in the complete Scopus retrieval and the selected AI-HRM corpus. The horizontal axis represents the cumulative percentage of publications ranked from the least cited to the most cited, while the vertical axis shows their cumulative share of citations.

Both curves deviate substantially from the line of perfect equality, indicating a pronounced concentration of citation impact among a relatively small proportion of publications. The Gini coefficient is 0.7217 for the complete retrieval and 0.7396 for the AI-HRM corpus.

The slightly higher Gini coefficient in the AI-HRM corpus indicates greater citation inequality within

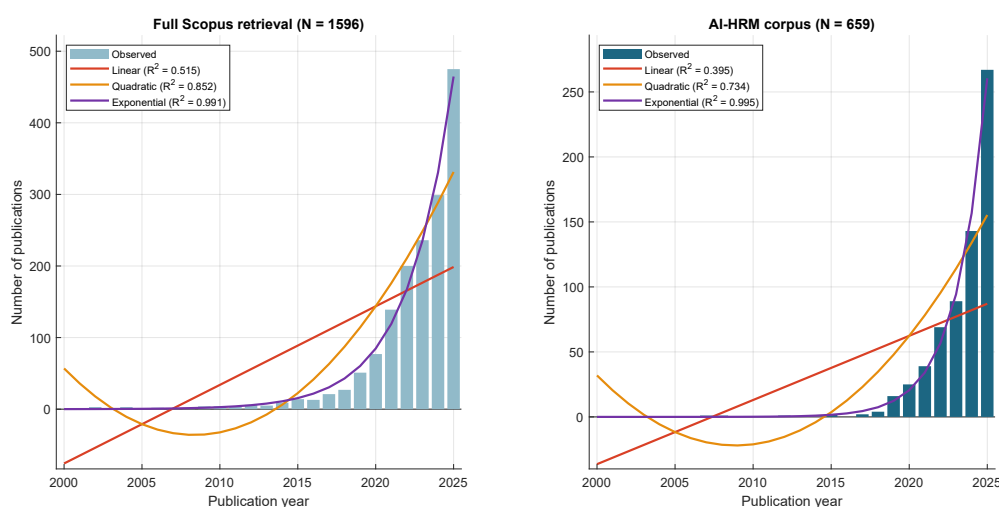


Figure 1. Annual scientific production and comparative growth-model fit for the full Scopus retrieval and AI-HRM corpus (2000–2025)

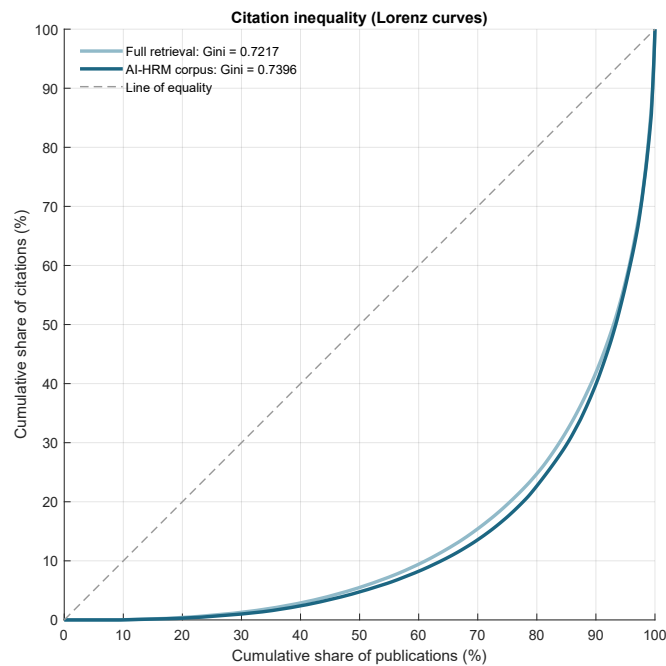


Figure 2. Citation inequality (Lorenz curves)

the thematically selected literature. This interpretation is supported by the citation-concentration indicators reported in Table 2, particularly the finding that the most-cited 10% of AI-HRM publications account for 60.16% of the corpus's total citations.

The observed inequality reflects the uneven distribution of scholarly attention among publications. It should not be interpreted as direct evidence of differences in research quality or practical effec-

tiveness, because citation counts are influenced by publication age, visibility, disciplinary practices, and other factors.

