MANAGEMENT IMPLICATIONS FOR HR ANALYTICS IN LIGHT OF SYSTEMS THEORY

IMPLICAÇÕES GERENCIAIS PARA HR ANALYTICS À LUZ DA TEORIA DOS SISTEMAS

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Resumo. Desde os anos 2000, o campo de HR Analytics experimenta constante crescimento de trabalhos publicados sob focos variados, mas visando a ampliação do valor da Gestão de Recursos Humanos. Recentemente, a literatura tem se concentrado nos fatores a serem considerados nos frameworks de HR Analytics, sugerindo a questão de "como" HR Analytics deve ser praticado e orientado por objetivos; ao contrário das abordagens iniciais (ainda abundantes) de "o que" deve ser feito. Este trabalho visa abordar lacunas que auxiliem na definição dos recursos de gestão, pesquisando nuances nos objetivos de HR Analytics que impliquem em formas distintas de gestão da atividade. Duas abordagens principais foram combinadas: (i) uma análise quantitativa e qualitativa de publicações recentes e (ii) uma abordagem sob os construtos da Teoria de Sistemas. Definições, abordagens, temas subjacentes, áreas de estudo relacionadas e lacunas acadêmicas foram analisadas a partir de 231 publicações na base de dados Scopus até 2021. A análise destacou características de interesse, cujo agrupamento levou ao desenho de distintos (mas relacionados) objetivos e formas de gerenciar HR Analytics. Além disso, comparações com a criação de conhecimento de atividades correlatas permitem a proposição de uma taxonomia como direcionadora de objetivos e uma agenda de pesquisa.

Palavras-chave: HR Analytics, Tecnologia da Informação, Teoria dos Sistemas, Análise Bibliométrica, Gestão de Recursos Humanos, Workforce Analytics, People Analytics

Abstract. Since the 2000s, the HR Analytics field has experienced a steady growth in published works, with a variety of focus, but aiming the value added to HR Management. Recently, the literature has been increasingly focused on factors to be considered in HR Analytics frameworks, suggesting the question of "how" HR Analytics should be put into practice and drove by objectives; unlike initial (but still abundant) approaches of "what" should be done. This paper aims to address gaps that could help setting management resources, researching if there are relevant nuances in HR Analytics objectives that may imply in distinct ways to manage the activity. Two main approaches were combined: (i) a quantitative and qualitative analysis of recent publications and (ii) an approach under the Systems Theory constructs. HR Analytics definitions, approaches, underlying themes, related areas of study and academic gaps were analyzed from 231 publications in the Scopus database until 2021. The analysis highlighted main features of interest, which were clustered and drove to the drawing of distinct (but related) objectives and ways of manage HR Analytics. Moreover, comparisons with knowledge creation of correlated activities led to the proposition of a taxonomy as a driver to objectives and a research agenda.

Keywords: HR Analytics, Information Technology, Systems Theory, Bibliometric Analysis, Human Resources Management, Workforce Analytics, People Analytics

INTRODUCTION

The topic "Human Resources Analytics" (HR Analytics) seems to have relevant space within the field of Human Resource Management (HRM): either by the authors of the field of Human Resources (HR) who approach the topic (such as Levenson et al., 2021, Marler & Boudreau, 2017; Angrave et al., 2016; Pape, 2016; Rasmussen & Ulrich, 2015; Dulebohn & Johnson, 2013; Aral et al., 2012; Davenport et al., 2010; Beatty et al., 2003), either by the ten-times increased evolution in publications from early 2010s to early 2020s, as shown in Graph 1.

Recently, the HR Analytics literature seems to concern about the question of "how" the topic should be put into practice and drove by objectives; unlike the initial and still abundant approaches of "what" (prescriptive texts on best practices) should be done (Coron, 2021, Angrave et al., 2016; Chahtalkhi, 2016).

Discussions about the variety of nomenclatures given to the activity does not seem to have generated a widely accepted definition of useful objectives (Margherita, 2021; Rasmussen & Ulrich, 2015, Lydgate, 2018); and, among a variety of terms, HR Analytics, People Analytics and Workforce Analytics seem to be the most widely accepted (see Table 1). In this paper, the term "HR Analytics" is adopted as a standard.

Throughout the period covered in this research, several works discuss the value added by the activity: if in the aggregation of value in the efficiency of the HR operation (that is, the use of resources versus management quality factors), in the business effectiveness (generating better business results) or both outcomes (Chatterjee et al., 2021; Gurusinghe et al., 2021; Jörden et al., 2021; Konovalova et al., 2021; Larsson & Edwards, 2021; Qureshi, 2020; Gal et al., 2017; Levenson & Fink, 2017; Minbaeva, 2017; Pape, 2016, Rasmussen & Ulrich, 2015, Cascio & Boudreau, 2010); or even as a means of creating new work systems not yet well understood (Manokha, 2020; Gaur et al., 2019; Khan & Tang, 2016, Angrave et al., 2016). The literature seems to be increasingly focused on critical factors to be considered in the frameworks already proposed and reinforcing that the models suggested so far may lack effectiveness and deserve a better debugging (Chatterjee et al., 2021; Hota, 2021; Konovalova et al., 2021; Margherita, 2021; Singh & Muduli, 2021; Speer, 2021; Gal et al., 2017).

This paper aims to address gaps that could help setting management resources, researching if there are different objectives to HR that may imply different and relevant ways to manage HR Analytics.

In particular, since Angrave et al. (2016) and Rasmussen & Ulrich (2015), currently reinforced by Karwehl & Kauffeld (2021), it is emphasized that the discussion on the differences between academic and practical views on HR Analytics still need to be harmonized, the way analytical practices in HR should focus not only on the efficiency of HR activities, but also on the effectiveness of the business and of the HR activities.

Such scenario presents an intersection of distinct areas of study such as HRM, Information Technology Management and Corporate Strategy (Huselid, 2018; Minbaeva, 2018; Tursunbayeva et al., 2018; Levenson & Fink, 2017; Angrave et al., 2016), an analysis of the quantitative panorama of recent publications in HR Analytics field seems to be a way to search by patterns of strategic and technological approaches.

In complement, given the objective of verifying management differences arising from HR Analytics objectives and practices, it was chosen an approach under the Systems Theory constructs. Combined, both approaches can be useful for describing an overview of HR Analytics issues: its definitions, approaches, underlying themes, related areas of study and academic gaps.

SAMPLE AND PROCEDURES

A bibliographic search was carried out on the papers with most currently accepted key terms in the title or abstract or keywords (namely: HR Analytics, People Analytics, Workforce Analytics, Talent Analytics, Human Capital Analytics). It is possible to find papers whose themes are the use of analytics in the context of HR, but do not use any of the chosen key terms. These papers are not part of this research to reduce the margin of subjectivity of relevance to the topic "HR Analytics".

From the references raised, it was proceeded:

- Reading of abstracts, to
    - filter papers not related to this research;
    - classification of the remaining papers under features of interest;
    - identification of adjacent study areas;
- Quantitative analysis and clustering under the classification's variables;
- Bibliometric analysis with using VOSViewer software;
- Analysis of classifications in the light of Systems Theory;
- Analysis of interrelationships with adjacent study areas.

THEORETICAL BACKGROUND

Analytics applied to HRM

HRM Topics Connected to HR Analytics

Line-of-business and Information Technology (IT) strategy pressures to adopt data-driven leadership lead HR to adopt analytics as a way to drive organizational strategy (Davenport et al., 2010) through processes and HR data.

According to Schwartz & Davis (1981), "Organizational Culture", a concept usually managed by HR, means a pattern of beliefs and expectations that are shared by the organization's members and may produce norms that shape the behavior of individuals and groups in the organization. So, it can be considered that HR, through HR Analytics, contributes to organizational performance by translating the Organizational Culture into objective elements, which is reinforced by Chatterjee et al. (2021); Gurusinghe et al. (2021), Jörden et al. (2021), Konovalova et al. (2021), Larsson & Edwards (2021), Gal et al. (2017).

Additionally, Levenson & Fink (2017), Jensen-Eriksen (2016) and Mishra et al. (2016) argue that there has been more focus on collecting HR data than on understanding how data can be applied to projecting the future aiming decision making.

The traditional approach presents prescriptive texts on best analytical practices under the theme Human Resources, as can still be seen in Pessach et al. (2020), Simón & Ferreiro (2018), Papoutsoglou et al. (2017), Varshney et al. (2014) and Aral et al (2012).

Through the search strings used in this study, these are the five papers with the most citations in the Scopus database (213 in Feb/2022; 64 in 2021), which seems to point the persistent interest in papers of this nature. Such papers describe specific case studies and propose best analytical practices applied to the analysis of HRM subsystems, such as training, performance, screening and human capital management. In general, they devote more attention to analytics applications than to IS management aspects. Aspects of Strategic Human Resources Management (SHRM) are presented, but they do not seem to be part of the main concerns in these papers.

