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Human resources analytics: A systematization of research topics and directions for future research

Alessandro Margherita *

University of Salento, Department of Engineering for Innovation, IBIL Building - Campus Ecotekne, Via Monteroni sn, 73100 Lecce, Italy

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ABSTRACT

The management of human resources is today significantly impacted by the emergence of the global workforce and the increasing relevance of business analytics as a strategic organizational capability. Whereas human resources analytics has been largely discussed in literature in the last decade, a systematic identification and classification of key topics is yet to be introduced. In particular, there is room for conceptual contributions aiming to provide a comprehensive definition of concepts and investigation areas related to HR analytics. Using a systematic literature review process, we deconstruct the concept of human resources analytics as presented in a vast although fragmented literature, and we identify 106 key research topics associated to three major areas, i.e. enablers of HR analytics (technological and organizational), applications (descriptive and diagnostic/prescriptive), and value (employee value and organizational value). We also speculate on an "exponential" view of HR analytics enabled by the affirmation of artificial intelligence and cognitive technologies. The article provides a large systematization effort and a research agenda for developing further studies in the field of HR analytics. By a practitioner perspective, the study offers insights to support the design of innovative analytics projects within organizations.

1. Introduction

The increasing relevance of business analytics as a strategic organizational capability has encouraged the development of data-driven human resource management and advanced analytics systems able to integrate employee performance with business value drivers (Becker, Huselid, & Ulrich, 2001; LinkedIn, 2018; van der Togt & Rasmussen, 2017) and business performance (Guenole, Ferrar and Feinzig, 2017). The process aimed to internally examining human resources management activities has been labelled using different concepts (van der Laken, Bakk, Giagkoulas, van Leeuwen, & Bongenaar, 2018). These include people analytics (Green, 2017; Kane, 2015), human resources analytics (Lawler, Levenson, & Boudreau, 2004; Levenson, 2005; Rasmussen & Ulrich, 2015), workforce analytics (Hota & Ghosh, 2013; Simón & Ferreiro, 2018), talent analytics (Davenport, Harris, & Shapiro, 2010), and human capital analytics (Andersen, 2017; Minbaeva, 2017, 2018; Levenson & Fink, 2017; Schiemann, Seibert, & Blankenship, 2017). Although with different perspectives, all the concepts refer to the approach to managing people within organizations and making more objective, rational and effective decisions about employees based on the analysis of data.

Human resources analytics started as a small administrative endeavor and it has gradually evolved to provide advanced diagnostic and predictive capabilities (Edwards & Edwards, 2016) able to enhance employee engagement and retention, and generate benefits for

* Corresponding author.
E-mail address: alessandro.margherita@unisalento.it.

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whole organizations through digitally powered analytics solutions (Deloitte, 2017). Although a particular focus was initially placed on practitioner applications, academic research has greatly developed in the last ten years. The research scenario on HR analytics is today large but also quite sparse and there is room for new contributions aiming to support the analysis of where the field stands and to drive the organizations to move from reporting to true analytics (Marler & Boudreau, 2017; Minbaeva, 2017). Despite analytics is a "game changer" for the future of HR, there is a need to clearly define what does really HR analytics encompass and to conduct comprehensive investigations aimed to analyze how analytics are applied in HR, to clarify what dimensions are involved, and to identify the barriers to adoption in organizations (Fernandez & Gallardo Gallardo, 2020).

In such endeavor, the goal of this article is to deconstruct the concept of human resources analytics as presented in a vast although fragmented literature and academic discussion. The aim is twofold: a) to provide an extended literature-based systematization of key concepts and investigation areas related to HR analytics; 2) to identify avenues for further development of the field along a number of different areas of research trajectories. To achieve this goal, the article is structured as follows. In section 2, we present the theory background by providing alternative definitions of HR analytics and the evolutionary stages of the field. In section 3, we describe the research process undertaken and illustrate the steps accomplished to realize a systematic review of literature and the extraction of key concepts and research topics. In section 4, we present the main findings of the study, which are then discussed in section 5 in terms of contribution and a number of research propositions. We conclude the article (section 6) with limitations and avenues for further research.

2. Background

2.1. Defining HR analytics

Most of literature contributions on HR analytics were presented in the last ten years and have addressed a number of crucial points and perspectives on how people or HR analytics can be defined. HR analytics is a fact-based approach to drive people-related decision-making and actions (Bassi, Carpenter, & McMurrer, 2010; Davenport & Harris, 2007). The use of objective facts and logical analysis, rather than subjective evaluations or perspectives, is able to provide company managers with insightful information needed to govern the employees for organizational success. HR analytics adopts logical and systematic methods of analysis and visualization of HR-related data (van den Heuvel & Bondarouk, 2017).

In line with the evolution of business analytics as core organizational capability, also the management of human resources has gradually increased the adoption of advanced data analysis and visualization models and techniques to enhance strategic decisions, thus serving the needs of executives and top decision makers of the organization. HR analytics includes different processes and applications and has a strong interdisciplinary nature, as it brings together HR and business related data for analyzing people-related risks, performance characteristics, engagement and culture, and identifying career paths (Bersin et al., 2016). The study of different definitions of HR analytics provided by scholars and practitioners allow to identify complementary perspectives and elements to consider in the characterization of the field. Table 1 reports some of the most structured definitions retrieved in the literature, along with references and (in italic) some peculiar aspects that can be identified in the definition.