Table 3 summarizes descriptive linear, quadratic, exponential, and segmented fits of the annual series, together with Poisson and negative-binomial count-model diagnostics. R^2 values refer to the reported outcome scale, and AIC comparisons are interpreted alongside convergence diagnostics.

Table 3. Comparative goodness-of-fit statistics for publication-growth models and count-model diagnostics

Measure	Full Scopus retrieval	AI-HRM corpus
Linear model R^2	0.5149	0.3955
Quadratic model R^2	0.8522	0.7341
Exponential model R^2 (publication-count scale)	0.9907	0.9945
Best minimum-SSE segment division	2019/2020	2020/2021
Two-segment descriptive R^2	0.975	0.948
Poisson GLM Pearson dispersion	4.31	2.56
Poisson AIC	163.13	90.21
Negative-binomial AIC	160.46	92.21*

Note: Linear and quadratic curves were estimated by ordinary least squares; the exponential curve was estimated by nonlinear least squares on the original publication-count scale. The exponential R^2 values are 0.990739 and 0.994508 before rounding. Segmented fits minimize combined SSE among 17 admissible splits (at least five observations per segment). Poisson and negative-binomial diagnostics were independently verified. For the AI-HRM corpus, the negative-binomial dispersion estimate reached the boundary without satisfactory convergence; its nominal AIC of 92.21 is shown for transparency but is not used to select a model. Descriptive growth curves are estimated in MATLAB, segmented and count models are independently reproduced in Python (SciPy/statsmodels).

Table 3 compares the descriptive fits of linear, quadratic, and nonlinear least-squares exponential growth curves. The exponential specification produces the highest in-sample R^2 for the complete retrieval (0.9907) and AI-HRM corpus (0.9945), compared with quadratic values of 0.8522 and 0.7341 and linear values of 0.5149 and 0.3955, respectively. These statistics measure fit to the observed annual counts rather than predictive performance; linear or quadratic fitted values may also become negative in early years. The segmented minimum-SSE split occurs at 2019/2020 for the full retrieval and 2020/2021 for the selected corpus without implying a statistically significant structural break. Poisson Pearson dispersion exceeds unity in both datasets (4.31 and 2.56). The negative-binomial fit has a lower AIC than Poisson for the full retrieval (160.46 versus 163.13); the nominal negative-binomial AIC of 92.21 for the selected corpus is not used in model selection because its dispersion estimate reached the boundary without satisfactory convergence.

Full counting by distinct affiliation country was used to describe geographical participation. Table 4 identifies the ten leading countries among the 659 AI-HRM articles and reviews; country counts are not mutually exclusive when an article has international co-authors.

India records the most publications in the selected corpus (132; 20.03%), followed by China (116; 17.60%) and the United States (74; 11.23%). Table 4 reports publication participation rather than the intensity of individual bilateral partnerships.

Table 4. Leading affiliation countries in the AI-HRM corpus (N = 659)

Country	Publications	Share of N = 659 (%)
India	132	20.03
China	116	17.60
The United States	74	11.23
The United Kingdom	49	7.44
Australia	38	5.77
France	26	3.95
Saudi Arabia	25	3.79
Germany	24	3.64
The United Arab Emirates	24	3.64
Malaysia	22	3.34

International collaboration was mapped in VOSviewer (Figure 3) from distinct affiliation countries using full counting, a minimum of two publications per country, and no citation threshold. Node size represents country publication output, weighted links reflect co-authored papers, and colors denote the software-generated network clusters. The resulting visualization illustrates connected participation of the United Kingdom, United States, China, India, and Australia; the publication-level country-pair counts provide the directly auditable measure of bilateral collaboration.

International co-authorship was identified in 211 of the 659 AI-HRM publications (32.02%), while eight records lacked identifiable country information. The leading bilateral partnerships include Australia and the United Kingdom (15 joint publications), China and Pakistan (10), India and the United Kingdom

