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Knowledge mapping of human resource analytics research: A visual analysis Using CiteSpace and VOSviewer

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Abstract: The present study aims to explore human resource analytics literature using a systematic literature review and bibliometric analysis. A sum of 179 articles extracted from the Scopus database for the years 2015–2022 with selected keywords (HR analytics, Human resource analytics, Workforce analytics, People analytics, Talent analytics, Human capital analytics) along with certain filters (subject–business, management and accounting; language-English; document–article, article in press, review articles and source-journals). Human resource analytics is discussed in this article with an emphasis on their application to human resource processes and their contribution to organisational goals. Based on the analysis, 14 influential research clusters were found: future trends, workforce analytics, talent management, human capital analytics, organisational learning, employee productivity, human resource analytics, big data challenge, adoption, evidence-based technology, recruiting, and intuition. Moreover, line managers and upper management are emphasised, making human resource analytics a strategic priority. The study presents valuable insights that aid academics and organisational practitioners in conceptualising human resource analytics practices. Additionally, this study contributes to the existing human resource analytics literature by identifying the keywords, authors, journals, and intellectual and conceptual structure.

Keywords: bibliometric analysis, human resource analytics, systematic literature review.

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INTRODUCTION

Human resource management (henceforth HRM) arose in the early twentieth century to effectively manage and rationalise the employment relationship (Ulrich & Dulebohn, 2015; Mathushan & Kengatharan, 2022b). HRM is gradually becoming a "science" that strives to advance firms' decisions on their human capital (Boudreau & Ramstad, 2007; Ratnamiasih et al., 2022). Lucidly, the workplace is undergoing a dynamic shift owing to breakthrough technologies, urging firms to craft compelling strategies to patronise success. Notably, innovative technologies are altering the human resource (HR) industry and making it easier to embrace analytics in routine HR operations (Chatterjee et al., 2022; Yoon et al., 2020). In this vein, changes in the workplace urge HR experts' knowledge, skills, and talents while also bringing new possibilities and tools to the HR industry (Jiang & Akdere, 2021; Falletta & Combs, 2021).

Human resource analytics (henceforth HRA) is an emerging paradigm in HRM. Academics and practitioners are becoming more interested in discussing HR big data and HRA (Qamar & Samad, 2021; Chatterjee et al., 2022; Aral et al., 2012; King, 2016; Khan & Tang, 2016). As McCartney et al. (2020) highlighted, conventional HR procedures and measurements have not entirely kept up with these developments (King, 2016). Analytics fosters business success (Wang et al., 2022; Newman et al., 2020). HRA has become popular due to technological advancements (Margherita, 2022). Researchers state that owing to the perceived complexity, firms fail to capitalise on analytics (Lunsford, 2019; Jiang & Akdere, 2021). HRA aims to access HR investments as a whole rather than just one area. Focusing on research relating to HRA is crucial since they have a wide-ranging impact on the company, consumers, investors, and other stakeholders outside the organisation, as well as key outputs like performance and competitive analysis (Hamilton & Sodeman, 2020; Holsapple et al., 2014).

HRA gathers and analyses data using cutting-edge technology to handle employee-related concerns, forecast future HR trends, and provide decision-makers with prospective solutions. As a result, it allows HR departments to improve employee and firm performance (Aral et al., 2012; Bassi & McMurrer, 2016). That is to say, HRA is a method for obtaining evidence-based analytical findings to improve people-related performance, operational effectiveness, and, ultimately, the influence of corporate strategy (Bassi & McMurrer, 2016). HRA affects many organisational levels using HR big data, from individual workers to HR functions and corporate strategy (Jiang & Akdere, 2021).

HR practice might benefit immensely by developing HRA and its multilevel effects on the company (King, 2016). Paradoxically, while research on data analytics has blossomed in several management domains (Qamar & Samad, 2021), this has not been the case in HRM. Further, a growing concern about understanding the fundamentals of people analytics in the HR field lacks; can delay HRA's effective implementation and operationalisation (Singh & El-Kassar, 2019; Giermindl et al., 2022). Thereby, prevailing barriers affect ongoing HR activities and HR's role as a strategic business partner.

Margherita (2022) posits while the past decade has seen significant work on HRA, systematic identification and categorisation of critical subjects have not yet been made. There is a need, in particular, for conceptual contributions that explain topics and research areas linked to HRA (Yasmin et al., 2020; Garg et al., 2022). Given the size and paucity of research on HRA, there is a potential for new contributions that aid analyses of where the field stands and encourage enterprises to switch from reporting to proper analytics (Marler & Boudreau, 2017; Minbaeva, 2017; Minbaeva, 2021). Although analytics is a "game changer" for the future of HR, it is vital to define what HRA entails and to conduct thorough investigations and explorations aimed at analysing the evolution of this field, clarifying what dimensions are involved, and identifying the barriers to adoption in organisations (Fernandez & Gallardo-Gallardo, 2020).

Notwithstanding, there are still some paucity and challenges that are chiefly reflected in the following: 1) there is a dearth of research on HRA; 2) cavity in integrating HRA applications into HRM; 3) vital areas and concepts in HRA is vague; 4) there is insufficient use of scientific measurements methods; 5) the research perspective needs to be extended; 6) there is a vacuum in the related concepts such as artificial intelligence, big data; 7) although there are many publications related to HRA, the overall knowledge structure of the HRA landscape is obscure.

Bibliometrics use statistical and mathematic techniques to assess the literature statistically. Understanding the research status, hotspots, and development enables researchers to quickly master the current basic information and development status in the research field (Batistič & van der Laken, 2019). It also more intuitively explains the relationship between analysis units through graphics and visualisation. Researchers have currently done bibliometric analyses of pertinent studies on land ecosystem services and have come to certain conclusions.

In light of a new research's significance, it is crucial to assess its nature and the intellectual foundation of the field. Therefore, the overriding aim of this study is to explore the HR analytics domain. The literature on HR analytics in the Scopus academic database is investigated using a bibliometric analysis approach. Through research, it is expected to achieve the following: 1) to understand the cooperation relationship of authors and countries in the field of HRA research; 2) to identify the most cited and most noteworthy references, authors, and journals; and 3) to clarify the structure of knowledge development and emerging trends in the field of discipline. The rest of the paper is organised as follows. The background of the study is presented in Section 2. Methodological details are provided in Section 3. Section 4 discusses the main findings. The discussion of the findings and future research agenda is presented in Section 5. Section 6 recapitulates the results and deliberates on the limitations of this study.

METHODS

One of the critical tasks for unfolding a specific study area is synthesising previous research findings. Researchers have previously used a structured literature review, which garners a qualitative approach and a meta-analysis (Schmidt, 2008). A third technique, known as "science mapping," is being increasingly grasped to map the structure and advancement of scientific areas and disciplines based on the quantitative approach of bibliometric research methods. Moreover, bibliometric methods are increasingly used to study the evolution, dynamics and interconnections between various scientific areas (Small, 1999; Boyack et al., 2013; Mathushan, 2022; Mathushan et al., 2022).

The bibliometric study uses statistical techniques to explore qualitative and quantitative transformations in specific scientific research and discover recent trends within the field (De Bakker et al., 2005; Mayr et al., 2014) such as research clusters, authors, keywords, publications, nations, organisations. Therefore, bibliometric analysis helps to determine how a field is gradually growing (Abramo et al. 2011). Bibliometric techniques offer the ability to provide a systematic, transparent, and repeatable review procedure, hence extending the reviews' quality. Following Van Eck & Waltman (2017), the paper adopts the bibliometric analysis to analyse and draw inferences from 179 articles retrieved from the Scopus database from 2015 to 2022. The Scopus database is used in this study, containing research from many areas. The bibliometric study is made possible by the Scopus availability of data on scientific research production, distribution, and impact. Scopus integrates a wide-ranging database of abstracts and citations, enhanced data, and related academic literature from various fields.

After defining the topic of the study, the researcher turned to preexisting literature studies to develop a list of relevant search terms. The search query is as follows: "HR analytics" OR "Human resource analytics" OR "Workforce analytics" OR "People analytics" OR "Talent analytics" OR "Human capital analytics." The keywords used in this study were also studied by (Qamar & Samad, 2021).

The query mentioned above was searched in the title-abstract-keyword field of the Scopus database. The initial search yielded 179 articles (excluding conference papers and book chapters) published in English between 2015 and 2022. Figure 1 depicts a schematic representation of the methods used. The process is shown in three steps: data gathering, data analysis, data visualisation, and interpretation. This process led to the identification of articles: human resource analytics (53 articles), resource analytics (24 articles), workforce Analytics (31 articles), HR Analytics (23 articles), Big Data Analytics (15 articles), People Analytics (17 articles), talent analytics (16 articles).

