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## Tackling the HR digitalization challenge: key factors and barriers to HR Analytics adoption

### ABSTRACT

**Purpose:** This paper contributes to the literature on HR digitalization, specifically on HR Analytics, disentangling the concept of analytics applied to HR, and explaining the factors that hinder companies from moving to analytics. Therefore, the central research questions addressed in this study are: What does HR Analytics encompass? What impedes the adoption of analytics in HR within organizations?

**Design/methodology/approach:** We performed a comprehensive literature review on analytics as applied in HR. We relied on two of the major multidisciplinary publication databases (i.e., Scopus and WoS). A total of 64 manuscripts from 2010 to 2019 were content analyzed.

**Findings:** The results reveal that there is an ongoing confusion on HR Analytics conceptualization. Yet, it seems that there is an emerging consensus on what HR Analytics encompasses. We have identified 14 different barriers for HR Analytics adoption grouped into four categories: data & models, software & technology, people, and management. Grounding on them we propose a set of 14 key factors to help to successfully adopt HR Analytics in companies.

**Originality/value:** This paper brings clarity over the conceptualization of HR Analytics by offering a comprehensive definition. Additionally, it facilitates business and HR leaders in making informed decisions on adopting and implementing HR Analytics. Moreover, it assists HR researchers in positioning their work more explicitly in current debates and encouraging them to develop some future avenues of research departing from some questions posed.

**Keywords:** HR Analytics, People Analytics, Workforce Analytics, Talent Analytics, Adoption Barriers, Digitalization

## INTRODUCTION

The world is going digital. There is little doubt that digitalization, or digital transformation, is one of the major trends changing economy, society and business (see, [UNCTAD, 2019](#); [World Economic Forum, 2018](#)). It refers to "the use of digital technologies and data as well as their interconnection which results in new or changes to existing activities" ([OECD, 2018](#), p. 11). Digitization is changing the way companies design, manufacture and deliver their products and services by means of digital technologies (e.g., smart mobile devices, 3D printing, cognitive computing, virtual reality, and the 'Internet of Things'). Indeed, companies are facing the digital imperative of adopting new technologies effectively, or facing competitive obsolescence ([Fitzgerald et al., 2014](#)).

'Big data' is considered the most significant 'tech' disruption in business since the rise of the Internet and digital economy ([Agarwal and Dhar, 2014](#)). It refers to 'large volumes of data generated and made available online in digital media ecosystems' ([Pappas et al., 2018](#), p.480). [Wamba et al. \(2015\)](#) offer the following integrative definition of 'big data': "a holistic approach to manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value [of the data]) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages" (p. 235). In this ever-increasing digitalized world, massive amounts of data are generated continuously from a growing number of sources (e.g., mobile phones, online shopping, social networks, and instrumented machinery) on any topic of interest to a business. Simultaneously, the exploitation of 'big data' has become very popular among organizations because the cost of storing data has fallen drastically while technology for the production of data has become cheap ([Mayer-Schönberger and Cukier, 2013](#)). Companies are realizing that exploiting these vast new flows of real-time information can provide them with a competitive edge ([Pappas et al., 2018](#)). An often-quoted study by [McAfee et al. \(2012\)](#) posited that 'big data' has the potential to revolutionize management since it has the capability of

transforming the decision making process by allowing enhanced visibility of firm operations and improved performance measurement mechanisms. These authors found that companies that use big data to inform their planning and decision-making functions were on average 5 percent more productive than those which do not.

Organizations that capitalize on big data are moving analytics into core business, operational, and production functions (Davenport et al., 2012). Maybe because, "in every value chain, the ability to collect, store, analyse and transform data brings added power and competitive advantages" (UNCTAD, 2019, p.7). In short, business analytics is about 'leveraging value from data' (Acito and Khatri, 2014), and its use provides new ways to solve problems and create value in contemporary business organizations (Chen et al., 2012; Elbashir et al., 2013). Several studies on business analytics have reported improvements in decision-making in some organization's functions such as sales (e.g., Jayaram et al., 2015), operations (e.g., Hazen et al., 2016), logistics (e.g., Wang et al., 2016), supply chain (Souza, 2014), and finance (e.g., Cao et al., 2015). Also, the potential benefits of analytics in human resources (HR) have been extolled (e.g., Boudreau and Ramstad, 2007; Cascio and Boudreau, 2011; Guenole et al., 2017). One of the main messages is that HR Analytics is associated with or can cause better performance (Aral et al., 2012; Houghton and Green, 2018).

Despite the use of data-driven methods and techniques to evaluate HR management is not a new topic in the literature (see, Marler and Boudreau, 2017; van den Heuvel and Bondarouk, 2017), the truth is that analytics in HR management (usually known as Workforce Analytics, HR Analytics, Talent Analytics, or People Analytics) is gaining momentum. Several authors (e.g., Fink and Sturman, 2017; Marler and Boudreau, 2017) suggest that this new approach is not just a rebranding of old practices, but rather represents a transformative digital disruption. In short, it involves the analysis of HR-related data, and the integration of other internal and external data, to support decision making in organizations (e.g., identification and selection of talented candidates,

and design effective training). The increased availability of HR data along with the new technological advancements make that possible. [McIver et al. \(2018\)](#) posits "with the advent of information technology, collecting and analyzing data has become easier, making workforce analytics accessible to virtually any organization. Furthermore, new sources of data, such as those collected from wearable technology, email, and calendars, provide opportunities for understanding employee behavior and improving performance in ways heretofore not thought possible" (p. 398). Indeed, the opportunities that big data offers to HR, together with the continuous pressure for greater effectiveness and productivity, have reinforced the calls for more analytical HR management ([Fink and Sturman, 2017](#)). According to [Agarwal et al. \(2018\)](#), "the use of workforce data to analyze, predict, and improve performance has exploded in practice and importance over the last few years, with more growth on the horizon" (p. 89). People data is recognized as a form of evidence important for improving decision-making, since it provides executives, HR professionals and line managers with information needed for workforce support and HR Analytics ([Houghton and Green, 2018](#)).

In today HR rhetoric, analytics is considered to have the potential to not only revolutionize what HR does, but also, the HR impact on organizations ([Andersen, 2017](#)). Even analytics have been called "a game changer for the future of HR" ([van der Togt and Rasmussen, 2017](#), p. 150). Yet the adoption of HR Analytics by organizations is 'very low' ([Boudreau, 2017](#); [Marler and Boudreau, 2017](#)). A recent survey involving more than 1,200 HR executives [KPMG \(2019\)](#), found that most HR executives (70 percent) recognize the need for workforce transformation; however, barely a third (37 percent) feel 'very confident' about HR's actual ability to transform and move them forward via key capabilities like analytics. More importantly, barely 20 percent of HR leaders believe analytics will be a primary HR initiative for them over the next one to two years, and only 12 percent cite analytics as a top management concern. "Most organizations know people analytics is no longer a nice-to-have but they don't have the confidence to make use of data or to begin

looking at their workforce in a different way - to consider 'work and value' instead of 'people and cost'", state another recent report ([OrgVue, 2019](#), p.3). In short, companies struggle to adopt HR analytics. Workplace culture is considered a top barrier to digital transformation [KPMG \(2019\)](#). Additionally, the lack of people with analytic skills, along with the lack of appropriate software and technology are not helping in such transformation ([OrgVue, 2019](#); [Deloitte, 2019](#)). As [McIver et al. \(2018\)](#) puts it "executives recognize its potential while acknowledging skepticism of their own organizations' readiness for adoption" (p. 398). Unfortunately, the lack of confidence and confusion of HR executives to adopt analytics matches the disparity of HR Analytics literature in its approach, definition, and results. There is scarce literature about the adoption of analytics in HR, not to mention on its potential adoption challenges. Moreover, the few publications that focus on the factors that hinder the adoption of HR Analytics offer the individual perspective (e.g., [Vargas et al., 2018](#)), leaving aside other organizational factors.

