# An ROI-based review of HR analytics: practical implementation tools

Hila Chalutz Ben-Gal

*Department of Industrial Engineering and Management,
Afeka College of Engineering, Tel Aviv, Israel and
School of Management, San Jose State University, San Jose, California, USA*

## Abstract

**Purpose** – The purpose of this paper is to provide a return on investment (ROI) based review of human resources (HR) analytics. The objectives of this paper are twofold: first, to offer an integrative analysis of the literature on the topic of HR analytics in order to provide scholars and practitioners a comprehensive yet practical ROI-based view on the topic; second, to provide practical implementation tools in order to assist decision makers concerning questions of whether and in which format to implement HR analytics by highlighting specific directions as to where the expected ROI may be found.

**Design/methodology/approach** – This paper is a review paper in which a four-step review and analysis methodology is implemented.

**Findings** – Study results indicate that empirical and conceptual studies in HR analytics generate higher ROI compared to technical- and case-based studies. Additionally, study results indicate that workforce planning and recruitment and selection are two HR tasks, which yield the highest ROI.

**Practical implications** – The results of this study provide practical information for HR professionals aiming to adopt HR analytics. The ROI-based approach to HR analytics presented in this study provides a robust tool to compare and contrast different dilemma and associated value that can be derived from conducting the various types of HR analytics projects.

**Originality/value** – A framework is presented that aggregates the findings and clarifies how various HR analytics tools influence ROI and how these relationships can be explained.

**Keywords** Quantitative, Literature review, Human resource management, Mixed methodologies, Return on investment, Strategic human resource management (SHRM)

**Paper type** Literature review

## Introduction

In recent years, there has been a trend in many organizations toward data-driven decision making in various aspects of business (Holsapple *et al.*, 2014) with the use of big data in daily activities (Chong and Shi, 2015). Albeit with an element of delay, the human resources (HR) departments of some organizations follow this trend. HR departments are experiencing a period of transformation as modern businesses both exploit opportunities and face numerous and complex challenges. Today's HR transformation is a direct result of rapid changes within organizations caused by the combined forces of demographics, globalization and information technology. Some HR departments rely on data to execute activities that were traditionally performed in a somewhat intuitive manner. This transformation plays a crucial role in firms' ability to achieve a competitive advantage in today's challenging economy (Kapoor and Sherif, 2012; Sparrow, 2012; Fulmer and Ployhart, 2014). In light of the rapid changes in technology and the environment, traditional HR metrics have become unsuitable for many situations (Fink, 2010; Handa and Garima, 2014; Sharif, 2015).

The use of data in HR is referred to in terms such as "workforce analytics," "human capital analytics" or "HR analytics," among others. In this paper, we use the last term, which seems to provide a wider context for the addressed challenges. Because HR analytics is an emerging discipline, there are several definitions of the term. HR analytics is defined as "the application of sophisticated data mining and business analytics techniques to the field of HR"

(Vihari and Rao, 2013, p. 1). It is also referred to as quantitative and qualitative data and information management that aims to gain insight and support decision-making processes with regard to managing people in organizations (Fitz-enz, 2000; Handa and Garima, 2014; Zhao and Carlton, 2015). A third definition pertains to "processes to collect, transform and manage key HR related data and documents; to analyze the gathered information using business analytics models; and to disseminate the analysis results to decision makers for making intelligent decisions" (Kapoor and Sherif, 2012, p. 1626). Recently, Marler and Boudreau (2017) conducted an evidence-based review of HR analytics, which they define as "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 to enable data-driven decision-making" (p. 15).

HR analytics has several goals. The first is "to gather and maintain data for predicting short and long-term trends in the supply and demands of workers in different industries and occupations and to help global organizations make decisions relating to optimal acquisition, development and retention of their human capital" (Kapoor and Sherif, 2012, p. 1627). The second is "to provide an organization with insights for effectively managing employees in order to achieve business goals quickly and efficiently" (Davenport *et al.*, 2010; Hota and Ghosh, 2013, p. 169). Third, some scholars emphasize that the goal of HR analytics is to positively influence the successful execution of an organization's strategy (Heuvel and Bondarouk, 2016; Huselid, 2015; Kapoor and Sherif, 2012; Levenson, 2005; Levenson, 2011; Zang and Ye, 2015).