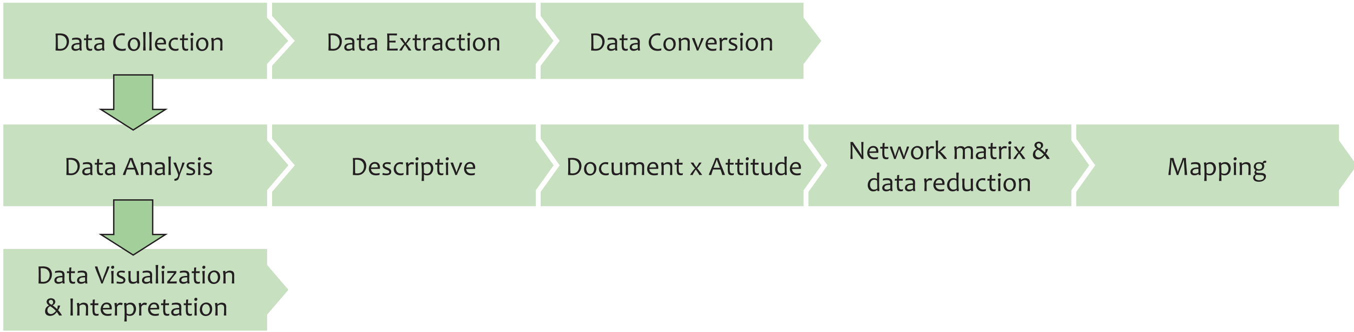

Figure 1 Overview of methodology

This research follows a four-step process that maps to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Figure 2): (I) identification; (ii) screening; (iii) eligibility; and (iv) inclusion. This technique allows for an unbiased, comprehensive, and open assessment of scientific output. Articles are discarded during the screening phase if their titles and abstracts fail to match the inclusion requirements (Meline, 2006). The inclusion criteria were the "empirical studies" published in "academic journals" in "English" on "human resource analytics" during the "2015-2022" period.

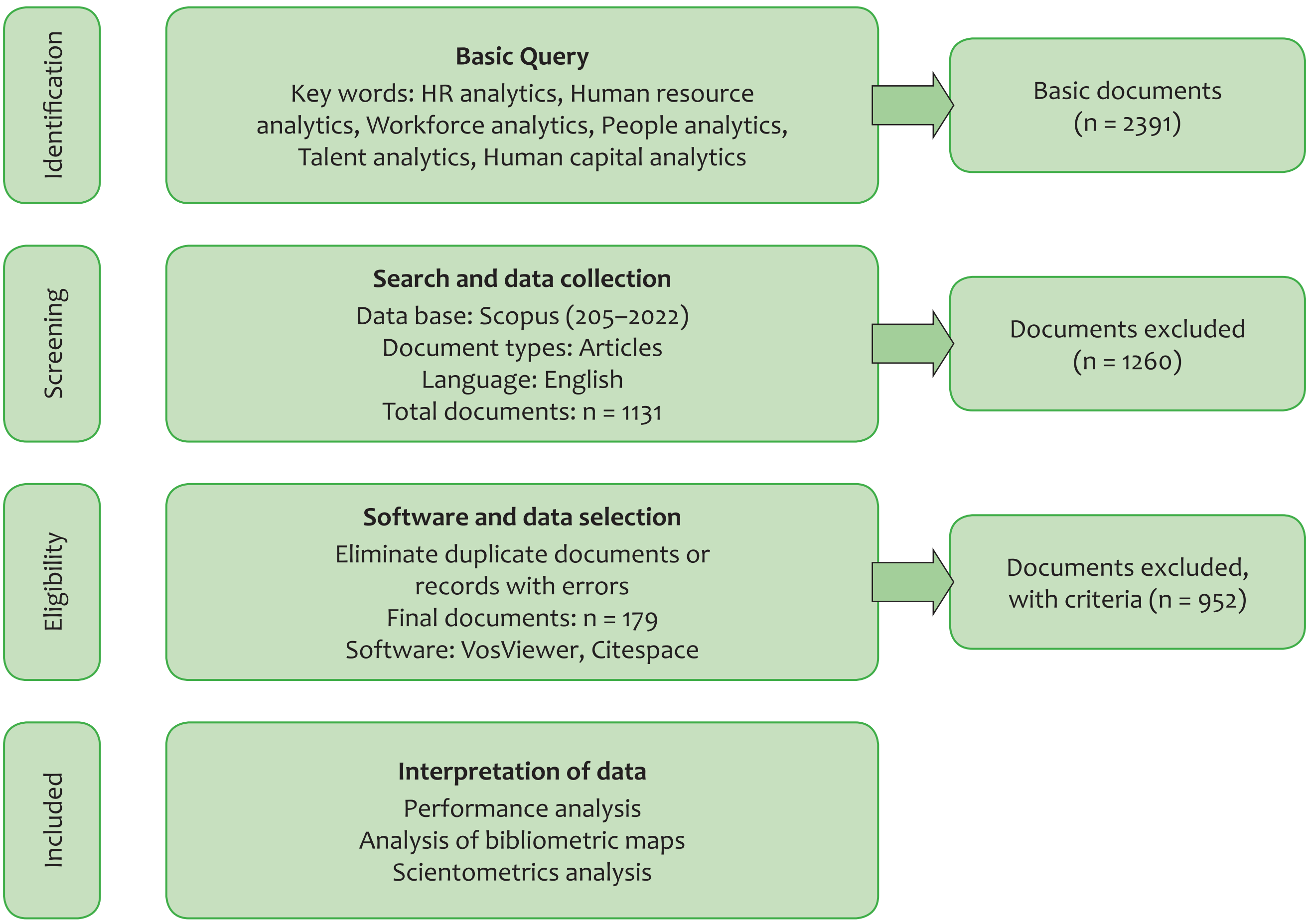

Figure 2 Diagram inspired by the PRISMA statement detailing the four phases of the bibliometric research methodology

The visualisation approach is the ideal way to simplify the presentation of data from a large quantity of information. To better perform tasks like outlier identification and pattern recognition, it uses computational tools to depict the underlying structure of knowledge graphically. VOSviewer is a programme that helps users build and observe aggregated bibliometric networks. In addition, VOSviewer has a clustering feature that places keywords into groups according to how often they appear together. In addition, CiteSpace is a Java-based analytical tool developed by Chaomei Chen at Drexel University (Chen, 2006) that generates tabular data and visual maps. CiteSpace is advantageous for locating pivotal spots and turning points by creating independent co-citations, constructing a complete co-citations network, and seeking key nodes with their respective significant characteristics (Chen, 2006, 2016) because of its ability to fuse co-citation and visual maps.

RESULTS AND DISCUSSION

Table 1 presents an overview of the data on HRA literature collected from the Scopus database. The collection comprises 179 articles from 87 journals that accounted for 298 authors and were published between 2015 and 2022 (as of November 8, 2022). Further, the data analysis shows that the average number of citations per document is 6.435.

Table 1 Synopsis of the data

Description	Results
Total articles	179
Sources	87
Time span	2006–2022
Authors	298
Author's keyword	196
Average citations per document	6.435
Keywords Plus	276

Figure 3 shows the growth of publications related to the construct of HRA between 2007 and 2022. According to the statistics, there has been a yearly growth in interest in this field of study. Except for the first three years (2007; n = 2 articles, 2008; n = 1 article, 2009; n = 0 article), which seem to have been a rather stable period, the number of publications has grown yearly. However, it can be observed from the graph that the growth of publications from 2010 to 2012 (2010; 3 articles, 2011; 5 articles, 2012; 6 articles) continues to evolve. Despite this, there was a notable stagnation from 2012–2013. It indicates that sufficient attention was not given to HRA research. From 2013, sufficient attention was given to the HRA research. The number of articles progressively rises from 2014 (n = 9 articles) to 2016 (14 articles). However, since 2017, this issue has garnered more scholarly attention. Although, from 2016-2017, a decline can be observed (2016; 15 articles, 2017; 10 articles). It is clear from figure 3 that the number of publications in the database fluctuated slightly until 2017, but after this year, there was a year-on-year increase in published documents. Nearly 15 articles on HRA were published in 2021 than in 2020. 50 papers were released in 2021, while 54 documents were published in 2022. The year 2022 brought the highest number of research papers in the database, while 54 documents were published on HRA.

