HR Analytics State of the Art and Future Directions: A Scoping Review Based on Natural Language Processing Technique

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Abstract: Interest in HR Analytics (HRA) has dramatically increased in the past years. Despite the disruptive potential of HRA, however, the literature studying this topic is characterised by great confusion around its conceptualisation and domain boundaries. This paper aims at reporting a comprehensive scoping review of HRA literature, defining its boundaries, its state of the art, and its main theoretical and empirical gaps. Analysing through natural language processing and topic modelling techniques 1,057 papers from Scopus, we identified six main clusters representing different areas of discussion within the research on HRA. For each cluster, key articles, reference journals and evolutionary paths have been defined. In the upcoming months, topic analysis will be enriched in order to define the most important research gaps and future research directions.

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1. Introduction

In the last decade, the diffusion of digital technologies has enhanced data collection and analysis in several organizational domains (Gandomi & Haider, 2015). As a result, the interest in analytics and data-driven management has increased in various business units (Holsapple et al., 2014), including Human Resource (HR) ones (Rasmussen and Ulrich, 2015; Van der Togt and Rasmussen, 2017; Sharma and Sharma, 2017; Boudreau and Cascio, 2017; Huselid, 2018). The availability of cheap digital technologies has not only increased data collection and processing capabilities (Schiemann et al., 2018), but also decreased data management and storage costs (Dalhbom et al., 2019), providing organizations with data and information to better understand employee's behaviour (McIver et al., 2018). Companies, thus, became increasingly interested in leveraging people-related data to enable an effective decisional process also in a complex, dynamic, and uncertain environment (Sharma and Sharma, 2017).

These organizational practices have become popular under the name of HR Analytics (HRA), even if academics and practitioners discussed about them using also other labels – i.e., talent analytics, people analytics, workforce analytics and human capital analytics (Margherita, 2021). Marler and Boudreau (2017) define HRA as a HR practice, based on digital technologies and statistical analysis, used to establish people-related business impact and enable data-driven decision-making. The promises related to HRA make it a potential game-changer for the future of organizations and their strategic talent management (van der Togt and Rasmussen, 2017). Academic literature infers that HRA will make data about employees and their behaviour more accessible, interpretable and actionable (Tursunbayeva et al., 2018, McCartney and Fu, 2021), improving people-related decision-making (Minbaeva, 2018), and, in turn, enhancing organizational performance (Aral et al., 2012). In addition, scholars emphasize that the successful utilization of analytics not only support organizations in their strategic execution, but may generate an important competitive advantage over competitors, especially in today's dynamic business environment (Qamar and Samad, 2021). Thus, It is not a coincidence that, while at the beginning of the new millennium HRA was not part of the business language (Levenson, 2018), today a Google search for the same term produces more than 4 billion of results. HRA is actually considered a business top-priority for companies and their HR departments

(Leonardi and Contractor, 2018). Organizations have been fascinated by the opportunity of replacing the traditional intuition-based operating mode with an evidence-based decisional process (Dalhbom et al., 2019). Despite the great interest around HRA and a substantial growth in practice (McCartney et al., 2020), companies are experiencing several difficulties in developing this capability (Angrave et al., 2016). The low adoption rate has been confirmed by a recent study conducted by Deloitte (2018), revealing that even if 78% of respondents rated HRA as "important for the business", only 7% of them reported consolidated capabilities in the application and use of people-related analytical practices (Papoutsoglou et al., 2017).

The above trend can be similarly found in scientific environment. HRA has been around for years (Huselid, 2018), but academics consider this research field still in its early stages of development (Tursunbayeva et al., 2018). Despite an increasing interest and a significant growth in publication in the last 5 years (Qamar and Samad, 2021), indeed, the number of scientific contributions on HRA is still limited if compared to other HRM research (Chalutz Ben-Gal, 2019; Marler and Boudreau, 2017). In addition, HRA and similar terms are not yet recognized keywords, making very difficult the effective identification and analysis of academic contributions (Edwards et al., 2021). HRA, thus, remains an underdeveloped and underexplored research field (McCartney and Fu, 2021), characterised by blurred research boundaries (Larrson and Edwards, 2021), definitional ambiguities (Rasmussen and Ulrich, 2015; Margherita, 2021) and conceptual confusion (Fernandez and Gallardo-Gallardo, 2020).

This paper aims at analysing and defining current research boundaries and state of the art related to HRA, providing a comprehensive scoping review based on a Natural Language Processing (NLP) technique. NLP aims at providing an objective text-driven document review that overcomes the limitation that typical query and content-based research has in ill-defined domains (Mazzei et al., 2021). In particular, Topic Modelling (TM) technique based on the latent Dirichlet allocation algorithm has been applied to extract research topics from a large corpus of scientific contributions related to HRA, enabling the adoption of a wider and more comprehensive search strategy. The remainder of the paper is organized as follows. In Paragraph 2, we discuss the theoretical background of the work and we present in detail the research problem, objectives and questions. In Paragraph 3 we present the methodology adopted for our scoping review. In Paragraph 4 and 5, we present the main results achieved through the NLP and TM techniques. In Paragraph 6, we present a preliminary discussion and future next steps.

2. Theoretical Background

Studying the evolution of HRA is difficult due to the ongoing confusion surrounding its definition and research boundaries (Fernandez and Gallardo-Gallardo, 2020). Several scholars have unofficially assigned the origin of the discipline to the first appearance of "HRA" term in academic literature (Marler and Boudreau, 2017), with the paper published by Lawler et al. (2004). Others have argued how the practical origin of HRA may be placed over a century ago, with the scientific management and the first human capital metrics applied by Ford and Taylor (Ulrich and Dulebohn, 2015). During this period, different organizations have applied sophisticated analytics techniques to select, train, retain and assess the performance of their HRs, achieving a competitive advantage over their competitors (Schiemann et al., 2018). Considering academic contributions, the first book dedicated to HRM quantification has been published more than 30 years ago (Margherita, 2021). In 1999, instead, the term "workforce analytics" was first introduced in the context of data analytics, preceding the terms HRA, talent analytics, people analytics and other synonymous (Marler and Boudreau, 2017). The number of papers related to data driven HRM, however, started to increase noticeably in 2011, after the publication of two major articles. The first discusses Google's Project Oxygen (Garvin et al., 2013). The second (Davenport et al., 2010) promoted the strategic benefits achieved by important firms, such as Sysco or Proctor&Gamble, by implementing HRA. Since then, interest has dramatically increased among academics. As represented in Figure 1, in the last six years scholars have published 84% of the articles related to HRA.

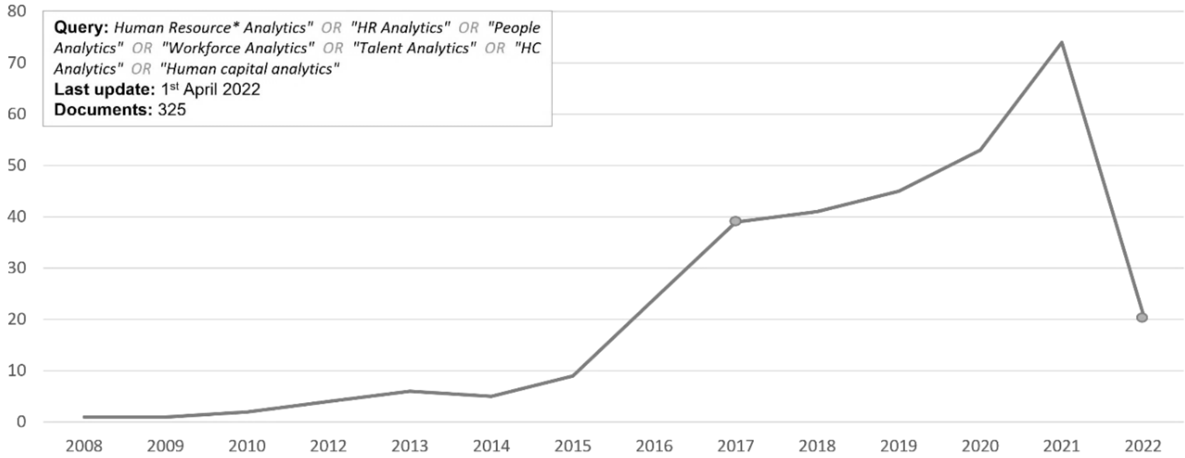

Figure 1. HR Analytics number of publications per year

Despite the historical contributions and the increasing interest, HRA is still considered by scholars as a discipline in its infancy (Qamar and Samad, 2021). In current academic literature there is an ongoing confusion about the conceptualization and operationalization of the term (Fernandez and Gallardo-Gallardo, 2020), with academics that have yet to agree on what HRA really encompasses (Angrave et al., 2016). The research field, thus, is still characterised by ambiguities and is not well understood by neither academics nor practitioners (Tursunbayeva et al., 2018). Why are research boundaries still so ill-defined? Which are the causes behind the confusion around HRA? According to the papers we have red for this review there are three primary sources of chaos.