There is little doubt that interest in analytics applied to HR has increased substantially among scholars and practitioners in recent years [Huselid \(2018\)](#); [Marler and Boudreau \(2017\)](#). Unfortunately, the ongoing confusion about what analytics in HRM entails, and the lack of clarity on the factors that prevent its adoption by organizations, are hindering the advancement of the field and the establishment of widely accepted practices. Thus, this paper contributes to the literature on HR digitalization, specifically on HR Analytics, by reporting the findings of a rigorous literature review on analytics as applied to HR. More precisely, it answers the call by [Marler and Boudreau \(2017\)](#) and [Minbaeva \(2018\)](#) for studies on explaining the factors that hinders companies to move to analytics. The central research question addressed in this study is therefore: What hinders adoption of analytics in HR within organizations? Yet, to answer it, and due to the different labels used to refer to analytics applied to HR, we first had to focus on disentangling the concept of analytics applied to HR. In other words, we also addressed the following research question: what does HR Analytics encompass? In answering these questions, we hope to bring some clarity

over this complex concept, and facilitate business and HR leaders in taking informed decisions on adopting and implementing HR Analytics. Moreover, we attempt to assist (aspiring or active) HR researchers in positioning their work more explicitly in current debates and encouraging them to think about how best to take advantage of analytics.

The paper is organized as follows. We first explain the methodology followed in carrying out this study. We move on to reflect on HR Analytics conceptualization and its applications. Then, we discuss the identified barriers that companies face when trying to adopt HR Analytics. Finally, in the conclusion section we reflect on the lessons learned, and discuss key factors to overcome the barriers that hinders HR Analytics adoption in organizations.

## METHODOLOGY

We followed a sequential two-step review approach so as to compile a database of relevant articles for our analysis.

### **Step 1: Data Collection and Cleaning**

We gathered data by conducting comprehensive literature searches on Web of Science (Thomson Reuters) and Scopus (Elsevier), two of the major multidisciplinary publication databases in the world. Scopus covers nearly 36,377 titles from approximately 11,678 publishers, and three types of sources: book series (including books from conferences), journals, and trade journals. Web of Knowledge cover approximately 12,000 high impact journals and 160,000 conference proceedings. Moreover, both databases are not only used as reference in a large number of bibliometric studies (cf. [Ciomaga, 2013](#)), but also, are the main sources for citation data ([Mongeon and Paul-Hus, 2016](#)).

In order to identify publications related to the use of analytics in HR, we applied keyword searches within the titles, keywords, abstracts and topics of the various research outputs. Guided by a preliminary literature review, the lexemes used in the searches were:

'talent analytics', 'HR analytics', 'human resource\* analytics', 'employee analytics', 'human capital analytics', 'workforce analytics', 'workforce scorecard', 'people scorecard' and 'people analytics'. As the aim is to analyze the barriers of analytics adoption related to HR in organizations, we opted to perform the searches only in the area of 'Business, Management and Accounting'. Moreover, [Tursunbayeva et al. \(2018\)](#) found that the majority of publications in this field come from this area. The time frame for the present study covers all existing publications up to 26 December 2019.

We restricted our search to English-language publications since non-English literature has little influence on the international academic debate about a topic ([Boselie et al., 2005](#)). As to be as inclusive as possible we didn't restrict our search to any specific outlet. This procedure resulted in 87 publications, after removal of duplicates. Then, researchers independently reviewed the titles and abstracts of all the identified publications to critically examine their information relevance to this study. In total, 23 manuscripts were eliminated from consideration, because they were not useful for our research (i.e., they were primarily dealing with the role of HR when hiring people for using analytics in other functional areas, such as customer, supply chain management or finance), and, in one case, we were not able to retrieve the full-text. Any issues regarding confusion and uncertainties about exclusion or inclusion decisions were shared and resolved between the authors.

In total, our final database comprised of 64 full-text publications (40 academic articles published in peer-reviewed journals, 10 conference papers, 11 articles from trade and practitioners' journals, 2 editorials, and 1 teaching note) from 2010 to 2019. We have detected that interest in analytics as applied to HR increases noticeably in the last three years, with more than 10 publications per year (2017: 17; 2018: 14; 2019: 12). In line with previous findings (e.g., [Marler and Boudreau, 2017](#)) up until 2010 publications on this field were quasi non-existent. Likewise, we have evidenced how scattered the literature on this topic is among journals, which indicates that this phenomenon is in a 'growing' state (cf. [Von Krogh et al., 2012](#)). The full list of the 64 publications analyzed in this paper can be

obtained from the first author upon request.

## **Step 2: Data Coding**

The descriptive data of each publication from the final database (i.e., author/s, year, title, journal, volume, issue, keywords and abstract) was imported into an Excel file. As for the content analysis, both authors jointly developed a coding template based on the research questions mentioned in the introduction. This coding template included the following sections: type of publication (i.e., academic or practitioner); research question (open text field); aim of the publication (open text field); sources of data; data types; methods used; lexeme used to refer to HR analytics (open text field); lexeme definition (open text field); lexeme goals (open text field); lexeme theoretical logic and frameworks (open text field); lexeme outcomes (open text field); and lexeme enablers and barriers (open text field). We first ran a pilot test of our coding template on a randomly selected set of four articles, with the aim of achieving an adequate level of inter-rater reliability. After comparing and discussing coding experiences, we stipulated a coding normative and divided the rest of the sample equally between both authors. Each researcher content-analyzed their allotted articles in another Excel file. On completion, we merged the files and discussed any issues of confusion and uncertain classifications in our respective analyses. Despite we sought to reduce the likelihood of error with this careful and rigorous cross-checking, we are aware of the possible subjectivity in our analyses due to our collective judgement. So, quoting [Boselie et al. \(2005\)](#), "all errors of interpretation are our own" (p. 70). Finally, we developed a set of concept maps that helped us to clearly depict suggested relationships between concepts. In short, they helped us to organize ideas. In the next two sections we present the results of our analysis.

## DISENTANGLING ANALYTICS IN HR

As mentioned before, analytics as applied to HR have been labelled with several lexemes. For instance, HR Analytics (e.g., [Marler and Boudreau, 2017](#)), People Analytics (e.g., [Wei et al., 2015](#)), Workforce Analytics (e.g., [Huselid, 2018](#)), Talent Analytics (e.g., [Davenport et al., 2010](#)), Human Capital Analytics (e.g., [Minbaeva, 2018](#)), HR Big Data Analytics (e.g., [Martin-Rios et al., 2017](#)), Hyper-personal Analytics (e.g., [Warshaw et al., 2015](#)), and Analytics-based HR Practices (e.g., [Ramamurthy et al., 2015](#)). Indeed, as [Huselid \(2018\)](#) put it, "this variance in monikers [...] is less than ideal" (p. 680). Moreover, a review of the different definitions under the same label does not clarify the concept either. It appears that it can mean whatever a writer wants it to mean, since everyone has their own idea of what the concept does and does not encompass. Thus, there is an ongoing confusion about the conceptualization and operationalization of HR analytics <sup>1</sup>. In short, what is meant by 'HR analytics'?, and what is it for? In this section we are going to address these issues.

### An overview of HR Analytics conceptualization

According to [Huselid \(2018\)](#), analytics is a relatively nascent discipline, which is growing in terms of stakeholders, methods, and impact. Therefore, it might not be surprising to not have 'a single overarching definition of (or even title for) the field' ([Huselid, 2018](#), p. 680). Indeed, we can say that the field has not have a single label, nor a single definition. To develop this statement we are going to offer a content analysis of the explicit definitions found in the literature.

We have only identified 20 manuscripts that gave an explicit definition of the lexeme they were using to refer to analytics as applied to HR. The majority of definitions (55 percent) were identified under the lexeme 'HR Analytics'. In [Table 1](#) we show them all.

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<sup>1</sup>We found, in line with [Marler and Boudreau \(2017\)](#), that the most frequently used lexeme to describe the field appears to be HR Analytics. Thus, from now on, we will use it to encompass all the other similar concepts above-mentioned

When authors give an explicit definition of HR Analytics they mostly opted for offering their own definition (73.8 percent) although, some of them (27.2 percent) just quoted other authors' definitions. Most of the definitions (63.6 percent) characterize HR Analytics, as either an analysis process or decision-making process, whereas some others as a method, and only one as an HR practice. Either way they rely on data, metrics, measures, and models to support (strategic) 'human capital' decisions (see, [Momin, 2014](#); [Patre, 2016](#); [Marler and Boudreau, 2017](#); [Saraswathy et al., 2017](#); [Sharma and Sharma, 2017](#)).