Owing to the rapid digital transformation, which has raised the need for HR analytics solutions, the Asia Pacific region is predicted to expand the quickest in HR analytics. HR analytics helps firms to make evidence-based strategic business choices, ultimately increasing organisational performance. The prevailing attention shows that HRA is salience for firms. Findings suggest that researchers can still focus on addressing such gaps the conceptual ambiguity of HR analytics, HR analytics theoretical perspectives are far less focused, fragmented empirical evidence, and lack of integration of HRA in firms. Therefore, HR professionals must assess the advantages and disadvantages of using analytical methodologies and create a solid data-gathering plan before applying HR analytics. This should include posing and responding to inquiries on generating and maximising the value of available data. It should also include ensuring that the HR unit's unique organisational requirements are considered while describing the present situation and the ideal future.

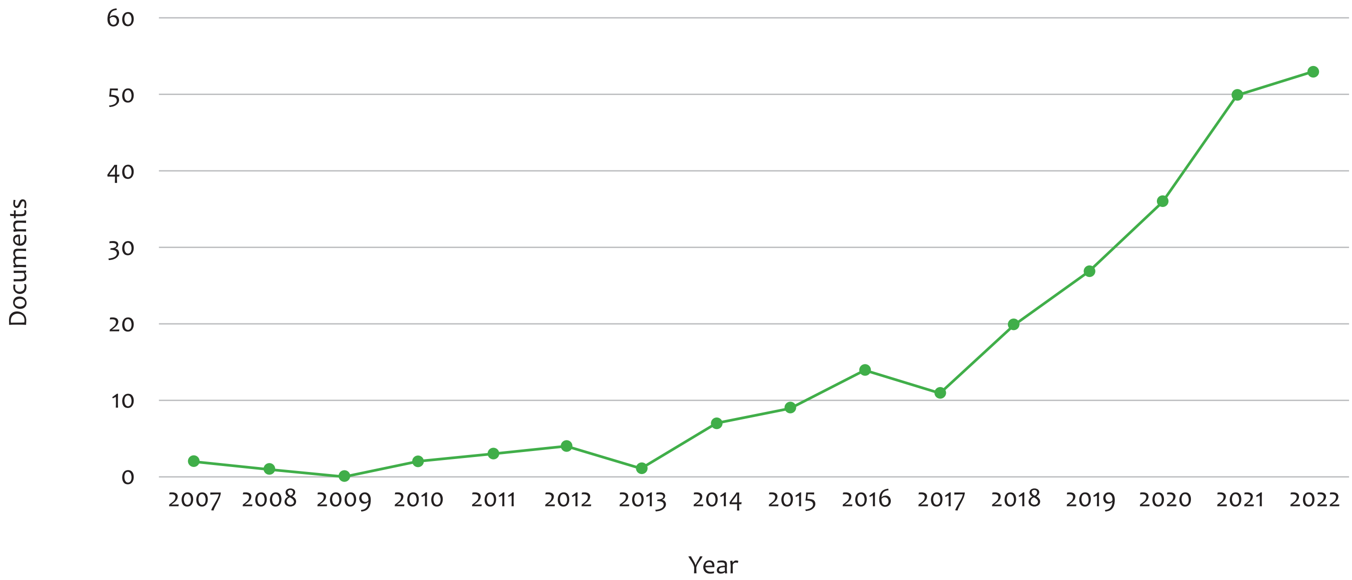

Figure 3 Year of publication

To some degree, the quantity of papers represents the nation or region's contribution to HRA research. Table 2 shows the top ten nations or regions and the institutions that produced publications on interpersonal trust between 2006 and 2022. According to the finding, 58 countries or regions have contributed to the research on HRA. Amid the United States has published the most, with a total of 66 articles published, accounting for 39.58%, showing that the United States takes a leading position on research on HRA. India comes in second on the list with 39 articles published, accounting for 19.16% of the total. The fundamental explanation for the significant disparity between the United States and India is that HRA research in India began late. The United Kingdom is third, with a total of 21 articles. Germany, China, Australia, Canada, France, Italy, Netherlands and other developed countries follow on the list (see table 2).

Additionally, the top 10 publication institutions are presented in the same Table. 2 of the top 10 high publication institutions are all in the United States. The remaining are RMIT University business school in Australia, Trinity College Dublin business school in Ireland, Copenhagen Business School in Denmark, Indian Institute of Technology Delhi and Management Development Institute, Gurgaon in India. In fact, except for India, the largest developing country, the present research institutions in the field of ARA come from developing countries. Thus, sufficient efforts and interventions should be taken to foster the research on HRA from a developing country perspective. In other words, research on HRA is a plethora in developed country contexts, while developing countries like Sri Lanka are still in the infancy stage. Therefore, this void should be addressed through robust research undertakings.

Table 2 Top 10 countries and institutions publication status

Rank	High publication countries		High publication institutions	
	Country	**Numbers**	**Institution**	**Numbers**
1	United States	66	RMIT University	4
2	India	39	University of Southern California	4
3	United Kingdom	21	USC Marshall School of Business	4
4	Germany	15	Trinity College Dublin	3
5	China	14	Copenhagen Business School	3
6	Australia	13	New York University	3
7	Canada	9	Vrije Universiteit Brussel	3
8	France	9	Indian Institute of Technology Delhi	3
9	Italy	8	Management Development Institute, Gurgaon	3
10	Netherlands	8	Amity University	3

Table 3 Most Active Sources

Rank	Sources	Total publications
1	Human Resource Management Journal	9
2	Journal of Business Research	8
3	Business Horizons	7
4	Human Resource Management Review	6
5	International Journal of Organizational Analysis	6
6	Journal of Organizational Effectiveness	6
7	International Journal of Human Resource Management	5
8	International Journal of Information Management	5
9	International Journal of Manpower	5
10	International Journal of Recent Technology and Engineering	5

Table 3 displays the most active source title based on at least five total publications. The Human Resource Management Journal is the most popular source title (9 articles), accounting for 12.03% of all articles. Journal of Business Research comes second (8 articles) with 4.48%, followed by Business Horizons (7 articles) with 5.10%. In contrast, the remaining source titles account for less than 10% of the total.

Using CitSpace's timezone view function, evolution analysis was performed to demonstrate the HRA research development process. Figure 4 presents the findings from the clustering of the literature in the form of a timeline fisheye diagram. Intuitively, the cold-to-warm colour change in the citation tree rings represents the ongoing expansion of scientific knowledge. The hottest area of study at the moment is yellow citation tree rings. The 67 primary clusters that make up the network are labelled with index words from their respective citations and are summed up with the symbol "#" on the right side of Figure 4. It should be emphasised that the clusters are labelled using title phrases and the log-likelihood ratio (LLR) weighting technique. The LLR algorithm calculates and determines each kind of label, presenting the fundamental idea of each cluster with correct terms (Fang et al., 2018). These extracted main clusters with '#' represent the discipline's research horizons. Thus, 'future trend', 'workforce analytics', 'talent management', 'human capital analytics', 'organisational learning', 'employee productivity', 'human resource analytics', 'predicting employee readiness', 'big data challenge', 'adoption', 'evidence-based-technology', 'recruiting', 'intuition' are the focal research area in the knowledge field of HRA.