The definitions above highlight a number of key elements about HR analytics: a) it is an evidence-based approach to people-related decision-making; b) it adopts systematic methods of analysis and visualization of HR data; c) it serves the needs of executives and top decision makers; d) it is a multi-process and multi-application endeavor with a broad spectrum of potential impacts. The characterization of such aspects has evolved over time and in relation to the advancement of technology and the increased awareness of organizations about the relevance of HR analytics.

Table 1
Definitions of analytics adapted from cited literature (chronological order).

Adapted definition	Source
Extensive use of data, statistical and quantitative analysis, *explanatory and predictive models*, and fact-based management to drive decisions and actions involving personnel	Davenport & Harris, 2007
A set of *six kinds of analytics* in terms of human-capital facts, analytical HR, human-capital investment analysis, workforce forecasts, talent value model, and talent supply chain	Davenport et al., 2010
Logical analysis that uses objective business data as a basis for reasoning, discussion, or calculation	Fitz-enz, 2010
Evidence-based approach to managing people and people processes within organizations	Bassi et al., 2010
Evidence-based HR driving *strategic impact* based on logic-driven analytics, segmentation, risk leverage, synergy and integration and optimization	Boudreau & Jesuthasan, 2011
Approaches for uncovering unique *insights* about people that enable faster and more accurate *decision-making* to executives	Guenole et al., 2015
Rigorously *tracking HR investments and outcomes*	Ulrich & Dulebohn, 2015
Multidisciplinary approach to integrate methodologies for improving the quality of people-related decisions	Mishra et al., 2016
Bringing *together HR and business data* for analyzing people-related risks, performance characteristics, engagement and culture, and identifying career paths	Bersin et al., 2016
A HR practice enabled by information technology that uses *descriptive, visual, and statistical analyses* of data related to HR capital and organizational performance to establish business impact and enable data-driven decision-making	Marler & Boudreau, 2017
HR analytics is the *systematic identification and quantification* of the people drivers of business outcomes	van den Heuvel & Bondarouk, 2017
Data, metrics, statistics and scientific methods, with the help of technology, to gauge the impact of human capital management practices on business goals	Kryscynski et al., 2017

2.2. Evolution and "types" of HR analytics

Analytics in human resource management has been around for years. The first book on '*How to Measure Human Resources Management*' was published in 1984 by the pioneer Jac Fitz-enz, (Fitz-enz, 1984). With the time, the meaning and the process of HR analytics has significantly evolved due to an increasing strategic relevance for organizations and the affirmation of digital technologies. Looking more in general at the evolution of business analytics, three main stages of evolution can be identified which are characterized by different levels of difficulty, value, and intelligence. First, "descriptive" analytics, aiming to answer questions related to *what happened*, *why it happened*, and *what is happening*. Second, "predictive analytics", answering questions such as *what will happen* and *why will it happen* in the future. Third, "prescriptive" analytics, aimed to answer questions such as *what should I do* and *why should I do it* (Akerkar, 2013; Krumeich, Werth, & Loos, 2016; Lepenioti, Bousdekis, Apostolou, & Mentzas, 2020; Sivarajah et al., 2017).

The descriptive "stage" of HR analytics is related to the use of organizational internal and external (benchmarking) data and HR administrative/workplace information to generate ratios, metrics, dashboards and reports on human resources, with a focus mostly placed on the past. Predictive analytics is about data-derived insights and decisions, and includes statistical techniques, data mining and advanced algorithms able to analyze process/workflow data and make predictions and scenarios. Predictive analytics have then led to a generation of prescriptive analytics, based on the availability or large and diversified HR data, where HR gets decision options to optimize performance and reshape entirely the HRM decision making process (Fitz-enz & Mattox II, 2014; Mishra et al., 2016). Naturally, whereas technologies evolved over time and supported more advanced forms of analytics, the development of HR analytics should not be described as simple chronological evolution but rather as a maturity evolution. Different forms or "types" of analytics (i.e. descriptive, predictive, prescriptive) may thus be adopted (and are actually adopted by organizations) into more articulated and integrated HR analytics initiatives and processes. Fig. 1 shows the "stages" or maturity levels of HR analytics.

HR analytics is today an increasingly an established discipline with a proven impact on business outcome and a strong influence in operational and strategic decision-making, and pervasive integration with data and IT infrastructures across organizational boundaries (van den Heuvel & Bondarouk, 2017). With the rise of big data, digital technologies and data science techniques in human resources scenarios (e.g. Angrave et al., 2016; Chitra & Srivaramangai, 2018; Edwards, 2019), the need and potential of building specific human resources analytics capabilities have received increased attention (Kryscynski et al., 2017). In particular, big data can be applied to every stage of the hiring process and the entire workforce planning and management cycle (Isson & Harriott, 2016), including attraction, acquisition, development and retainment. Another area of potentially disruptive innovation is Artificial Intelligence (AI). Whereas the first application of AI in HRM (Lawler & Elliot, 1996) focused on the impact of expert systems in job evaluation (considering both performance and psychological outcomes), the potential of AI today can be explored across a number of different scenarios. These include turnover prediction, candidate search, staff rostering, HR sentiment analysis, and résumé data acquisition with information extraction and employee self-service (Strohmeier & Piazza, 2015). AI applications may support advanced analytics to unearth deep, actionable insights and predictions about human resources.