Of the 11 definitions offered in Table 1, six of them refer to statistical tools, techniques and models needed to analyze the data and "transform it into actionable business intelligence" [Momin \(2014\)](#) or "show connections, correlations and even causality between human resource metrics and other business measures" [Vargas et al. \(2018\)](#). However, few definitions detail the specific statistical analysis, techniques or models required ((for an exemption, see, [Sharma and Sharma, 2017](#)). To sum up, one could say that HR Analytics aim to provide reliable foundations for people-related decisions (i.e., data-driven decisions) that affect the individual and organizational outcomes. We agree with ([Marler and Boudreau, 2017](#), p.15) when saying that HR Analytics is about "linking HR decisions to business outcomes and organizational performance". In fact, 7 out of these 11 definitions on HR Analytics explicitly refer to improve/direct/enhance organizational outcomes (namely, performance) or establish business impact. Here it comes its strategic side.

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Insert TABLE 1 about here.

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In Table 2 we present the explicit definitions found related to the following lexemes used to refer to HR Analytics: 'People Analytics (PA)', 'Hyper-personal Analytics', 'Workforce Analytics', and 'Human Capital Analytics (HCA)'. In this case, the authors opted for offering their own definition. All the definitions of PA characterize it as a process, mostly a decision-making one. In short, we could say that PA is an analytical process that helps

managers to take better decisions related to their employees. Only [Singer et al. \(2017\)](#), link the analyses with information gathering about how people work together in order to help them improving in collaborating. We found two general definitions (see, [Leonardi and Contractor, 2018](#); [Gaur et al., 2019](#)) that basically refer to PA as a process that offers information to make better decisions. On the other hand, [Nielsen and McCullough \(2018\)](#) and [Shrivastava et al. \(2018\)](#) offer a more detailed definition and highlight several analytical techniques (e.g., data mining, prediction, and experimental research) that PA use to offer higher-quality information. When referring to PA, individuals' attributes are the basic data considered. A step further would be 'Hyper-personal Analytics', which is defined as a way of learn all about individuals' personal traits ([Warshaw et al., 2015](#)).

According to [Leonardi and Contractor \(2018\)](#), up until now, most companies when using PA only rely on individuals' attributes instead of considering their relationships with other employees (i.e., relational analytics), which is hindering the full potential of PA. These authors argue that with relational analytics it would be possible to estimate the likelihood of achieving performance goals by an employee, a team or the entire organization, to tailor staff assignments to changes in employee networks or to a specific managerial need, and of course, to build healthier, happier and more-productive organizations. In fact, these authors are adopting a more strategic approach, which we found in some other definitions. For instance, [Huselid \(2018\)](#) justifies his preference for using 'Workforce Analytics' instead of any other lexeme since the focus should be beyond the HR function. This author claims that the essence of the field is to understand and facilitate the impact of the workforce on the organization success. He emphasizes the strategic side of this kind of analytics. Likewise, [Minbaeva \(2018\)](#) adopt an strategic approach by adopting insights from the organizational capabilities perspective and the micro-foundational view of strategy when defining 'Human Capital Analytics (HCA)'. In fact, for her, HCA is an organizational capability rooted in individuals, processes, and structure, and comprises three dimensions: data quality, analytical competencies and strategic ability to act.

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Insert TABLE 2 about here.

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Regardless the lexeme used, all these definitions are about collecting, analyzing and reporting data to improve people-related decisions, and, in turn, improve individuals and organizational outcomes. Thus, HR Analytics can be seen as a strategic process that although relies in data and statistics models, it is beyond HR metrics and measures. Despite we could not find too much detail on the sort of statistical analyses that should be taking into account, some authors stress the need to go beyond the usual descriptive analyses by carrying out predictive (Khan and Tang, 2016), prescriptive (King, 2016) and causality analyses (Cheng, 2017). At this point, not only analytical and statistical skills become crucial, but also it is of real need to draw attention to the role of the technology needed to perform these analyses. The huge quantity of data from several origins, the complexity of some statistical models, and the need to communicate the results in a comprehensible way, make that the role of technology and the interaction between machine-person become key to the design, implementation and use of HR Analytics by the employees of the organization.

Moreover, most authors when referring to the data needed highlight the need to use not only existing data from the HR department, but also, from different internal functions and data external to the organization (e.g., Davenport et al., 2010; Wei et al., 2015). In fact, several authors (e.g., Rasmussen and Ulrich, 2015; McIver et al., 2018; Marler and Boudreau, 2017) suggest that HR Analytics should not remain within the HR department but should be part of a larger structure that also contains other departments such as finance or production, in order to be able to offer a complete picture. In Rasmussen and Ulrich (2015, p. 238) own words: "This may sound drastic, but when HR analytics matures, it initially starts cooperating more with other departments' teams (in finance, operations, etc.), and eventually becomes part of cross functional/end-to-end analytics-looking at human capital elements in the entire value-chain". In fact, as mentioned before,

these type of analytics seek to have a significant impact at an organizational level, and not only on the HR function. Unfortunately, the unit of applicability of HR Analytics is not explicitly discussed in any publication. Some publications (e.g., [Ramamurthy et al., 2015](#)) analyze the use of HR Analytics to evaluate one or more core activities of the organization, but we also observe the use of HR Analytics in projects or sub-projects of an organization, or even in specific activities, that will not significantly affect the organization outcomes until their results are used by other activities or larger units (e.g., [Wei et al., 2015](#)). So, a cross-functional interconnected approach is needed to get the most of HR Analytics.

### What is 'HR Analytics' for?

As early as 2010, [Davenport et al.](#) suggested six critical people-related issues that could be answered by using HR Analytics. These were (p. 4): (a) *What are the key indicators of my organization's overall health?*; (b) *Which units, departments, or individuals need attention?*; (c) *Which actions have the greatest impact on my business?*; (d) *How do I know when to staff up or cut back?*; (e) *Why do employees choose to stay with- or leave-my company?*; and, (f) *How should my workforce needs adapt to changes in the business environment?*. [Ulrich and Dulebohn \(2015\)](#) posed that analytics in HRM help line managers and HR professionals to better justify, prioritize and improve HR investments, which at the same time, help "HR move toward professional respectability and decision-making rigor" (p. 202). Indeed, the increasing level of accountability of line manager's role in talent management and, ultimately, strategy execution ([Huselid et al., 2005](#)) has boosted the growth in demand for the insights and information that workforce analytics can generate ([Huselid, 2018](#)). Unfortunately, the HR analytics has only recently started to attract the necessary attention ([The Economist Intelligence Unit, 2016](#)). As a result, progress and adoption of HR analytics has been slow ([Boudreau, 2017](#); [Marler and Boudreau, 2017](#)).

In 2014, A Harvard Business Review analytic study ([HBR, 2014](#)) found that 11 percent

of companies rarely use workforce data to inform workforce decisions, 40 percent use it reactively (i.e., ad hoc reporting) to inform critical workforce decisions, 26 percent use data proactively via operational reporting, 15 percent analyze their workforce proactively (i.e. via dashboards and visuals that are up to date and available on demand), and interestingly, 9 percent use predictive analytics to inform workforce decisions. In short, more than half use data only on an ad hoc basis or, what is worrisome, use no data in workforce decision making. However, this report suggested an increase reliance on workforce analytics in the following years.

In 2016, a report published by the Society for Human Resource Management (SHRM) Foundation ([The Economist Intelligence Unit, 2016](#)), showed that companies have used workforce analytics to drive competitive advantage in a variety of ways. For instance, by identifying which training programs lead to improved performance, or which managerial actions improved the retention rate. Also, some retailers use analytics to predict incoming call-center volume as well as adjust hourly employees' schedules to maximize efficiency and resource planning. A recent study ([OrgVue, 2019](#)) found that 89 percent of organizations already use HR Analytics. Yet, they are doing so in very different ways and intensity. In fact, most companies are using HR Analytics for routine tasks (such as, aggregating HR data -45 per cent-, and headcount cost analysis -41 per cent), while only 10 per cent of companies say they are using HR Analytics in an extensive way.