According to Karwehl & Kauffeld (2021), research is still needed to analyze whether there is a type of configuration or general process when implementing HR Analytics. The researchers say that the field is still "opaque", as there is no clarity on how to define the implementation of the activity that helps to understand the effects and interactions of the different stages of implementation, which would shed light for optimization and improvement of practical methods.

In this sense, also between 2015 and 2020 and using the same search strings, the five most cited papers that aims to analyze the structuring of HR Analytics are Leonardi & Contractor (2018), Minbaeva (2018), Sivathanu & Pilai (2018), Tursunbayeva et al. (2018) and Davenport et al. (2010), with 311 citations (126 in 2021). These papers analyze the context of adoption of the activity linked to aspects of IS and SHRM or suggest scenarios and conditions for the implementation of HR Analytics (the "how"). Comparing the number of citations, the structuring of HR Analytics seems to be capturing more attention nowadays, which suggests a reversal of what Chahtalkhi (2016) and Angrave et al. (2016) pointed out.

As for definitions of terms, Margherita (2021) (who makes no relevant distinction between "HR Analytics" and "People Analytics") provides 12 proposals for HR Analytics between 2007 and 2017. Although there does not seem to be a single definition for the term, both Margherita (2021) and Marler & Boudreau (2017) converge citing elements that seem common to most definitions:

- Its objective is to support decision-making related to people;
- "HR Analytics" includes more sophisticated calculations, modeling and data visualization than "HR Metrics";
- It aims to connect HR decisions and business results of the company;
- Analytics go beyond the use of functional data and involve the integration of a wide range of data, with broad potential business impacts;
- IT is a relevant element in the execution of the activity to collect, manipulate analyze and report data.

The three papers collected with "Workforce Analytics" in the title and with the highest number of citations (Huselid, 2018; McIver et al., 2018; Levenson, 2018; with 83 citations up to Feb/2022) present approaches to the term that intersect with the various definitions of HR Analytics, but they seem to point a tendency towards analysis for decision making especially focused on operations and business results, in which line managers seem to be the stakeholder with the greatest weight.

Figure 1 brings together the 231 papers published in the last 14 years in the Scopus database that results from the search strings used. The curve accounts an approximate rate of increase in publications of 38% per year.

Analytics management frameworks can be found in the propositions of Cascio & Boudreau (2010), Andersen (2017) and Lydgate (2018), which have the merit of seeming to be sufficiently applicable to the operational issues of HR Analytics, as they explore issues related to "what" to pay attention to and, in particular, also draw attention to the question of defining the activity. More than an accessory issue, this concern is related to the objectives of the activity, in order to understand if, for example, any applications of analysis and algorithms in the context of HR can be classified as HR Analytics. In this scenario, it is possible to find features linked to the Gig Economy and Personnel Economics.

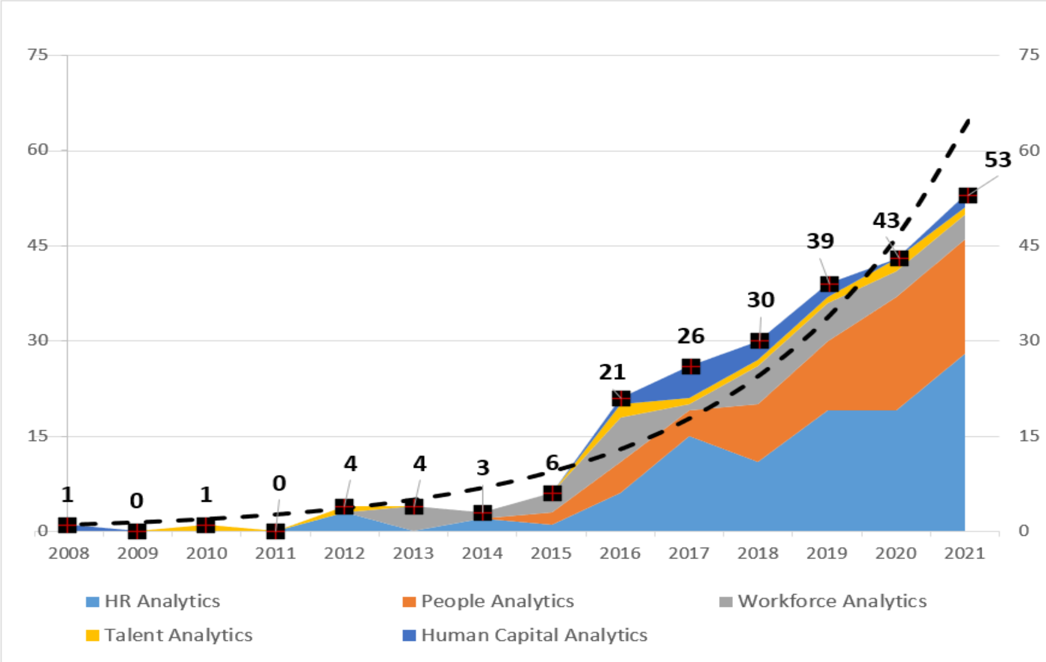

Figure 1. Evolution of papers under the topic HR Analytics published in Scopus database (to December 2021). Source: produced by the authors

HR Analytics seems to focus on managerial benefits for HR and a source of competitive advantage for organizations, as HR analysis are focused on aspects related to policies and operations, focusing HR actions on organizational effectiveness (Becker et al., 2001). In a complementary way, Davenport et al. (2010) say that efficiency factors are also relevant for their contribution to company results. Finally, Witte (2016), Chahtalkhi (2016) and Jensen-Eriksen (2016) reinforce that analytically-based decisions may reduce decision biases, leading to more robust results and mitigating possible losses of HR power in comparison to other corporate functions, which approximate a definition of HR Analytics to those of Business Intelligence (BI), Management Information System (MIS) and Decision Support System (DSS).

Gig Economy and Algorithmic Management

Duggan et al. (2020) analyze work relationships intermediated by applications and whose management is mainly carried out through algorithms. This seems to be another scenario to the application of algorithms in the dynamics of HRM and it is connected to labor economy field concepts such as the "Gig Economy" (a term coined by Tina Brown, former editor of the New Yorker magazine, in 2009, says Hasija et al., 2020).

According to Taylor et al. (2017), the Gig Economy can be defined as the labor market supplied by people who use applications (or "platforms") to sell their work and may be managed by algorithmics that evaluate and regulate the relationship. According to Duggan et al. (2020), the Gig Economy should not be confused with any informal work, given the existence of an employment contract, even without personal recognition between the job offer agent (which may be understood as an employer) and the demand agent (which may be understood as an employee).

Gandini (2019), argues that the technology platforms of the Gig Economy are an example of "techno-normative" centered control over workers, who deliver the result of their work under gamification rules (simulating game rules): job offers and rewards are offered according to evaluations carried out by clients or contractors without direct contact with the work.

From this point of view, it is possible to verify some similarity to what Walton (1989) calls the "double potentiality" of IT: the ability of an application to produce opposite effects, depending on the implementation scenario, organizational culture, etc. As an example, Gandini (2019) says sometimes it changes the nature of the rewards (when the "employee" performs "emotional labor" aiming for ratings instead of "tips"), sometimes increasing their profit and decision-making power (if they are committed to their tasks).

Finally, it is worth noting the issue of precariousness of the work relationship, that is, the imbalance of forces between work providers (workers) and demanders (organizations), as told by Friedman (2014). Although workers' autonomy is greater, digital mechanisms, benefits, rewards and incentives are specific as they expose workers to relationships in which substitution and shadows in labor legislation (as well as the absence of regulatory figures as unions), make workers' reactions and demands fearful (Gandini, 2019). Since there is a wide use of algorithms to support a form of management, the Gig Economy seems to dialogue with the scenario of HR Analytics.

Personnel Economics

A third way of connecting analytics concepts to HRM is Personnel Economics, defined by Lazear (1999) as the use of labor economics principles to understand the inner workings of the organizations. This field addresses the macro implications of theories related to employee incentives, engagement, salary management and the relationship between co-workers, among other topics.

The theme derives from Labor Economics (Lazear, 1999), which can be defined as the analysis of how labor relations relate to the economic operation of companies (Abbott, 2014). A relevant part of the papers on the topic seems to be dedicated to the study of the impacts of wage management and labor management on labor supply, demand issues and on company results (Johnson & Stafford, 1999; Gallen, 2018). It should, however, be noted that the context of the topic is broader and any policies impacting labor relations can be fitted into it. Thus, since there is also the possibility of applying analytics to the context in which policies and HRM strategy may be better understood to be managed, the conceptual approximation between HR Analytics and Personnel Economics can be drawn (in accordance with the connection cited by Rasmussen & Ulrich, 2015).