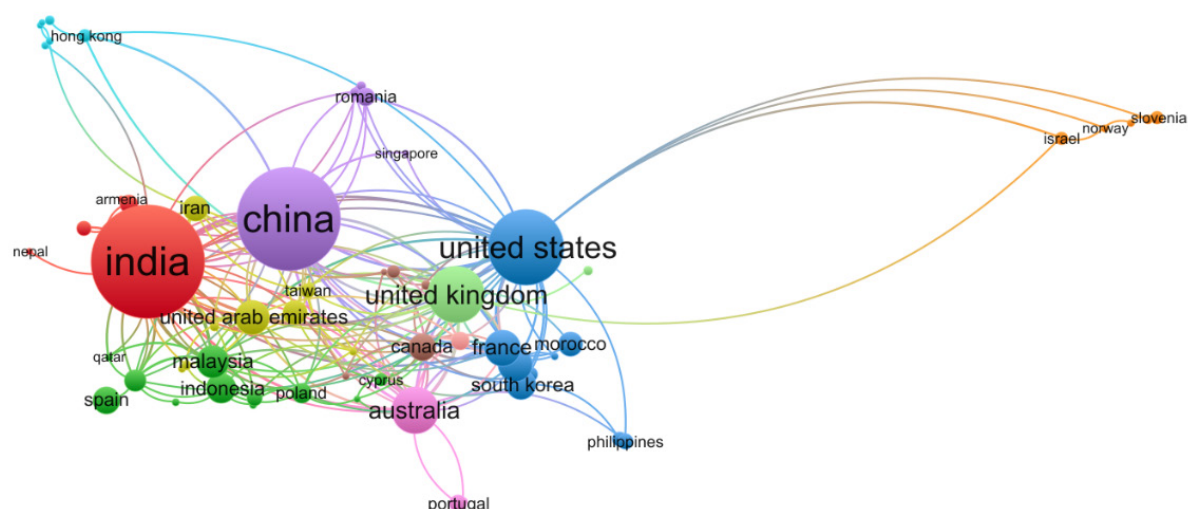


Figure 3. International co-authorship network by country

(10), and the United Kingdom and the United States (8). These findings highlight the central role of several countries in connecting international research networks, although collaboration strength does not necessarily indicate research quality.

Author productivity was computed by unique Scopus Author ID, with full credit assigned to each identified co-author. Table 5 combines publication totals, accumulated citations, and publication-year ranges for the leading authors in the selected corpus.

Table 5. Leading Scopus Author ID entities in the AI-HRM corpus

Author (Scopus ID)	Papers	Citations	Publication years
Budhwar P.	10	1,902	2021–2025
Malik A.	10	1,845	2021–2025
Benabou A.	6	34	2024–2025
Touhami F.	6	34	2024–2025
Dutta D.	6	216	2023–2025
Pereira V.	5	2,248	2022–2024
Varma A.	4	854	2022–2025
Chowdhury S.	4	1,851	2023–2024
Prikshat V.	4	423	2021–2023
Nawaz N.	4	260	2019–2024

Budhwar and Malik each appear in ten AI-HRM publications, followed by Benabou, Touhami, and Dutta with six papers each. Among 659 records, 572 are multi-authored, 84 have one identified author, and three lack identifiable authors. Comparisons of cumulative author citations should be read in conjunction with the years shown in Table 5.

3.2. Highly cited documents and cited-reference relationships

The most-cited documents are identified using citation counts recorded in the fixed Scopus export. Table 6 reproduces the full titles and years of the

ten highest-cited papers among the included 659 EIDs.

The first three ranked papers address AI challenges in HRM (1,111 citations), advanced technologies in HRM (897), and AI capability frameworks (810). Table 6 also contains literature on generative AI, AI-related employee outcomes, and AI-enabled personnel selection.

Cited-reference frequencies were calculated from the bibliographies of the 659 AI-HRM publications using parsed and standardized reference records. Each cited source was counted once per citing publication. Table 7 presents the 15 most frequently cited references, distinguishing contributions directly related to AI-HRM from broader interdisciplinary and methodological foundations.

Tambe et al. (2019) is the most frequently cited reference (138 publications), followed by Budhwar et al. (2022; 83), Chowdhury et al. (2023; 73), and Vrontis et al. (2022; 61). These studies form a prominent intellectual foundation for AI-HRM research. The presence of interdisciplinary contributions, including Jarrahi (2018) and Huang and Rust (2018), alongside methodological references such as Fornell and Larcker (1981), highlights the field's reliance on both management theory and established analytical approaches.

Cross-domain references also occur in the cited-reference rankings. For example, Huang and Rust (2018) examine AI in service settings; their appearance in Table 7 indicates a bibliographic connection to research outside HRM-specific applications and should not be read as evidence of a separate HRM research stream.