Jia, Guo, Li, Li, and Chen (2018) developed a framework to show how AI applications can be combined and applied to enhance the basic dimensions and processes of human resource management, which include human resource planning, recruitment, selection, training and development, performance management, salary evaluation, and employee relationship management (Noe, Hollenbeck, Gerhart, & Wright, 2006). AI-enhanced operations include recruitment, selection, onboarding, training, performance management, advancement, retention, employee benefits (Cappelli, 2018). Upadhyay and Khandelwal (2018) presented the application of AI on the hiring process and the recruitment industry whereas Verma and Bandi (2019) discussed the application of Artificial Intelligence in the Indian IT Sector.

Despite the increasing attention on how AI can enhance the management of human resources, progress of AI in HRM is still quite slow due to a number of barriers like talent gap, concern over privacy, ongoing maintenance, integration capabilities, and still limited proven applications (EY, 2018). Moreover, the application of algorithms to manage people entails multiple ethical and practical complexities (Gal, Jensen and Stein, 2017). Tambe, Cappelli, and Yakubovich (2019) identified four challenges, i.e. complexity of HR phenomena, constraints imposed by small data sets, questions associated with fairness and ethical and legal constraints, and possible adverse employee reactions.

The impact of digital technologies is also particularly relevant in web-based applications and systems for human resources management. In particular, professional social networking websites are gradually evolving from text-based towards infographics-based systems (e.g. *facecv*, *vizify*, *vizualize.me*), which integrate advanced rendering and graphical capabilities able to represent the expertise of individuals using effective and information-rich charts. Besides, self-recognition of professional knowledge and expertise is increasingly accompanied or replaced by the development of community-based and/or quantitative mechanisms (e.g. *skillsmatch*,

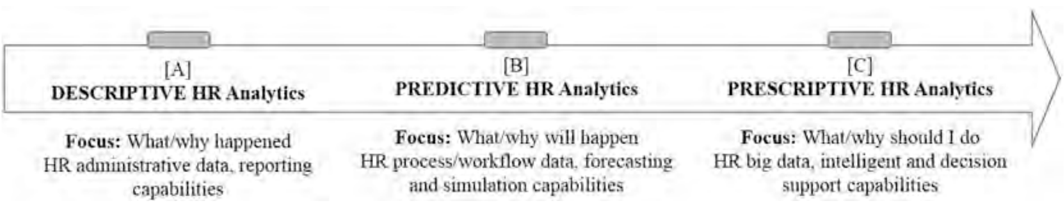

Fig. 1. Stages of the evolution or maturity of HR analytics.

viadeo, *xing*) able to offer more objective statements of individual capabilities. Another clear example of the impact of digital technologies on HRM is represented by the diffusion of advanced recruitment platforms providing conversational AI, chatbots and hiring tools (e.g. *Mya*, *Jobvite*, *Telemetry*, *Lytmus*, *Bullhorn*, *Lever*), and talent experience management platforms that provide analytics aimed to enhance employee satisfaction, retention, and lifecycle value (e.g. *Ceridian*, *Phenom People*, *Smashfly*, *Talentsky*, *Vizier*).

3. Research process

A large stream of literature provides different perspectives of analysis on HR analytics. This article aims to contribute with an integrated classification effort. At this purpose, we realized a systematic review (Denyer & Tranfield, 2009; Wolfswinkel, Furtmueller, & Wilderom, 2013) to build a systematization framework of topics and research areas in the field of human resource analytics. To achieve our goals, we realized four activities, which are illustrated in Fig. 2. First (step 1), we defined the goal and the scope of the systematic review, which is to build a literature-based systematization of macro-areas and topics describing the different perspectives of HR analytics. Since the field has different disciplinary implications, the scope of the review was not limited to HR studies and included general management, psychology and information systems studies.

In step 2, we defined criteria for inclusion and exclusion of literature and we gathered research articles, which we reviewed to refine search and obtain the final sample of articles. Using the Scopus® database, we searched (June 2020) the keywords *"people analytics"*, "*human resources analytics*", "*HR analytics*", "*workforce analytics*", "*talent analytics*", "*human capital analytics*" and "*data analytics AND HR*" in articles' titles and abstracts, without limitation of time. We used such differentiated sample of keywords to obtain a comprehensive gathering of works focused on data-driven approaches to develop human resource intelligence. The most of papers (91) were found associated to "*HR analytics*" whereas few papers (13) were found using the keyword "*human capital analytics*". We then refined the search by only selecting journal papers, so to gather more high quality and consolidated research outcomes. Table 2 shows the number of research works found, both in total (301) and only considering journal articles (166).

We performed a draft analysis of abstracts of the 166 works and removed duplications, as well as articles not specifically focused on HR analytics or with a marginal focus on HR, and articles not written in English. We obtained a final list of 68 research works. We did not select further based on the quality of Journal (e.g. based on impact factor or using classifications such as ABS) since we wanted to include the largest sample possible of journal papers so to have a broader material to build the framework. Table 3 shows a detail of retrieved articles, with the indication of publishing venues and authors (using the form "et al" for multiple authors, to enhance clarity of the table).