Systems Theory and Research in Information Systems

According to Boulding (1956), General Systems Theory is the name created by L. von Bertalanffy to describe the construction of theoretical models that lie between what is highly generalizable by pure mathematics and the specific theories of specialized disciplines. Also according to Boulding (1956), mathematicians aim to organize general relationships into coherent systems, however, the systems do not necessarily have a connection with the so-called "real" world.

Lunsford (2019), presents IS as a set of inputs, processing, outputs and feedback to stabilize and improve the system itself, as illustrated in Figure 2. This model can be used as a parameter for the characterization of different applications for HR Analytics: if there is a relevant difference between the set of elements that enter and leave under each type of processing, there is the possibility of different definitions and particular analyses.

If there is no relevant difference, they can be taken as the same process and therefore equalized.

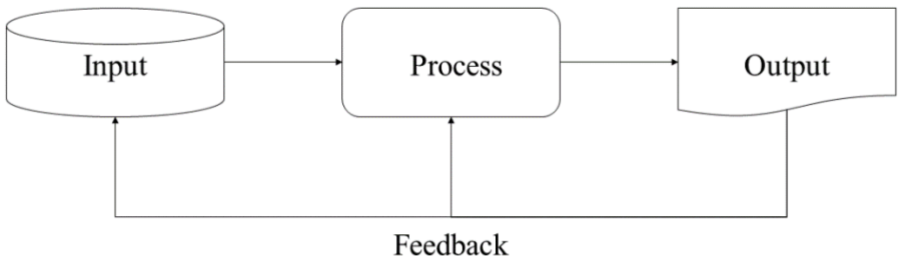

Figure 2. General system model, according to Lunsford (2019). Source: adapted from Lunsford (2019).

Churchman (1972) defines "system" as a set of coordinated parts to carry out a set of activities and considers (for analysis in management science) that the "total system" is composed of three major elements: the environment in the which the system is inserted, the objectives to this system and the elements that provide the search for these objectives (namely: its resources, components and its administration). Also according to this author:

"Environment" is what is situated "outside the system", that is, requirements that are beyond the action of an agent, but that are relevant to the achievement of its objectives.

"Objective" is the purpose of the system, which must be verified for objective statements and accomplishments so that the real objective is studied and not the declared one.

As for the elements that support the pursuit of goals, Churchman (1972) notes that:

- "Resources" are elements that are internal to the system, sensitive to technological progress and on which the system has decision-making capacity.
- "Components" inform about the activities of this system, which originate from mission statements.
- "Management" determines resource allocation and the tracking of component performance results.

Lim et al. (2009) identified 154 different theories proposed for application in IS Research. Of these, the 10 most used account for 90% of the total use calculated by these authors, who conclude that these numbers indicate that IS use (and should use) their own theories, which are classified by these authors under five major classifications: "IT and Organization", "IS Development", "IT and Individuals", "IT and Markets" and "IT and Groups".

According to Österle et al. (2011), Research in IS has as main approaches the Behavioral Approach (descriptive, mental, according to Mintzberg et al., 1998) and the Design Oriented Approach (prescriptive, of conception, according to Mintzberg et al., 1998). The Behavioral Approach has the natural sciences as its paradigm, seeking to develop hypotheses and empirically justify theories to explain phenomena (human and organizational) around the analysis.

Design Oriented Approach emerges from engineering and aims to create artifacts that incorporate ideas, techniques, capabilities and objectives (or products). It develops normative instructions in the sense of moving the applied practice by artifacts (means and ends sufficiently resolved) to generate actions aimed at specific benefits (Österle et al., 2011; Hevner & March, 2003).

Data Gathering and Processing

Collection of Papers

The approach of this paper aims to broaden the understanding of the focus given to the topic HR Analytics as a tool to boost HRM, that is, as a tool to be applied to organizational learning for the evolution of policies and action plans generated by HR. Thus, as mentioned in item 2, papers that use similar terms were also searched for the construction of search strings in the Scopus database.

Margherita (2021), Lydgate (2018), Marler & Boudreau (2017), Davenport et al. (2010), Mishra et al. (2016) and Rasmussen & Ulrich (2015) cite several keywords linked to the keyword "HR Analytics". Key terms listed by these researchers include, in alphabetical order: Evidence-based HR and Management, High Performance Work Practices, HR Analytics, HR Metrics, Human Capital Analytics, Human Resource Data, People Analytics, People Research, Personnel Economics, Talent Analytics, Talentship Decision Science, Workforce Analytics and Workforce Science.

Based on these terms, searches in the Scopus database using these terms in the title or abstract or keywords of the papers aimed to filter only the most applied terms. This search returned 231 papers under the following keywords (in order of number of papers and with duplicates): HR Analytics (127), People Analytics (80), Workforce Analytics (50), Talent Analytics (19) and Human Capital Analytics (15). Table 1 presents a quantification of the results for the researched period with and without duplicates.

Table 1. Amount of search results in the Scopus database for the main keywords related to HR Analytics from 2008 to 2021.

Main String term	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008	Total	
															With duplicates	**Free of duplicates**
HR Analytics	28	19	19	11	15	6	1	2		3					127	104
People Analytics	18	18	11	9	4	5	2								80	67

Workforce Analytics	4	4	6	6	1	7	3	1	4						50	36
Talent Analytics	1	2	1	1	1	2				1		1			19	10
Human Capital Analytics	2		2	3	5	1								1	15	14
Total (free of duplicates)	**53**	**43**	**39**	**30**	**26**	**21**	**6**	**3**	**4**	**4**	**0**	**1**	**0**	**1**	**231**	

Source: produced by the authors.

During the searches in the Scopus database, other papers with themes related to the use of analytics in the context of HR could be found, such as e-HRM (electronic Human Resources Management, related to IT support in the construction and implementation of IS prepared for the HR demands, according to Schalk et al., 2013), Artificial Intelligence and Big Data in specific HR practices and subsystems (such as talent management and admissions, for example), according to Hamilton & Sodeman (2020), Pillai & Sivathanu (2020), Vaidya et al. (2020), Garcia-Arroyo & Osca (2019), Oentaryo et al. (2018), Brynjolfsson and Mitchell (2017), Aral et al (2012), Yasodha & Prakash (2012) and Jantan et al (2009). Such applications are sometimes addressed without the use of typical keywords such as "Human Resources Analytics" or "People Analytics" and may delineate a field derived from the use of technology in the context of HRM, but perhaps not central to HR Analytics, as suggest Cheng & Hackett (2021).

According to Cheng & Hackett (2021), the recent increase in publications regarding the analysis of HRM-related data makes several distinctions between the typical use of algorithms and more traditional statistical applications. These applications of algorithms do not aim to explore the "HR black box" (evoked by Martín-Alcazar et al., 2005 and Legge, 1995), but to create management heuristics. This description seems to be connected to the issue of the Gig Economy, but these papers do not fit the objective of this study, despite constituting a research universe whose comparison with HR Analytics is of interest for a deepening of this research.

Another universe of papers detected concerns approaches close to HR Analytics, but which also do not fit this research objective: they are reflections on the impacts of technological advances on the future of work, as, for example, Frank et al. (2019), Mitchell and Brynjolfsson (2017), Brynjolfsson & Mitchell (2017), Brynjolfsson & Mcafee (2015) and Aral et al. (2012).

Processing and Classification

The abstracts of all papers were read to classify and filter those that are really related to the topic of this study. It was discarded 47 papers, whose main theme are psychology, analytics in a broader context and without managerial implications, military or sports themes, introductions to special editions, duplicate papers in the Scopus database and papers without a summary available.

The 184 remaining papers were then classified under criteria approaches presented in Table 2, in order to allow a general analysis of the key terms versus the classifications and the verification of the possibility of grouping the papers into broader groups.

Table 2. Criteria used for the classification of the works' approach.

Subject	Nomenclatures / Classifications adopted
General topic of the paper[1]	HRA: Tactical HR Management using analytics, building HR Intelligence and studies focusing on Competitive Intelligence with the application of HR data analysis SHRM: Strategic HR Management, HR Strategy, HR IT Management
Role of IT in the paper context[2]	IS: IT's role is to provide IS, such as HR or software management systems. ML: IT's role is related to the development of analytics and algorithms.
Application or Frameworks or Input to Frameworks[1]	AP: papers whose theme is analysis and/or algorithms to describe or analyze "best practices" or HRM policies targeting HR subsystems, such as selection, training, etc. FR: papers whose theme is to propose papering structures (systems) or that present critical views on how analytics can be practiced in the context of HRM. InFR: papers whose theme is related to the proposition of Critical Success Factors, recommendations for Frameworks, managerial barriers, etc.