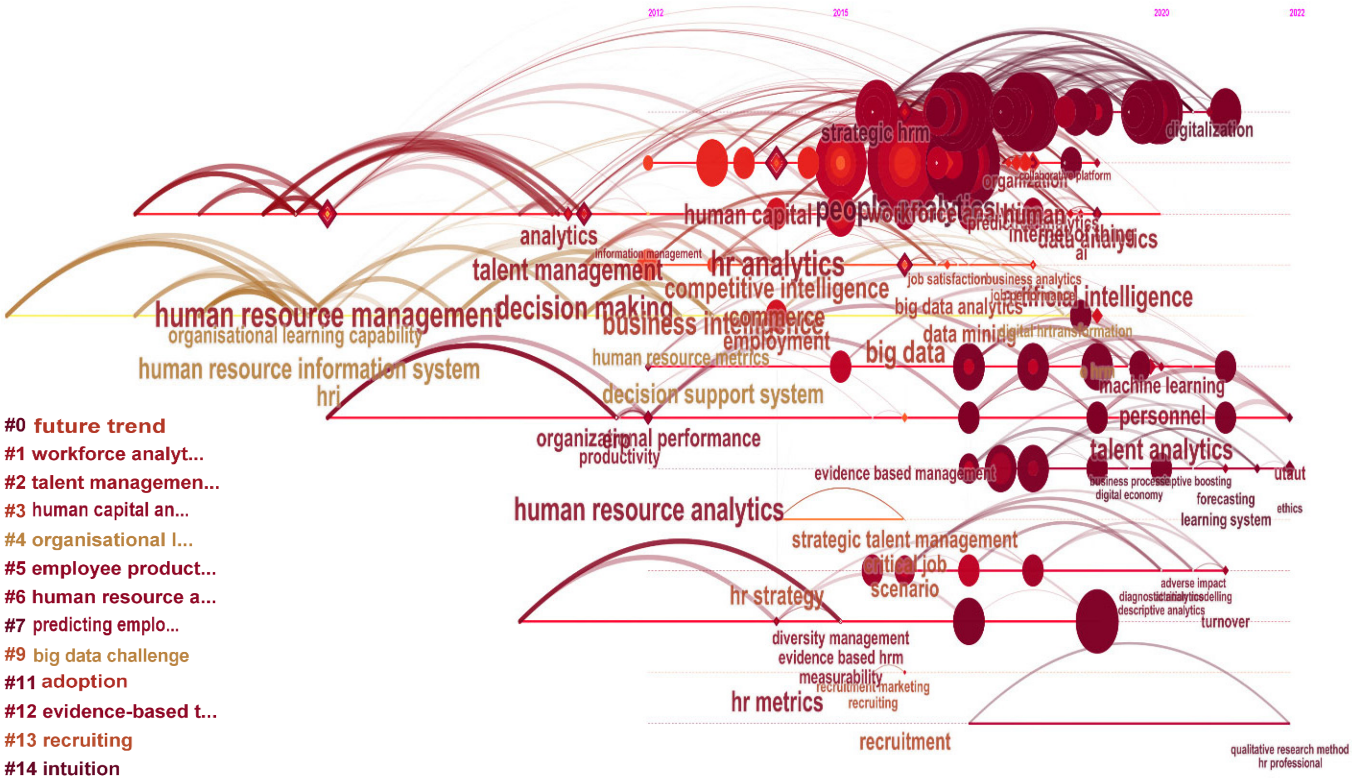

Figure 4 A timeline map of the references in HRA

In co-citation analysis (McCain, 1990), co-citation counts are used to generate similarity metrics between texts, authors, or journals. The frequency with which two units are cited together is known as co-citation (Small, 1973). Co-citation analysis implies that the more frequently two documents are cited, the more likely the content is closely connected. The co-citation graphic represents the field's current status in the past rather than necessarily how it is now or how it could be tomorrow since publishing takes time. Co-citations can also be used to spot changes in paradigms and schools of thought over time (Pasadeos et al., 1998). Co-citation analysis determines the degree of closeness between two different articles. Co-citation occurs when two articles share at least one reference (Walter & Ribiere, 2013). Co-citations often show that these co-cited papers are on homogenous areas and deal with similar study areas. Therefore, the present study employs co-citation analysis on the cited references of all 196 publications to establish the academic structure in HRA.

Co-citation analysis is a scientometric approach for investigating and establishing a field's key topics and knowledge structure. It may cluster together articles with relevant research information. Using CiteSpace, co-citation and cluster analysis were performed to uncover key aspects in the retrofitting of residential structures. The maximum number of links per node was set to 10, look back years was set to 5, and the link retention factor was set to 3. CiteScape detected 11,232 valid references, representing 100% of the original references. Figure 5 depicts co-citation analysis clusters with 679 nodes and 107 connections. The cluster with the greatest number of studies is #0. CiteSpace gives cluster labels based on their structure rather than their content.

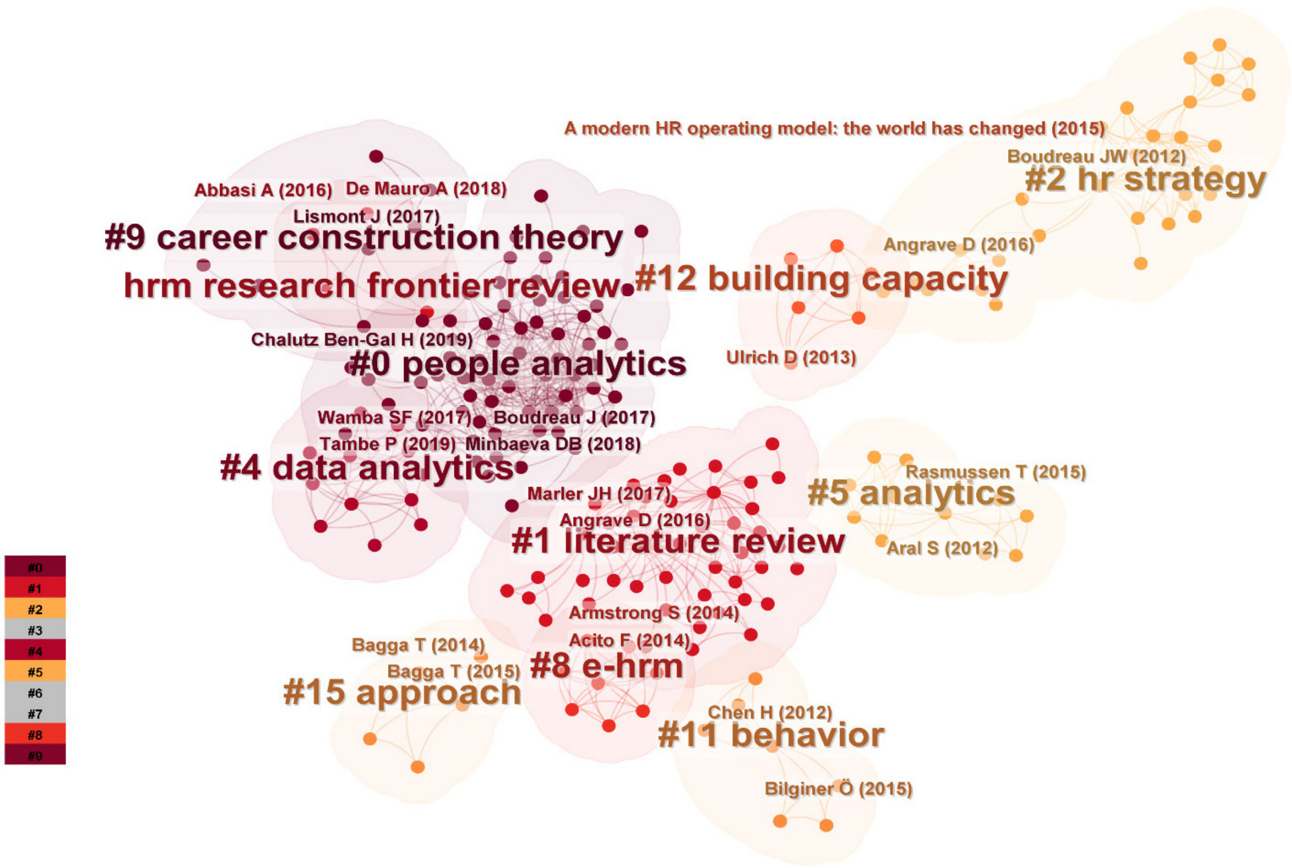

Figure 5 Co-citation network analysis

The silhouette is an indicator used to quantify the homogeneity of a cluster; the greater the silhouette score, the more homogeneous the cluster. When the silhouette score is equal to 0.7, the clustering outcome is deemed to be reliable. The clustering result is satisfactory when the silhouette score is more than 0.5. The silhouette scores of the ten greatest clusters are more than 0.7, indicating that these clusters are effective and persuasive.

The overview begins with discovering important clusters, such as citing articles and cited references. The significance of nodes is described using citation-based measures like citation counts and citation bursts, as well as network-based metrics like degree centrality and betweenness centrality.

The largest cluster (#0) has 67 members and a silhouette value of 0.86. It is labelled as people analytics. The major citing article of the cluster is *"human resources analytics: a systematisation of research topics and directions for future research"* (Margherita, 2022). This article reports that HRA is critical for improving organisational people-driven performance. Margherita (2022) claimed that the rise of the global workforce and the growing importance of business analytics as a strategic organisational capability substantially influence HRM today. While HRA has received considerable attention in the literature, systematic identification and categorisation of underlying themes have yet to be offered. There is especially the potential for conceptual contributions to explain topics and research areas linked to HRA. Their findings show that, despite the substantial interest in this field, organisations have had trouble switching from operational reporting to human capital analytics (HCA). This is primarily due to analytics teams' failure to create reliable internal HCA and show its usefulness. The relevance of understanding HCA as an organisational capability is emphasised by Minbaeva (2018), who also offers a strategy for its operationalisation. Working with the three HCA dimensions of data quality, analytical skills, and strategic capacity to respond is necessary for the growth of HCA. Additionally, this has to be initiated at the person, process, and structural levels.