Table 6. Ten most-cited documents in the 659-publication AI-HRM corpus

Rank	Year	Source	Citations
1	2019	Tambe et al. (2019)	1,111
2	2022	Vrontis et al. (2022)	897
3	2023	Chowdhury et al. (2023)	810
4	2023	Budhwar et al. (2023)	772
5	2023	Pereira et al. (2023)	433
6	2021	Tong et al. (2021)	418
7	2021	Kong et al. (2021)	383
8	2020	Pillai and Sivathanu (2020)	359
9	2023	Rodgers et al. (2023)	358
10	2022	Malik et al. (2022)	340

The intellectual structure was examined in VOSviewer by full-counting co-citations of cited references, selecting 50 references that met the minimum frequency of 12 citing publications. The resulting visualization displays three interconnected software-derived clusters of 22, 19, and 9 references. Node size reflects within-corpus citation frequency, and link weights represent the strength of joint citation. Because cited-reference strings can contain abbreviated or nonstandard author labels, substantive interpretation uses the matched reference identities summarized in Table 7 rather than attributing a VOSviewer label to a uniquely validated first author.

The VOSviewer map identifies three interconnected cited-reference clusters (Figure 4), but these groupings mix core AI-HRM publications with



interdisciplinary and methodological sources. In particular, the cited-reference set includes Fornell and Larcker (1981), so the groups should not be regarded as three independently validated theoretical schools. The values correspond to the source-level citing-publication frequencies reported in Table 7; they are not pairwise co-citation edge weights.

3.3. Author-keyword structures and time-normalized contrasts

Author-keyword co-occurrence was calculated by full counting with a five-publication minimum. The 659-record dataset yields the same 40 original, unmerged author-keyword labels and seven VOSviewer-assigned clusters documented in Table 8. The most frequent original labels are artificial intelligence (304 papers), human resource management (165), machine learning (95), recruitment (42), and HR analytics (38). To improve legibility, Figures 5 and 6 show the same 40 node occurrences and verified full-counting relationships in a reproducible redraw, with only links observed in at least two documents displayed and the most important original terms identified by numbered labels. The underlying network is not renormalized into conceptual synonyms: terms such as AI, artificial intelligence, and artificial intelligence (AI) remain separate nodes.

The seven color-coded groups show overlaps among recruitment and talent management, HR analytics, employee outcomes, organizational AI adoption, and generative-AI terminology. One group contains only ‘systematic review’; other groups include ‘bibliometric analysis’ and ‘literature review’. Such methodological vocabulary should not be interpreted as a distinct substantive HRM research stream, and the seven software clusters are not evidence of seven independently validated theoretical dimensions.

Figure 5 presents a reconstructed author-keyword co-occurrence network with numbered labels. Node sizes represent keyword occurrence frequencies, line thickness indicates the strength of co-occurrence across publications, and colors distinguish the seven clusters identified by VOSviewer. Total link strength (TLS) values for all 40 keywords were calculated using the complete set of co-occurrence links, while only links occurring in at least two publications are displayed to improve readability. Artificial intelligence (TLS = 424), human resource management (TLS = 287), machine learning (TLS = 142), and recruitment (TLS = 111) are the most strongly connected original author-keyword labels. These figures describe patterns of keyword co-occurrence rather than causal relationships between concepts.

Table 8. Thematic interpretation and occurrence frequencies of author-keyword clusters identified by VOSviewer

Cluster	Author keywords (occurrences)	Thematic interpretation
1 (9 terms)	HR analytics (38); human resources (24); management (9); performance management (7); predictive analytics (13); recruitment (42); selection (10); talent management (30); training and development (5)	Recruitment, talent management, and HR analytics
2 (8 terms)	AI adoption (9); artificial intelligence (AI) (48); decision-making (10); efficiency (7); human resource management (HRM) (25); personnel selection (8); talent acquisition (11); technology (16)	AI adoption, organizational decision-making, and personnel selection
3 (7 terms)	Big data (11); employee attrition (15); employee engagement (19); employee performance (14); employee turnover (10); machine learning (95); people analytics (15)	Machine learning, people analytics, and employee outcomes
4 (6 terms)	ChatGPT (11); digital transformation (13); ethics (12); generative AI (12); human resource management (165); sustainability (9)	Generative AI, ethical considerations, and digital transformation in HRM
5 (6 terms)	Artificial intelligence (304); bibliometric analysis (13); deep learning (11); human resources management (29); Industry 4.0 (12); systematic literature review (9)	AI technologies, Industry 4.0, and bibliometric research
6 (3 terms)	AI (31); HRM (37); literature review (9)	General AI-HRM terminology and literature reviews
7 (1 term)	Systematic review (13)	Systematic review methodology

Note: Entries are original, unmerged author-keyword labels from VOSviewer, with document-level occurrence counts. The seven algorithmic groups include methodological vocabulary and are not interpreted as independent latent topics. Table 9 uses a different, explicitly normalized keyword variable.