Note:
[1] The papers were classified using the indicated nomenclatures, which are mutually exclusive.
[2] Papers can receive one of the classifications, both or neither.
Source: produced by the authors.

Considering the classifications in Table 3, the evolution of the 184 selected papers can be presented in Figures 3, 4 and 5.

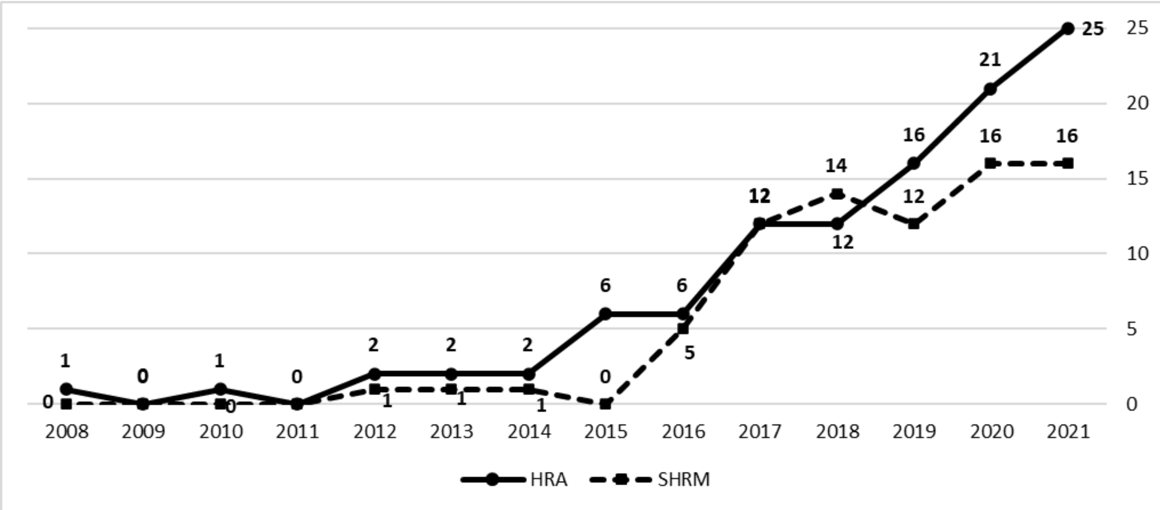

Figure 3. Evolution of the papers according to the general theme.
Focusing on management using analytics (HRA) or on deepening Management issues (SHRM).
Source: produced by the authors.

In Figure 3, although the papers with a general theme more related to HR management are more numerous (106 against 78). Roughly speaking, the interest in the two approaches is relatively similar.

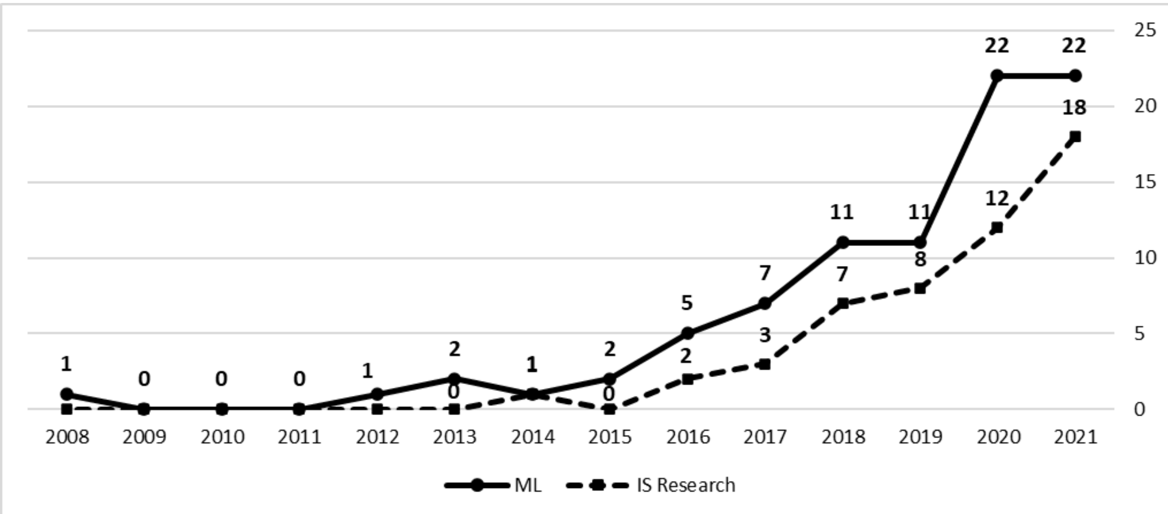

Figure 4. Evolution of papers according to the focus on the role of IT.
As an IS provider (IS Research) or as an analytics developer (ML).
Source: produced by the authors.

Figure 4 also shows a relative balance between the IT focus approach. Following the logic of Figure 3, there are more papers in which the role of IT is related to analysis (85) than as a provider of IS (51).

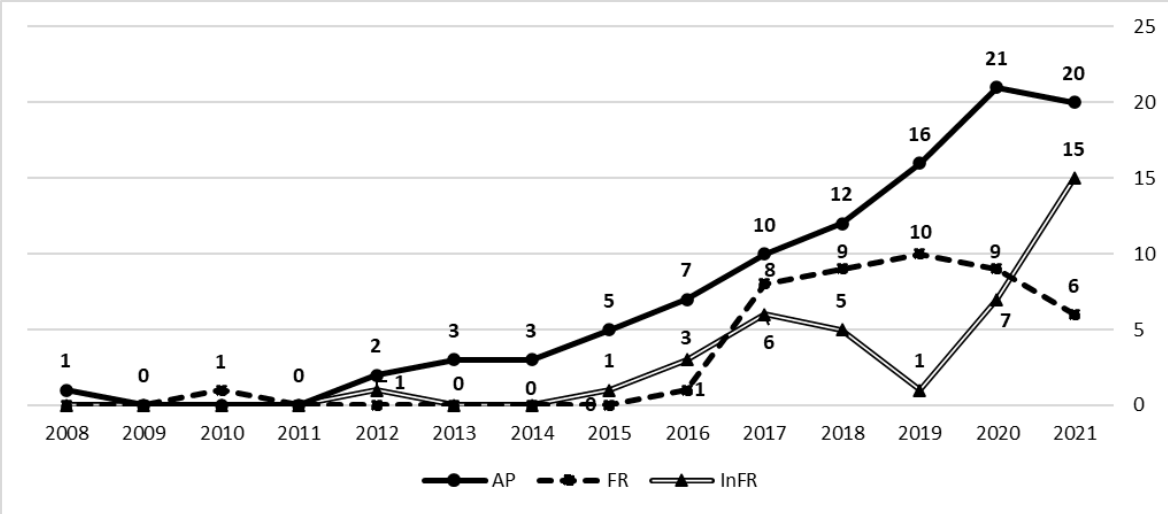

Figure 5. Evolution of papers according to the focus on practical or theoretical conclusions. Presentation of analyzes (AP), proposal of Frameworks (FR) or inputs to Frameworks (InFR).
Source: produced by the authors.

In Figure 5, the papers that explore the practice have a greater number of papers (100 papers), but if you add the papers that propose frameworks (44) to those that provide inputs for frameworks (39), there is a relative balance. The momentary inversion between the FR and InFR curves is noteworthy. It is certainly too early to draw any conclusions, but the future follow-up of these classifications may point to the emergence of "2nd generation" models, considering the criticisms over the frameworks already proposed in the InFR curve papers.

Data Analysis

Characterization of Papers by Clustering Variables of Interest

All 184 papers were clustered under the variables shown in Table 2 by using the k-means algorithm programmed in Python using Jupyter v.6.4.1. Analyzing the number of clusters varying between 2 and 9, the elbow rule pointed to an optimization in 4 clusters (WCSS = 63.89), leading to groups that divide the papers as can be seen at Table 3. The percentages are relative to the total of papers in each cluster, for each group of observed features.

Clusters C1 and C4 clusters gathers papers that are similar, considered that their main contribution is strategic management (IT or HR) and as they bring together papers whose role of IT is predominantly linked to IS and their management. The difference between the clusters lies in the proposition of frameworks or in the proposition of inputs for frameworks. In a simplifying way, both clusters contribute target HR Analytics management scenarios.

Clusters C2 and C3 have also similarities, as they approach HRM with the use of analytics and develop analyzes and/or algorithms aiming to propose best management practices. Clusters C2 and C3 differ in their approach to the role of IT: C2 is mostly focused on IT in the role of analysis provider and in cluster C3 this role is analyzed exclusively from the approach of data provider systems (which happens in only 6 papers). It is interesting that there are analytics applications that have an approach focused on IT analysis more as a provider of data than of analysis. However, given the low number of papers that differentiates these clusters and the strong similarity in their features, for the purposes of bibliometric analysis, both will be considered as a single cluster.