In this paper, we propose a new definition for the adoption of HR analytics by focusing on the return on investment (hereafter ROI) gained by an organization when utilizing HR analytics tools. We propose an ROI-based focus in HR analytics, which enables organizational insights and supports decision makers with respect to the human capital dilemma by providing business insight and consequently helping them make better business decisions. Our proposed ROI-based approach is grounded upon a systematic review and analysis of the literature in the field. In recent years, the connection between data analytics and HR has resulted in a growing body of literature that proposes various approaches to combining the two disciplines, sometimes in an unstructured, blunt manner. Moreover, despite notable evidence of a growing interest in HR analytics, researchers have found very limited scientific evidence to help decision makers determine whether and how to adopt HR analytics (Rasmussen and Ulrich, 2015).

This paper aims to bridge this gap by proposing an ROI-based review of HR analytics in the sense that the efforts required to adopt analytic methods to HR tasks must be justified. This study has two objectives. The first objective is to provide an integrative analysis of the literature on the topic of HR analytics through the lens of ROI to provide scholars, executives and practitioners with a comprehensive but practical view of the topic (Huselid, 2015). The study emphasizes the developments in HR analytics research in recent years, particularly by highlighting works that have been published within the past five years (Vihari and Rao, 2013; Rasmussen and Ulrich, 2015; Heuvel and Bondarouk, 2016; Bamber *et al.*, 2017). The second objective is to systematically analyze the literature from the ROI perspective, highlighting scientific evidence to assist decision makers in determining how to adopt HR analytics (Rasmussen and Ulrich, 2015). This work aims to aid both researchers and practitioners with respect to specific directions within HR in which an expected ROI may be found.

Understanding what we have learned and how it has changed the HR field helps direct future research. To this end, our paper asks and answers three interrelated research questions (Cuozze *et al.*, 2017):

RQ1. What are the major themes that have been developed within HR analytics research?

RQ2. What are the focus and ROI-based critique of HR analytics research?

*RQ3.* What is the future of HR analytics research?

This paper has three sections. The methodology section outlines the database development approach. The results and discussion section answer the first two research questions through descriptive statistics and a critique of the results from categorizing the HR analytics literature. This section also discusses how we developed and applied the ROI theoretical framework. In the third section, we answer the last research question by discussing key implications for scholars and practitioners and noting a few directions for future research.

## Methodology

The methodological approach for the review and analysis comprised four steps. First, we developed a database by undertaking a comprehensive and systematic search to identify and extract all the relevant literature on HR analytics that has been published in peer-reviewed academic journals. Second, in an iterative process between theoretically derived and empirically emerging themes, we developed a template for analyzing the reviewed articles (Table AI). Third, a manual content analysis of the retrieved articles, based on the template, was used to extract descriptive and qualitative conceptual data. Finally, the results were interpreted and the findings meaningfully synthesized (Short, 2009; Webster and Watson, 2002). This method was used to ensure a comprehensive, meaningful and high-quality data compilation (Cuozzo *et al.*, 2017).

### Database development
The initial step comprised the identification of the relevant research. To capture previously published research, we used 11 EBSCO online databases.[1] We conducted a Boolean search using "HR analytics" as a key search term within the title, abstract or subject terms.[2] We continuously updated the database throughout the period of our research project by means of a Google Scholar alert specific to our key terms. The selection criteria are based on the following items: the paper was published between 2000 and 2016, the search terms appear in the title, abstract or paper and the paper appears in a peer-reviewed journal. Overall, the searches resulted in a database of 80 articles.

### Categorization
In reviewing and analyzing the selected papers, we identified four HR analytics research clusters: empirical, conceptual, case-based and technical. These research clusters are depicted in Figure 1. This categorization is useful in developing an ROI-based analysis of HR analytics (Webster and Watson, 2002; Gilbert *et al.*, 2008; Bukhari *et al.*, 2017).