The above mentioned is very much in line with the findings of our literature review. Little is published on how companies have adopted HR Analytics. In fact, most of the articles are basically prescriptive. For instance, [Lal \(2015\)](#) refer to five areas (i.e., workforce planning, the management and improvement of business performance, learning and development, retention and compensation) in which workforce analytic can help. [Sinha et al. \(2012\)](#) explain how organizations can use social media analytics as an effective assessment tool from behavioral perspectives. [Russell and Bennett \(2015\)](#) highlight the importance of having hard data to making sound decisions in the area of talent

management. In line, [Pape \(2016\)](#) offers a prescriptive framework to prioritise data items for business analytics and applies it to human resources. Nevertheless, we found some articles trying to illustrate how analytical tools may be successfully applied. [King \(2016\)](#) provides a case study on how a firm move from descriptive to predictive analysis in order to proactively manage workforce attrition. [N'Cho \(2017\)](#) shows, by means of another case study conducted in the French aerospace industry, how firms can use talent analytics to enhance their talent management process by identifying and selecting the best talent based on the requirements of each project phase, collecting and analyzing information to attract millennial people, defining the right time in the right way to develop talent appropriately, and when needed, redeploying talent across the project phases to meet emerging challenges.

Recently, [Davenport \(2019\)](#) posits that currently many "HR departments are making use of advanced analytical methods like predictive and prescriptive models, and even artificial intelligence" (p.2). Yet, we have found scant evidence on advanced HR Analytics. Hereafter, we are going to mention some exceptions. [Ramamurthy et al. \(2015\)](#) developed a talent management framework which incorporate a predictive model of employee commitment through propensity to leave (PTL) scores. [Wei et al. \(2015\)](#) develop a data analytics algorithm, built upon data on employee expertise, that enables the internal transfer of people to grow areas. [Malisetty et al. \(2017\)](#) shows how predictive business intelligence tools can offer HR pioneers assistance with issues related to employee profiling and attrition, and forecasting of HR capacity and recruitment needs, among others. [McIver et al. \(2018\)](#) show an example of HR Analytics to predict store performance improvement from hiring results using data from the online assessment and in-store interview processes. Finally, [Shrivastava et al. \(2018\)](#) briefly mentions how Google has incorporated advanced analytics in day-to-day decision-making.

The appropriate utilization of advanced analytical methods is what could better differentiate HR Analytics from simple HR metrics or reporting. Maybe due to the basic usage of HR Analytics done up until know, its real value to organizations is not coming to

light. This is reflected in the fact that only 15 percent of CEO's recognize that they have changed a business decision as a result of people data GARTNER 2018. We agree with [McIver et al. \(2018\)](#) when saying that "a challenge remains for understanding how organizations can successfully use workforce analytics to influence organizational outcomes" (p.398).

## BARRIERS TO HR ANALYTICS ADOPTION

From the analysis done of the publications, we have identified 14 barriers to HR Analytics adoption by organizations. We have grouped them into four main categories: (a) Data and Models, (b) Software and Technology, (c) People, and (d) Management. The first three categories are linked to the resources needed to carry out a HR Analytic process, whereas the fourth one refers to the actions needed to implement it. Below, we are going to discuss each category in detail.

### Data and Models

Several authors (e.g., [Davenport et al., 2010](#); [Rasmussen and Ulrich, 2015](#); [Marler and Boudreau, 2017](#); [McIver et al., 2018](#)) emphasize the need for a HR process using a HR data, along with data from the rest of the functional areas of the organization (e.g., production, and finance), and even from outside the organization. In fact, [Malisetty et al. \(2017\)](#) suggest to use external data from the market. The integration of data enables what Peter Cheese, chief executive of the Charter Institute of Personnel and Development, calls "collective intelligence and debate" across the enterprise by which leaders can test their hypotheses and ground their decisions on the links between people and business performance ([HBR, 2017](#)). However, there is no evidence of such 'collective intelligence', nor about interdepartmental collaboration. [Douthitt and Mondore \(2014\)](#) lamented that data are not integrated across functions, geographies or divisions. In fact, a recent report ([OrgVue, 2019](#)) found that despite HR and Finance both see themselves as responsible for

HR Analytics, there is a huge gap in how well each side thinks they collaborate. Finance thinks collaboration is lower (25 percent) than HR does (45 percent). Only 28 percent of the respondents across departments have reporting systems and tools that connect. Thus, few real data sharing is done. Additionally, as [Angrave et al. \(2016\)](#) put it: "Silo mentalities within organisations prevent HR-related data being combined with data on other determinants of productivity and performance, so it is often hard to build analytical models that examine the role of HR-related factors while controlling for other relevant factors" (p. 4). As a result, there may be insufficient data to be able to 'ask the right questions' (i.e., to use HR Analytics in an optimal way). Indeed, the lack of existing data items has been identified as one of the major barriers for succeeding in implementing analytics, above all in small and medium enterprises (see, [Pape, 2016](#)). In line, [Lawler III et al. \(2004\)](#) found that HR managers are aware that their HR metrics fall short of what is needed to address most key business decisions. In their own words: "there is a felt need" of HR metrics.

In our literature review we have not identified any exhaustive list of types of data or metrics used in HR Analytics. One could say that we do not have a consistent business language of HR ([HBR, 2017](#)). It should be noted that [Cascio and Boudreau \(2011\)](#) offered a categorization of HR metrics according to sophistication (i.e., according the use that these metrics are going to have), whereas [Boudreau and Ramstad \(2007\)](#) categorize HR metrics according on the nature of what is being measured. The latter classification lead to HR metrics of efficiency, of effectiveness and of impact. [Fink and Sturman \(2017\)](#) used the latter classification for doing an in-depth discussion on HR metrics, which is beyond the point of this article. Yet, we would like to highlight that the success of HR Analytics depends on the appropriateness of HR metrics. We have grouped the data used by HR Analytics according to its level of belonging. Namely, individual, and organizational. Unsurprisingly, we have found we find a great variety in the types of data at the individual level (see [Table 3](#) for more detail). Regarding the organizational data used in HR Analytics

literature, some examples are: turnover ([Ramamurthy et al., 2015](#)), customer satisfaction ([Rasmussen and Ulrich, 2015](#)), revenue ([Russell and Bennett, 2015](#)), sales ([Aral et al., 2012](#)), and consumer loyalty ([Malisetty et al., 2017](#)). Regardless of the type of data used, its quality is crucial. All authors agree on the fact that HR Analytics results depend on the quality of the raw material. Therefore, data quality is one of the most crucial requirements to succeed in the use of HR Analytics ([Harris et al., 2011](#); [Russell and Bennett, 2015](#); [N'Cho, 2017](#)), or as [Minbaeva \(2018\)](#) puts it: "one of the most crucial barriers to the development of credible organizational HCA [human capital analytics]" (p. 702).

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Insert TABLE 3 about here.

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But, which are the the data and metrics needs of the HR function? [Dulebohn and Johnson \(2013\)](#) lamented the limited on this aspect, and provided a framework that describes the data needs, decision characteristics and HR metrics to the different levels of HR activity and decision-making. Similarly, [Pape \(2016\)](#) proposed a framework based on multi-criteria decision analysis to estimate the value of data items for conducting business analytics. The point was to use this framework to inform the discussion about data items that should be gathered on a routine basis by a business function to assess its activities. However, the reality is that there is a lack of standards for HR metrics in organizations (see, [HBR, 2017](#); [King, 2016](#)).

We agree with [Boudreau \(2017\)](#) that there has been an increase in the complexity of the models and methods for doing analytics. This is somewhat explained because of the increase of authors from disciplines well known for their deep analysis (e.g., mathematics and computer science). For instance, [Pape \(2016\)](#) suggest a procedure for prioritizing data items for business analytics and HR Analytics. [Luo et al. \(2019\)](#) develops a Latent Ability Model (LAM) as a generative probabilistic learning framework by introducing latent variables to capture the randomness of service time by modeling it as a stochastic value

generated based on the probability distribution of latent variables. [Kalpana et al. \(2019\)](#) focus on the Emotional Measurement tool for assessing Emotional Intelligence and Self-Efficacy. However, these publications focus solely on the statistical part of the models used for the analysis without deepening on their strategic aspects. In other words, these publications using complex models lack a clear link between their solutions and the impact on the business outcomes.