Table 3. Clustered features of the researched papers.

clusters	HRA / SHRM		ML / IS		AP / FR / InFR			Total
C1	31%	69%	10%	41%	0%	0%	100%	39
C2	94%	6%	100%	13%	100%	0%	0%	72
C3	82%	18%	0%	21%	100%	0%	0%	28
C4	7%	93%	20%	44%	0%	98%	0%	45

	Predominance		
groups	HRA / SHRM	ML / IS	AP / FR / InFR
C1	Tends to SHRM	IS	Inputs for Frameworks
C2	HRA	ML	Applications
C3	HRA	IS	Applications
C4	SHRM	tends to IS	Frameworks

Source: produced by the authors

In summary, the analysis leads to there are three major groups of papers:

- Papers focused on the internal organization of HR and its relationships with IT, in which the main role of IT is a provider of IS and there are propositions of theoretical elements for the construction of frameworks (cluster C1),
- Papers focused on the internal organization of HR and its relationships with IT, in which the main role of IT is to provide IS and there are propositions of inputs to frameworks (cluster C4) and
- Papers focused on managing people matching business needs with the use of analytics, in which the main role of IT is an analytics provider focused on proposing or describing management "best practices" (clusters C2+C3).

Characterization of Papers Clusters by Bibliometric Analysis

To deepen the content of each cluster, they were analyzed using VOSviewer software, version 1.6.17. The key terms "HR Analytics", "People Analytics" and "Workforce Analytics" were consolidated into a single term "HR Analytics" as a simplifying factor.

Figure 6 presents the relationship between keywords of the papers in cluster C1, with the relationships between the 24 main keywords. From the analysis of the relationship between keywords and the reading of all the abstracts, it can be summarized that the texts present the connection of elements of information management applied to the context of HRM to factors of interest for the creation of frameworks, such as ethical issues, behavioral, results and business processes and information management. The papers are mainly based on a largely hybrid bibliography, originated in the Data Science literature (as defined by Provost & Fawcett, 2013) applied to SHRM. The papers target the role of IS management: how are conducted analyses that allow to suggest factors relevant to SHRM. In special, they present factors to be considered in best management practices in HR Analytics for HR managers and, to a lesser extent, also line managers. Examples of these IS elements dealt with in these texts are cloud-based systems, employee IS, statistic tools, platforms to software and applications, IT centralization / decentralization, data governance, level of processes automation and databases, etc. Examples of factors relevant to SHRM are organizational factors such as ethical issues, privacy issues, HRM team preparation, HR policies, corporate culture, HR subsystems issues, leadership development issues, employee digital monitoring issues, algorithmic management, etc. (Chatterjee et al, 2021; Hota, 2021; Konovalova et al., 2021; Margherita, 2021; Singh & Muduli, 2021; Speer, 2021; Gal et al., 2017).

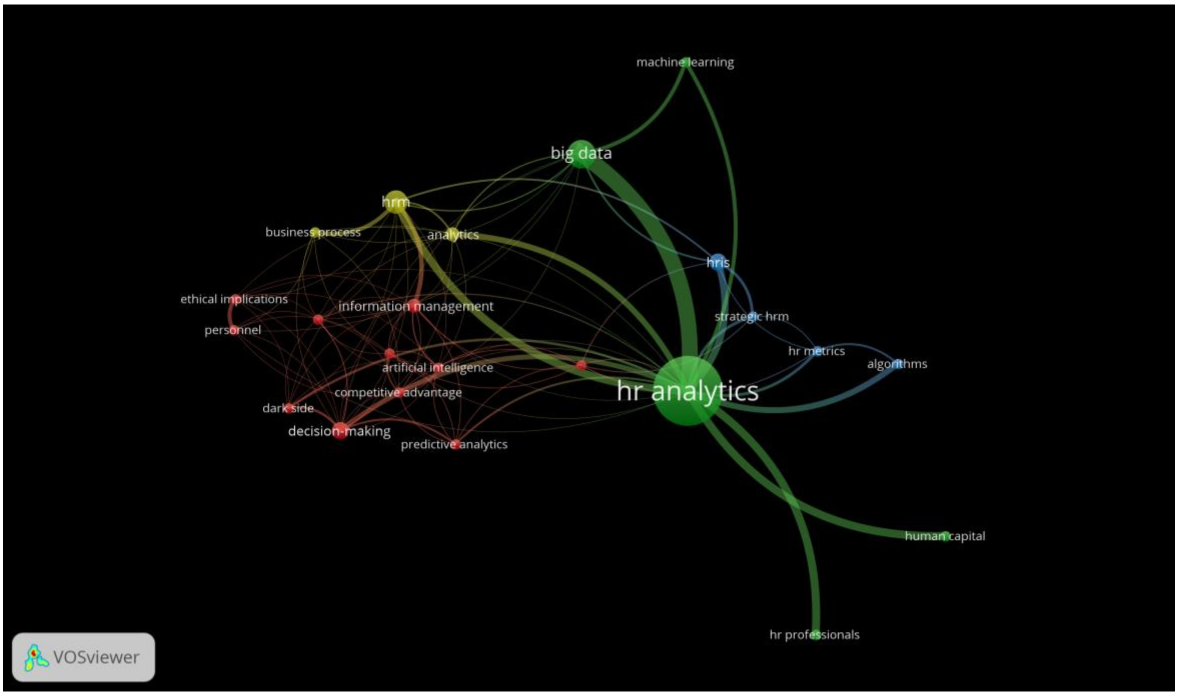

Figure 6. Co-occurrence of keywords in cluster C1. Source: produced by the authors.

Figure 7 presents clusters C2+C3, with the relationships between the 27 main keywords. From the analysis of the relationship between keywords and the reading of all the abstracts, it can be summarized that the papers present cases of predictive analysis and modeling in the context of HR subsystems. The texts explore how analytical methods can contribute to organizational results, whether reducing costs of HR processes, or driving better results through management and/or choice and/or application of HR in the context of specific business or processes. In this context, the roles of the HR manager (to adjust organizational policies to the business context) and the line manager (to direct human capital features) are relevant. There are recommendations on IS management, but the conclusions focus on how analysis models can improve decision making focused on business results or management processes (Aviv et al., 2021; Pessach et al., 2020; Gaur et al., 2019; Simón & Ferreiro, 2018; Papoutsoglou et al., 2017; Varshney et al., 2014; Aral et al., 2012).

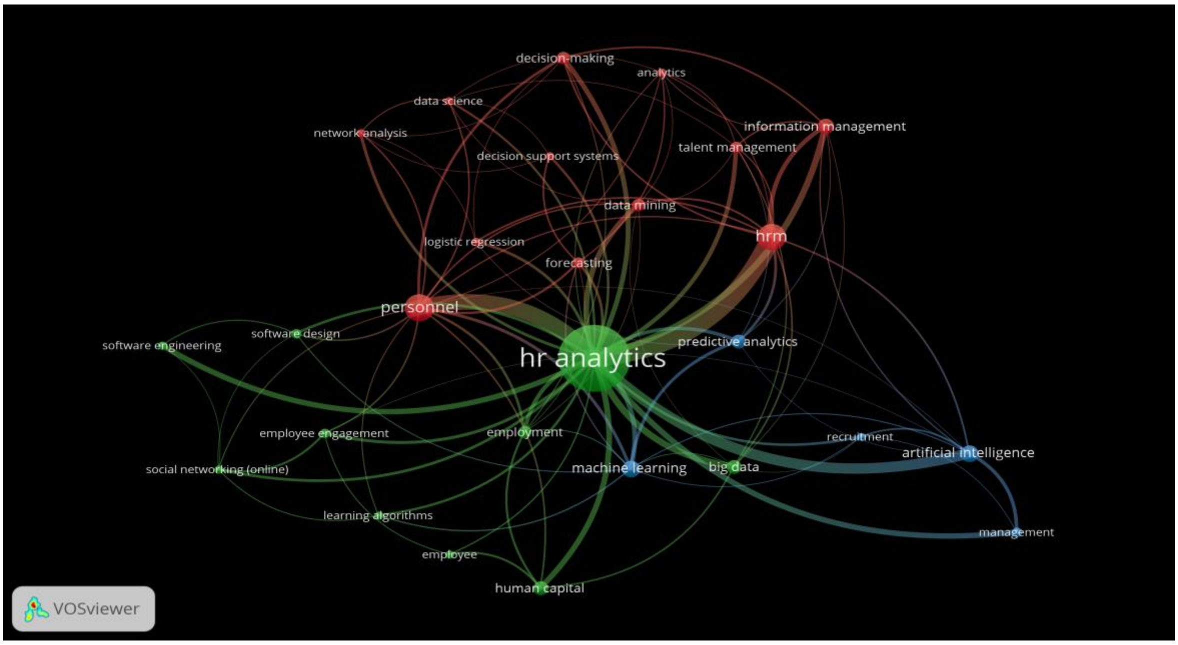

Figure 7. Co-occurrence of keywords in clusters C2+C3. Source: produced by the authors.