The first, connected to the emerging nature of the topic, is related to the scientific adoption of different labels to indicate the same concept. HRA has been labelled using different terms, such as HR analytics (Lawler et al., 2003; Patre, 2016; Marler and Boudreau, 2017; van den Heuvel and Boundarouk, 2017; Fernandez V., Gallardo-Gallardo E., 2020), people analytics (Singer et al., 2017; Tursunbayeva et al., 2018; Larsson and Edwards, 2021), talent analytics (Davenport et al., 2010), workforce analytics (Huselid, 2018; McIver et al., 2018) and human capital analytics (Andersen, 2017; Levenson and Fink, 2017; Minbaeva, 2018). Human capital and workforce analytics have been initially the most searched keywords, while, in the last 10 years, the most popular terms have been people analytics and HRA (Fernandez and Gallardo-Gallardo, 2020). The different labels, albeit using different perspectives, all refer to the same talent management approach based on data collection and analysis (Margherita, 2021). The use of different labels, over time, has not made it easier for researcher the identification of relevant contributions and a clear definition of the discipline.

The diverging labels proposed by different authors reflect the variety of definitions in the literature (Levenson and Fink, 2017; Qamar and Samad, 2021; McCartney and Fu, 2021). In the last 5 years only, scholars have proposed more than 20 different definitions and descriptions to illustrate HRA. Table 2 represents the most relevant definitions for each label. Margherita (2021) reported four main common themes related to HRA conceptualisation: (i) it is a HR managerial approach based on data analysis; (ii) it uses statistical and visualisation techniques to analyse people-related data; (iii) it supports organizations in solving business issues; (iv) it is a “multi-process and multi-application endeavour, with a broad spectrum of potential impacts”. The variety of definitions, however, rather than adding clarity, has generated inconsistencies around analytics conceptualisation. Over time, HRA has been defined as an organizational capability (Minbaeva, 2018), an HR practice (Marler and Boudreau, 2017), a wide set of principles and methods (Fernandez and Gallardo-Gallardo, 2020) or as a process (Huselid, 2018; McIver et al., 2018). Through their definition, some academics highlighted the role of enabling digital technologies (Marler and Boudreau, 2017; McIver, 2018), some focused their attention on the statistical techniques and methods adopted to analyse data (Patre, 2016; Margherita, 2021), some have proposed the main outcomes promised by an evidence-based talent management (van den Heuvel and Boundarousk, 2017). All definitions are reasonable and potentially shareable, as they reveal different facets of the same concept, depending on the discipline and the theoretical lens considered by the author. However, their large number have made HRA kaleidoscopic in nature, increasing conceptual ambiguities and confusion.

The last source of confusion regards the lack of clarity and agreement on several terms often associated and confused with HRA and synonymous. Academics have discussed about HR managerial approaches based on data by referring to HR metrics, HR scoreboard, HRM quantification, evidence-based HRM, or data-driven HRM. However, there is no clear distinction between the meaning of these terms. Consider, for instance, the terms HR metrics and HRM quantification. Van de Heuvel and Boundarouk (2017) argued that metrics and analytics are significantly different because metrics do not provide robust insights about people-related phenomena. Huselid (2018) indicated that “metrics precede analytics”, both on a temporal and conceptual level. The dichotomy between metrics and analytics, however, occurs because academics and practitioners, using the term “analytics”, often imply sophisticated statistical analysis and techniques – i.e., predictive models. Nevertheless, analytical techniques can be applied and declined at multiple levels, considering their scope and level of sophistication. From this viewpoint, HR metrics can be placed at the descriptive level of HRA. Bassi (2016), indeed, defined HRA as a “systematically reporting on an array of HR metrics or more sophisticated solutions”, highlighting the different levels of application of HRA solutions. A similar argument can be made for HRM quantification. Coron (2021) argued that this term “covers a wider field than metrics and analytics” because it includes concepts such as metrics, analytics, big data, algorithms, and artificial intelligence. The source of ambiguities, again, is related to the meaning given to the term “analytics”. If by analytics you identify predictive and prescriptive models, then there is a significant difference between HRA and quantification. On the other hand, if you consider the various dimension of HRA, conceptual boundaries become much more blurred. Academic literature on HRA if full of scientific contributions related to big data, artificial intelligence, and other advance techniques (Angrave et al., 2016). The same reasoning can be applied to the concepts of evidence-based HRM or data-driven HRM, to which are associated the same methods and outcomes discussed in HRA literature – i.e., statistical analysis for improved decision-making in HR (Wolfe et al., 2006; Coron, 2021).

Thus, the ambiguities about the conceptualization of these terms are substantial and rooted in the interpretation that scholars have given over time to the concept of "analytics". The large number of labels, definitions, and terms used to discuss HRA, combined with a rapid evolution and growth in publications, add further difficulties in the clarification of existing literature (Marler and Boudreau, 2017; Chalutz Ben-Gal, 2019; Qamar and Samad, 2021). Previous research has tried to address these concerns through different studies. Several reviews can be found into the literature, as reported in Table 1, against a limited number of actual papers to be reviewed.

Table 1. Previous literature reviews dedicated to the HR Analytics research field

Reference	*Cit.**	*Research Question/Objective*	*Method*	*Search Strategy*	*Sample*
Marler and Boudreau, 2017	128	• What is HRA? • How does HRA work? • Why does HRA work? • What does HRA produce? • What is required for HRA to succeed?	Integrative synthesis of existing high-quality research	'HR Analytics', 'Talent Analytics', 'Workforce Analytics', 'People Analytics' or 'Human Resource Analytics'	14 papers from ASC, BSC and Scopus
Tursunbayeva et al., 2018.	38	• Analysing the emergence of People Analytics (PA) over time and its relationship with other HR-related concepts • Analysing the contexts in which PA is being used • Analysing the value propositions advanced by providers of PA • Analysing if are there training courses currently aimed at PA practitioners	Quasi-Systematic Scoping Review	"HR analytics" OR "Human Capital analytics" OR "Human Resource analytics" OR "People analytics" OR "Talent analytics" OR "Workforce analytics" OR "Employee analytics")	54 papers from Scopus
Chalutz Ben-Gal, 2019	17	• What are the major themes that have been developed within HRA research? • What are the focus and ROI-based critique of HRA research? • What is the future of HRA research?	ROI-based review	'HR Analytics'	80 papers from 11 EBSCO online databases
Fernandez and Gallardo-Gallardo, 2020	19	• What does HRA encompass? • What impedes the adoption of analytics in HR within organizations?	Comprehensive literature review	"Talent analytics." "HR analytics," "HR* analytics," "employee analytics," "human capital analytics (HCA)," "workforce analytics," "workforce scorecard," "people scorecard" and "PA."	64 papers from Scopus and WoS
Peeters et al., 2020	16	• What are the enabling resources of a PA team? What types of products should this team deliver to contribute to organizational performance? Who are the stakeholders of this team, and how should they be managed? • What are the elements of a PA team's proper governance structure to?	Narrative literature review	First Step - "People analytics," "HR analytics," "Workforce analytics," "Talent analytics", "Business intelligence", "Finance analytics", "Marketing analytics." Second Step – Snowball technique	Not specified
Tursunbayeva et al., 2021	7	Understanding how ethical considerations are being discussed by researchers, industry experts and practitioners, and to identify gaps, priorities and recommendations for ethical practice	Iterative scoping review focused on academic and grey literature	Academic – "(("Human resource*" OR Workforce OR Labor OR Staff OR Employee OR "human capital" OR Personnel) AND Analytic* AND Ethic*) Grey – Combination of HRA terms and ethics tags	14 peer-reviewed papers and 68 documents from grey literature
Qamar and Samad, 2021	3	Identifying the current research trends and set the future research agenda in the area of HRA by an extensive review of the existing literature	Systematic review using quantitative bibliometric techniques	"HR analytics" OR "Human resource analytics" OR "Workforce analytics" OR "People analytics" OR "Talent analytics" OR "Human capital analytics."	125 papers from Scopus
Margherita, 2021	12	• Providing an extended literature-based systematization of key concepts and investigation areas related to HRA • Identifying avenues for further development of the field along a number of different areas of research trajectories	Systematic review	"people analytics", "human resources analytics", "HR analytics", "workforce analytics", "talent analytics", "human capital analytics" and "data analytics AND HR"	68 papers from Scopus
Coron, 2021	1	• What are the data sources used to quantify HRM? What are the methods used to quantify HRM? • What are the objectives of HRM quantification? • What are the representations of quantification in HRM?	Integrative and systematic synthesis procedure	"HR metrics", "HR scorecard", "HR analytics", "HR algorithms", "HR accounting", "workforce metrics", "talent metrics", "talent analytics", "workforce analytics", "HRM Big data", "HRM AI", "HR accounting", "HR dashboards", "HRM algorithmic management"	94 peer-reviewed papers
McCartney and Fu, 2022	0	What debates and challenges are emerging as a result of PA adoption?	Systematic literature review of peer-reviewed articles and thematic analysis	"Workforce Analytics"; "HR Analytics"; "Human Resource Analytics"; "People Analytics"; "Human Capital Analytics"; "Talent Analytics"	46 papers from ABI/Inform, BSC, Emerald, Scopus and Wiley