### Classification system
The articles were first coded by the lead category (i.e. cluster) and then checked for consistency by an external judge who had extensive experience with the topic. Any discrepancies were reviewed and discussed before a final classification was agreed upon.
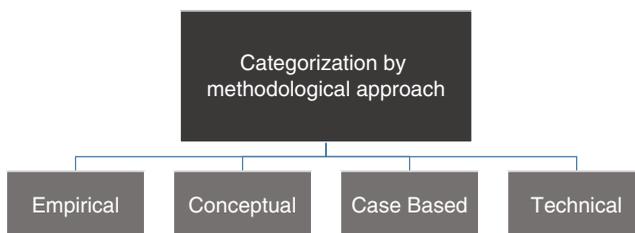


Figure 1.
Human resources
analytics clusters

Rather than describe each category in the framework as presented in Table AI, we outline each at the beginning of the corresponding discussion in the descriptive results (Cuozzo *et al.*, 2017).

## Results and discussion
In this section, we use descriptive statistics and commentary to answer the first two research questions: *RQ1* and *RQ2*. The data reported in Figure 2 and in Table AI and Tables I–III form the basis for this section. Additionally, the discussion is complemented by further analysis that delves deeper than the descriptive results.

We analyze the findings of our systematic review of a sample of 80 articles associated with research in HR analytics according to the chronological development of this research (presented in Table I and Figure 2). We thereby identify shifting trends over time and extract key themes of existing HR analytics literature. Additionally, we analyze and present key trends in HR analytics research in Table II in a unique synthesis.

### Emergence of HR analytics research
The results of our research, displayed in Table I, clearly show an increasing interest in the topic of HR analytics over time (see also Figure 2). We identified three periods of HR analytics research. The first is a period of incubation (2000–2005) during which 4 percent of the HR analytics research was published. The second was a period of incremental growth (2006–2010) during which 10 percent of the HR analytics research was published. Finally, there was a period of substantial growth (2011–2016) when 86 percent of the HR analytics research was published. In line with this typology, and consistent with previous research (Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017), our study results demonstrates that the research attention devoted to HR analytics has increased in recent years. The shift in publication over this 17-year period underscores the growing academic interest in the field of HR analytics (Bose, 2015; Kazakovs *et al.*, 2015). Moreover, the understanding of HR analytics has changed over time. While early publications examined HR analytics from a narrow economic and personnel perspective by highlighting technical aspects (for example Lazear, 2000), the relevance of HR analytics has gained relevance both in research and in practice from a strategic and managerial perspective, which has transformed it into a vibrant and interesting topic of research.

More specifically, HR analytics research has evolved such that in the incubation period (2000–2005), none of the publications found their way into management nor business journals, whereas almost 40 percent (37 percent) of the publications did so in the substantial growth period (2011–2016). Moreover, the study results indicate that a vast share of HR analytics research (91 percent) was published in either HR management or in management and business journals.
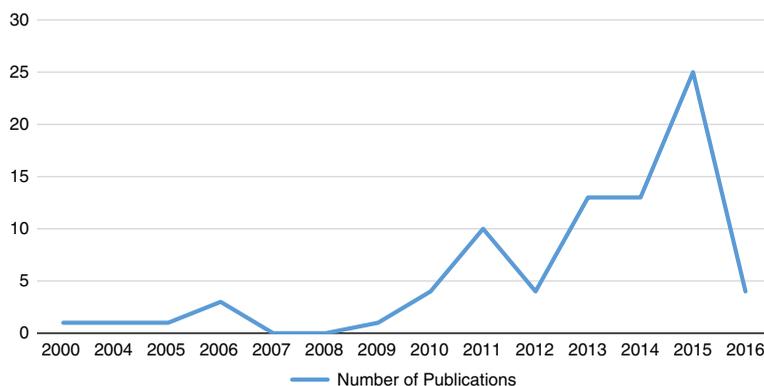


**Figure 2.**
Publications over time

| Year of publication | 2000–2005 (6 years) incubation period (1 ⩾ publications) $n = 3$ (4%) | 2006–2010 (5 years) incremental growth (1 < publications < 4) $n = 8$ (10%) | 2011–2016 (6 years) substantial growth (publications ⩾ 10) $n = 69$ (86%) | 2000–2016 total (17 years) $n = 80$ (100%) |
|---|---|---|---|---|
| *Type of journal* | | | | |
| HRM | 2 (3) | 4 (5) | 32 (40) | 38 (48) |
| Management and business | 0 | 4 (5) | 30 (37) | 34 (43) |
| Engineering | 0 | 0 | 2 (3) | 2 (3) |
| Other | 1 (1) | 0 | 5 (6) | 6 (7)* |
| *Research cluster* | | | | |
| Empirical | 2 (3) | 1 (1) | 11 (14) | 14 (18) |
| Conceptual | 1 (1) | 3 (4) | 32 (40) | 36 (45) |
| Case based | 0 | 2 (3) | 9 (11) | 11 (14) |
| Technical | 0 | 2 (3) | 17 (21) | 19 (24)* |
| *Geographical region* | | | | |
| North America | 1 (1) | 3 (4) | 49 (61) | 53 (66) |
| Europe | 2 (3) | 2 (3) | 8 (10) | 12 (15) |
| Asia | 0 | 2 (3) | 8 (10) | 10 (13) |
| Africa/middle East | 0 | 1 (1) | 4 (5) | 5 (6) |