In step 3, we conducted a more in-depth review of the selected papers to identify concepts and perspectives of investigation of HR analytics. We defined a coding protocol to extract concepts and annotate the same into framework design tables. The protocol included constructs, classifications, approaches, methods and processes mentioned with reference to people, workforce, talent, human resources and human capital analytics. For each article, we annotated the identified concepts into our design tables. We obtained a long list of 106 concepts, which we classified into categories according to their prevailing nature or focus. Finally (step 4), we completed the taxonomy of concepts by doing a further consolidation of concepts and by submitting the taxonomy to three HR experts, including the innovation manager of a leading temporary job company, the HR manager of a large technology consulting company, and a senior education executive and coordinator of large international education programs. The experts provided useful insights related to wording and classification of retrieved concepts. Next section presents the outcome of the taxonomization effort.

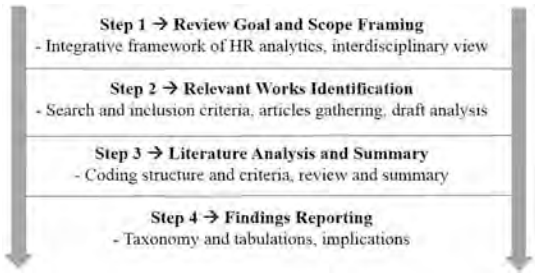

Fig. 2. Systematic review process.

Table 2
Search keywords and number of research articles found.

Search keyword	All Articles	Only Journal Articles
HR analytics	91	56
Workforce analytics	59	28
People analytics	50	21
Data analytics AND HR	44	25
Human resource analytics	28	20
Talent analytics	16	8
Human capital analytics	13	8
Total	**301**	**166**

Table 3
Number of articles retrieved, publishing journals and authors.

Journal (by N and then alphabetical)	N	Authors (year)
Human Resource Management	**5**	Schiemann et al., 2017 Levenson, 2018 Minbaeva, 2018 Simón et al., 2018 van der Laken et al., 2018
Journal of Organizational Effectiveness	**4**	Andersen, 2017 Boudreau et al., 2017 van den Heuvel et al., 2017 van der Togt et al., 2017
Int. J. of Advanced Trends in Computer Science & Engineering	**3**	Escolar-Jimenez et al., 2019a Escolar-Jimenez et al., 2019b Baakeel, 2020
International Journal of Psychosocial Rehabilitation	**3**	Gupta & Srivastava, 2020a, 2020b; Srivastava & Mohsin, 2020
International Journal on Emerging Technologies	**3**	Kakkar & Kaushik, 2019 Jain & Jain, 2020 Zeidan & Itani, 2020
Business Horizons	**2**	McIver et al., 2018 Hamilton & Sodeman, 2020
IEEE Transactions on Knowledge and Data Engineering	**2**	Luo et al., 2018 Xu et al., 2019
Indonesian J. of Electrical Engineering and Computer Science	**2**	Jabir et al., 2019 Berhil et al., 2020
International Journal of Advanced Science and Technology	**2**	Mayank et al., 2020 Mukhopadhyay et al., 2020
International Journal of Human Resource Management	**2**	Marler et al., 2017 Vargas, et al., 2018
International Journal of Recent Technology and Engineering	**2**	Bhanu Prakash et al., 2019 Meena & Parimalarani, 2019
International Journal of Scientific and Technology Research	**2**	Singh & Malhotra, 2020 Sri Harsha et al., 2020
Management Research Review	**2**	Sharma et al., 2017 Rombaut & Guerry, 2018
Baltic Journal of Management	**1**	Dahlbom et al., 2019
Decision Support Systems	**1**	Pessach et al., 2020
Expert Systems	**1**	Gelbard et al., 2018
Future Generation Computer Systems	**1**	Nicolaescu et al., 2019
Human Resource Development Review	**1**	King, 2016
Human Resource Management International Digest	**1**	Lal, 2015
Human Resource Management Journal	**1**	Angrave et al., 2016
Human Resource Management Review	**1**	Ulrich & Dulebohn, 2015
IEEE Engineering Management Review	**1**	Sahota & Ashley, 2019
Indian Journal of Public Health Research and Development	**1**	Malisetty et al., 2017
Information and Organization	**1**	Gal et al., 2020
Information Resources Management Journal	**1**	Wang & Katsamakas, 2019
Int. Journal of Applied Business and Economic Research	**1**	Saraswathy et al., 2017
International Journal of Economic Research	**1**	Alamelu et al., 2017
International Journal of Engineering and Technology	**1**	Escolar-Jimenez et al., 2018
International Journal of Organizational Analysis	**1**	Sivathanu & Pillai, 2019
Journal of Advanced Research in Dynamical and Control Systems	**1**	Sripathi & Madhavaiah, 2018
Journal of Cases on Information Technology	**1**	Kapoor & Kabra, 2014
Journal of Forecasting	**1**	Safarishahrbijari, 2018
Journal of General Management	**1**	Khan et al., 2017
Journal of Intellectual Capital	**1**	Royal & O'Donnell, 2008
Journal of Intelligence Studies in Business	**1**	Nienaber et al., 2016
Journal of Interdisciplinary and Multidisciplinary Research	**1**	Momin & Mishra, 2014
Journal of Leadership Studies	**1**	Bassi et al., 2016
Journal of Management Information and Decision Science	**1**	Ekawati, 2019
Journal of Teaching in Travel and Tourism	**1**	Martin-Rios et al., 2017
Management Science	**1**	Aral et al., 2012
McKinsey Quarterly	**1**	Arellano et al., 2017
Organizational Dynamics	**1**	Rasmussen & Ulrich, 2015
Research Technology Management	**1**	Gobble, 2017
Social Sciences	**1**	Nocker & Sena, 2019
South Asian Journal of Human Resources Management	**1**	Patre, 2016
Sustainability	**1**	Necula & Strîmbei, 2019
Test Engineering and Management	**1**	Cheripelli & Ajitha, 2020
Total	**68**	