* Search performed on 20th February 2022

Thus, why would another review on HRA be necessary or even useful? Our research generates relevant contributions for two main reasons: the volume of analysed articles and the objective of the review. Previous literature reviews have answered to specific research questions analysing a limited sample of articles and documents. As it is possible to see in Table 1, scholars have focused their attention on those articles that explicitly cited HRA or synonymous in their title, abstract, or keywords, using a restricted search strategy – i.e., 'HRA', 'talent analytics', 'workforce analytics', 'people analytics' or 'HR analytics'. In practice, however, labels denoting the concept of HRA are not yet recognized as a keyword in many research fields. Larrson and Edwards (2021) highlighted that several research projects have been published in other fields – e.g., econometrics. These studies have been often ignored by academics interested in HRA because of their keywords and titles, not always known in HR research field (Edwards et al., 2021). In addition, Edwards et al., (2021) reported how HRA research "is conducted and published with reference to their substantive focus, whether that is employee engagement, job performance, performance related pay, voluntary and involuntary turnover and so on". Thus, a lot of high-quality contributions related to HRA are not recognized as such because they do not explicitly mention terms such as HRA, talent analytics or people analytics. For instance, Boudreau (1983) and Sturman (2003) are two precious contributions related to the use of people-related analytics, but they have never been included in previous literature review. The consequence of this practice, thus, is that many valuable contributions have been ignored, limiting the real understanding of HRA.

This research, thus, aims at investigating scientific literature in order to solve part of the ambiguities surrounding HRA. The first objective is to understand which documents can be associated to HRA discipline, defining its research boundaries. Once defined these boundaries, we will analyse its contents to extrapolate useful insights and discover the main topics of discussion and research gaps. Eventually, this work will provide future research directions, supporting academics in their strategic placing and definition of future research activities. This review addresses the calls from Larsson and Edwards (2021) and Edwards et al., (2021), who required a review capable of widening the search strategy, consistently with the novelty and interdisciplinary of HRA. In addition, a more comprehensive and in-depth review has been called also by Qamar and Samad (2021).

3. Methodology

Considering the current state of HRA literature and our research objectives, scoping review has been selected as research method. Scoping review is a structured technique used to analyse a certain research area, providing information about the volume of available contributions, its state of the art, and the relative gaps (Armstrong et al., 2011; Arksey and O'Malley, 2005). This method has been selected for three main reasons. First, scoping reviews are extremely useful to investigate emerging areas in their early stages of research (Tursunbayeva et al., 2018). Second, they represent a useful technique to map ill-defined research fields, where it is difficult to define the volume of available literature (Arksey and O'Malley, 2005). Third, they allow addressing broader research questions, providing contributions in those areas that have never been reviewed comprehensively before (Mays, Roberts, & Popay, 2001; Arksey and O'Malley, 2005). In particular, this work followed an adapted version of the methodology proposed by Arksey and O'Mally (2005), composed by six main phases.

3.1. Identifying the research question

The research questions have been defined to solve part of the research problems revealed in Section 2. This research, thus, will answer three main research questions: (RQ1) Which are the actual boundaries of the HRA research field?; (RQ2) What is the current state of the art of HRA literature?; (RQ3) Which are the main research gaps of HRA discipline? Defining research boundaries is necessary to identify articles that contributed to the HRA research field. Once the boundaries are defined, it will be possible to analyse the current state of the art and to reveal the main research gaps. Considering these gaps, future research will be proposed at the end of the study in order to support academics in their research activities focused on HRA. Research questions, thus, have guided the strategic choices of methods adopted in each phase of our review.

3.2. Searching and extracting relevant scientific papers

The definition of HRA concept is fundamental to conduct an effective scoping study. A confused or vague definition of the field would negatively affect the search process, introducing out-of-scope documents or using a too narrow approach. Thus, it has been decided to adopt a qualitative approach, decomposing the second phase into three further sub-processes: (A) a content-based literature review focused on HRA conceptualisation; (B) the process of query definition; (C) the process of documents collection.

A. HRA conceptualisation. The objective of this sub-process is to define a clear criterion for searching and collecting papers that may have contributed to the HRA field. Thus, a clear identification of the concepts behind HRA is necessary to build a broad and effective query strategy. To reach the above objective, we have conducted a content-based review focused on the definitions of HRA provided by previous research. The query used for this first review has been defined considering the search strategies adopted by previous reviewers, without applying any type of further filter. The search strategy has been executed in September 2021 using the Scopus database. This approach, eventually, led to the collection of 216 papers. Figure 2 summarises the search process and the final sample of reviewed articles. The collected documents have been reviewed using a coding sheet where relevant definitions, related concepts, and keywords used to identify the HRA field have been recorded.

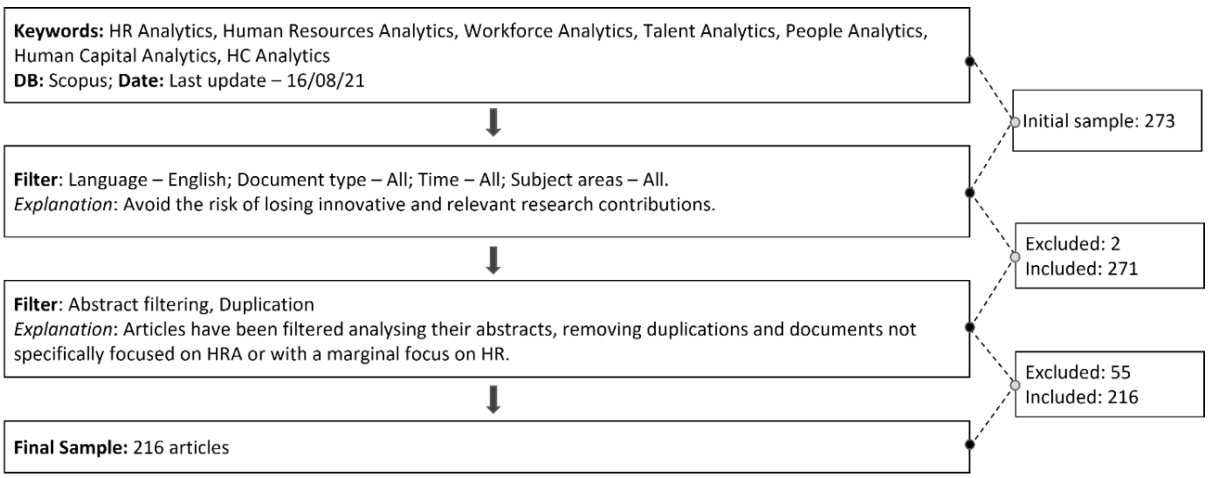

Figure 2. Search process and final sample of documents

*Table 2 r*eports the 16 most relevant definition recorded during the coding process and relative concepts. Through the coding, it has been possible to identify a set of concepts and keywords to be used to define the query of our scoping review.