**Notes:** Values = Number of articles; values in brackets = % of articles. *Adds to 101 percent due to percentage rounding

**Table I.**
HR analytics research characteristics by period of publication

| Trend | Challenges and outcomes | ROI | Example references |
|---|---|---|---|
| HRA as strategic management tool | Management–HR interface Business impact | High | Levenson (2005), Levenson (2015), Newcomer and Brass (2015), Welbourne (2015) |
| Evidence-based approach in HRA | Adoption of correct tool technological | High | Bassi (2011), Marler and Boudreau (2017) |
| HRA as decision-making support tool | Various analytical techniques multi-step process | High | Dulebohn and Johnson (2013), Singh and Roushan (2013), Holsapple *et al.* (2014), Rasmussen and Ulrich (2015), Pape (2016) |
| HRA as management fad | HRA is not part of HRM HR professional's role in HRA | Low | Rasmussen and Ulrich (2015), Marler and Boudreau (2017) |

**Table II.**
Trends in HR analytics research

In total, 48 percent of HR analytics research was published in HR management journals, while 43 percent of HR analytics research was published in management and business journals.

These findings indicate the increase in the strategic importance of the field. One explanation is the growing centrality of human capital as a key organizational asset (Bontis and Fitz-enz, 2002; Fitz-enz, 2000). Both HR analytics and HR as a broader field are in a constant state of change (Bamber *et al.*, 2017; McIver *et al.*, 2018). A second explanation is the growing availability of readily accessible data, which can be transformed into valuable and actionable insights through the implementation of HR analytics tools (Macan *et al.*, 2012; Strohmeier, 2018). These findings also show that our ROI-based analysis is an appropriate platform to expand upon in order to determine precisely how management and HR professionals can benefit from HR analytics.

| Study authors | Research cluster | Logic | Analytics | Measurements | Processes | ROI |
|---|---|---|---|---|---|---|
| Harrison and Getz | Empirical | X | | X | X | High |
| Hou | Empirical | X | X | X | X | High |
| Ramamurthy et al. | Empirical | X | X | X | X | High |
| Sharif | Empirical | X | | X | X | High |
| Bose | Conceptual | X | | | X | Medium |
| Church et al. | Conceptual | X | | | X | Medium |
| Huselid | Conceptual | X | | X | X | High |
| Levenson | Conceptual | X | X | X | X | High |
| Momin and Mishra | Conceptual | X | | | X | Medium |
| Newcomer and Brass | Conceptual | X | | | X | Medium |
| Perrin | Conceptual | X | | | X | Medium |
| Rasmussen and Ulrich | Conceptual | X | | | X | Medium |
| Sharma et al. | Conceptual | X | | | X | Medium |
| Steffi et al. | Conceptual | X | | | | Low |
| Ulrich and Dulebohn | Conceptual | X | | | X | Medium |
| Zang and Ye | Conceptual | X | | | X | Medium |
| Zhao and Carlton | Conceptual | X | X | X | X | High |
| Frigo et al. | Case based | X | | | | Low |
| Russell and Bennett | Case based | X | | X | | Medium |
| Chong and Shi | Technical | X | | | | Low |
| Karasek | Technical | X | | | | Low |
| Kazakovs et al. | Technical | | | | X | Low |
| Korpela | Technical | X | | | | Low |
| Stone et al. | Technical | X | | | X | Medium |
| Welbourne | Technical | X | | | | Low |

**Notes:** $n = 25$. Included in analysis 2015 publications only (represents the highest publishing year in the Substantial Growth period)
**Source:** Boudreau (2006)