4. Integrative definition of human resources analytics

4.1. Literature-based systematization

The systematic review of literature has allowed to isolate 106 key concepts associated to HR analytics, divided into 3 main categories and 6 sub-categories, as showed in Fig. 3.

First, concepts are related to the enabling factors allowing or supporting HR analytics initiatives. These include both technology factors and organizational enablers. Second, concepts concern the different types of applications of analytics in the HR field, and include descriptive applications (more traditional or standard) and predictive/prescriptive applications. Finally, literature contribution focus on value generated by HR analytics, with a twofold attention on employee-related value and organizational or business value. Tables 4-9 report the outcomes of the review, transcription and clustering work, with the identifications of extracted concepts and the main references (the form "et al" is used for all the references to enhance the clarity of the table). Naturally, since the mentioned papers may have a broad focus on more than one perspective of observation, the positioning in one if the tables is based on the predominant emphasis recognized in each work.

The taxonomy of categories, sub-categories and concepts is a comprehensive inventory of HR analytics ideas and research topics, and a preliminary attempt to cluster concepts into a high-level classification. The output can be used as a core nucleus of constructs for building an ontology to support the further development of the field. Besides, the exploration of literature, and especially the cross-disciplinary view adopted on information systems, organization and management works, has provided insights useful to conceptualize the emergence of an "exponential view" of HR analytics.

4.2. An exponential view of HR analytics

Advanced analytics, digital technologies and artificial intelligence are considered "exponential technologies" able to generate discontinuities in most industries (Deloitte, 2018; Fountaine, McCarthy, & Saleh, 2019; Kurzweil, 2005). The adoption of such technologies is at the core of the emergence of "exponential organizations" characterized by extremely high growth rate, reactivity to external factors, and innovativeness. Examples include Uber, Twitter, GitHub, and Dropbox. Exponential organizations exhibit a disruptive approach to managing operations and human resources as well, with capabilities such as the systematic use of on-demand

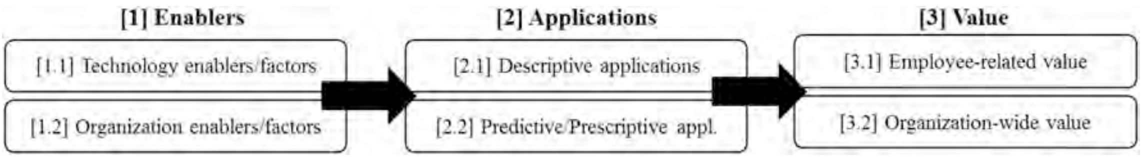

Fig. 3. Areas of concepts found in reviewed works associated to HR analytics.

Table 4
Concepts and sources related to technology enablers in HR analytics.

Concepts	Sources (alphabetical)
1. Artificial Intelligence 2. Chatbots 3. Cloud-based systems 4. Data clustering tools 5. Employee information systems 6. HR big data 7. HR databases 8. HR information systems 9. HR platforms 10. HR software and applications 11. HR statistic tools and algorithms 12. Internet of things devices and sensors 13. Job search engines 14. Machine learning applications 15. Multi-cue semantic information 16. Natural language processing 17. Neural fuzzy networks 18. Social media and professional networks	Angrave et al., 2016; Aral et al., 2012; Baakeel, 2020; Berhil et al., 2020; Bhanu Prakash et al., 2019; Boudreau et al., 2017; Cheripelli & Ajitha, 2020; Dahlbom et al., 2019; Escolar-Jimenez et al., 2019a; Gal et al., 2020; Kapoor & Kabra, 2014; Martin-Rios et al., 2017; Mayank et al., 2020; Vargas et al., 2018; Wang & Katsamakas, 2019

Table 5
Concepts and sources related to organizational factors in HR analytics.