Table 2. Most relevant definition for HR Analytics discipline

Topic	Authors	Cit.*	Definition	Concepts
HR Analytics	Marler and Boudreau, 2017	128	A HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making	HRM, information technologies, people data, statistical technique, data-driven, improved decision-making, business impact
	Van den Heuvel & Boundarouk, 2017	44	The systematic identification and quantification of the people-drivers of business outcomes, with the purpose of making better decisions	People data, HRM, business impact, decision making
	Fernandez and Gallardo-Gallardo, 2020	19	A set of principles and methods that address a strategic business concern that encompasses collecting, analysing, and reporting data to improve people-related decisions	Statistical techniques, business impact, people data, improved decision making, reporting
	Vargas et al., 2018	18	The statistical measures that can show connections, correlations and even causality between human resource metrics and other business measures	People data, business impact, HRM, statistical techniques, HR Metrics
	Patre, 2016	3	A methodology for understanding and evaluating the causal relationship between HR practices and organizational performance outcomes (such as customer satisfaction, sales or profit), and for providing legitimate and reliable foundations for human capital decisions for the purpose of influencing the business strategy and performance, by applying statistical techniques and experimental approaches based on metrics of efficiency, effectiveness and impact	HRM, business impact, improved decision-making, statistical techniques, people data, HR Metrics, reporting
	Momin and Mishra, 2014	3	The integration of quantitative data along with statistical tools and modelling to mine the data and transform it into actionable business intelligence to make a fact-based [strategic human capital] decision	HRM, statistical techniques, people data, data-driven, business intelligence
	Saraswathy et al., 2017	3	An approach for appreciating and gauging the causal relationship between HR practices and organizational performance outcomes (such as customer satisfaction, sales or profit) and for offering authentic and steadfast bases for human capital decisions for the purpose of persuading the business strategy and performance, by applying statistical techniques	HRM, business impact, statistical techniques, improved decision-making, data-driven
	Cheng, 2017	2	A tool that encompasses statistical models to add strategic influence in HR management	Statistical techniques, HRM
Workforce analytics	Huselid, 2018	34	The processes involved with understanding, quantifying, managing, and improving the role of talent in the execution of strategy and the creation of value. It includes not only a focus on metrics (e.g., what do we need to measure about our workforce?), but also analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?)	HRM, improved decision-making, HR Metrics, analytics techniques
	McIver et al., 2018	25	A process that is continuously advanced by improving problem solving through sound measurement, appropriate research methods, systematic data analyses and technology to support organizational decision-making	Improved decision-making, HR Metrics, statistical techniques, data-driven, information technologies
People analytics	Tursunbayeva et al., 2018	38	An area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualisation tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to optimise organisational effectiveness, efficiency and outcomes, and improve employee experience	HRM, information technologies, statistical techniques, analytics techniques, improved decision-making, business impact
	Leonardi and Contractor, 2018	37	The use of analytical techniques such as data mining, predictive analytics and contextual analytics to enable managers to take better decisions related to their workforce	HRM, analytics techniques, improved decision-making
	Gal et al., 2018	4	Computational techniques that leverage digital data from multiple organizational areas to reflect different facets of members' behaviour	Statistical techniques, analytics techniques, people data
	Larsson and Edwards, 2021	2	A business practice involves using data-driven analyses to enable evidence-based decision making, and at its core, focuses on empirical (data) analyses that aim to measure and evaluate employee performance and the value (or Return on Investment, ROI) of investments into HR practices and link these to business outcomes	Data-driven, improved decision-making, HR Metrics, business impact
	Singer et al., 2017	2	The use of data, quantitative and qualitative analysis methods and domain knowledge to discover insights about how people work together with the goal of improving collaboration	Statistical techniques, analytics techniques, improved decision-making,
Human capital analytics	Minbaeva, 2018	51	An organizational capability that is rooted in three micro-level categories (individuals, processes, and structure) and comprises three dimensions (data quality, analytical competencies, and strategic ability to act)	Organizational capability

***** Search performed on 20th February 2022

During the review, in addition, two independent researchers have added some recurring themes in the HRA field to the obtained a set of concepts and keywords. Examples of such concepts are *artificial intelligence*, b*ig data*, and *digital transformation*. The set of concepts and keywords defined in this step has been used as input for the second sub-process.

B. Query definition. The objective of a scoping review, as already indicated, is to be "as comprehensive as possible in identifying primary studies (published and unpublished) and reviews suitable for answering the central research question" (Arksey and O'Malley, 2005). This second process, thus, aims at defining a comprehensive query able to identify relevant studies for HRA, without placing strict limitation on search terms. The process of query definition has been iterative, repeating and refining the final query in order to ensure an adequate coverage of the academic literature. The first part of the query is based on the labels used by previous researchers to identify explicit HRA contributions, such as w*orkforce analytics*, p*eople analytics*, t*alent analytics* and h*uman capital analytics*. Manpower analytics, personnel analytics and staff analytics have been excluded because no longer in common usage among academics and practitioners (Tursunbayeva et al., 2018). The remaining query has been created combining the concepts obtained from the first literature review with HRM-related terms. For instance, different *analytics techniques* (e.g., data mining, machine learning) have been combined with terms identifying *HRM* (e.g., talent management). We decided to include also terms referring to information systems (e.g., HRIS) and d*igital technologies* (e.g., digitalisation) because they have been considered an enabler of HRA practices (Peeters et al., 2020). Two independent researchers have iteratively tested the query, verifying that at least 70% of the first 20 articles provided by Scopus by number of citations were inherent to the HRA topic. In this way we ensured that our sample of documents was not characterised by excessive noise. Furthermore, to increase the precision of our study, the query has been applied to title, abstract, and authors' keywords of the articles. The keywords automatically assigned by Scopus have been excluded to decrease the "dirtiness" in our sample of papers. The result of this process is available in Appendix A.

C. Documents collection. The documents have been retrieved from Scopus database, which has been selected for its popularity and its update rate. Scopus has been selected also because of its API, which facilitates the searching process. The Scopus API, indeed, provides abstracts, citation data, and other useful information from all selected papers and respective indexed journals (Mazzei et al., 2021). The final query, executed on 10th February 2022, returned 1,626 papers.

3.3. Qualitative study selection

The strategy adopted in Section 3.2 enabled the collection of a large number of papers, some of which may be irrelevant or out of scope with respect to our research objectives. The phase, thus, aims at filtering the sample of papers in order to eliminate studies that did not address our research questions. Thus, two independent researchers have read the title and the abstract of each document, eliminating duplicates and irrelevant studies. Through this process it has been possible to build a final dataset of 1,057 documents, all related to HRA. Considering the large number of papers, the next steps have been applied to the abstract of the articles only, automatically retrieved by Scopus.

3.4. Text pre-processing

Text pre-processing aims at structuring text into a form that is analysable by further statistical models (Mazzei et al., 2021). The process of text preparation and text pre-processing is constituted by different steps, described in Table 3. Each step has been applied to the abstract of each paper included in the dataset.

Table 3. Main phases constituting text preparation and text pre-processing process

Phase	Description
Empty abstract removal	Removing all the papers for which the Scopus API does not retrieve the abstracts
N-Grams extraction	Extraction of different n-grams from the set of abstracts. A n-gram (or multi-word) is a sequence of words from a given sample of text (Chiarello et al., 2021)
Data preparation - Tokenization	The text is split in tokens, which are single words or previously tagged multi-words
Data preparation - Speech tagging	Procedure that provides information concerning the morphological role of a word (or multi-words) and its morphosyntactic context
Data preparation - Lemmatization	Process aimed at determining the root of a word, in order to understand if two words have the same root despite their surface differences (e.g., am, are, and is have the shared lemma be)
Feature selection	Considering the entire text corpus, it is necessary to apply a series of words unification and removal steps, to select the relevant words (and multi-words) for representing each abstract

3.5. Topic modelling

Topic Modelling (TM) is an unsupervised machine learning technique able to analyse a set of documents and automatically detect and cluster word patterns (Chiarello et al., 2021). TM is an extremely useful technique to identify the underlying topics of an ill-defined research field (Kumari et al., 2019). In addition, TM ensure a data-driven and objective analysis of the articles included in the review, reducing the risk of potential bias or subjective judgements. In particular, our TM is based on the latent Dirichlet allocation algorithm, which is a popular generative model used in field of information retrieval from text corpora (Mazzei et al., 2021). The application of this technique produces three main outputs. First, it generates K clusters, each one representing a particular topic in HRA domain. The optimal number of clusters has been determined considering four metrics that evaluate the goodness of the clustering process: (i) Kullback Leibler divergence of the salient distributions (Arun et al., 2010); (ii) density-based approach to intra-cluster similarity and minimise inter-cluster dissimilarity (Cao et al., 2009); (iii) Jensen-Shannon divergence of topic distribution (Deveaud et al., 2014); and (iv) maximum likelihood estimator (Griffiths et al., 2004). Then, given a cluster, the algorithm indicates the words and multi-words better representing each of them. Finally, TM also provide several meta-data regarding each topic.

3.6. Summarizing and reporting

The objective of the final phase is to interpret data and information from TM, collating, summarising and reporting relevant results for each cluster. In this phase, each cluster is described using both a quantitative and qualitative approach. For each topic, a set of meta-data have been presented in the review, such as the list of words characterising the cluster, the list with the top-5 articles, or the list of top-5 journals/conferences. The results of this phase, reported in Section 4, have been used as input to answer to the central research questions, discussed in Section 5.

4. Results

Our dataset is constituted by 1,057 documents, representing with good approximation the corpus of scientific contributions on HRA. The first step of TM, thus, is to define the optimal number of clusters (topics) that better represent the segmentation of our corpus. The method explained in Section 3.5 has been applied, producing the results represented in Figure 3.