The second largest cluster (#1) has 45 members and a silhouette value of 0.788. It is labelled as people analytics. The major citing article of the cluster is *"expanding the methodological toolbox of HRM researchers: the added value of latent bathtub models and optimal matching analysis"* (van der Laken et al., 2018). Researchers frequently rely on general linear models to investigate the impact of HRM decisions, but there is growing interest in using multilevel models to understand the processes at work better. A research group led by Paul van der Laken from the Shell International, the Hague, the Netherlands (2017) reported in 'Expanding the methodological toolbox of HRM researchers' that human resource management (HRM) emerged as a function in the early 20th century to manage and rationalise the employment relationship effectively. HRM is increasingly becoming a "science" that aims to enhance organisations' decisions regarding their human capital. HRM scholars have primarily relied on general linear modeling (GLM), such as linear regression, to create a basis of evidence for such decisions. Methods other than GLM may better account for the complex effects of these new forms of HR data. An optimal matching analysis is proposed as applicable to examine the longitudinal patterns that occur in repeated observations over a prolonged time frame (van der Laken et al., 2018).

The third largest cluster (#2) has 30 members and a silhouette value of 0.951. It is labelled as an HR strategy. The major citing article of the cluster is HR strategy: *"HR strategy: optimising risks, optimising rewards"* (Cascio & Boudreau, 2014). Risk-optimisation frameworks in HR and general management have largely focused on minimising or controlling unwanted outcomes. Still, the emerging arena of human capital risk requires balanced attention to risk-taking. The HR field has much to offer as organisations struggle to respond to demands that they address the risks that lead to financial crises, operational disasters, etc.

Organisations, people, and society confront an increasingly "VUCA" (volatile, uncertain, complex, and ambiguous) environment. It is hardly unexpected that greater academic and practical attention is being paid to the organisational risk and risk management solutions. It is also necessary and appropriate that such increasing focus on general organisational strategic risk draws attention to the role of personnel, HR practises, and HR strategy in risk management. Human capital risk often occurs in general strategic-risk frameworks, gets increased attention from financial and other authorities, and is generally incorporated in modern HR competence frameworks, strategy definitions, and mission statements (Cascio & Boudreau, 2014).

The 4th largest cluster (#4) has 12 members and a silhouette value of 0.96. It is labelled as data analytics. The major citing article of the cluster is *"data analytics and performance: the moderating role of intuition-based HR management in major league baseball"* (Kim et al., 2021). By emphasising a crucial boundary condition of intangible resources over time in a highly competitive and specialised business, Kim et al. (2021) contribute a fresh viewpoint to the prior resource-based view (RBV)-centric methods. This study proposes and empirically tests the aspect of big data analytics that may either enable or constrain a firm's social complexity and causal ambiguity. Decision-making processes in organisations are being revolutionised through technology and access to large amounts of data. Kim et al. (2021) found that the dissemination of big data knowledge through social networks and personnel mobility results in a less durable competitive advantage that predominantly uses data analytics to make analytics-based human resource (HR) decisions that creates g a boundary for resource-based view (RBV). Their findings imply that firm specificity of data analytic expertise might become generic over time due to the system's rollout to all ballparks and the ensuing dispersion of specialised human capital throughout this sector. Additionally, data-driven and intuitive decisions are sought to understand better strategic personnel deployment to achieve organisational goals, especially for hybrid organisations. In the big data era, enabled by infinite storage and computational capacities, it isn't easy to discern where intuition-based approaches play a role since intuition-based HR management requires idiosyncratic knowledge, which could potentially make firms self-assertive (George et al., 2014).

The 5th largest cluster (#5) has 11 members and a silhouette value of 0.983. It is labelled as a big data challenge. The major citing article of the cluster is *"HR and analytics: why HR is set to fail the big data challenge"* (Angrave et al., 2016). The central argument of this article is that a lack of understanding of analytical thinking by the HR profession is hampering the development of HR analytics. In 'HR and analytics', Angrave et al. (2016) reported that the HR function is lagging behind other functional areas of management in adopting analytics technology and analysing big data. A lack of understanding of analytical thinking by the HR profession is hampering the development of HR analytics. Unless HR professionals upgrade their skills and knowledge to become defenders of this new approach, the existing forms of HRA are likely to seal the exclusion of HR from strategic, board-level influence while doing little to benefit organisations. The HR analytics industry is primarily based on products and services, which too often fail to provide the tools for HR to create and capture the strategic value of HR data. The development of academic theory and research into HR analytics over the last 15 years suggests several key lessons HR professionals should heed. A different approach to HR analytics is needed, which starts with the question of how HR data can be used to create, capture, leverage and protect the value and seeks to develop answers to these questions through more advanced forms of longitudinal multivariate modelling. Academics could play a constructive role in these developments but could do more to elucidate the praxis of strategic HR analytics.

The 6th largest cluster (#8) has 8 members and a silhouette value of 0.987. It is labelled as adoption. The major citing article of the cluster is *"E-HRM in a cloud environment implementation and its adoption: a literature review"* (Ziebell et al., 2019). This article provides a new perspective on the E-HRM. This article reveals that the underlying technological foundation is expanding quickly with the increasing digitalisation of HR procedures in businesses. The digital transformation of HRM processes using electronic HRM solutions is increasing rapidly. It is argued that e-HRM began with the advent of the first computers in 1940 and has evolved over several decades from information provisioning to transaction automation. The focus is less on mapping the entire HR process cluster in a cloud environment. This systematic literature review is the digital transformation of human resources processes into new cloud-based environments. They recommend that the adoption rates of HR analytics are comparatively low; research is not taking the lead here and investigates this topic in depth. It could open additional research fields, for example, which describe which key figures are relevant or which key values can be used to measure the success of HR transformation projects.

The 7th largest cluster (#9) has 7 members and a silhouette value of 0.971. It is labelled as career construction theory. The major citing article of the cluster is *"Employees' adoption of HR analytics – a theoretical framework based on career construction theory"* (Dhankhar & Singh, 2022). Using career-building theory, (Dhankhar & Singh. 2022) propose and tests a mediation model that investigates the relationship between technological readiness, HR analytics uptake by HR professionals, and organisational career growth. The research presented evidence for the mediation function of individual HR analytics adoption between organisation career development and technological readiness. First, the findings support the career formation theory regarding HR professionals' use of human resource analytics. Second, the study's results support the technological readiness model's validity in adopting HR analytics. Thirdly, and perhaps most importantly, the research suggests a new theoretical framework for HR practitioners in firms to utilise HR analytics.

The 8th largest cluster (#11) has 7 members and a silhouette value of 1. It is labelled as exploring organisational change readiness employee attitude. The major citing article of the cluster is *"big data in an HR context: exploring organisational change readiness, employee attitudes and behaviours"* (Shah et al., 2017). Dhankhar & Singh (2022) describe a contextual use for big data in the context of an HR case study. This is accomplished by creating a normative conceptual model that aims to include employee behaviours and attitudes in the context of organisational change preparedness. To better assess employee attitudes and behaviours as part of broader HR predictive analytics (HRPA) approaches, (Dhankhar & Singh 2022) highlight how, where, and why such a normative approach to employee factors may be limited. And propose a focal framework that integrates big data, implementation approaches, and management commitment requirements.

The 9th largest cluster (#12) has 6 members and a silhouette value of 0.996. It is labelled as building capacity. The major citing article of the cluster is *"HR transformation within the hotel industry: building capacity for change"* (Francis & Baum, 2018). This paper aims to identify emerging patterns in the hospitality industry's strategic repositioning of the HR function and to examine the difficulties HR professionals face as they implement plans to build employee skills and organisational capacity while also adapting to new roles and responsibilities. Contradictory trends in the strategic repositioning of the HR function and the influence of electronic HR systems are laid out in detail in the report. The importance of "higher-order" HR capabilities, such as the functions' ability to implement talent and organisational development plans, is highlighted. Findings highlight the difficulties inherent in transitioning from "operational" to "strategic" HR. It provides suggestions for practice in continuous professional development, skill-building for HR and line managers via discussion and project management, and using new technologies and personnel data and analytics.

The 10th largest cluster (#18) has 4 members and a silhouette value of 0.996. It is labelled as HRM research frontier review. The major cited article of the cluster is *"human resources for Big Data professions: A systematic classification of job roles and required skill sets"* (De Mauro et al., 2018). Big Data Analytics' rapid growth is causing businesses to reevaluate their human resources (HR) demands. However, what specific work positions and competencies fall under this category is also unclear. By examining many online real-world job postings, De Mauro et al. (2018) clarify the varied nature of skills needed in Big Data professions. Their analysis uses many job postings found online using web scraping to provide an understandable taxonomy of employment categories and skill levels. It aids in the establishment of clear plans for the correct skill acquisition and development necessary to fully use big data by company executives and HR managers. Additionally, the organised categorisation of job categories and skill sets will help create a shared lexicon that HR recruiters and educational institutions can use better to match supply and demand in the labour market.