Concepts	Sources (alphabetical)
19. Academic and practitioner integration 20. Agile workforce analytics 21. Analytics function centralization 22. Analytics skills of HR professionals 23. Analytics team creation 24. Awareness of analytics opportunities 25. Awareness of challenges and criticisms 26. Data governance and ethics 27. Degree of individual adoption 28. Employees' perceived accuracy and fairness 29. Ethics issues in HR data analysis and use 30. Focus on actionable insights 31. HRM team preparation and expertise 32. Knowledge and competence hubs 33. Organization and industry implementation barriers 34. Organizational complementarities 35. Organizational readiness 36. Outside-in approach with focus on actionable metrics 37. People specialist team creation 38. Performance pay policy 39. Privacy issues in HR data analysis and use 40. Six thinking hats approach 41. Virtue ethics approach	Andersen, 2017; Angrave et al., 2016; Aral et al., 2012; Baakeel, 2020; Bhanu Prakash et al., 2019; Boudreau et al., 2017; Dahlbom et al., 2019; Gal et al., 2020; Hamilton et al., 2020; Jain & Jain, 2020; King, 2016; Marler et al., 2017; Mayank et al., 2020; McIver et al., 2018; Nocker & Sena, 2019; Patre, 2016; Rasmussen & Ulrich, 2015; Sharma et al., 2017; Simón et al., 2018; Sripathi & Madhavaiah, 2018; Srivastava & Mohsin, 2020; Ulrich & Dulebohn, 2015; Vargas et al., 2018; Wang & Katsamakas, 2019

Table 6
Concepts and sources related to descriptive applications in HR analytics.

Concepts	Sources (alphabetical)
42. Adaptive scoring algorithm 43. Competence analytics 44. Employee engagement 45. Employee sentiment analysis 46. Expertise estimation and competence assessment 47. HR information retrieval, fusion and completion 48. Intelligence applicants shortlisting 49. Job scheduling 50. Latent ability modelling 51. Occupational skills normalization 52. Online recruitment 53. Real-time data collection 54. Semantic web human resource résumés 55. Skill assessment, identification and normalization 56. Talent hiring, engagement and retention	Alamelu et al., 2017; Escolar-Jimenez et al., 2018; Escolar-Jimenez et al., 2019a; Gupta & Srivastava, 2020a; Luo et al., 2018; Mukhopadhyay et al., 2020; Necula & Strîmbei, 2019; Nicolaescu et al., 2019; van der Laken et al., 2018; Xu et al., 2019

staff, the ability to leverage the community (crowd), the pervasive adoption of algorithms and interfaces, and the ability to encourage experimentation and autonomy of human resources (Ismail, 2014). At the basis of such exponential management of HR, it is possible to identify three drivers: a) the availability of massive quantities and varieties of HR data sources (input); b) the adoption/development of sophisticated methods and tools to process HR information (process); c) the design of value-added HR metrics and advanced visualization/reporting systems (output).

An unprecedented amount and variety of employee-related information and HR data is today available to organizations, both in structured and unstructured forms. Whereas company-owned data (e.g. employee profiles, job descriptions, employee reports, labour

Table 7
Concepts and sources related to predictive/prescriptive applications in HR analytics.

Concepts	Sources (alphabetical)
57. Dynamic talent flow analysis 58. Expertise recommendation and allocation 59. Prediction human resources modelling 60. Predictive data profiling 61. Proactive predictive decision on people matters 62. Probabilistic learning framework 63. Propensity modeling 64. Sentiment analysis 65. Turnover costs and recruitment decision 66. Voluntary turnover prediction 67. Workforce forecasting modelling 68. Workplace attendance, accidents, injuries tracking	Alamelu et al., 2017; Escolar-Jimenez et al., 2018; Gelbard et al., 2018; Gupta & Srivastava, 2020b; Luo et al., 2018; Rombaut & Guerry, 2018; Royal & O'Donnell, 2008; Safarishahrbijari, 2018; Xu et al., 2019

Table 8
Concepts and sources related to employee-related value of HR analytics.

Concepts	Sources (alphabetical)
69. Appropriate recruitment profile selection 70. Employee attrition and loyalty analysis 71. Employee attrition prediction 72. Employee churn prediction 73. Employee engagement and commitment 74. Employee fraud risk management 75. Employee performance evaluation and rewards 76. Employee profiling 77. Employee reskilling and competence update 78. Employee sentiment analysis 79. Forecasting of HR capacity and recruitment needs 80. Global recruitment optimization 81. HR external and internal marketing 82. Improved employee experience 83. Job turnover and transition networks 84. Leadership development 85. Real-time workforce performance awareness 86. Skill-job fit, customized training/pay and loyalty 87. Sustainable talent acquisition 88. Wage transparency	Arellano et al., 2017; Bassi et al., 2016; Ekawati, 2019; Escolar-Jimenez et al., 2019a; Escolar-Jimenez et al., 2019b; Hamilton et al., 2020; Lal, 2015; Malisetty et al., 2017; Pessach et al., 2020; Safarishahrbijari, 2018; Sri Harsha et al., 2020; van der Togt et al., 2017; Zeidan & Itani, 2020

market information) are crucial as they are accumulated over time, other sources of HR data and big data have an increasing relevance for HR analytics (Angrave et al., 2016; Dahlbom et al., 2019; Hamilton & Sodeman, 2020; Isson & Harriott, 2016; Nicolaescu et al., 2019; Nocker & Sena, 2019). First, user-provided data are crucial for assessing candidates (e.g. curriculum vitae, professional pitch, video-interviews, cognitive tests) and current resources (e.g. employee satisfaction surveys, engagement and expectations analyses). Web-derived data (e.g. websites, blogs, and social networks data) are useful to understand social attitudes and interactions among individuals, as well as employee engagement and sentiment. Finally, sensors and digital devices can provide data about employee mobility and build unprecedented understanding and insights about how people work and collaborate (Waber, 2013).