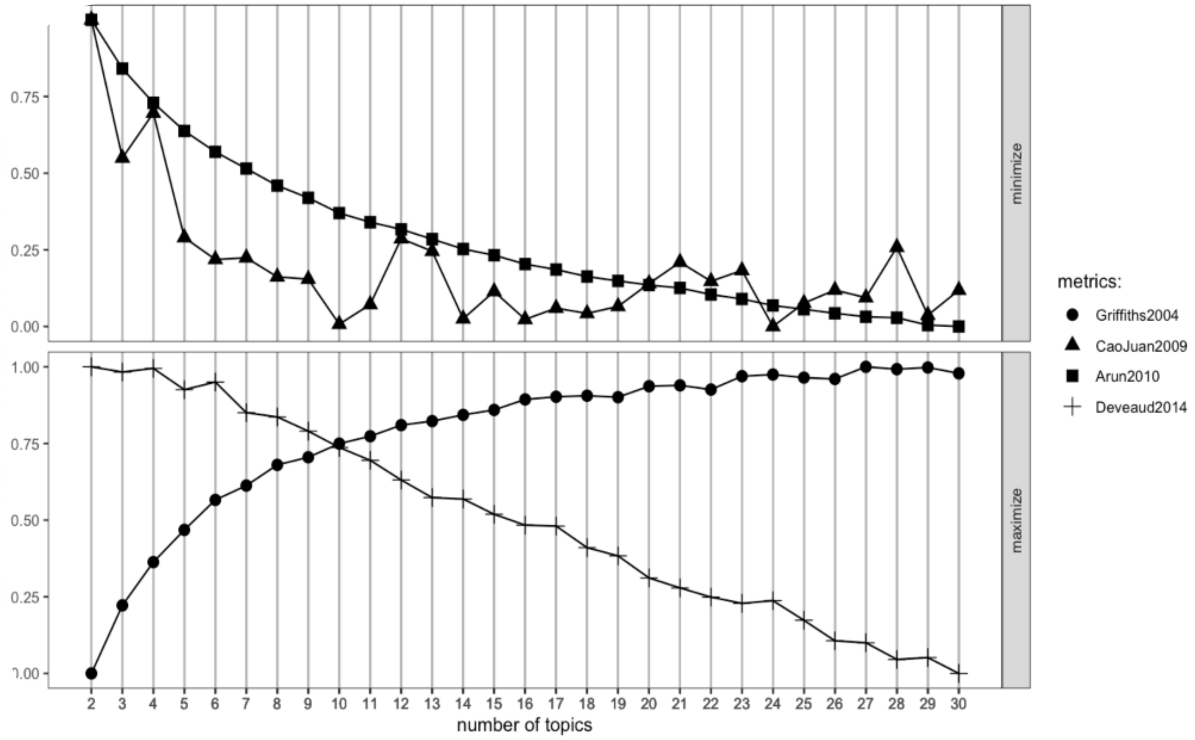

Figure 3. Quality measures of the topic modelling results for a growing number of topics. The figure distinguishes minimizing (top) and maximizing (bottom) metrics

Measures have been minimised or maximised by the optimal value of K, revealing: (i) a local minimum for the CaoJuan2009 and a local maximum for the Deveaud2014 metric for K equal to 6; (ii) a local minimum for the CaoJuan2009 metric for the K values of 10 and 14. Three model outputs have been produced, considering K values for 6, 10 and 14. The authors have selected the output associated to the K value of 6 as the most interpretable and able to describe the entire corpus, producing six topics represented in Figure 4.

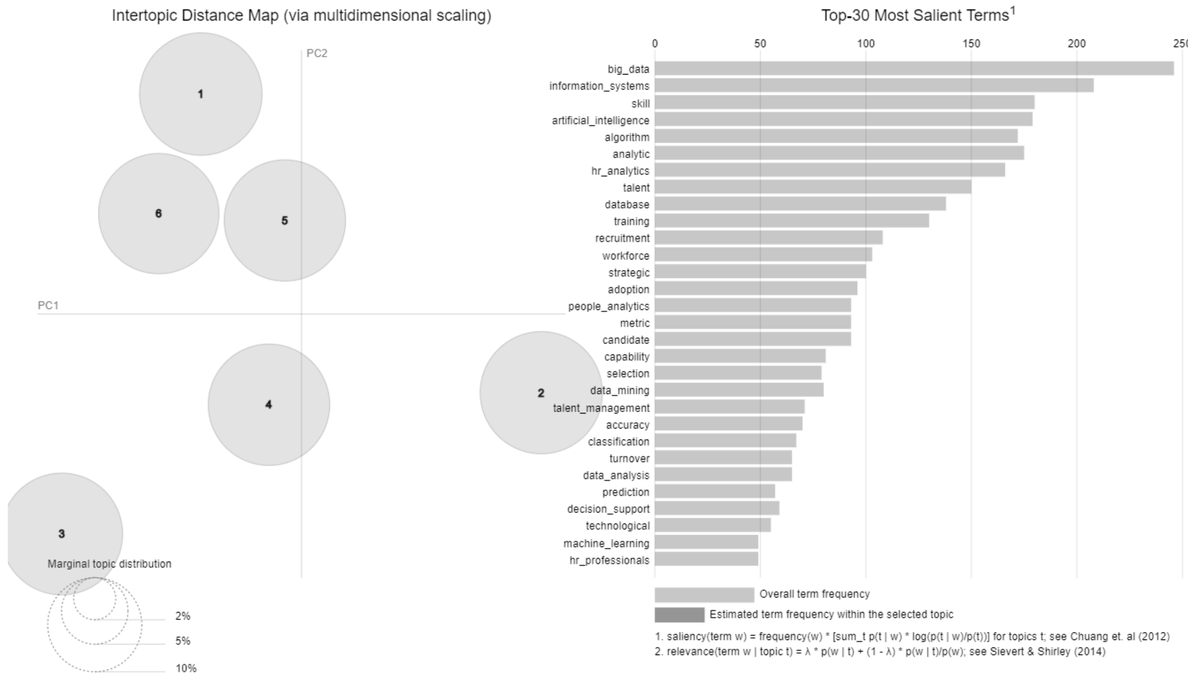

Figure 4. Multidimensional scaling visualization to project the inter-topic distances onto two dimensions

Clusters have been represented as circles in a two-dimensional space. The centre of each cluster is defined calculating the Jensen-Shannon divergence between topics (Dagan et al., 2004), maximising this divergence, and using multidimensional scaling to represent the inter-topic distance onto two dimensions (Mazzei et al., 2021). The authors developed an interactive dashboard available online[1] for an in-depth navigation of these topics. The dashboard, created using LDAvis, provides a clear representation of the results and the list of terms most highly associated with each topic. The degree of association between a term and a cluster is calculated through the beta values, which represents the probability that a word belongs to a specific topic. Figure 5 reports the top 10 terms with corresponding beta values of each cluster.

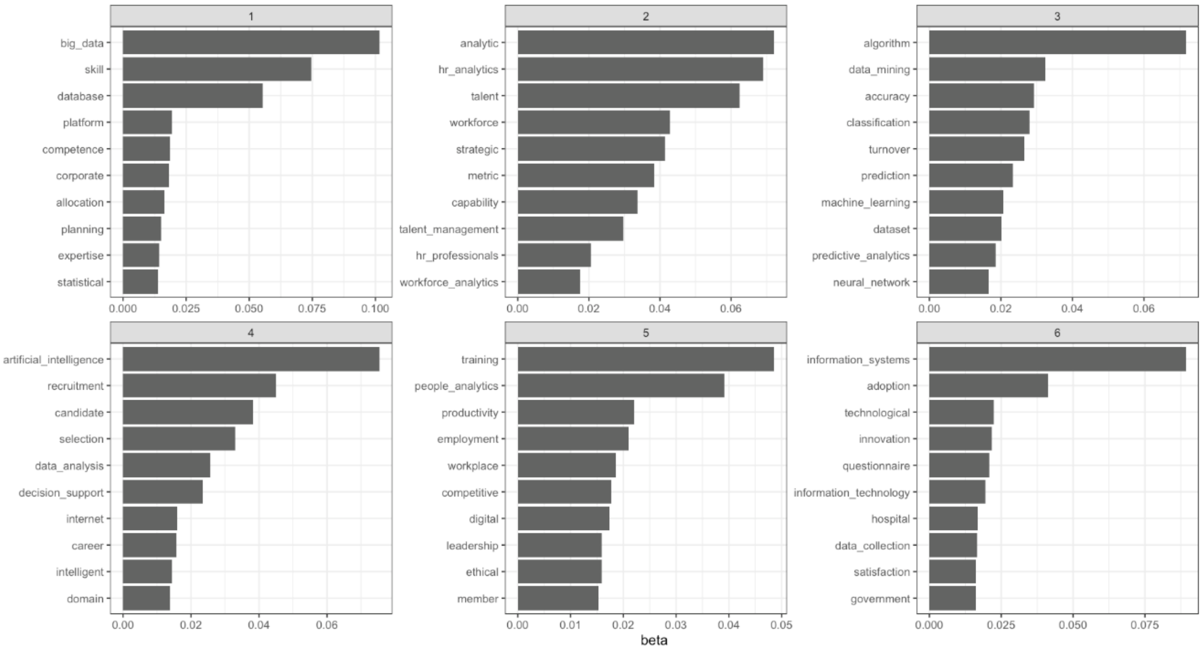

Figure 5. Top 10 most common terms for each topic

From the analysis of the top terms, it is possible to propose a label and a brief description for each topic:

1. Big data and analytics to support employee's management and skill evaluation;
2. HRA strategic development, implementation and possible impact;
3. Advanced statistical and analytics techniques to solve employee's related problems (e.g., turnover, retention, absenteeism);
4. AI and analytics to support employee's recruitment process;
5. Analytics for people management;
6. HRA technological infrastructure.