**Table III.**
ROI-based analysis of human resources analytics

Research results suggest an emerging shift over time regarding the geographical regions upon which HR analytics research focuses. Most articles on the topic of HR analytics that specified a geographical region in the substantial growth period shifted from Europe (10 percent of publications) to North America (61 percent of publications). This focus on North America could be linked to the emerging trend, which originated in the USA, of linking HR and technology along with the major effect that technology has on HR as a whole (Chamorro-Premuzic et al., 2017). It has been acknowledged that "technology has transformed the way HR processes are currently managed, mainly in terms of how organizations collect, store, use and disseminate information about applicants and employees" (Stone et al., 2015, p. 217).

Most of the research articles are conceptual (45 percent) rather than purely technical (24 percent). The conceptual studies in HR analytics provide management and analytical tools to facilitate working processes and procedures. They include talent analytics (Burdon and Harpur, 2014), tools for improved organizational decision making (Minbaeva and Collings, 2013; Pape, 2016) and a conceptual framework (Boudreau and Ramstad, 2006). The focus has thereby shifted over time from a predominance of conceptual articles to technical articles, which comprise nearly one quarter (24 percent) of the total number of articles (see Table I). To a certain extent, this may be due to the growing interest in specific topics within HR analytics (Macan et al., 2012; Yadav, 2014; Momin and Mishra, 2015).

*Trends in HR analytics research*
Our integrative review reveals that HR analytics research is dominated by four trends (see Table II). We synthesize these trends by depicting their key challenges, outcomes and ROI.

The first identified trend in HR analytics research is the exploration of HR analytics as a strategic management tool. This approach yields a high ROI for the organization because its impact may be on the organization as a whole and on the business level for the purpose of continuous improvement (Delbridge and Barton, 2002). Where HR analytics is presumed to be an integral part of management processes, the key challenges associated with this trend include answering questions regarding specific strategic measures. One example is organizational turnover, which has a long-term business impact on the organization as a whole (Levenson, 2005; Levenson, 2015; Newcomer and Brass, 2015; Welbourne, 2015). Along these lines, one researched theme associated with this trend is the management and HR interfaces within organizations (Huselid, 2015; Xiu *et al.*, 2017; McIver *et al.*, 2018).

The second identified trend in HR analytics research is the evidence-based approach to HR analytics research. This approach also yields a high ROI for the organization because it uses a variety of methodological and technological tools to predict improved individual or organizational performance. The key challenges associated with this trend include answering key questions regarding which tool would be the correct one to adopt for a specific people analytic challenge and which form of technology to use (Marler and Boudreau, 2017; Strohmeier, 2018).

The third identified trend in HR analytics research that uses HR analytics for effective organizational processes involves incorporating HR analytics as an effective decision-making support tool (Dulebohn and Johnson, 2013; Singh and Roushan, 2013; Holsapple *et al.*, 2014; Chamorro-Premuzic *et al.*, 2017). The ROI associated with this trend is high because it suggests efficiency in the decision-making processes. The key challenges associated with this trend include the efficiency of the process itself, e.g., collecting and analyzing the data, thereby raising issues of efficiency and effectiveness (Rasmussen and Ulrich, 2015; Pape, 2016).

Finally, the studies focusing on the future of HR analytics incorporate a fourth trend in HR analytics research. This approach yields a low ROI because it is speculative in nature. The key challenges associated with this trend include discussions of whether HR analytics should be part of the HR function and the role of HR professionals (Rasmussen and Ulrich, 2015). This paper builds upon this trend and pinpoints specific practical directions regarding how to implement HR analytics.

To conclude, we highlight the most salient findings of the most comprehensive exploration of HR analytics to date by Marler and Boudreau (2017); they note that extant research is overly focused on the evidence-based approach, and they offer an analysis of five key questions and potential explanations for the paradox of low adoption of HR analytics (p. 22). We thus move to our substantive contribution, an ROI-based analysis of HR analytics that sets the ground for our proposed future research avenues in HR analytics.

*Theoretical framework: ROI-based analysis of HR analytics*
The theoretical framework of ROI guided our analysis. The literature suggests that ROI is an important measurement tool that may assist stakeholders in managerial decision making. ROI is rooted in early theoretical research in the accounting and management professions that aimed to provide a qualitative approach to decision making. ROI is also used in various academic fields (Philips, 2012; Bontis and Fitz-enz, 2002; Bukhari *et al.*, 2017). One example is in the corporate training and education literature, where ROI is used to measure the impact of training and educational investments on an organization's "bottom line," i.e., organizational performance measures (Charlton and Osterweil, 2005).