With reference to data processing, more sophisticated approaches and tools for information retrieval, fusion and analysis are today available to organizations. Advanced HR algorithms can incorporate a large number of variables associated to the professional "genes"

Table 9
Concepts and sources related to organizational value of HR analytics.

Concepts	Sources (alphabetical)
89. Automated decision-making 90. Automated management style 91. Business and organizational performance 92. Business value creation and business model innovation 93. Competitive advantage and enterprise analytics 94. Customer satisfaction 95. Data-driven decision making 96. Data-oriented leadership 97. Evidence-based predictive decision-making 98. Managerial efficiency 99. Organizational agility 100. Organizational effectiveness 101. Organizational resilience 102. People-driven competitive advantage 103. Strategic change 104. Strategic execution of organizational plans 105. Support to agile project management 106. Support to organizational change management	Arellano et al., 2017; Bassi et al., 2016; Escolar-Jimenez et al., 2019a; Hamilton et al., 2020; Jabir et al., 2019; Khan et al., 2017; Kakkar & Kaushik, 2019; Levenson, 2018; Meena & Parimalarani, 2019; Momin & Mishra, 2014; Nienaber et al., 2016; Safarishahrbijari, 2018; Sahota & Ashley, 2019; Saraswathy et al., 2017; Schiemann et al., 2017; Singh & Malhotra, 2020; Sivathanu & Pillai, 2019; van den Heuvel et al., 2017; Zeidan & Itani, 2020

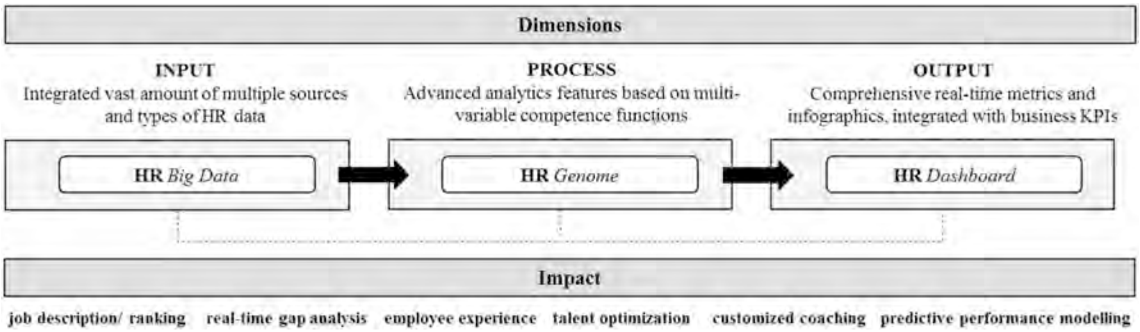

Fig. 4. Conceptual view of exponential HR analytics.

of the employee (e.g. knowledge, skills and accumulated expertise) as well as to personal characteristics of the same (e.g. socio-demographic and attitudinal aspects). Next-generation HR analytics can generate advanced reporting and visualization features, and dashboards of people-related metrics that are integrated with business and process KPIs. Exponential technologies can thus support HR analytics with new potentialities of data acquisition, processing and visualization, with capabilities such as real-time analysis of competence gaps, normalization of job descriptions and rankings, optimized talent management, customized coaching and onboarding, and predictive modelling of performance and engagement. Fig. 4 shows a conceptual view of "exponential" HR analytics, which leverages the potential offered by exponential technologies to define a new generation of workforce intelligence.

5. Discussion and new research propositions

5.1. Contribution

In this article, we attempted to contribute to the growing discussion on analytics as a strategic capability within modern organizations. In particular, HR analytics (or workforce/people analytics) is emerging as a relevant field in both academic research and in practitioner-related applications. The research scenario on HR analytics is today quite large but also sparse, and there is thus room for new contributions aiming to define where the field stands through systematization efforts conducted on a comprehensive population of research works. We conducted a review of specialized literature and identified 68 research articles from which we extracted 106 key concepts related to HR analytics. Such concepts are associated to 3 major areas, i.e. a) enablers of HR analytics (at both technological and organizational level); b) HR analytics applications (descriptive and diagnostic/prescriptive applications); and c) value of HR analytics (employee value and organizational value). In terms of contribution, our systematization effort advances extant knowledge and it can be a basis upon which to build a more comprehensive definition of the field.

Our work represents a progress respect to two recent attempts to study HR analytics by an integrated view. We provide an advancement respect to the work of Marler and Boudreau (2017), who identified 14 articles in quality peer-reviewed journals with the aim to address crucial questions related to five issues, i.e. the evolution of HR analytics, its processes, antecedents/consequences, outcomes, and success factors (moderators of the analytics-outcome relationships). First, we considered a larger population of articles (68, without constraints in terms of journal quality or impact factor) in order to increase the scope of the systematization effort. Second, we went beyond the qualitative discussion of retrieved articles along a number of perspectives of investigation, as we derived a structured inventory of 106 specific concepts framed within a purposeful classification framework. We also provide an advancement respect to the work of Fernandez and Gallardo Gallardo (2020), who used 64 research works (40 from journals) to provide an analytical overview of definitions of HR analytics and barriers to HR analytics adoption at data, technology, people, and management level. Whereas the work of Gallardo-Gallardo (2020) is thus much more focused and useful in terms of HR implementation, our work leverages a larger database of journal articles to build a more comprehensive identification of enablers, applications and value creation drivers associated to HR analytics.