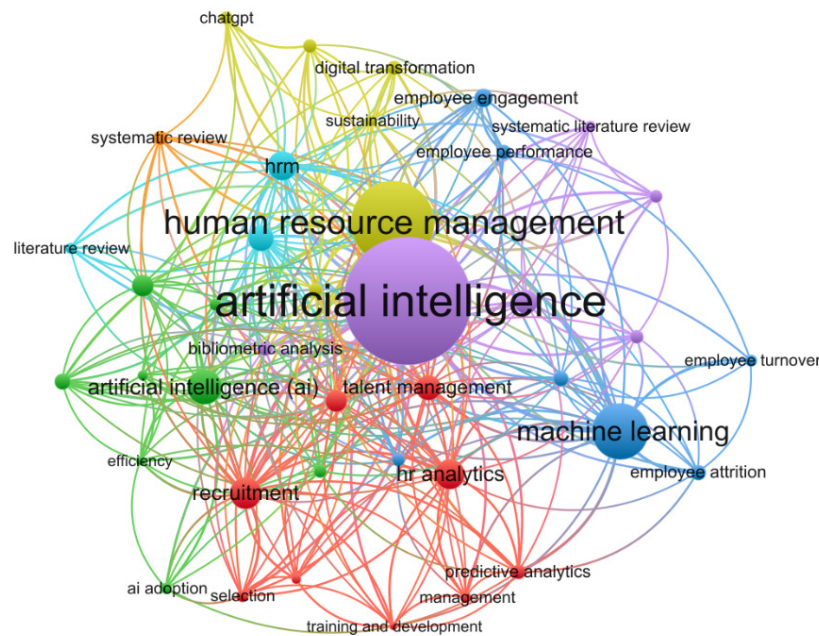


Figure 5. Author-keyword co-occurrence network in AI-HRM research

Figure 6 displays the same 40-node raw-label network, colored by the mean publication year of papers that contain each keyword. Recalculation directly from the selected Scopus CSV gives a mean-year range of 2022.0–2024.7 across the 40 labels. For example, generative AI and ChatGPT have mean publication years of approximately 2024.67 and 2024.64, respectively, whereas machine learning averages 2023.19. These values indicate relative timing in this publication sample, not a first-use

date, a rate of growth, or replacement of earlier research themes.

To complement this raw-label network analysis, Table 9 reports period-normalized frequencies of selected keyword concepts for 2000–2019 ($n = 27$), 2020–2022 ($n = 133$), and 2023–2025 ($n = 499$). Unlike Table 8, synonymous labels and explicit abbreviations were merged before each term was counted once per publication. The reproducible

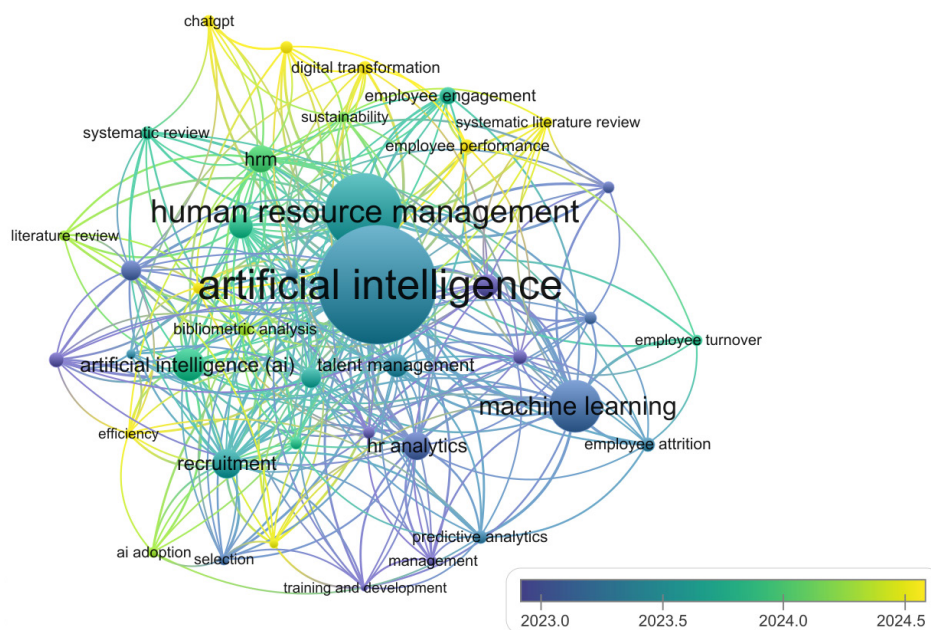


Figure 6. Author-keyword network by mean publication year

Table 9. Period-normalized frequencies of selected author keywords (N = 659)