We examine the results of this study from an ROI-based perspective for two reasons. First, we believe that this framework is suitable in light of the limited high-quality research that has been conducted in the field (Fink, 2010; Handa and Garima, 2014; Xiu *et al.*, 2017). Second, we believe that analyzing HR analytics from an ROI-based perspective can increase the chances

of the practical adoption of HR analytics. We therefore categorized the research reported in this paper based on the LAMP framework (Boudreau and Ramstad, 2006). We identified this framework as a suitable framework to analyze ROI in the field of HR analytics. In particular, the LAMP framework assists in analyzing useful components of HR analytics, i.e., "logic," "analysis," "measurement" and "process" (Boudreau and Ramstad, 2006, p. 27). Using this categorization, we found that the majority of articles from the empirical and conceptual research clusters resulted in high or medium levels of ROI. Additionally, we found that most studies focusing on cases or technical aspects of HR analytics resulted in medium or low levels of ROI. We summarize the coding of our sample in Table III.

*Empirical studies*
Empirical studies attempt to obtain knowledge in the field of HR analytics. The majority of studies were conducted by direct and indirect observations and/or experience (Aral *et al.*, 2012). Their analyses were either quantitative or qualitative. An advantage of empirical studies is that by quantifying evidence or making sense of it in a qualitative manner, scholars answer empirical questions that are clearly defined and answerable based on data and the use of the evidence collected. The research designs vary by field and by the question being investigated. Some scholars perform mixed-methods research, combining qualitative and quantitative forms of analysis to better answer their research questions, especially in the social sciences and education (Gilbert *et al.*, 2008; Aral *et al.*, 2012; Kandogan *et al.*, 2014).

The contributions of empirical studies in the literature are evident as they explore new and current trends in HR analytics research in all or some of the following ways. First, they conduct interviews with practitioners in a variety of organizations from different industries on the topic of HR analytics. Additionally, they conduct interviews with thought leaders in the area of human capital analytics and research. Finally, they attempt to draw informative conclusions in the area of HR analytics (Lazear, 2000; Fink, 2010; Hausknecht, 2014; Kandogan *et al.*, 2014; Sharif, 2015).

As documented in Table III, a review of the literature suggests that most empirical studies apply the LAMP model (Boudreau and Ramstad, 2006) in a meaningful manner, thereby yielding a high level of ROI. Moreover, our results indicate that most empirical studies are consistent with the LAMP model because they focus on at least three of the model's components by providing meaningful content to the "logic," "analytics," "measurement" or "process" of HR analytics (Boudreau and Ramstad, 2006; Gilbert *et al.*, 2008; Marler and Boudreau, 2017). Moreover, empirical studies yield the highest ROI because they focus on organizational practices and business performance. Furthermore, empirical studies highlight the HR metrics used by organizations as well as the impact of HR analytics on business outcomes (Lazear, 2000; Lawler *et al.*, 2004). Finally, empirical studies tend to use strategic HR tools, such as forecasting techniques to predict various HR measures (Bondarouk and Ruël, 2013; Del Angizan *et al.*, 2014).

To conclude, there appear to be clear benefits to exploring HR analytics from an empirical standpoint. Some of the benefits include increased organizational performance, greater accuracy regarding performance specifications, accurate and rapid assessment processes, and better HR processes (Harrison and Getz, 2015; Hou, 2016; Ramamurthy *et al.*, 2015).

*Conceptual studies*
Some of the studies covered in this systematic review offer conceptual contributions to the field of HR analytics. The advantage of the conceptual studies is that their contributions are wide; they range from providing management tools (Davenport *et al.*, 2010; Wiblen *et al.*, 2010; Kapoor, 2010; Snell, 2011; Harris *et al.*, 2011) to providing an ethical perspective to talent analytics (Burdon and Harpur, 2014) and adopting an analytics-based approach (Ramamurthy *et al.*, 2015). Their contributions relate to various content areas in the HR

analytics field (Gilbert *et al.*, 2008). Some studies apply statistics, technology and expertise to large sets of people data, which results in improved organizational decisions (Minbaeva and Collings, 2013; Pape, 2016). Other studies emphasize analytical processes to enhance an organization's competitive advantage (Burdon and Harpur, 2014).