## Software and Technology

Within the realm of business analytics, three perspectives exist ([Evans, 2016](#); [King, 2016](#); [Tan et al., 2014](#)): (a) Descriptive analytics, which gains insight from historical data to understand past and current business performance and make informed decisions. This type of analytics transform data into meaningful charts and reports (e.g., budgets, sales, revenues or cost); (b) Predictive analytics, which analyze historical data, and detect patterns or relationships in these data, in an effort to predict future scenarios; it employs predictive modeling using statistical and machine learning techniques; and (c), Prescriptive analytics, which uses optimization and simulation to identify the best alternative to minimize or maximize some objective. It is related to causal analysis.

Descriptive analytics are the most well understood type of analytics and the most commonly employed by organizations ([Evans, 2016](#); [King, 2016](#)). Thus, unsurprisingly current studies and tools used in HR Analytics focus mainly on descriptive analytics (e.g., [Saraswathy et al., 2017](#); [Huselid, 2018](#)). In fact, a recent study ([OrgVue, 2019](#)) found that organizations are basically using analytics for routine tasks such as aggregating and cleansing HR data (45 percent) and headcount cost analysis (41 percent). Likewise, this study shows that many organizations are still using office software such as spreadsheets to do activity analysis, and use PowerPoint to build organizational charts. Only 10 percent of the respondents say that they were using workforce analytics specialist software extensively. Another report ([KPMG, 2019](#)) shows that most companies are planning

investments, over the next year or two, on predictive analytics. The truth is that if HR Analytics is not able to move on from descriptive analytics, it is in real risk of being regarded as a 'management fad' (Rasmussen and Ulrich, 2015). In other words, HR Analytics will fail to add real value to companies by transcending the HR function, and consequently, it won't help HR to gain a seat at the strategy table. Only those organizations that have the capability to do strategic analysis are the ones that are most likely to position HR as a strategic partner (Lawler III et al., 2004).

Angrave et al. (2016) suggest a double explanation to this phenomenon: (1) that developers of software for predictive and prescriptive HR Analytics do not understand the context-specific causality of each organization, and (2) that managers do not have the knowledge and skills to adapt their environment to the standard model proposed in the software. In short, the software for carrying out predictive and prescriptive HR Analytics is design by and targeted to people with analytical skills, rather than on HR professionals. Falletta (2014) lamented that in spite of the advancements and innovations made by leading edge software firms incorporating workforce analytical capabilities within their suite of products, much of work is still done manually by expert HR researchers. As Boudreau (2017) suggested it is necessary a more friendly-user interface in this kind of software.

A recent report OrgVue (2019) shows that 55 percent of decision makers in HR and finance said that technology is a barrier to conducting effective workforce analytics. The same report shows that only 28 percent of HR and Finance departments say that they have shared reporting systems OrgVue (2019). More optimistic is a report from 3,852 professionals (mainly from HR and finance) which show that 39 percent of organizations has a shared system to access the HR and finance data Houghton and Green (2018). Taking into account the need to use HR data and organizational outcome, such as financial data, the incompatibilities between systems, and consequently the problems of merging data, generate barriers in the development of new HR Analytics.

As we have discussed, technology and software alone are not enough. Having the right

analytical capability is a must as we are going to discuss below.

## People

[Levenson \(2011\)](#) provided an initial list of analytical competencies needed for HR professionals to perform HR Analytics effectively. These were divided in those related to statistical techniques (i.e., basic data analysis, intermediate data analysis, basic multivariate models, and advance multivariate models), and other analytic competencies (i.e., data preparation, root cause analysis, research design, survey design, and qualitative data collection). Some years later, Levenson and his colleagues found that even not higher level statistical skills were in an inadequate supply (see, [Marler and Boudreau, 2017](#)). There is no need to say that the requirements to perform HR analytics have change since then. Machine learning and artificial intelligence (AI) are considered to drive significant value for HR, although they are in minority by far. According to a recent study ([KPMG, 2019](#)), only 36 percent of HR functions have started to introduce AI. Also, the supply of these skills is limited ([Nocker and Sena, 2019](#)). Indeed, the shortage of analytically skilled HR professionals have been concluded to be a great barrier to HR Analytics adoption within organizations ([Angrave et al., 2016](#); [Marler and Boudreau, 2017](#)). The lack of analytic acumen or skills among HR professionals was documented as the second biggest obstacle to achieve better use of data, metrics and analytics ([HBR, 2014](#)). Last year, another report ([OrgVue, 2019](#)) found that 62 percent of HR professionals agree on the fact that acquiring the right skills is the single biggest barrier to better HR Analytics, and the most difficult to overcome. Indeed, HR executives recognize not feeling 'very confident' about HR's actual ability to transform and move them forward via key capabilities like analytics and AI [KPMG \(2019\)](#).

Based on our review of the literature, we have identified several sets of knowledge, skills and competences needed to perform HR Analytics. We have clustered them into three groups. First, what we have labeled as 'business expertise', which refers to topics

such as HR expertise, behavioral science, and change management (e.g., [McIver et al., 2018](#); [Rasmussen and Ulrich, 2015](#); [Andersen, 2017](#)). Second, those related to an 'analytical mindset', which covers a set of principles, techniques and tools for data analysis, which includes science methodology, mathematics and statistics, and programming languages ([Martin-Rios et al., 2017](#); [McIver et al., 2018](#); [Rasmussen and Ulrich, 2015](#); [Andersen, 2017](#); [Minbaeva, 2018](#)). Third, those competencies related to 'selling the story' that include visualization, communication and storytelling ([Rasmussen and Ulrich, 2015](#); [Martin-Rios et al., 2017](#); [McIver et al., 2018](#); [Andersen, 2017](#); [Minbaeva, 2018](#)). As [Minbaeva \(2018\)](#) emphasize, "analytical competencies include the ability to communicate the results of sophisticated models to managers in terms of "telling the story" beyond p values" (p. 703). The development of these skills, competences and knowledge may allow people to achieve a high level of technology and quantitative self-efficacy ([Vargas et al., 2018](#)).

However, as [Huselid \(2018\)](#) state: "it is unlikely that any one individual possesses all of the skills needed to design and implement an effective workforce analytics system. Larger firms may have the luxury of having entire teams focused on workforce analytics, with individuals focused on the specifics of data collecting and warehousing, research design and methodology, statistical analyses, and reporting and change management. Smaller firms may need to reach out to outside consultants or partner with capable internal employees in finance, accounting, marketing, or supply chain, where relevant skills may also be found" (p. 683). In line, [Andersen \(2017\)](#) propose to assemble a team with a range of competencies, since it is unlikely to found one or two individuals with all the abilities needed. Specifically, he suggests the following six: excellent statistics and numbers skills, strong data management skills, captivating storyteller, visualization techniques, strong psychological skills, and understand the business. According to him, the lack of varied competencies is one of the reasons for not having reach HR Analytics its full potential.

Indeed, it is not all just about statistical or computing skills. [Rasmussen and Ulrich \(2015\)](#) emphasize the need to have chief human resource officers with a clear business

focus. These authors stated that an 'outside-in' approach that transcends the HR functional boundaries is what is needed. There is a need of people able to use the outcomes of the analysis by connecting them to business outcomes (Bassi, 2011). In fact, a recent study found that current HR analytics is often focused exclusively on HR themes without relating them to business outcomes (van den Heuvel and Bondarouk, 2017), which explains its descriptive approach (reporting and metrics) rather than what should be its strategic one (true analytics). In sync, Levenson (2011) posited that the problem for HR is not a lack of analysis, but the targeting of that analysis to insights that really matter to the organization.

## Management

One important element of debate is, who should develop and implement HR Analytics? Although we might intuitively believe that the team of HR Analytics should be made up of HR professionals, some authors (e.g., McIver et al., 2018) argue that an appropriate collaboration between HR and other functional leaders of the organization is key for developing value-added HR Analytics. Several authors (Rasmussen and Ulrich, 2015; CIPD, 2013) justify this collaboration to the fact that people from HR departments lack of the skills, knowledge and insights to ask the 'right' questions. This lead Rasmussen and Ulrich (2015) to suggest that the organizations should take HR Analytics out of HR department to get an strategic business approach to HR Analytics. On the other hand, Bassi (2011) says that HR (not any other department) has to take the lead on HR Analytics. She posits that if HR does not lead analytics, two negative issues arise: HR lose any strategic aspiration within the organization, and, most importantly the people side of the business will be out of equation (i.e., 'the people side of the business has historically not been a strength of either IT or finance' (p. 17). Interestingly, a recent study (OrgVue, 2019) shows that HR and Finance leaders agree on that the responsibility for getting the right people with the right skills working on the right tasks falls to HR. However, when

asking about analyzing the workforce is less clear (54 percent considers that Finance should do it, whereas 56 percent believe that HR should do it), and when asking about strategic workforce planning there were also division (55 per cent said that Finance should own it, whereas 76 percent said it should clearly be HR). Given the above mentioned, one thing is clear: more collaboration among functions is needed.