Figure 8 presents cluster C4, considering the 28 main keywords. The analysis of the relationship between keywords and the reading of all the abstracts points these papers discuss strategy and management factors (competitive advantage, decision making, strategy), HRM (organizational culture, personnel management, human capital) and IS management (as in Levenson et al., 2021; Huselid, 2018; Leonardi & Contractor, 2018; McIver et al., 2018; Tursunbayeva et al., 2018; Andersen, 2017; Levenson & Fink, 2017; Davenport et al., 2010).

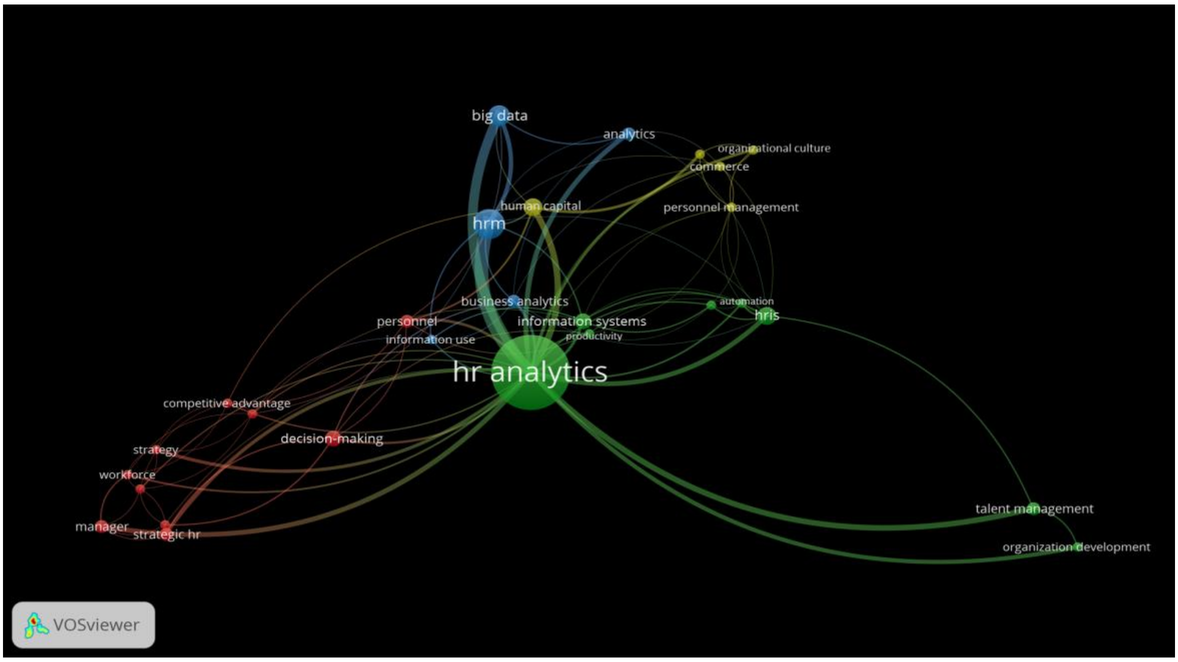

Figure 8. Co-occurrence of keywords in cluster C4. Source: produced by the authors.

Figures 6 and 8 point to "formatting factors" of the HR Analytics activity, which demands knowledge of HR processes and how works the alignment between organizational actors, such as Business, HR, IT and senior leadership. Figure 7, on the other hand, seems to suggest a use of HR Analytics more focused on operations, direct management of resources and business results, in which the main actors are HR and line managers.

Discussion

It was not found studies proposing debugging objectives and definitions to the use of analytics in HRM applying a classification of features of interest, leaving this approach vacant. Thus, analyzing the content of each cluster and the relationships between keywords, it is possible to suggest two visions for objectives of HR Analytics.

Huselid (2018), McIver et al. (2018), Levenson (2018) and Davenport et al. (2010) classify the use of analytics directly linked to the business as Workforce Analytics, but, as a whole, the literature does not advocate different definitions between HR Analytics, People Analytics and Workforce Analytics, using them synonymously. For the purpose of a better separation between the use of analytics in the context of HRM, a separation of definitions based on the features analyzed and the definitions cited in the literature is made as follows.

The interpretation of the features in the papers represented in clusters C1 and C4 seems to suggest a vision of **HR Analytics** as **the activity that articulates the organization of the management scenario and HRM through analytics and HR IS, seeking to create policies of HR and being moderated by the alignments with IT and Business.**

The interpretation of the features in the papers represented in clusters C2 and C3, on the other hand, seem suggest a view of **Workforce Analytics** as **the activity that has management policies as a driving factor, but whose focus turns to the analysis of the effects of HRM decisions in the context of the search for business results and management practices by the line leadership.**

Moreover, according to Gao et al. (2008), Organizational Knowledge Management comes from both content and process management. In particular, content management is connected to people, that is, to social interactions, culture, contextual information, environment, leadership role and incentives aimed at mobilizing the knowledge of individuals to generate company results (Gao et al., 2008, Yeh et al., 2006; Davenport & Prusak, 1998; Nonaka, 1994; Crossan et al., 1999).

It is possible, in general, to adopt indistinctly the nomenclatures HR Analytics and Workforce Analytics. However, considered the paper clustering, the bibliometric analysis and the objectives of the papers in each cluster are interpreted according to Churchman (1972), it is possible to suggest differences between HR Analytics and Workforce Analytics, as shown in Table 4.

Table 4. Comparison of proposed definitions of HR Analytics and Workforce Analytics according to Churchman (1972) Systems Theory.

Element	**HR Analytics**	**Workforce Analytics**
Environment	The strategic management of organizational resources, the demands arising from the competitiveness of business and human capital markets.	
System	Organizational culture management.	Human resource management in business and processes.
Objective	Efficient production of HR subsystems: creation of HRM policies that guide a management culture common to all businesses and corporate functions.	Optimizing the effectiveness of Human Capital based on HR policies and the constraints and idiosyncrasies of each business or organizational function.
└ **Resources**	• Analytical tools (analytics techniques, indicators, data mining etc), • HR IS, • Analytics knowledge, • Knowledge of human capital architectures, • Knowledge of HR subsystem processes.	• Analytical tools (analytics techniques, indicators, data mining etc), • HR IS, • Analytics knowledge, • Knowledge of human capital architectures, • Knowledge of HR policies, • Knowledge of line leaders' management policies.
└ **Components**	• Alignment between IT and HR, • Alignment between analytics professionals and HR professionals, • Governance of HR data, • Governance of corporate culture definitions and assumptions, • Ability to translate corporate culture into objective elements, • Specialist HR subsystems and HR analytics teams.	• Alignment between HR and the business and other corporate functions, • Governance of definitions and assumptions of Human Capital results for business and corporate processes, • Ability to adjust HRM policies to line management idiosyncrasies, • HRBPs and HR and business analytics teams.
└ **Administration**	• Senior management of the organization • Senior management of the HR function • Managers of HR subsystems	• Business Managers and other organizational functions • Leading HRBPs (or equivalent roles)

Source: produced by the authors

Taking the definitions of HR Analytics and Workforce Analytics researched and compared with the definition of "System" by Lunsford (2019), it is possible to affirm that both definitions are equivalent. A more detailed analysis (as shown in Table 4), however, can point out relevant differences for the practice of these activities.

The lack of differentiation of objectives in literature to the use of analytics in HRM context (despite its impacts to practitioners) may point out it is still a factor to be recognized by researchers and practitioners. Workforce Analytics seems to be complementary to HR Analytics, as it is more connected to HRM with the business; and HR Analytics seems more focused on the HR processes and policies (setting the way to run Workforce Analytics), which sets up different purposes and, therefore, different administrations.

Contrasts to Personnel Economics and Algorithmic Management

The literature surveyed brings other terms that may point to the influence of other areas of study for an evolution in the understanding of analytics in the context of HRM.

"Personnel Economics" and "Algorithmic Management" were defined in this paper. Terms such as e-HRM (electronic Human Resources Management), HRIS (HR IS), as well as the themes "Future of Work" and "Digital Transformation in HR" or "HR Digitization" are present in the references raised, but they were not addressed here as they seem more connected to IT resources shared for HR Analytics and Workforce Analytics than closely linked to differences in the administration of both.

A closer examination of these activities in order to search some logic in their articulation with each of the definitions suggested here. In general, however, it seems possible (from the definitions for HR Analytics, Workforce Analytics, Personnel Economics and Algorithmic Management) to suggest a macro relationship between these concepts as shown in Figure 9.