Analytics is used by high-performing businesses to support rational decision-making. However, findings show that many firms' human resource (HR) departments have been sluggish in implementing HRA for several reasons. Big data and the revolutionary potential of HR analytics are hot topics in the HR profession. HR analytics is a "must have" ability to assure HR's future as a strategic management function and improve organisational performance.

The keyword co-occurrence networks could be used to determine the knowledge structure and research topics. In a co-occurrence network, each node reflects an object (e.g., article, author, country, institution, keyword, journal), and concerning Figure 6, a keyword, wherein: (1) the magnitude of nodes designates the occurrence of keywords (i.e., the number of times that the keyword occurs), (2) links amid the nodes indicates the co-occurrence among keywords (i.e., keywords that co-occur or occur together), (3) the width of the link indicates the occurrence of co-occurrences among keywords (i.e., the number of times that the keywords co-occur or occur together), (4) the larger the node, the greater the occurrence of the keyword, and (5) the thicker the link between nodes, the greater the occurrence of the co-occurrences between keywords. Each colour epitomises a thematic cluster, in which the nodes and links in that cluster could be employed to define the cluster's coverage of nodes and the associations between the nodes cluster.

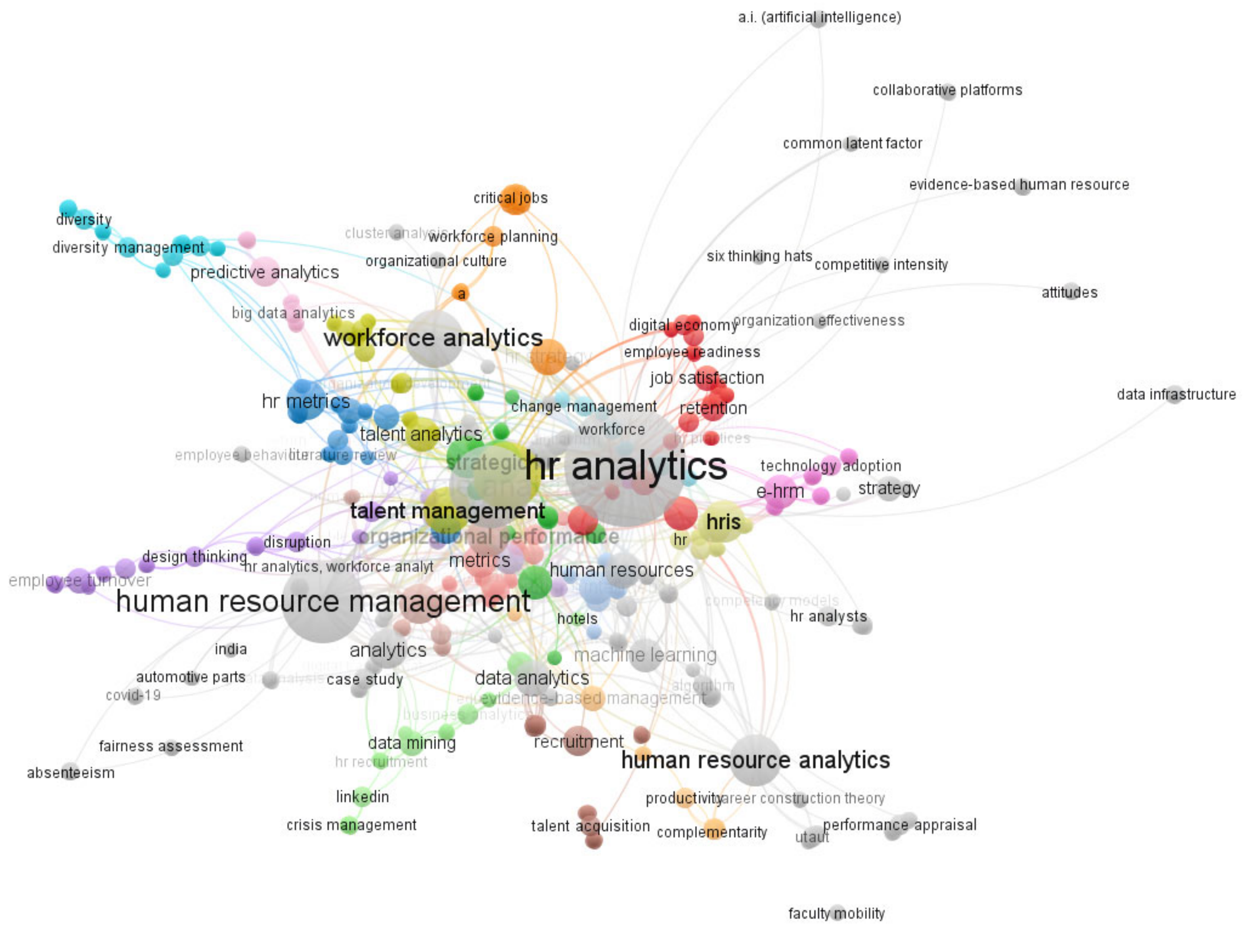

Figure 6 Co-occurrence network

Figure 6 shows the co-occurrence data for the author's keywords in VOSviewer to identify the hotspots in the HR analytics study area. The structure of the co-occurrence network of author keywords was analysed to identify the primary study topics in the field of HRA literature. Only the keywords that occurred at least 15 times were considered to leave out less significant themes from the research and get a clearer structure of examined notions. From the 3875 keywords that the authors employed, the 57 most crucial ones appeared, creating the network in Figure 6. Seven clusters reflecting the main study subfields in the literature on HRA were identified via analysis. According to the analysis's findings, HR analytics, talent management, human resource management, workforce analytics, and predictive analytics were the strongest overall connection strengths.

It can be observed that the majority of network influence is executed by the HR analytics concept, indicating a total link strength of 254 and 35 occurrences (together with concepts of Human Resource Information Systems, change management, big data analytics, talent analytics, workforce analytics, workforce planning, technology adoption, employee readiness, six thinking hats, artificial intelligence) comprise the grey cluster. Further, this cluster comprises several keywords such as AI, Collaborative platforms, common latent factor, data infrastructure, strategy, and competitive intensity.

The red cluster concerns employees' satisfaction, retention, and readiness to adopt. It has 26 links, with a total link strength of 69 and 11 occurrences. This cluster mainly focused on employees' willingness to adopt HRA in organisations. Further, the findings stressed that the major concern is placed on the retention and satisfaction of employees. This implicitly indicates that firms should focus on employee-related aspects while crafting and implementing HRA strategies. The light blue cluster focused on diversity. In all research, diversity and diversity management are recognised as central areas in implementing HRA. The yellow cluster is more related to talent analytics, facilitating workforce analytics and HRA. The focal keywords "talent analytics, workforce analytics, HRIS, talent management" with 56 links and a total link strength of 32 occurrences. Blue cluster is more focused towards HR metrics, resource-based theory, business intelligence, return on investment, and organisation development in supporting organisational performance and competitive advantage. The main keyword in this cluster is "HR metrics", with 14 links, a total link strength of 23, and five occurrences. The purple cluster centres on HR analytics, human resource strategies, and employee behaviour in light of employee turnover. The most frequent keyword is "HR metrics", with 31 links, a total link strength of 56, and 6 occurrences.

The green cluster is more focused on strategic HR, human capital, and workforce analysis to facilitate HRA decision-making. The most notable keyword in this cluster is "Strategic HR", with a total link strength of 63 in 45 links and five occurrences.

Density is used to assess and measure the intensity of interactions between terms. The greater the density rating, the less separation there is. Because it offers a robust graphical user interface, VOSviewer software is used to produce density maps. Figure 7 illustrates the term co-occurrence heat map of HR analytics based on density value, which interprets density values using various hues ranging from white to yellow to red. A more often used concept is highlighted in a greater intensity red hue. Aside from HR analytics and people analytics, the greater density of red hue on the word "human" and "human capital" led to an intriguing perspective in HRA research. An important component of HR analytics can be emphasised: the essence of "human capital" in human resource management should not be lost when applying HR analytics. During the HRA design and execution stages, HR managers should focus on human aspects. HR strategy and strategic HR are other intriguing topics which are important aspects of HRA. Strategic HR practices such as talent retention, talent acquisition and workforce planning may help firms save a lot of money and directly impact the entire company's performance.