Culture is considered another top barrier to HR Analytics adoption [KPMG \(2019\)](#); [Vargas et al. \(2018\)](#). A recent study [Houghton and Green \(2018\)](#) found that people analytics culture is positively associated with overall business performance. Specifically, they found that people analytics culture is positively associated with business and HR strategy. According to this study: (a) HR professionals who have a negative perception of their organization's HR strategy are significantly less likely to use people data in their practice; and (b), HR professionals who view HR strategy and business strategy as integrated in their organizations are significantly more likely to use people data in their practice. So, not only strategic alignment and engagement by HR professionals, but also improving the link between business strategy and HR strategy is important for improving the use of people data. In sync, [Vargas et al. \(2018\)](#) state that social influence is positively related to the level of individual adoption of HR analytics.

Finally, [Rasmussen and Ulrich \(2015\)](#) remind us that HR Analytics doesn't replace the traditional decision-making process. HR Analytics is a methodology that allow the improvement of people-related decision making, giving new evidences and enriching the discussion before taking a decision. Based on the same premise, HR Analytics is not a set of processes that can be used indiscriminately and without direction. [Minbaeva \(2018\)](#), and [Rasmussen and Ulrich \(2015\)](#) highlight the need to carry out HR Analytics in a targeted manner and with a business impact. For this purpose, they suggest that any HR Analytics should start with the precise definition of a business problem, according to the previous conceptualization of HR Analytics.

## CONCLUSIONS

The present study adopted a systematic review of the literature on HR Analytics with the purpose of providing a clear and comprehensive picture of the factors that hinders organizations to adopt them. This provides a useful starting point for new research and HR Analytics practice. We understand that the study findings are useful in many ways we convey below.

First, we are in a position to support the fact that HR Analytics research is not in a mature stage of development. Despite the growing interest that HR Analytics has attracted in recent years, there is an ongoing confusion about what HR analytics encompasses, not to mention regarding its implementation. Unfortunately, academic research does not give much support in finding the right answers; so, we echo [Marler and Boudreau \(2017, p. 14\)](#) in saying that "there is still much room for academic researchers to add to the HR Analytics literature and conversation". Indeed, HR Analytics research has been lagging behind businesses in offering vision and leadership in this field. We have also witnessed a variety of lexemes used to refer to this topic (e.g., HR Analytics, Talent Analytics, Workforce Analytics, and People Analytics), which can be seen as evidence of its earliest stage of development. There is no doubt that this variety of lexemes is helping to the ongoing confusion regarding its conceptualization. Yet, it seems that there is a consensus emerging on the use of *HR Analytics* over the rest of lexemes. It is not only the most prevalent one in the last years, but also, the concept more comprehensively defined. So, we are going to opt for using it. Having said that, we believe that the debate about the appropriate lexeme to use will be alive for a while. For instance, [Huselid \(2018\)](#) justifies the use of 'Workforce Analytics' instead of 'HR Analytics' just for making sure that the focus on this kind of analytics is beyond the HR function.

Second, through the review we gained insight into HR Analytics conceptualization. We can conclude that is beyond reporting people-related data or simply understanding

workforce-related issues. It is about helping in turning analytical insights into efficient and effective concrete business actions. More specifically, HR Analytics has emerged as a methodology that allow the improvement of people-related decision making, using a data-driven approach, to help to achieve strategic organizational objectives. Based on the findings we can present the following comprehensive definition: "HR Analytics is a set of principles and methods that address a strategic business concern that encompasses collecting, analyzing and reporting data to improve people-related decisions". HR Analytics is, by nature, strategic and should go beyond the HR department silo. Yet, this does not imply that we are there. In fact, a more undeveloped version of HR Analytics is usually displayed. Maybe this is due to the barriers that an organization should overcome to successfully implement proper HR Analytics.

Third, we have found that the adoption of HR Analytics is subjected to the emergence of several barriers. Specifically, in the literature, we have identified 14 barriers that we have grouped into four main categories: Data & Models, Software & Technology, People, and, Management (see, Table 4).

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Insert TABLE 4 about here.

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Fourth, based on the findings, we suggest 14 key factors that will help organizations overcome the above mentioned barriers to HR Analytics adoption. We have organized them in four main categories, labeled: Preparation, Development, Dissemination, and Team. The first three refer to the stages of an standard project, whereas the last one refers to the people responsible for carrying it out. These factors provide a starting point from where define specific practices and actions that help to remove, or at least, mitigate the barriers to HR Analytics adoption. Table 5 shows a summary of these key factors along with the barriers identified in the literature that they help to overcome. Below, we are going to discuss each category of key factors.

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Insert TABLE 5 about here.

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## Preparation

The first category concerns the proper definition of a business problem and all issues related to the data that is needed to resolve it. As [Harris et al. \(2011\)](#) and [Rasmussen and Ulrich \(2015\)](#) highlight, there are different areas where we can apply HR Analytics, but we should focus the efforts on those problems that give us the most value to our business. In short, we need to identify relevant business problems where to apply HR Analytics; not just exciting business problems. So, the first step to take full advantage of HR Analytics features is to answer: *What are the business concerns that keep the C-Suite worried?* From here, we can define a relevant business question to resolve through HR Analytics.

After getting a clear definition of a relevant business problem, we need to take into account that the efficiency of HR Analytics is only as good as the valuable and accurate information that HR and business data provides ([Harris et al., 2011](#); [Russell and Bennett, 2015](#); [N'Cho, 2017](#); [Minbaeva, 2018](#)). So, managers should establish data quality assurance systems that ensure the usefulness of the organizational data available before carrying out HR Analytics. On the other hand, we can classify this data depending on its processing level. For instance, an analytics system during a selection process may need the personality traits of the candidates. But there are many different ways to identify their personality traits (e.g., interviews, psychometric tests, and posts in social networks). Thus, the first question should be: *Do we need information for another analytics system?* In the example offered before, we can use other analytic systems to obtain data on the candidate's digital footprint, and combine that with more traditional sources of data (e.g., interviews or psychometric tests). The fit between traditional methods of data collection and the generation of new data by analytics as a source of HR Analytics is underexplored. A wide range of possibilities emerges, which complicates data quality assurance. So, some

questions arise: *What kind of data is the best one for each type of analysis (e.g., external talent identification)?, Which mechanism can we follow to assurance the quality of data?, and How to manage the prioritization of HR Analytics?* These questions deserve further research.

Another aspect to consider about data is related to its accessibility. As we have seen, HR Analytics goes beyond the HR department. Data from other functions inside the organization and even from outside the organization could be needed. Therefore, sharing information is a necessary requirement for HR Analytics to reach its full potential (Davenport, 2019). However, the wall of HR's functional silo (and of other departments) could become a significant barrier (?). Although 82 per cent of respondents of a survey involved 1,510 senior managers, directors, and VPs from 23 countries (Davenport and Anderson, 2019) agreed or strongly agreed 'Integrating HR and Finance data is a top priority for us this year', there's still a lot of work to be done (Davenport, 2019). Some critical questions pending to be answered are: *How to ensure the availability of data from the rest of the company?, and Which are the best ways to assure the collaboration between the HR department and the rest of departments?* These questions relate to the location of the HR Analytics Team that we will discuss below. On the other hand, few authors dare to introduce or discuss the use of external data for HR Analytics (Malisetty et al., 2017). However, external pressures cannot be neglected if we wish to obtain results that may affect the performance of the organization. But, *How can we gather systematically the external data that we need? and Who are in charge of the identification and selection of this data?*