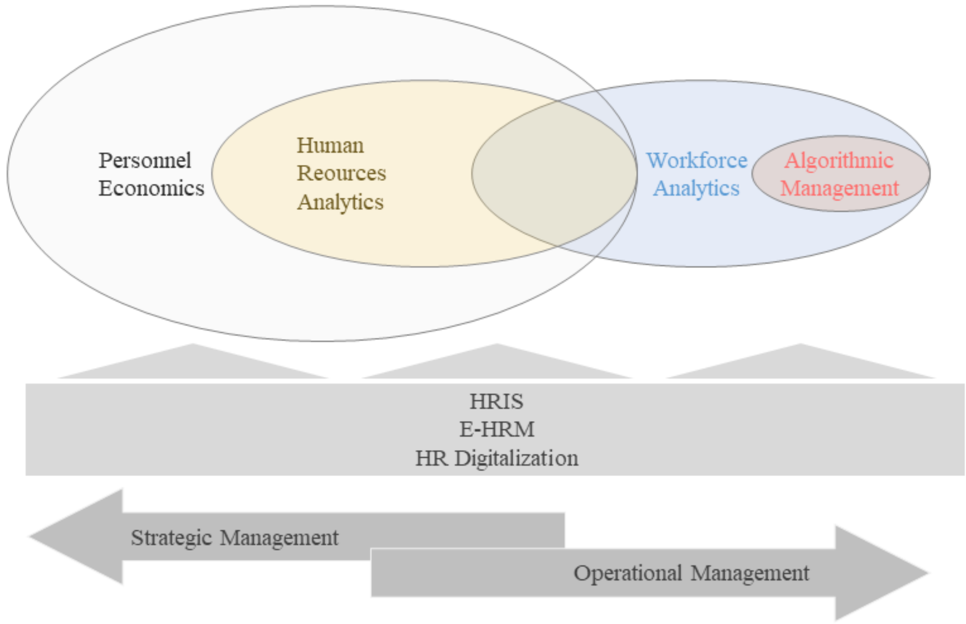

Figure 9. A proposed taxonomy connecting HR Analytics, Workforce Analytics, Personnel Economics and Algorithmic Management. Source: produced by the authors.

Personnel Economics, according to Lazear (1999), is based on the principles of labor economics and analyzes how corporate policies impact labor relations, giving scope (according to Rasmussen & Ulrich, 2015) for the fit of HR Analytics inputs.

Van den Heuvel & Bondarouk (2017) place the interaction of HR Analytics not only with HR teams, but with finance, IT, marketing and the company's leadership as a critical factor. Jensen-Eriksen (2016) gathers literature that suggests that knowledge sharing towards cooperation between teams (analysis specialists, business leaders and HR leadership) is expected to increase with increasing analytics maturity. In a low cooperation environment, it is also expected greater difficulties in Combination (Nonaka et al., 2000) in analytics knowledge creation cycle (a well-known issue to knowledge management, according to Yeh et al., 2006 and Massingham, 2014).

HR Analytics, in its turn, presents strong connections with Workforce Analytics already mentioned, but this last activity can evolve in its own context as well there is room enough to part of Workforce Analytics be framed as part of the context of Personnel Economics, given the supply and job demand issues (Johnson & Stafford, 1999; Gallen, 2018), in special when associated with specific business contexts and other organizational functions.

Oltra (2005) reports that there is a positive relationship between customization and success in knowledge management initiatives. Once it seems good to boost knowledge sharing between HRM and line managers (Ameer et al., 2020), the use of these same dashboards may not be helpful to analyze HR comprehensive policies, an important issue in knowledge sharing between HR leaders (Ellmer & Reichel, 2021). Using the same dashboards to accomplish to this both objectives may connect, but also blurs boundaries between HR Analytics and Workforce Analytics, despite it seems to put forward Externalization and Combination (Nonaka et al., 2000), once there are different Bas (knowledge environments, objectives and actors) involved.

Algorithmic Management, reduced to its elements of work analysis for decision-making, seems, due to this simplification, to fully fit into the definition of Workforce Analytics. There are elements of this management format that are outside the scope of this analysis, such as the understanding of labor relations, regulatory elements and labor legislation that elevate the discussion to the context of the Gig Economy.

Theoretical Implications: a wide research agenda, with a focus on "how to"

The analytics in HR research agenda has still a wide range of issues as notice since Angrave et al. (2016) to Margherita (2021). Focusing in the processes issue, since Angrave et al. (2016) and Marler & Boudreau (2017) to Gal et al. (2020) and Margherita (2021), the question "how" to make analytics in HR work is still under the spotlight.

Observing the definitions in the literature and the analysis of this study from the point of view of Churchman (1972), HR Analytics and Workforce Analytics seem to be inserted in the same Environment and use similar Resources and Components. On the other hand, they seem to have different Objectives and also to be managed by different agents, which means that practitioners may be misleading the use of human, technical and knowledge resources.

Boulding (1956) says that the systemic view is the first one that emerges when approaching a new topic and that this happens in two moments: first, the empirical universe is observed and general phenomena are positioned. In a second moment, the approach turns to the empirical arrangement in a hierarchy of complexity of organization of the parts of the phenomenon aiming at a more general abstraction.

The evolution presented in Figure 5 seems to confirm this narrative. The rapid rise of paper on analytics applied to HR subsystems seems similar to Boulding's (1956) "first moment" description. Only more recently the "second moment" seems to be emerging, as can be proposed (and confirmed in the future) by the data observed in Figure 5. New papers begin to present notes and gaps to be considered for the proposition of new frameworks.

A Proposed Research Agenda on "how to"

Ellmer and Reichel (2021), Karwehl and Kauffeld (2021), Qamar and Samad (2021), Nocker and Sena (2019), Minbaeva (2018), Andersen (2017) and Minbaeva (2017) propose that it seems necessary to understand whether there is a kind of setup or general process for structuring HR Analytics. These researchers claim that there is more information about experiences on developing applications (see curve AP in Figure 5) than about planned experiences or about objectives and strategic choices made in the process of structuring HR Analytics processes (see curves FR and InFR in Figure 5). The recent increase in works related to the structuring of HR Analytics may point out to a greater recent focus on this gap, addressing a possible search for understanding basic conditions for incorporating HR Analytics in HRM.

In this context, it seems valid listing and organizing gaps pointed out in the literature. Peres and Laurindo (2020) sought to organize the HR Analytics problem from the point of view of Competitive Intelligence, Knowledge Management and IT Management. The organization suggested by these authors follows the data, information, knowledge and wisdom (DIKW) hierarchy (Rowley 2007): starting from the strategic alignment between HR and IT, to the effectiveness of HR Analytics. The gaps on "how to" pointed out by the HR Analytics literature are summarized in Table 5.

Table 5. Gaps on "how to" pointed out by the HR Analytics literature.

HR Analytics problematic (Peres & Laurindo, 2020)	Literature gaps
(6) Effectiveness of Policies, Practices and Processes (Creation of Sustainable Competitive Advantages)	**Organizational Performance** • Has HR Analytics a positive impact on organizational performance? Berhil *et al.* (2020), Gaur (2020), Liu *et al.* (2020), Pessach *et al.* (2020), Durai *et al.* (2019), McIver *et al.* (2018), Van der Laken *et al.* (2018), Alamelu *et al.* (2017), Sharma and Sharma (2017) and Singh *et al.* (2017) defend the proven existence of this impact, but Caron and Batistic (2019), Minbaeva (2017) warn that there is no understanding of the transience of the observed improvements. **Automation and Human Capital Management** • Does HR Analytics drive to a rupture of current HRM models (Hansen *et al.,* 2017; Minbaeva, 2017)? • Have increasing HR automation been changing the ways in which HR effectiveness is measured (Minbaeva, 2017)? • Has HR become more dependent on automations (Hansen *et al.*, 2017)? Have automations led to a distancing between managers and employees? (Duggan, 2020; Gandini, 2019; Friedman; 2014)?
(5) Transformation of Knowledge into Policies and Platforms for Innovation	**Understanding or absorption capacity in processes** • What is the actual ability to apply analytically generated knowledge to management processes (Ellmer & Reichel, 2021; Nocker & Sena, 2019; Van den Heuvel & Bondarouk, 2017; Werkhoven (2017)? • Is the centralization of decision-making an inhibiting factor in understanding the potential of HR Analytics? (Gal *et al.*, 2020)? **Scope of management improvements** • Is a greater specificity required in the analysis of management processes, so that the advantages of adopting HR Analytics can be perceived (Qureshi, 2020); Nocker & Sena, 2019; Shrivastava *et al.,* 2018)?
(4) Analytical Learning Capacity in HR	• Giermindl *et al.,* (2021) and Gal *et al.* (2020) raise ethical issues arising from the use of information obtained through HR Analytics. • How to expand the ability to convert data into knowledge for decision-making in HRM (Gal *et al.*, 2020; Andersen, 2017; Werkhoven, 2017; Davenport *et al.*, 2010)? • Under what conditions HR Analytics reduces group learning ability (Shet *et al.*, 2021)?
(3) Transformation of data into information	**Boundaries of stakeholders' responsibilities** • What is the ideal sharing of responsibilities among the participants of the HR Analytics activity (Fernandez e Gallardo-Gallardo, 2021)? • How to connect information and justifications to action plans in a visual, user-friendly way (Andersen, 2017; Welbourne, 2015)? **Ability to recognize and take advantage of opportunities** • Nocker and Sena (2019), Andersen (2017), Marler and Boudreau (2017) and Angrave *et al.* (2016) point out that a generalized low digital literacy seems to be a limiting factor for recognizing opportunities for using analytics in HRM. • According to Fernandez and Gallardo-Gallardo (2021), McIver *et al.* (2018), Minbaeva (2018), Andersen (2017), Martín-Rios *et al.* (2017) and Rasmussen and Ulrich (2015), HRM leaders are responsible for a lack of incentives in creating an analytics culture.