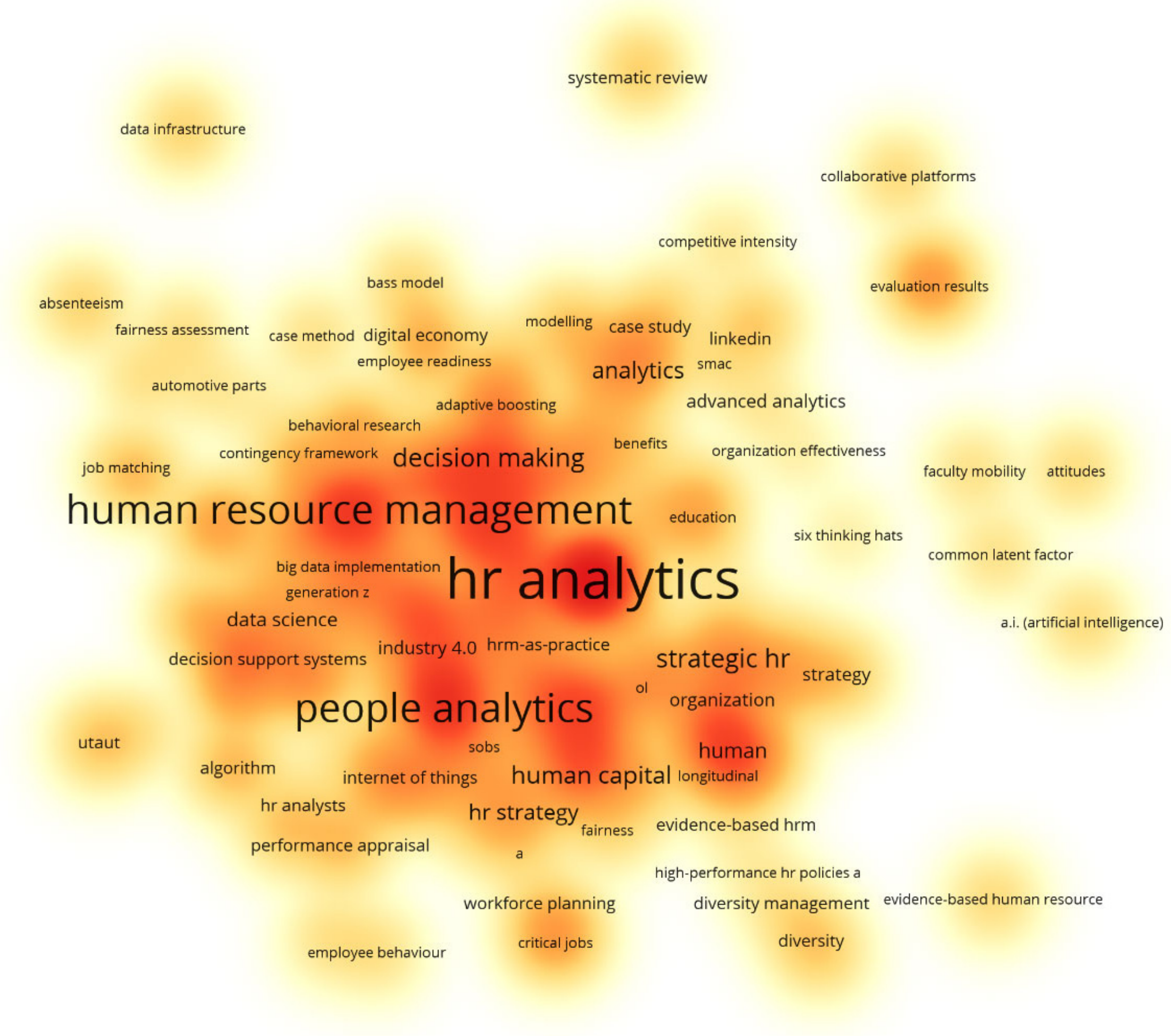

Figure 7 Keyword co-occurrence heat map of HR analytics

Further, it can be observed that researchers have chiefly focused on linking the HRA to some other research domains. Figure 8 visualises the evolution of the author's key terms used progressively in HRA literature and discloses that researchers attempted to integrate HRA into keywords such as strategic human resource, data infrastructure, high-performance HR policies, HR strategy, organisation effectiveness, talent acquisition and later lifted onto various specific concepts like artificial intelligence, data mining, learning systems, data science, internet of things, performance appraisal, competitive intelligence, diversity management, employee retention. In a nutshell, findings suggest that researchers have successfully built the idea of HR analytics by embracing human capital as a salient source for competitive advantage, developing tools like contingency framework, people analytics, learning systems, big data analytics and artificial intelligence to garner and analyse data from human capital, and eventually forecasting the result of HR practices based on that data. Additionally, it can be noted that researchers located a strong emphasis on HR-related decision-making in HRA research. Ideal decision-making mechanisms contribute to organisational effectiveness. Top management can use HRA to make decisions concerning HRM functions such as performance appraisal, employee turnover, talent acquisition, employee retention and absenteeism.

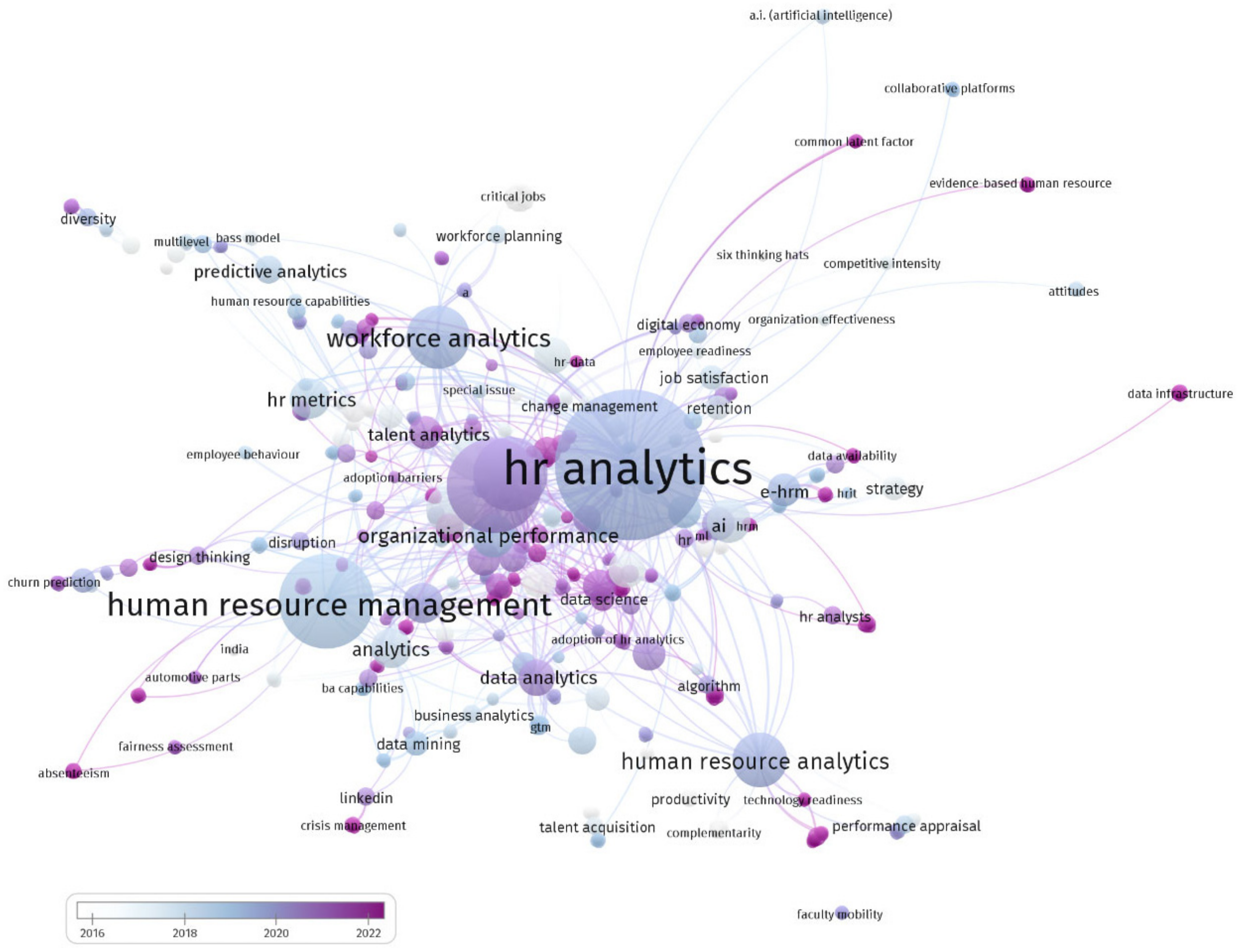

Figure 8 Keyword co-occurrence evolution

The keywords analysis on a temporal dimension of HRA published documents is shown in Figure 8. The node's size represents the number of keyword occurrences, while the node's colour shows the average publication year of the term (Van Eck & Waltman, 2017).