## Development

HR Analytics is not Big Data. According to Zikopoulos and Eaton (2011), the three V's which define Big Data are Variety (the use of different forms of data), Velocity (the need of streaming data analysis) and Volume (the large scale of data). HR Analytics doesn't satisfy these three conditions. It indeed use a wide variety of type of data (e.g.,

emails, spreadsheet, documents, reports, and assessments); however, the HR data is static if we compare it with customer and production data. Likewise, the information about the employees, recruitment, training programs, etc. don't change so fast to need to analyze the data on-the-fly. *How many times per year does an organization change the information about employees' performance, their personality traits, or the list of training programs?* Finally, HR Analytics also doesn't satisfy the volume condition because the quantity of HR data is rather small. Thus, we cannot use in HR Analytics the same principles and techniques of analysis than in Big Data analysis. Some questions arise from here: *What knowledge, practices and techniques can be transferred from Big Data to HR Analytics? How should the analytical approach change in the case of HR Analytics?*

King (2016) emphasizes that most of the literature on HR Analytics is more promotional than descriptive. More precisely, most publications are qualitative case studies, which draw upon well-accepted management frameworks, but typically at a very broad general level (Marler and Boudreau, 2017). Many of them mention the HR Analytics can help in the main functions of talent management (attraction, identification, development, engagement, retention and deployment of talented people) without going into detail on specific problems or opportunities. On the other hand, we had found that most empirical papers about HR Analytics don't use academic theoretical frameworks for their analysis (e.g., Pape, 2016; Luo et al., 2019). Additionally, we had witnessed a lack of standardized HR metrics, which prevents to have clear paths to follow as happens in finance and operations. All these facts can explain the lack of confidence of HR executives to adopt HR Analytics in their departments (see more details in the next two categories). As a result, new questions arise: *Which analytical models can we use for assessing the business impact of applicants' job choice, employee turnover, selection system validity, training effectiveness, goal setting, employee development, performance-based rewards, and performance evaluations? Which are the HR metrics that better fit to assess their business impact? Which contextual elements do we need to include in these analyses?, and How do*

*these models and analysis take into account the extensive academic literature about HRM?*

Finally, scholars need to keep working in the development of statistical and optimization models and specific software that allow predictive and prescriptions analysis. And, most importantly, they need to get into conversation to HR practitioners in this respect. However, they need to bear in mind some, along with the questions formulated in this section, the non-analytical profile of most of the current HR people to avoid generating models without a strategic need or real business impact for the organization.

### **Dissemination**

One of the features of HR Analytics is the use of large amounts of data and increasingly complex models (e.g., [Singer et al., 2017](#); [Luo et al., 2019](#)). The results of such models are complex to understand and interpret, so tools (or new ways) to make the results and their implications understood by executives become one of the main challenges in the use of analytics (see, [Davenport and Anderson, 2019](#)). A second challenge of the use of complex models is the credibility and the trust of these results by executives. For example, machine learning and neural networks usually offer a high predictive capacity, but due to their idiosyncrasy they do not allow to explain the causes of their success ([Shmueli et al., 2010](#)). This does not occur with traditional statistical models based on correlations, such as linear regression models and structural equation modeling. So, executives may not be able to understand the causes of the results obtained in any way, even it may conflict with their own experience and intuition. Indeed, making decisions data-driven is a real challenge for executives. It requires a complex culture change.

HR Analytics are not only complex models for data analysis. Their outcomes are as valuable as perceived. So, research on data visualization for non-data scientists is crucial in order to involve managers in the development and use of HR Analytics. Some key questions about this issue could be: *Which visualizations fit best with each type of HR analysis (and perhaps for each type of managerial profile)? What level of depth and*

*complexity best suits the profile of this type of managers?*, and *How to train these managers in the use and interpretation of HR Analytics results?*

In line with the increased attention to data visualization, the figure of storytelling has recently emerged within the field (Green, 2017). This role or skill is crucial in order to avoid boring and confusing outputs, and consequently avoid mistrust in HR Analytics. But, some questions arises from here: *Are we talking about a skill that some people from the HR Analytics Team have to get and develop?* Or, on the contrary, *Is it a skill that a specific person who works together with the manager need to have?* In that case, *which is the relation between this person and the HR Analytics Team? How do they coordinate with each other?*

## **Team**

The last category refers to the people who should carry out HR Analytics. Several studies suggest that these people should have an analytical mindset (Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017; Mirski et al., 2017) together with some previous experience in HR and business (Martin-Rios et al., 2017; McIver et al., 2018; Simón and Ferreiro, 2018). However, these proposals are very generic and difficult to achieve in the current organizational context. Although some authors suggest training current members of the HR department on analytical tools, it is often difficult to implement due to the complexity of the analysis needed, and the non-statistical skills of these employees. On the other hand, other authors (e.g., Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017) propose to move external personnel (experts in analytics, but not in HR issues), to the HR department for the development of HR Analytics. This proposal also has its cons since an external person, who is not very familiar with neither the culture nor the objectives and practices of HR, is trying to answer appropriately the HR needs. Rather than talking about the ideal profile of the employees who should be involved in HR Analytics, the right questions would be: *What different profiles are needed in the development team of HR*

*Analytics?, What roles and responsibilities should each of them have?, How should each of these profiles be coordinated in the development of HR Analytics?, What role should experience and analytics play in HR Analytics?, and How should we bring them together?*

As we have mentioned, some proposals suggest training current HR employees with an analytical mindset, but it is not clear that this employee profile can assume a classical analytic training. Therefore, further consideration should be given to which specific aspects should be developed and how to develop them taking into account their current skills. So new questions appear: *How to develop analytical mindset in people not specialized in analytics?, Which kind of training fits better to this people?* Finally, the literature does not mention IT experts and their role in the development of HR Analytics. Therefore, new questions also arise, such as: *What role does the department and IT experts play? and How should they coordinate with the rest of the HR Analytics staff?*

Another interesting hot topic about the Team in charge of HR Analytics is to where it belongs. Taking into account that HR Analytics need to use HR data but also data from other departments (e.g., finance and operations) or even from outside the organization, it seems that the most sensible decision is to locate it outside the HR department, and even outside any other department (perhaps by creating a proper Analytics department). As [McIver et al. \(2018\)](#) and [Minbaeva \(2018\)](#) highlight HR Analytics do have a the strategic nature. Several questions arises about the team in charge of HR Analytics: *Where to place it? What kind of relationship does the Team need to establish with the rest of departments, specially the HR department? How to coordinate the Team with other Business Analytics Teams inside the same organization?, and, finally, Who in the C-suite should lead this Team?*

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Characterization	Definitions	Authors
Decision-Making Process	HR or workforce Analytics can be defined as the integration of quantitative data along with statistical tools and modeling in order to mine the data and transform it into actionable business intelligence to make a fact based [strategic human capital] decision.	(Momin, 2014, p. 87)
Method	‘a method of logical analysis that uses objective business data as a basis for reasoning, discussion, or calculation’ in order to predict and direct business outcomes (Fitz-enz, 2009).	(Khan and Tang, 2016, p. 57)
Method	HR analytics is a multidisciplinary approach to integrate methodology for improving the quality of people-related decisions in order to improve individual and organizational performance.	(Mishra et al., 2016, p. 33)
Method	a methodology for understanding and evaluating the causal relationship between HR practices and organizational performance outcomes (such as customer satisfaction, sales or profit), and for providing legitimate and reliable foundations for human capital decisions for the purpose of influencing the business strategy and performance, by applying statistical techniques and experimental approaches based on metrics of efficiency, effectiveness and impact. (Boudreau & Ramstad, 2006; Lawler, Levenson, & Boudreau, 2004)	(Patre, 2016, p. 194)
Decision-Making Process	the systematic identification and quantification of the people drivers of business outcomes, with the purpose to make better decisions.	(van den Heuvel and Bondarouk, 2016, p. 130)
Analysis Process	Human Resource analytics is a part of analytis that focus on metrics and measures related to human processes in an analytic way. It enhances the productivity of employees and ensures the measure of investment on HR. It authenticates the decision process involved from recruitment to integration of employees in the organisation.	(Alamelu et al., 2017, p. 417)
Analysis Process	HR Analytics is a tool that encompasses statistical models to add strategic influence in human resource management.	(Cheng, 2017, p. 2)
Practice	A HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.	(Marler and Boudreau, 2017, p. 15)
Analysis Process	HR analytics is an approach for appreciating and gauging the causal relationship between HR practices and organizational performance outcomes (such as customer satisfaction, sales or profit), and for offering authentic and steadfast bases for human capital decisions for the purpose of persuading the business strategy and performance, by applying statistical techniques.	(Saraswathy et al., 2017, pp. 345-346)
Analysis Process	HR analytics is more than just metrics and/or scorecards (Mondore, Douthitt and Carson, 2011), it consists of various modeling tools like behavioral modeling, predictive modeling, impact analysis, cost-benefit-analysis and ROI analysis (Levenson, 2005) required for strategic HR decision-making.	(Sharma and Sharma, 2017, p. 8)
Analysis Process	HR Analytics are the statistical measures that can show connections, correlations and even causality between human resource metrics and other business measures.	(Vargas et al., 2018, p. 3055)