Normalized author keyword	2000-2019 (n = 27)	2020-2022 (n = 133)	2023-2025 (n = 499)
Artificial intelligence	17 (62.96%)	75 (56.39%)	278 (55.71%)
Human resource management	8 (29.63%)	46 (34.59%)	193 (38.68%)
Machine learning	3 (11.11%)	31 (23.31%)	68 (13.63%)
Recruitment	3 (11.11%)	7 (5.26%)	32 (6.41%)
Generative AI	0 (0.00%)	0 (0.00%)	26 (5.21%)
ChatGPT	0 (0.00%)	0 (0.00%)	11 (2.20%)
Bibliometric analysis	0 (0.00%)	0 (0.00%)	13 (2.61%)
Employee attrition	1 (3.70%)	3 (2.26%)	11 (2.20%)

Note: Frequencies are document-level, and the denominator is the number of selected publications in each period. A single concept is counted once per paper after consolidating exact variants and explicit abbreviations, including AI/artificial intelligence (AI), HRM/human resources management (HRM), ML/machine learning (ML), and generative AI/generative artificial intelligence (GenAI or GAI). Table 8 retains the original, unmerged labels for the VOSviewer map.

mappings include ‘AI’/artificial intelligence (AI) → ‘artificial intelligence’; ‘HRM’/human resources management (hrm) → ‘human resource management’; ‘ML’/machine learning (ml) → ‘machine learning’; and forms such as ‘generative artificial intelligence (GenAI)’ and ‘generative AI (Gen-AI)’ → ‘generative AI’. Thus, the raw network and Table 9 intentionally measure different forms of the same bibliographic metadata, without treating repeated synonyms in one article as additional publications.

Period-normalized frequencies indicate that the proportion of selected papers using the consolidated term ‘human resource management’ rises from 29.63% (2000–2019) to 38.68% (2023–2025). The normalized ‘machine learning’ concept is observed in 31 of 133 records (23.31%) in 2020–2022 and 68 of 499 (13.63%) in 2023–2025. In the last period, the normalized term ‘generative AI’ appears in 26 publications (5.21%) and ‘ChatGPT’ in 11 (2.20%). These counts describe author-supplied vocabulary within the screened Scopus sample, not the population prevalence, effectiveness, or date of invention of these technologies.

4. DISCUSSION

A comparison with previous studies by Palos-Sánchez et al. (2022), Bansal et al. (2025), and Koştı and Kayadibi (2025) demonstrates that bibliometric research on artificial intelligence in human resource management (AI-HRM) encompasses publication activity, citation analysis, scientific collaboration, and thematic mapping. Our study extends these approaches through an integrated

assessment of citation concentration, bilateral international research collaboration, and changes in author-keyword structures over 2000–2025. Table 10 summarizes the main characteristics of the selected studies.

The findings reveal a high concentration of citations within AI-HRM research. The Gini coefficient reaches 0.7396, while the most-cited 10% of publications account for 60.16% of total citations. Furthermore, 86.19% of the selected publications appeared between 2022 and 2025, indicating a substantial expansion of research activity during the later years of the observation period. Together, these indicators characterize the distribution of scholarly attention and the dynamics of the bibliometric corpus.

International scientific collaboration represents an important dimension of AI-HRM research development. Internationally co-authored publications account for 211 of the 659 documents (32.02%). The strongest bilateral partnerships include Australia and the United Kingdom (15 joint publications), China and Pakistan (10), and India and the United Kingdom (10). These findings characterize the geographical structure of international research collaboration.