The purple colour represents the keywords considered during or post-2022, while light blue reflects those used during 2018/2020. The white colour indicates keywords employed during or before 2016 (Figure 8). It is apparent from figure 8 that keywords like analytics, HR metrics, talent management, artificial intelligence, data mining, change management, business analytics, algorithm, employee readiness, productivity, workforce model, and human resource information system emerged around 2016. Much of the emphasis was on assessing HRA tools for HRM. Keywords that were used in 2018-2020 included keywords: talent analytics, people analytics, workforce analytics, human resource analytic, data analytics, predictive analytics, employee turnover, design thinking, and organisational performance etc. During this timeframe, much prominence was given to integrating HRA applications into HRM functions. In 2022, HRA focused on human capital analytics, change management, absenteeism, data infrastructure, institutional theory, HR decision support, ethics, digital technologies, intrafirm analysis, and unsupervised learning.

Based on this, it can be deduced that the temporal display of keywords leads to the development of a landscape and shifts in HRA research across settings. This trend results from an emerging consensus that HRA characteristics and applications are more weighted toward quality HRM practises and performance. Regarding research settings, it is evident that HRA studies have recently gained popularity in Asian (developing) nations (Figures 7 and 8).

Analytics is the discipline which has evolved at the intersection of engineering, computer science, decision-making, and quantitative methods to organise, analyse and make sense of the increasing amounts of data being generated by contemporary societies (Pape, 2016; Mortensen et al., 2015). Inevitably, HRA gained salience among researchers and organisational practitioners as a vibrant strategy to reap a competitive advantage. Owing to the exponential technological advancements, researchers claim that HRA is one of the impending emerging drifts (Benson et al., 2006; Fu et al., 2022) and urge firms to craft and implement HRA strategies to boost firm performance (McCartney et al., 2020; Tambe et al., 2019). Interest in bibliometric research is growing due to its advances in information, management and communication technologies. Bibliometrics enable data processing and offer avenues for visualising the findings in bibliometric maps (Costache et al., 2021). Because the data is helpful for researchers in carrying out their research activities, knowledge gathered from bibliometric research is progressively becoming part of decision-making processes, assisting in identifying new trends (Martínez-López et al., 2018; Merigo et al., 2018).

Ironically, owing to the paucity of bibliometric investigations on HRA, the present study aimed to explore the influential articles, authors, sources, key terms, and clusters in the HRA domain. The findings of this study support earlier studies (Rasmussen & Ulrich, 2015; Marler & Boudreau, 2017; Qamar & Samad, 2021), demonstrating HR analytics received a surge in research interest.

Additionally, findings contribute to the HRA body of knowledge by conducting bibliometric analysis to provide a more thorough and systematic understanding of the field and to pinpoint the most critical study areas, sources, authors, keywords, and clusters.

The findings show that very few researchers were engaged in the bulk of significant investigations on HRA. Additionally, several researchers have risen to add to this body of literature on expanded HR practises due to the area's considerable improvement. The publication timeline of all 179 publications reveals an exponential surge in academic interest in the HR analytics topic after 2015. The research carried out in recent years deals with the issue with a broader viewpoint and practical examples. Simultaneously, prior studies on HRA primarily focused on technical and analytical abilities. The present study found that such analytical terms directly coincide with human resources, such as 'digital data', 'human capital analytics', 'talent analytics', 'data mining', people analytics', 'business analytics', 'workforce analytics', 'internet of things', and 'big data', are covered in the evaluated articles' keywords. Further, this study found that the internet of things, high-performance HR policies, big data, and artificial intelligence are critical for the effective application of HR analytics. The findings also support prior arguments that the technologies used for HR analytics must be far more suitable for the organisational structure (Minbaeva, 2018; Levenson, 2018).

A lack of understanding of analytical thinking by the HR profession is hampering the development of HR analytics. This problem is compounded by the HR analytics industry, which is based mainly on products and services which too often fail to provide the tools for HR to create and capture the strategic value of HR data. The central problem is that, in the main, the ideas about HR data and analytics set out in the previous section have not penetrated the thinking of much of the HR profession.

Thus, prioritising education and information exchange in the digital era is vital (Tortorella et al., 2020). Utilising data analytics and creating information and decision support systems are necessary for digital preparedness. Investment in HR is also essential for education and skill development (Mathushan & Kengatharan, 2022a). Studies have shown that data quality is crucial regardless of the kind of data utilised. The findings of HR analytics are dependent on the quality of the input data.

Consequently, data quality is critical for HR analytics (Minbaeva, 2018; Fernandez & Gallardo-Gallardo, 2020). This study found big data is one of the invaders in HRA. Big data quality impacts big data-driven HR practices and the quality of HR services (King, 2016; De Mauro et al., 2018). Other studies demonstrate the link between the calibre of big data and the calibre of HR services (Iqbal et al., 2018). Big data quality has a bright future in the HR function within strategic management (Avrahami et al., 2022; Garcia-Arroyo and Osca, 2021; Tursunbayeva et al., 2018). The topic of strategic HRM may benefit from a viewpoint offered by another research that links HR analytics with economic data. It also examines insider econometrics and the longitudinal analysis technique (Larsson & Edwards, 2022).

According to this viewpoint, people analytics is a commercial application focusing on empirical analysis to gauge employee performance. The absence of empirical, analytical applications is mentioned in certain publications on HR analytics. Yassine & Singh (2020) developed an analytical solution to the people assignment issue by including the human aspect in the model and achieved by providing a multi-criteria problem solution with a mathematical model for the sustainable supply chain requirement. Further, the present study argues that solutions for electronic human resources (e-HRM) are used to map different HR procedures. But implementing such systems has several effects beyond only technical ones and includes organisational and functional changes inside the organisation. The cloud environment also adds new elements to the adoption of e-HRM and helps to improve its capabilities.

The article delves into several HRA-related ideas, including "resource analytics, workforce analytics, HR analytics, big data analytics, people analytics, and talent analytics." In addition, this paper's thorough analysis of HRA in the era of data analytics and talent analytics aids HR professionals and researchers in better comprehending HRA literature. Whilst data analytics studies have recently blossomed in the management disciplines at large, this has not been the case for human resources. This is becoming more problematic since HR professionals often lack a firm grasp on the foundations of people analytics. This may slow HRA's efficient deployment and operationalisation and create other obstacles that dampen HR's position as a strategic business partner. Understanding HRA and its potential implications for the business on various fronts might considerably improve HR practice.

CONCLUSION

Although interest in HR analytics has increased, there is still a considerable avenue for its theoretical development. The study serves as the foundation for research in HRA to comprehend trends during the last eight years in terms of prolific authors, most influential journals, significant issues, emerging keywords, clusters and the intellectual structure of the HRA field. According to the finding, HRA is still in its early stages of growth. Therefore, more rigorous studies are required to create a more profound knowledge of this emerging discipline. In this review,' future trend', 'workforce analytics', 'talent management', 'human capital analytics', 'organisational learning', 'employee productivity', 'human resource analytics', 'predicting employee readiness', 'big data challenge', 'adoption', 'evidence-based-technology', 'recruiting', 'intuition' were found as most compelling research clusters which are now being associated and studied with HR analytics. Furthermore, this study contributes to the HRA literature by discovering such keywords (artificial intelligence, big data, predictive analysis, design thinking, data analytics, HRIS, data infrastructure, e-HRM, talent analytics, and data mining) that comprise the core area of HRA research and providing new and plausible avenues for future research. Findings report that owing to the worldwide competition, HRA is gaining popularity as a strategic player in enabling firms to implement and formulate HRA strategies concerning talent management, change management, crisis management, performance appraisal, and recruitment and aid them in attaining organisational performance. The present study findings could be used by human resource (HR) professionals, line managers, and top management to make robust decisions about how to build a work environment that fosters and rewards the kind of behaviour that advances the firm's strategic goals. The present research, like any other, has certain limitations. First, this review covers a lot but doesn't cover everything. The Scopus database is used for this investigation. In future studies, WOS and other databases should be used for comprehensive comparative analysis. Second, this study excluded dissertations, book chapters, and books from our research and focused on journal articles. Other understanding might be acquired by including additional credible sources. Further, although this study attempted to be accurate and complete, future research may be theory-based. Researchers could also look at how line managers and upper management may help advance HRA as a critical component of business goals. Although this review covered the literature on HR analytics, a quantitative content analysis of the current studies would allow researchers to conduct a systematic, rule-governed, theory-driven investigation of HRA (Qamar & Samad, 2021). Finally, these findings can be a road map for the researchers to investigate the field of HRA further.

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