In addition to the extraction of the most common terms, useful to get an initial idea of the content of each topic, several metadata will be extrapolated and investigated to provide a more detailed analysis of the topics. First, to get a general understanding of the distribution of papers, articles have been assigned to each topic considering their gamma values, defined as the probability of a paper to belong to a specific topic. Each article has been assigned to the topic for which it had the highest gamma value. The six topics consist of a similar number of studies – i.e., each topic covers approximately the 16% of the total number of documents. The equal distribution of publications can be seen also in Figure 4, where topic's overall prevalence is encoded using the areas of the circles. Figure 6 reports

[1] https://bl.ocks.org/FilippoChiarello/raw/782b0a823d0011cc9d54fac14f767e35/?raw=true

the publication trend for each cluster (2000-2020), revealing an exponential growth of the research field in the last 5 years. It is interesting to notice that all topics have a similar evolution in terms of publication, explaining a good correlation among clusters.

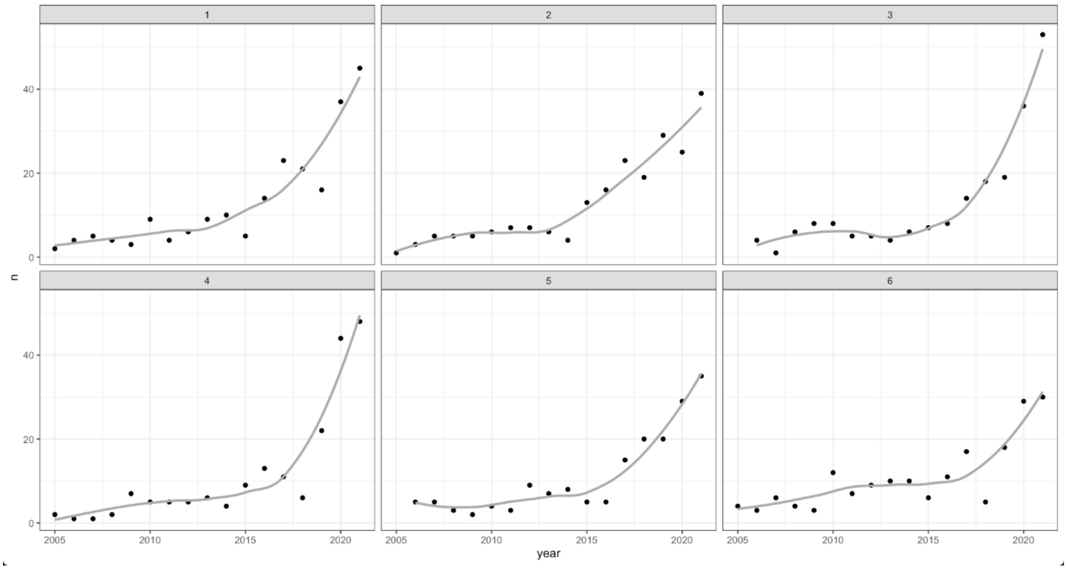

Figure 6. Trend over time of the number of papers associated to each HR related topic

Table 4 and Table 5, instead, provides information about the documents contained in each topic. Table 4 presents the top five articles associated to each specific topic, with at least 1 citation per year since it was published. The degree of association between a paper and a topic has been calculated using gamma values. In general, considering the number of clusters (6), gamma values greater than 0.25 have been considered acceptable. At equal gamma values, articles with the highest number of citations in relation to the year of publication have been selected. In Table 4 articles are ordered considering their degree of correlation with the topic (gamma value). For instance, the article most correlated with topic 3 is the one provided by Rombaut and Guerry (2020).

Table 4. Top 5 most correlated articles for each topic, with at least 1 cit. for each year since the paper has been published

Topic	Title	Year	Cit.*	Gamma
1	*Big data application framework and its feasibility analysis in library*	2017	10	0.455
	Optimal allocation model of enterprise human resources based on particle swarm optimization	2020	1	0.383
	Pre-processing Method of Structured Big Data in Human Resource Archives Database	2020	2	0.353
	Human resources for Big Data professions: A systematic classification of job roles and required skill sets	2018	83	0.349
	Mining people analytics from stack overflow job advertisements	2017	14	0.333
2	*A reflection and integration of workforce conceptualisations and measurements for competitive advantage*	2016	9	0.415
	HR metrics and workforce analytics: it is a journey, not a destination	2019	3	0.371
	Workforce analytics: Increasing managerial efficiency in human resource	2020	3	0.369
	The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support	2017	33	0.368
	Tackling the HR digitalization challenge: key factors and barriers to HR analytics adoption	2021	9	0.333
3	*The effectiveness of employee retention through an uplift modelling approach*	2020	4	0.382
	Evaluation of machine learning models for employee churn prediction	2018	17	0.368
	A study of job involvement prediction using machine learning technique	2020	2	0.358
	Application of fuzzy data mining algorithm in performance evaluation of human resource	2009	13	0.350
	Modelling the determinants of turnover intentions: a Bayesian approach	2018	4	0.345
4	*An integrated e-recruitment system for automated personality mining and applicant ranking*	2012	64	0.508
	Economics applicants in the UK labour market: University reputation and employment outcomes	2015	11	0.484
	Optimizing Recruitment Process Within Businesses: Predicting Interview Attendance Using C4.5 Algorithm	2021	1	0.314
	Efficient multifaceted screening of job applicants	2013	15	0.296
	Use of Artificial Intelligence as Business Strategy in Recruitment Process and Social Perspective	2021	4	0.278
5	*Social network analysis of sustainable HR management from the employee training's perspective*	2019	19	0.386
	People analytics effectiveness: developing a framework	2020	8	0.369
	The ethics of people analytics: risks, opportunities and recommendations	2021	3	0.362
	Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics	2021	21	0.306
	Talent management under a big data induced revolution	2019	3	0.305
6	*Human capital measures, strategy, and performance: HR managers' perceptions*	2010	57	0.381

	Usability evaluation of Human Resource Management Information System (HRMIS)	2015	7	0.375
	HR Information System implementation readiness in the Ethiopian health sector: A cross-sectional study	2017	8	0.366
	Green innovation and organizational performance	2019	187	0.359
	Human resource information systems: A review and empirical analysis	2006	82	0.346

***** Search performed on 20th February 2022

Table 5 reported the top five most relevant articles for each cluster, considering a minimum gamma value equal to 0.25. The relevance of a paper has been assessed by two independent researchers by considering different factors: (i) number of citations; (ii) qualitative analysis of the abstract; (iii) publisher; (iv) consistency with topics' most common terms. For instance, Angrave et al. (2016) and Marler and Boudreau (2017) are considered two seminal papers for topic 2 because they introduce HRA to the general public, laying the groundwork for the development of its research field. In Table 5 articles are ordered considering their number of citations.