5.2. A research agenda for HR analytics

The three areas of investigation represented by HR analytics enablers, applications, and value drivers can be also used to define a potential research agenda for the development of the field in the coming years. Concerning enablers, although analytics is a 'must have' capability to improve organizational performance, HR professionals should better understand the potential and drawbacks and engage to develop better analytical abilities, methods and approaches able to deliver transformational change (Angrave et al., 2016; Kryscynski et al., 2017). The effective implementation of HR analytics requires today an understanding of how disruptive technologies (such as artificial intelligence) can be integrated with traditional human resources management practices. Besides, it is important for HR analytics projects that they are positioned strategically, focus on business impact with support by key roles (Bright and Company, 2016), and that the right attention is dedicated to effective change management (Fitz-enz & Mattox II, 2014). In such perspective, the organization model (e.g. the adoption of project and process-based approaches) and the decision making patterns of the organization can have a relevant impact on the successful adoption of HR analytics.

Digital transformation is driving an unprecedented discontinuity in organizations, which are increasingly focused on aligning their HR strategy with the overall business goals (Momin & Mishra, 2015). Advanced people analytics models and algorithms can valorise multiple sources of user-generated and user-related data (e.g. social network data), with the ultimate goal to create dashboards providing HR managers and project managers with real-time, quantitative, synthetic, and self-updating data and infographics about their resources. The advancements in technology and data analytics capabilities support the evolution from "descriptive and diagnostic" to "prescriptive and predictive" HR intelligence (DiClaudio, 2019; Fitz-enz, 2010) and such "transition" may leverage the organizational maturity in terms of existing business intelligence and integrated reporting approaches and systems.

Finally, concerning value of HR analytics, two relevant aspects are the study of how employees perceive analytics and the impact of such perceptions on employee outcomes (Khan and Tang (2017), and the understanding of the mutual impact between human capital and business (Lawler et al., 2004). People analytics has the potential to re-shape the employee experience and behaviour. However, it is important to establish complementarities among technology, rewards, and practices (Aral et al., 2012). Organizations need to identify ways for assessing the business performance impact of HR and the process needed to maximize productivity (e.g. Muscalu & Şerban, 2014; Phillips & Phillips, 2014). HR analytics have the potential to bring a great value to decision-making. However, it has often taken an "inside-out," HR-centric, and academic approach. A shift towards actionable, high-impact analytics is needed, and technology can strongly accelerate such transition (Rasmussen & Ulrich, 2015) to drive organizational agility and operational performance. Based on the considerations above, the following propositions can be identified as potential research hypothesis to be tested in future purposeful studies:

P1: *The increased level of awareness of exponential technologies can be associated with more successful implementation of HR analytics within organizations*;

P2: *The effectiveness of adopting advanced HR analytics methods and applications can be higher in process and project-based organizations*;

P3: *Social networking platforms provide large sources of user-generated data, which can be embedded into advanced human resource evaluation algorithms*;

P4: *Advanced HR analytics may be applied with greater success in organizations with high maturity in terms of business intelligence and integrated reporting approaches*.

P5: *HR analytics can have a positive influence on the level of employee job engagement and workplace motivation*;

P6: *The maturity of HR analytics may be associated to a stronger organizational agility and overall operational performance of the organization*.

6. Conclusions

The emergence of the global workforce is increasing the relevance of talent management as one of the fastest growing academic areas in management (Cascio & Boudreau, 2016; Collings, Scullion, & Vaiman, 2015; Gallardo-Gallardo, Nijs, Dries, & Gallo, 2015;

McDonnell et al., 2017). In particular, the "datification" of human resources (Gobble, 2017) and the development of HR and workforce analytics represent crucial trends and essential needs for modern organizations (Srivastava & Mohsin, 2020). Over the past three decades, a shared consensus has developed on the importance to focus on HR systems (Boon, Den Hartog, & Lepak, 2019) and to develop holistic approaches to managing and analyzing the performance of human resources.

Our study has addressed such trends and requirements defined in the extant literature. We have provided an extended literature-based systematization of key concepts and investigation areas related to HR analytics, and we have identified avenues for further development of the field along a number of different areas of analysis (including the affirmation of exponential technologies). The paper is not without limitations. First, the integrative conceptual framework needs further effort based on the use of more advanced methodological approaches (e.g., cluster and factor analysis) aimed to reinforce the classification of concepts. The framework could be also validated using real cases and expert feedback. Besides, the study of factors placed at ethics, privacy/legal and acceptance levels should integrate the process and technological discussion. Next research will be addressed to identify cases of organizations attempting to introduce innovation into human resources analytics, and to use such organizations as testing and refinement contexts for our framework.

Author Statement

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Declaration of Competing Interest

None.

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