TABLE 1: Explicit Definitions of HR Analytics

Lexeme Used	Characterization	Definitions	Authors
People Analytics	Analysis Process	People Analytics is the use of data, quantitative and qualitative analysis methods, and domain knowledge to discover insights about how people work together with the goal of improving collaboration.	(Singer et al., 2017, p. 125)
People Analytics	Decision-Making Process	People Analytics is a new way to make evidence-based decisions that improve organizations.	(Leonardi and Contractor, 2018, p. 13)
People Analytics	Decision-Making Process	People analytics — defined as the use of data about human behavior, relationships and traits to make business decisions — helps to replace decision making based on anecdotal experience, hierarchy and risk avoidance with higher-quality decisions based on data analysis, prediction, and experimental research.	(Nielsen and McCullough, 2018, p. 3)
People Analytics	Decision-Making Process	People analytics or human resource (HR) analytics refers to the use of analytical techniques such as data mining, predictive analytics and contextual analytics to enable managers to take better decisions related to their workforce.	(Shrivastava et al., 2018, p. 3)
People Analytics	Decision-Making Process	People Analytics helps HR managers to utilize the big employee data to make decisions related to various HR functions.	(Gaur et al., 2019, p. 555)
Workforce Analytics	Analysis Process	Workforce Analytics refers to the processes involved with understanding, quantifying, managing, and improving the role of talent in the execution of strategy and the creation of value. It includes not only a focus on metrics (e.g., what do we need to measure about our workforce?), but also analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?)	(Huselid, 2018, p. 680)
Workforce Analytics	Decision-Making Process	Workforce analytics is a process—one that is continuously advanced by improving problem solving through sound measurement, appropriate research methods, systematic data analyses, and technology to support organizational decision making.	(McIver et al., 2018, p. 406)
Human Capital Analytics	Organizational Capability	[...] an organizational capability that is rooted in three micro-level categories (individuals, processes, and structure) and comprises three dimensions (data quality, analytical competencies, and strategic ability to act).	(Minbaeva, 2018, p. 701)
Hyper-personal Analytics	Analysis Process	Rather than just demographics and interests, they aim to be deep-delving portraits of individuals' personal traits and motivations.	(Warshaw et al., 2015, p. 797)

**TABLE 2:** Explicit Definitions of other related concepts to analytics applied to HR

<b>Data related to . . .</b>	<b>Type of data</b>	<b>Some examples</b>
Employees outside the organization	Demographic data	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Angrave et al., 2016</a> ; <a href="#">Malisetty et al., 2017</a> )
	Education	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Wei et al., 2015</a> ; <a href="#">Angrave et al., 2016</a> )
	Participation in Social Networks	(e.g., <a href="#">Malisetty et al., 2017</a> ; <a href="#">Sinha et al., 2012</a> )
The position of the employee in the organization	Type of hire	(e.g., <a href="#">Ramamurthy et al., 2015</a> )
	Status of the position	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Wei et al., 2015</a> )
	Salary and compensations	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Wei et al., 2015</a> ; <a href="#">Malisetty et al., 2017</a> )
	Changes in the organization Date of the last promotion	(e.g., <a href="#">Ramamurthy et al., 2015</a> ) (e.g., <a href="#">Ramamurthy et al., 2015</a> )
The work carried out in the organization	Individual performance	(e.g., <a href="#">Davenport et al., 2010</a> ; <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Wei et al., 2015</a> )
	Performance evaluations	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Malisetty et al., 2017</a> )
	Sentiments assessments	(e.g., <a href="#">Hans and Mnkandla, 2017</a> )
	Content and the receivers of their messages in organizational platforms	(e.g., <a href="#">Angrave et al., 2016</a> )
The employee himself/herself	Personality traits	(e.g., <a href="#">Russell and Bennett, 2015</a> ; <a href="#">Papoutsoglou et al., 2017</a> )
	Cognitive abilities and skills (mainly, communication and negotiation skills)	(e.g., <a href="#">Angrave et al., 2016</a> ; <a href="#">Malisetty et al., 2017</a> ; <a href="#">Russell and Bennett, 2015</a> ; <a href="#">Papoutsoglou et al., 2017</a> )
	Expertise	(e.g., <a href="#">Ramamurthy et al., 2015</a> ; <a href="#">Wei et al., 2015</a> ; <a href="#">Angrave et al., 2016</a> ; <a href="#">Papoutsoglou et al., 2017</a> )
	Trainings in the organization	(e.g., <a href="#">Angrave et al., 2016</a> ; <a href="#">Malisetty et al., 2017</a> )

**TABLE 3:** Information gathered at the individual level of data

ref.	Barrier Description	Authors
D1.	Lack of data integration and sharing	(Davenport et al., 2010; OrgVue, 2019; McIver et al., 2018; Douthitt and Mondore, 2014)
D2.	Insufficient data and metrics	(Angrave et al., 2016; Pape, 2016; Lawler III et al., 2004)
D3.	Lack of standards for data and HR metrics	(HBR, 2017; King, 2016; Dulebohn and Johnson, 2013)
D4.	Low quality of HR data	(Harris et al., 2011; Russell and Bennett, 2015; Werkhoven, 2017; Minbaeva, 2018)
D5.	Lack of strategic HR focus in complex models	(Boudreau, 2017)
T1.	Absence of advanced HR Analytics software designed for the common profiles of HR professionals	(Angrave et al., 2016; Boudreau, 2017)
T2.	Incompatibilities between systems to merge data from different units	OrgVue (2019); Houghton and Green (2018)
P1.	Lack of knowledge, skills, and competences related to analytics	(Angrave et al., 2016; CIPD, 2013; HBR, 2014; KPMG, 2019; Marler and Boudreau, 2017; OrgVue, 2019; Andersen, 2017)
P2.	Lack of strategic business view	(Rasmussen and Ulrich, 2015; Bassi, 2011; Levenson, 2011; Andersen, 2017)
P3.	Lack of storytelling skills	(Rasmussen and Ulrich, 2015; McIver et al., 2018; Andersen, 2017; Minbaeva, 2018)
M1.	Keeping HR Analytics only within the HR department	(Rasmussen and Ulrich, 2015; McIver et al., 2018; CIPD, 2013)
M2.	Underestimate the impact of culture	(Vargas et al., 2018; KPMG, 2019; Houghton and Green, 2018)
M3.	Replace the management discussion by HR Analytics	(Rasmussen and Ulrich, 2015)
M4.	Focus on interesting problems, instead of business problems	(Huselid, 2018; Minbaeva, 2018; Rasmussen and Ulrich, 2015)

**TABLE 4:** Data and Models ( $D_i$ ), Software and Technology ( $T_i$ ), People ( $P_i$ ), and Management ( $M_I$ ) Barriers

<b>Category</b>	<b>Description</b>	<b>Barriers</b>
Preparation	Starting with a business problem, instead of an HR problem	D5, P2, M1, M4
	Development of data quality assurance systems	D1, D3, D4, T2
	Use of both raw and processed data	D1, D3
	Cooperation among departments	D5, T2, M1, M4
	Use of internal and external data	D2, D5
Development	Avoid comparison with big data processes	D3, T1
	Use of contextual models	T1, P2
	Develop standard HR metrics (a standard language)	D1, D3, D4, T1
	Use of (HR) academic theoretical frameworks	D5, T1, P2, P3
Dissemination	Increase the understanding of managers about the results	P1, P3, M1, M3
	Increase the trust and credibility of managers in the results	P1, P3, M2, M3
Team	Focus on team skills, instead of people skills	P1, P2, P3, M2
	Balance business, analytical, and storytelling skills	P1, P2, P3, M3
	Locate the team outside of the HR department	M1, M4

**TABLE 5:** Key Factors to succeed in HR Analytics adoption