Author-keyword analysis provides additional insights into the thematic structure of the field. Figures 5-6 and Table 8 retain the original author-keyword labels, whereas Table 9 presents normalized frequencies after consolidating synonyms and abbreviations. During 2023–2025, the concept of generative AI appeared in 26 of 499 publications (5.21%), reflecting its presence in the contempo-

Table 10. Comparison with previous AI-HRM bibliometric studies

Study	Database and coverage	Methods and analytical focus	Research characteristics
Palos-Sánchez et al. (2022)	Scopus and Web of Science; 73 articles	Bibliometrix; publication activity, authors, documents, and keywords	Bibliometric characterization of AI-HRM publications and thematic structures
Bansal et al. (2025)	Scopus; 659 documents; 2012–2023	VOSviewer; citation analysis, co-citation, co-occurrence, and clustering	Analysis of the intellectual and thematic structure of scientific publications
Koştı and Kayadibi (2025)	Scopus; 522 publications; 2020–2024	Bibliometrix and VOSviewer; publication dynamics, networks, and thematic analysis	Characterization of publication activity and thematic relationships
Our study	Scopus; 1,596 records, including 659 selected publications; 2000–2025	Citation concentration, international collaboration, co-citation, and keyword normalization	Integrated assessment of publication dynamics, citation distributions, and international scientific collaboration

Note: Corpus characteristics are reported according to the respective studies. Their coverage reflects the databases, search strategies, and observation periods employed.

rary HRM research agenda. The VOSviewer clusters characterize relationships among technological, organizational, and methodological research themes.

Publication-growth modeling indicates that the exponential specification provides the strongest fit to the observed annual publication series for the selected corpus ($R^2 = 0.9945$). The Poisson model yields a Pearson dispersion statistic of 2.56, indicating overdispersion relative to the Poisson specification. These estimates complement the biblio-

metric assessment of publication-growth intensity and variability.

Overall, the study provides an integrated understanding of AI-HRM research development by combining publication dynamics, citation concentration, international scientific collaboration, and thematic changes. The identified patterns characterize the structure and evolution of Scopus-indexed publications selected according to the specified criteria over 2000–2025.

CONCLUSION

The aim of the study was to analyze publication dynamics, citation inequality, author and country participation, international scientific collaboration, cited-reference relationships, and author-keyword structures in Scopus-indexed research on artificial intelligence in human resource management (HRM) published between 2000 and 2025. An EID-based topical selection identified 659 relevant publications within 1,596 in-period records. The selected corpus accumulated 25,072 citations (38.05 per publication), exhibited substantial citation inequality (Gini 0.7396; top-decile citation share 60.16%), and grew from 16 publications in 2019 to 267 in 2025 (CAGR 59.86%). International co-authorship was observed in 211 papers (32.02%). These results answer the descriptive research objective by identifying where bibliographic output, attention, and scientific collaboration are concentrated.

The principal contribution is to link citation-distribution measures and country-pair collaboration with independently defined co-citation and keyword analyses in a traceable AI-HRM corpus. The original 40-term keyword network and the period-specific normalized concept frequencies are explicitly separated; after applying the documented normalization rules, generative-AI keywords occur in 26 of 499 papers from 2023–2025 (5.21%). Findings must be interpreted as properties of a selected scientific literature, not as evidence of organizational benefits, AI implementation quality, or future publication trends. Their reproducibility is strengthened by the supplied EID membership manifest and transparent keyword mappings, subject to the stated limitations of the original screening documentation and licensed Scopus metadata.

AUTHOR CONTRIBUTIONS

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Visualization: Assem Bukhatova.

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Writing – review & editing: Yerzhan Domalatov, Zhibek Rakhmetulina, Aigerim Rakhmetulina, Assem Bukhatova, Aikerim Narimbetova.

DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

In preparing this manuscript, the authors used ChatGPT (OpenAI) to assist with language editing, improving academic style, and enhancing the clarity of the text. After using this tool, the authors carefully reviewed, revised, and edited the manuscript and take full responsibility for the content and conclusions of the publication.

DATA AND CODE AVAILABILITY

The analysis uses a fixed Scopus bibliographic and citation snapshot covering publications dated 2000-2025, together with the EID-level inclusion log for the 659-publication topical sample. Citation distributions and descriptive publication-growth curves were calculated in MATLAB; the segmented and count-model diagnostics were independently reproduced using Python (SciPy and statsmodels). Country, co-citation, and author-keyword maps were generated in VOSviewer, while period-normalized keyword indicators were calculated from the underlying Scopus metadata using an explicit synonym mapping. Derived summary tables, permissible identifier-level metadata, settings, and analysis scripts can be made available to the journal subject to Scopus licensing conditions.

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