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(continuation of Table 5)

HR Analytics problematic (Peres & Laurindo, 2020)	Literature gaps
(2) Alignment with IT	**Data and IS Integration** • Fernandez and Gallardo-Gallardo (2021), Huselid (2018) and Andersen (2017) point out that there is little sharing of group knowledge between HR and IT. • Madhvapaty e Rajesh (2018) comment on the lack of integration between hiring HR professionals and hired HR Techs. **Requirements guidance** • Andersen (2017), Van den Heuvel and Bondarouk (2017), Angrave *et al.* (2016), Chahtalkhi (2016) and Jensen-Eriksen (2016) discuss that excessive operational concerns minimize the contextualization between HR and IT about technological needs of processes. **Formal structure** • What are the determining factors for choosing the best "location" of the HR Analytics structure: internal to HR or outside HR (Shet *et al.*, 2021; Andersen, 2017; Rasmussen; Ulrich, 2015; Bassi, 2011)?
(1) Data Governance	**Data governance process** • The essential mutability of data needs by the HR is used as an argument by Ellmer and Reichel (2021), Fernandez and Gallardo-Gallardo (2021), Liu *et al.* (2020), Jabir *et al.* (2019), Levenson (2018), Werkhoven (2017) to justify the limitations of formal IT in making data available at the speed required by management processes. • Fernandez and Gallardo-Gallardo (2021), McIver *et al.* (2018), Marler and Boudreau (2017) and Angrave *et al.* (2016) state that there is little integration between HR data and other corporate functions, making it difficult to analyze value and search for relevant data. **Recognition of data gaps** • Werkhoven (2017) connects shared data governance gaps between IT and HR to business analytics. • Marler and Boudreau (2017), Angrave *et al.* (2016) and Pape (2016) point out the decentralization of data information as a barrier to the process of recognizing data gaps.

Source: produced by the authors.

Practical Implications

Different objectives, different managements. This study search to shed some light over the processes needed to run analytics in HRM environment. A relevant finding of this research is the detection of important differences in objectives to analytics in the HRM context. Such differences seem to point out to the recommendation of differences in the management of analytics in the context of HRM, which may explain gaps in the literature such as difficulties in implementing and sustaining the activity, lack of clarity of objectives and management difficulties (Chatterjee et al., 2021; Hota, 2021; Margherita, 2021; Singh & Muduli, 2021; Speer, 2021; Gal et al., 2017; Andersen, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015).

These differences were illustrated in this study with (i) the differentiation of the terms HR Analytics and Workforce Analytics (despite their indistinct use by the literature in general), (ii) the evidencing of management differences to practicians under the light of Systems Theory analysis (see Table 4) and (iii) the differentiation of the execution context when compared to related activities (see Figure 9).

Size may matter. According to Bassi (2011) and Pfau & Cohen (2003), it is possible that, in organizations without dedicated or smaller resources, HR Analytics and Workforce Analytics may be performed indistinctly within the same organizational structure, which may lead to indistinct definitions and treatments of HR Analytics and Workforce Analytics by practitioners and academia.

Taxonomy as a driver to knowledge sharing. The effects of proposing different definitions in this paper go beyond a mere taxonomic study and brings practical implications to the effects of careless communication and coordination of knowledge sharing (Deng et al., 2021). Activities with different objectives (even when sharing knowledges, resources and components) may demand different knowledge sharing to boost management from leaders and teams to a better job performance and knowledge sharing in analytics (Deng et al., 2021; Enwereuzor, 2021).

Limitations and Future Research

As limitations for this paper, it is worth noting that the cluster analyzes were carried out considering macro elements of HR and IS management, as well as the objective of the papers written under the theme of analytics in HRM. Characterizations from complementary approaches may indicate new nuances not captured.

Also, it was used a simplified range of features of Algorithmic Management a Personnel Economics, just enough to build comparisons to HR Analytics and Workforce Analytics (as defined in this paper). New features may bring nuances to draw a more detailed taxonomy.

It is also a limitation the use a single database (Scopus). Literature absent from this database may provide valuable inputs for analysis. In the same way, practical texts, journals, congresses and book chapters were not differentiated in the bibliometric analysis, which can be used for a better differentiation of debate trends. Finally, it is also a limitation the lack of characterization of analytics application literature by size of the studied organizations, which can provide a more detailed view on the use of resources and analytics administration in HRM.

As a recommendation (and previously noted by Bassi, 2011; Pfau & Cohen, 2003), case studies or surveys focused on the way these activities are developed and managed in companies of different sizes seem recommendable. In this way, one can deepen the understanding of the situations in which the definitions proposed here can be useful, unified or separately, as well as the relationships with Personnel Economics and Algorithmic Management.

Also related to this recommendation, following the framework proposed by Hevner & March (2003), carry out field research to quantify and identify companies that apply analytics in their HR functions, but, regardless of the nomenclature they give to this activity, check their "fits" in the definitions of HR Analytics, Workforce Analytics and analytics to support the Gig Economy or Personnel Economics (including checking the proposal presented in Figure 9 and issues related to the "double potential" of IT).

Analyzing the stages of evolution of frameworks and other proposals on how HR Analytics is applied from the point of view of Boulding's (1956) theoretical discourse levels can also help to identify the real stage of evolution of HR Analytics as a particular system or component of a larger HRM system.

It also seems interesting to investigate the studies collected from three segmentations: (i) segregating the papers published in academic journals, (ii) in congresses and (iii) in professional journals. Conference production, specifically, can provide insight into points of view being tested by researchers and can be contrasted with other academic and professional views.

Finally, field research may be of interesting to shed some light on answering whether choices made in the adoption of specific IS lead to different approaches to the management of HR Analytics or whether they also lead to different forms of HRM mediated by analytics (which can be fit in the context of the Gig Economy).

Based on the future researches above discussed, the following propositions may be useful as potential research hypothesis to be further tested:

P1: The increasing use of dashboards shared between HR leaders and line managers boosts knowledge sharing between these two actors, but do not increase knowledge sharing between HR leaders to new organizational policies.

P2: The size of the organizations is inversely proportional to the perception of the entropy in knowledge sharing related to analytical knowledge in HR.

P3: More sophisticated levels of analytical maturity in HR are directly related to the perception of different levels of analytical management.

P4: More sophisticated levels of analytical maturity in HR are directly related to the existence of different levels of knowledge sharing between actors in this process.

P5: The more intense use of automated IS is related to a more operational profile on HRM analytical activities and a stronger knowledge sharing between HR actors and line managers than between HR leaders.

P6: The more intense use of flexible information systems analysis in HR are related to a strong focus on HRM policy assessment processes and a stronger knowledge sharing between HR leaders than HR actors and line managers.

CONCLUSION

This study observed IT and HRM macro features in 184 papers published from 2008 to 2021 in Scopus database searching to address process gaps addressed in HR Analytics literature (Margherita, 2021, Qamar & Samad, 2021; Marler & Boudreau, 2017). The features were analyzed systematically by clustering and by bibliometric analyzing the papers in search for relevant features that could explain the results found in systematic analysis.

Systems thinking (Churchman, 1972) seemed to be useful to explain a series of issues in HR Analytics research Agenda as (i) the search to better explain the processes, (ii) success factors and (iii) value drivers behind analytical approaches in HRM (Margherita, 2021, Peeters et al., 2020; Davenport et al., 2010, Angrave et al., 2016), as well as (iv) a finding brought by this study as the notable increase in analytics papers with a practical focus in the context of HRM. It is also worth notice, the systems thinking approaching to analyze analytical objectives seems to fit well in the "HR black box" panorama (Martín-Alcazar et al., 2005; Legge, 1995).

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