Reviewing the conceptual literature, we identified four main themes: HR analytics' ROI, the conceptual framework contribution, the HR analytics process and the domain of HR analytics. The conceptual contribution of HR analytics' ROI is discussed by Levenson (2005), Ingham (2011), Huselid (2015), Rasmussen and Ulrich (2015) and Zang and Ye (2015). A conceptual framework contribution is provided by Boudreau and Ramstad (2006). A discussion of the HR analytics process is provided by Baron (2011), Hota and Ghosh (2013), Dulebohn and Johnson (2013), Handa and Garima (2014) and Bose (2015). Finally, the domain of HR analytics is presented and discussed by Carlson and Kavanagh (2011).

Interestingly, the results presented in Table III indicate that like the empirical studies, the majority of conceptual studies apply the LAMP model (Boudreau and Ramstad, 2006) in a meaningful manner, thereby yielding a medium to high level of ROI. Moreover, our results indicate that most conceptual studies are consistent with the LAMP model because they focus on at least two of the model's components, i.e., "logic," "analytics," "measurement" or "process" (Boudreau and Ramstad, 2006).

Conceptual studies in HR analytics yield a medium to high ROI because some propose new frameworks to analyze and implement employee data (Davenport *et al.*, 2010; Wiblen *et al.*, 2010; Garcea *et al.*, 2011), while others discuss the roles and responsibilities of HR in this transformational era of technological change and globalization (Kapoor, 2011; Snell, 2011; Burdon and Harpur, 2014). Some of the reviewed literature focuses on performance management (Schläfke *et al.*, 2012; Ding Zhang and, 2014; Church *et al.*, 2015; Ryan and Herleman, 2016)[3] and may provide a new method for HR managers to obtain insight into the effectiveness of employee performance and, ultimately, organizational performance (Ding Zhang and, 2014, p. 5). Some of the conceptual studies take a broader approach to the measurement of human capital in light of constant organizational change (Baron, 2011; Carlson and Kavanagh, 2011; Ingham, 2011; Dulebohn and Johnson, 2013).

The increased level of ROI that is derived from the conceptual literature on HR analytics (medium to high level of ROI, as indicated in Table III) is also derived from some of its strategic implications. Some conceptual studies in HR analytics provide tools for workforce analytics and emphasize the strategic importance of HR analytics within the organizational context (Huselid and Becker; 2011; Van Barneveld *et al.*, 2012; Hota and Ghosh, 2013; Boudreau, 2014; Guszcza and Richardson, 2014; Handa and Garima, 2014; Holsapple *et al.*, 2014; Bose, 2015; Huselid, 2015; Rasmussen and Ulrich, 2015; Ryan and Herleman, 2015; Sharma *et al.*, 2015, Steffi *et al.*, 2015, Zang and Ye, 2015; Ulrich, 2016).

To conclude, the common feature of the conceptual studies is that they articulate a clear connection between the HR investment in analytics and organizational effectiveness. Moreover, they all have indicators of increased level of ROI. Finally, the conceptual research studies present a robust approach for strategic alignment with state-of-the-art organizational processes (Boudreau and Ramstad, 2006), which complements their overall effectiveness.

*Case-based studies*
The case-based literature has two foci. First, it covers studies that provide practical examples of organizations that have implemented HR analytics and recommendations for successful implementation. Second, some studies were written by scholars or practitioners who have consulting experience in the area of HR analytics and share it with their readers. An advantage of the case-based studies is their practicality in the field of HR analytics (Gilbert *et al.*, 2008).

The results presented in Table III indicate that in contrast to the empirical and conceptual studies, most case-based studies do not apply the LAMP model (Boudreau and Ramstad, 2006) in a meaningful manner, and they therefore yield a medium to low level of ROI. Moreover, our results indicate that most case-based studies are inconsistent with the LAMP model and therefore yield lower levels of ROI because they focus on only one or two of the model's components, i.e., "logic," "analytics," "measurement" or "process" (Davenport, 2006; Fitz-enz, 2000; Briggs, 2011; Mondore *et al.*, 2011; Boyd and Gessner, 2013; Singh and Roushan, 2013; Varshney *et al.*, 2014; Frigo *et al.*, 2015; Russell and Bennett, 2015).