Table 54. Top five most relevant articles for each topic

Topic	Title	Year	Cit.*	Gamma
1	*Human resources for Big Data professions: A systematic classification of job roles and required skill sets*	2018	83	0,349
	Estimating Industry 4.0 impact on job profiles and skills using text mining	2020	37	0,258
	SKILL: A system for skill identification and normalization	2015	35	0,306
	Skill networks and measures of complex human capital	2017	18	0,318
	Enterprise human resource management platform based on FPGA and data mining	2021	17	0,320
2	*HR and analytics: why HR is set to fail the big data challenge*	2016	129	0,263
	An evidence-based review of HR Analytics	2017	102	0,305
	Learning from practice: How HR analytics avoids being a management fad	2015	75	0,256
	Building credible human capital analytics for organizational competitive advantage	2018	35	0,256
	The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support	2017	33	0,368
3	*Data mining to improve personnel selection and enhance human capital*	2008	234	0,251
	Impact and determinants of nurse turnover: A pan-Canadian study	2010	146	0,32
	GA-based method for feature selection and parameters optimization for machine learning regression applied to software effort estimation	2010	126	0,378
	Integrating fuzzy data mining and fuzzy artificial neural networks for discovering implicit knowledge	2006	53	0,282
	Employee turnover prediction with machine learning: A reliable approach	2018	19	0,338
4	*An integrated e-recruitment system for automated personality mining and applicant ranking*	2012	64	0,508
	Artificial intelligence techniques in human resource management—A conceptual exploration	2015	33	0,254
	Artificial intelligence interchange human intervention in the recruitment process in Indian software industry	2019	19	0,282
	Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming	2020	18	0,262
	Efficient multifaceted screening of job applicants	2013	15	0,296
5	*Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics*	2020	21	0,306
	Social network analysis of sustainable HR management from the employee training's perspective	2019	19	0,379
	Strengthening People Analytics through Wearable IOT Device for Real-Time Data Collection	2019	17	0,263
	People analytics effectiveness: developing a framework	2020	8	0,369
	Ethically aligned opportunistic scheduling for productive laziness	2019	7	0,255
6	*Human resource information systems: A review and empirical analysis*	2006	82	0,346
	Human resource information systems (HRIS) and technology trust	2005	75	0,272
	Human capital measures, strategy, and performance: HR managers' perceptions	2010	57	0,380
	The evolution of the field of human resource information systems	2016	38	0,259
	Antecedents and outcomes of human resource information system (HRIS) use	2016	38	0,259

** Search performed on 20th February 2022*

The abstract of articles reported in Table 4 and Table 5 have been red by the authors to better understand each topic and provide useful insights about their contents. Finally, Table 6 and Table 7 report top five journal/conference in terms of publication for the entire sample of documents and for each topic.

Table 5. Top five journal/conference on HRA

Publisher	Subject Areas	H-Index	Papers
Advances in Intelligent Systems and Computing	Computer Science, Engineering	41	29
Lecture Notes in Computer Science	Computer Science, Mathematics	400	18
Communications in Computer and Information Science	Computer Science, Mathematics	51	14
Human Resource Management International Digest	Business, Management and Accounting	12	14
International Journal of Human Resource Management	Business, Management and Accounting	114	13

HRA publications have a wide distribution among journals and conferences, with the top five collecting 8% of total publications. The main outlets are all scientific journals belonging to the *Computer Science* or *Human Resource Management* research areas, confirming the interdisciplinary nature of HRA.

Table 6. Top five publisher for each topic

Topic	Publisher	Papers
1	*Advances in Intelligent Systems and Computing*	10
	Communications in Computer and Information Science	4
	Journal of Advanced Oxidation Technologies	4
	Lecture Notes in Computer Science	3
	Sustainability (Switzerland)	3
2	*Human Resource Management*	9
	Human Resource Management International Digest	7
	Human Resource Management Journal	6
	Human Resource Management Review	6
	Lecture Notes in Computer Science	5
3	*Advances in Intelligent Systems and Computing*	7
	Lecture Notes in Computer Science	5
	CEUR Workshop Proceedings	4
	Human Resource Management Journal	3
	Lecture Notes in Electrical Engineering	3
4	*Advances in Intelligent Systems and Computing*	6
	Communications in Computer and Information Science	5
	International Journal of Scientific and Technology Research	4
	Human Resource Management International Digest	3
	International Journal of Advanced Trends in Computer Science and Engineering	3
5	*Sustainability (Switzerland)*	6
	International Journal of Human Resource Management	5
	Human Resource Management International Digest	4
	Journal of Organizational Effectiveness	4
	Lecture Notes in Computer Science	3
6	*Human Resources for Health*	5
	International Journal of Human Resource Management	4
	International Journal of Human Capital and Information Technology Professionals	4
	Management Decision	3
	Advances in Intelligent Systems and Computing	2

5. Topic description

Considering TM results and available data, the authors developed an in-depth analysis of each cluster in order to describe the state of the art and the main gaps in HRA research. The interpretation of each topic has been data-driven, in order to ensure objectivity during the review. In the coming months, most cited and relevant articles for each topic will be red in their entirety by two independent researchers in order to enrich the qualitative component of this research.

5.1. Topic 1. Big data and analytics to support employee's management and skill evaluation

Analysing in detail this cluster it is possible to reveal three main groups of terms. The first is associated to data and data sources (e.g., *big data*, *database*, *social media, internet*). The second one is associated to analytical techniques (e.g., *simulation, visualisation, network analysis*). The third one represents the possible HR application and impact of big data and analytics (e.g., *skill*, *competence*, *allocation*, *planning*). This topic, thus, includes studies that discuss opportunities and implications generated by the interaction between the world of data and big data and the world of people management. On the one hand, research studied the effect that digital technologies in general and big data in particular have brought to HR and organisational needs. De Mauro et al., (2018), for instance, studied the effect that rapid big data and analytics expansion had on HR needs, providing suggestions to establish clear strategies for the acquisition and development of the right skills. On the other hand, researchers revealed how data and analytical techniques can be used to assess and evaluate Knowledge, Skills, and Abilities (KSA) of employees and possible candidates. Authors analysing skill measurement and assessment are often interested in labour market research field. An example is the study produced by Anderson (2017), who proposes a network-based approach to measure and evaluate market worker's skills, comparing organizational needs, employee's KSAs, and market wages. Other researchers provided valuable contributions to the HRM field, proposing methods and techniques to improve talent acquisition, workforce planning, and employee's allocation processes through data exploitation. Liu et al., (2021), for instance, proposed a neural network optimal allocation model to support organizations and their HR in defining the ideal distribution of resources withing the enterprise. An interesting insight derived from the analysis of the terms associated to this first topic is the complete absence of words such as HRA, people analytics or synonymous.

5.2. Topic 2. HRA strategic development, implementation and possible impact

The second topic can be reasonably defined as the "heart" of HRA literature. In terms of documents, this topic includes articles intentionally dedicated to the HRA domain, already discussed and analysed by previous reviews (Table 2). Examples are the articles written by Aral et al. (2012), Levenson and Fink (2017), Boudreau and Cascio (2017), Levenson (2018), or Larsson et al. (2021). Topic's most common terms refer to HRA strategic conceptualisation (e.g., *strategic, capability, competitive*), its definition (i.e., *HR Analytics, workforce analytics*), its standard techniques (e.g., *metric, analytic, business intelligence*), its generic application (e.g., *talent management, HR practices*), and its main promised outcomes (e.g., *data-driven, advantage, decision-making, organizational performance*). Our data-driven analysis, thus, provides quantitative and objective confirmations for qualitative insights from previews literature reviews. First, studies included in this topic discuss analytics from a managerial and strategic viewpoints, providing contributions that are often descriptive, conceptual, and promotional in nature (King, 2016). Second, contributions related to this topic are often targeted to a business or HR-oriented audience, as it is possible to understand observing the main sources of publications. Among the top five outlets, fours are journals dedicated to the HRM research field. Finally, analysis reveals that the terms *HRA* is correlated just to this topic, without appearing in other clusters, not even with synonyms (except for topic 5). This support the idea, stated by Edwards et al., (2021), that HRA is not yet recognized in several research areas.

5.3. Topic 3. Advanced statistical and analytics techniques to solve employee's related problems

From the analysis of the terms, it is evident that the third topic focuses on the more advanced statistical and analytical techniques adopted in HRA solutions (e.g., *algorithm, data mining, decision tree, machine learning, classification, predictive analytics, logistic regression*). Most popular application uses these analytical methods to better understand why employee's leave or stay in the organization, defining models to predict and prevent employee's turnover (e.g., *turnover, employee turnover, attrition, retention*). For instance, Zhao et al. (2015) proposed reliable guidelines on the selection, use, and interpretation of machine learning methods for predicting turnover. Dickinson and Painter (2009), O'Brien-Pallas et al. (2010), and Sisodia et al. (2018) focused on employee's turnover and retention. Other researchers, furthermore, explained how using these analytical techniques to improve HR practices and processes. For instance, Chien and Chen (2008) proposed a data mining approach able to generate decision rules to support hiring and personnel selection processes, relating individual information with work performance and retention. The topic includes a wide variety of studies revealing how statistical and analytical techniques can be applied to different people-related issued. It is possible to find contributions on personnel selection (Huang et al., 2004), implicit knowledge analysis (Huang et al., 2006) or resource allocation (Oliveira et al., 2010). These articles, collecting more than 300 citations, testifies that researchers provided relevant contributions on HRA for quite two decades. However, most of these contributions have been produced technical and technological oriented research, without using HRA or synonymous as keywords. As it is possible to see in Table 7, studies included in this topic have been mainly published from “technical” journals (e.g., Computer Science, Electric Engineering). *Human Resource Management Journal* is the only business journal among top five topic’s publishers.

5.4. Topic 4. AI and analytics to support employee’s recruitment process

The fourth topic is focused on personnel recruitment optimisation through analytics and on AI used to support people management practices. Considering most common terms, articles included in this topic can be divided into two main areas. The first one is constituted by studies focused on AI and its possible implications on personnel management (e.g., *AI, intelligent, automation, technologies*). An example is the literature review provided by Strohmeier and Piazza (2019), who offers a comprehensive exploration of AI and computational intelligence techniques applicable in talent management. The second area includes articles dedicated to analytics (e.g., *data analysis, text analytics, decision tool*) and its adoption in various steps of the recruitment process (e.g., *selection, talent acquisition, recruiting, candidate*). Analytical techniques find fruitful application in these phases, which are often characterised by time consuming, repetitive, and then automatable activities. Authors proposed different solutions, such as online recruitment systems to automate applicants pre-screening (Faliagka et al., 2012), decision support systems to manage and optimise screening activities (Pessach et al., 2020), and decision support tool to improve hiring and placement decisions (Mehta et al., 2013). Similar to clusters 1 and 3, high-quality contributions related to this topic are published primarily in technical research fields, oriented towards engineering and computer sciences (e.g., *International Journal of Advanced Trends in Computer Science and Engineering*). Studies aimed at business managers or HR professionals are still underdeveloped or available in lower quality journals.

5.5. Topic 5. Analytics for people management

From a semantic viewpoint, the fifth cluster is poorly defined and difficult to describe. Analysing cluster’s most common terms, it is possible to recognise different topic of discussion related to HRA field. There are terms that refer to people-related variables (e.g., *engagement*), to managerial issues (e.g., *leadership*), to HR processes (e.g., *training*), to analytics techniques (e.g., *network analysis*) and to analytics impact (e.g., *ethic, privacy*). The variety of arguments is reflected also in the articles associated to this topic. Some scholars discussed the ethical implications of HRA (Tursunbayeva et al., 2018; Gal et al., 2020), other revealed the key ingredients required to an HRA team to contribute to organizational performance (Peeters et al., 2020). Gaur et al., (2019), instead, provided information about the HR opportunities related to the adoption of internet of things and wearable devices. It is interesting to notice that this topic is the only one correlated to a HRA synonym (i.e., *people analytics*). “People analytics” term has emerged and become popular in the last decade, from the term used by Google to describe their data-driven approach to HRM (Marler and Boudreau, 2017). Considering available data, the term seems indicating a broader concept than HRA. People analytics refer to the application of analytics to any people-related issues, without necessarily considering the role of HR and its strategic dimension. However, further analyses are needed to have an in-depth understanding of the contributions associated to this topic.

5.6. Topic 6. HRA technological infrastructure

The last topic includes research focused on HR Information Systems (HRIS) and digital technologies, considered the technological antecedent and precursor to HRA. Terms describing the technological infrastructure (e.g., *information systems, information technology, communication technologies, HRIS*), often required to build effective HRA systems, are associated to the topic. Research in this topic studied different aspects of HRIS (e.g., *barrier, adoption, innovation, competitiveness*). Scholars, thus, investigated antecedents (Kassim et al., 2016), success factors (Shibly, 2011) and outcomes (Lippert and Swiercz, 2005) related to HRIS adoption. The review from Ngai and Wat (2006), for instance, revealed most important benefits (i.e., access to information) and barriers to HRIS implementation (i.e., financial support). The topic is also correlated with terms that refer to accounting and financial activities related to people management (*e.g., data collection, financial, accounting*). Gates and Langevin (2010), for example, investigated the importance of implementing human capital measures and metrics to evaluate employee's value. From an evolutionary perspective, despite the contributions related to this topic should precede HRA on a conceptual level, this is not the case in practice. The distribution of publications, greater than all other topics between 2005 and 2015, indeed, reveals that the topic has undergone an effective growth in recent years (see Figure 6). Finally, it is interesting to notice that much of this research is conducted in healthcare contexts. This is confirmed both by the analysis of specific topic's terms (e.g., *hospital, healthcare*) and most important publishers (i.e., *HR for Health*).

6. Preliminary discussion

HRA is an interesting research field that had an exponential growth in the last five years, attracting attention both from practitioners and academics. However, the identification of documents belonging to HRA field has been complicated by its conceptual ambiguities and its interdisciplinarity. The term HRA has been defined, used, and searched primarily by academics interested in business and HR management. Although many researchers have produced valuable contributions also in other research areas, limited references can be found for the terms HRA or synonyms. This has created a mismatch between scholars who have contributed to this research field and scholars who have tried to identify and organize academic contributions. In this context, our research is a good starting point to take a step forward in the definition of research boundaries and systematization of scientific knowledge on HRA. First, through a comprehensive query, this study identified 1,057 papers that may have generated valuable contributions for this research field. Then, using NLP and TM techniques, six topics have been generated and analysed on the basis of their main terms and a set of meta-data. Topic 2 represents the theoretical foundation of HRA research field. Topic 3 and 4 provide contributions related to different analytics techniques and people-related applications (see Section 5.3 and 5.4). Topic 1 provides more peripheral contributions, related to the big data, labour market, and skill evaluation domains. However, big data have been recognised by different authors as an important antecedent (Rasmussen and Ulrich, 2015) and an opportunity for HR evolution and HRA development (King, 2016). In addition, Larrson and Edwards (2021) already discussed labour market analysis and econometrics techniques, highlighting their potential contribution to the HRA domain. The first 4 topics, thus, clearly identify articles that provide valuable contributions to HRA field. Topic 5, instead, is less defined. The topic includes several articles dedicated to PA, and thus, related to HRA by definition. However, the cluster is associated also with a wide variety of papers providing unorganized contributions. In the coming months furthers analyses will be performed to better understand the topic. Finally, papers associated to Topic 6 focused on the technological infrastructure required to develop HRA solutions. HRIS and high-quality IT infrastructure have been considered critical elements for an effective HRA system (Peeters et al., 2020). Thus, despite authors in this topic does not directly discuss analytics application in HRM, contributions in this topic may be interesting for academics and practitioners interested in HRA.

This first part of analysis, thus, answer our RQ1: "Which are the actual boundaries of the HRA research field?". The qualitative analysis of each topic (see Section 5), then, provides an initial description of the actual state of art of HRA academic literature. In the coming months, the analysis will be improved with an in-depth analysis of the papers associated with each cluster. In addition, other meta-data will be extracted in order to facilitate the interpretation of each topic, understanding their evolution and possible conceptual relations. In this way, it will be possible to provide a more detailed answer to the first two research questions (i.e., RQ1, RQ2) and to identify the main HRA research gaps, providing answer to the last research question (i.e., RQ3).

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Appendix

Appendix A - Query

TITLE-ABS-KEY("Human Resource* Analytics" OR "HR Analytics" OR "People Analytics" OR "Workforce Analytics" OR "Talent Analytics" OR "HC Analytics" OR "Human capital analytics") OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Information system*")) AND TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("information system*")) OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("information technology")) AND TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("information technology"))) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("HRIS")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("HRIS")) OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Digitalization")) AND TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Digitalization"))) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Digital transformation")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Digital transformation"))) OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Big data")) OR TITLEABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Big data")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data warehouse")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Data warehouse")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("DWH")) OR TITLEABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("DWH")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Database")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Database")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data collection")) OR TITLE-ABS(("Human Resource*" OR 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("Artificial intelligence")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data mining")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Data mining")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("descriptive analytics")) OR TITLEABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("descriptive analytics")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("predictive analytics")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("predictive analytics")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Prescriptive analytics")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Prescriptive analytics")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data analytics")) OR TITLEABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Data analytics")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Machine learning*")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Machine learning*")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("social network* analysis")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Social network* analysis")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("advanced analytic*")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("advanced analytic*")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("network* analysis")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("network* analysis")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("text mining")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("text mining")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("artificial neural network*")) OR TITLE-ABS(("Human Resource*" OR 25 "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("artificial neural network*")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Visualization")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR

"Talent management" OR "Workforce management") W/5 ("Visualization")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data science")) OR TITLEABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Data science"))) OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Metric*" OR "Dashboard")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Metric*" OR "Dashboard")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Data driven" OR "Data-driven")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Data driven" OR "Data-driven"))) OR (AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Business analytic*")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Business analytic*")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Business intelligence*")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Business intelligence*")) OR AUTHKEY(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") AND ("Decision support system*" OR "DSS")) OR TITLE-ABS(("Human Resource*" OR "Human Capital" OR "People management" OR "Talent management" OR "Workforce management") W/5 ("Decision support system*" OR "DSS"))).