To conclude, the common grounds for what we categorized as case-based studies (Gilbert *et al.*, 2008) is that the majority do not articulate a clear connection between HR analytics investment, organizational effectiveness and ROI. Moreover, they provide limited scientific evidence to aid decision-makers concerning whether to adopt or implement HR analytics tools within an organization (Marler and Boudreau, 2017; Strohmeier, 2018).

*Technical studies*
The technical literature analyzed in this study has four focus areas: the studies present informative research on the topic of HR analytics (Welbourne, 2015), focus on a specific subject within HR analytics (Perrin, 2015), present a literature review (Vihari and Rao, 2013; Chong and Shi, 2015) or illustrate future trends in HR analytics (Yadav, 2014; Momin and Mishra, 2015). Thus, the advantage of technical studies is their specificity (Gilbert *et al.*, 2008).

The results presented in Table III indicate that similar to the case-based literature, and in contrast to the empirical and conceptual studies, the majority of technical studies do not apply the LAMP model (Boudreau and Ramstad, 2006) in a meaningful manner, and they therefore yield a medium to low level of ROI. Moreover, our results indicate that most technical studies are inconsistent with the LAMP model because they focus on only one or two of the model's components, i.e., "logic," "analytics," "measurement" or "process" (Mayo, 2006; Rivera and Smolders, 2013; Stone and Dulebohn, 2013; Vihari and Rao, 2013; Fernández-Delgado *et al.*, 2014; Yadav, 2014; Chong and Shi, 2015; Karasek, 2015; Kazakovs *et al.*, 2015; Korpela, 2015; Momin and Mishra, 2015; Perrin, 2015; Stone *et al.*, 2015; Ulrich and Dulebohn, 2015; Welbourne, 2015; Ryan and Herleman, 2016).

To conclude, the common ground of what we categorized as technical studies (Gilbert *et al.*, 2008) is that similar to case-based studies, most papers do not articulate a clear connection between HR analytics investment and organizational effectiveness. Moreover, they provide limited scientific evidence to aid decision makers concerning whether to adopt HR analytics.

### HR Analytics – practical implementation tools and expected ROI
*Implications for organizations*
Our review of the literature underscores the importance of two notable fields within the HR analytics research, namely, empirical and conceptual research. Acknowledging two notable paradoxes detected recently in the HR analytics literature – that is, "despite the popularity of HR analytics there is very limited high-quality scientific evidence-based research on this topic and the second is the apparently limited adoption of HR analytics when the available research seems frequently to suggest that it is associated with positive organizational outcomes" (Marler and Boudreau, 2017, p. 22) – this conclusion led us to further explore specific HR tasks and challenges in light of practical implementation tools and the expected ROI within HR functions and within the organization as a whole.

From a practical perspective, the ROI-based approach presented is important for a data-driven decision-making process in the field of HR analytics. It also provides a step-by-step procedure for handling data and subsequently utilizing these data to attain meaningful managerial insights. Moreover, the need for a better focus in conducting and

implementing HR analytics projects within organizations is clear. Albeit with an element of shortage, some HR analytics efforts in organizations today could be defined as reactive rather than proactive. Hence, it is not unusual for practitioners to use data that they receive access to in order to perform interesting analyses by addressing a question or set of questions with various levels of viability to the organization (Huselid, 2015). The ROI-based approach to HR analytics presented in this study provides a robust tool to compare and contrast different dilemmas and associated value that can be derived from conducting various types of HR analytics projects. The ROI-based approach also supports continuous improvement in organizations (Delbridge and Barton, 2002).

From a theoretical perspective, the proposed categorization (Gilbert *et al.*, 2008) provides a robust ROI framework for conducting research in the field of HR analytics, thus enabling scholars and practitioners to focus on a desired topic in a more structured manner (Becker, 2009; Lipkin, 2015; Rasmussen and Ulrich, 2015; Ghosh and Sengupta, 2016; Pape, 2016).

In Table IV, we illustrate the implications of HR analytics for organizations. We present how addressing HR challenges using various analytical tools, namely, descriptive and predictive, may impact the expected ROI. This analysis may further assist scholars and practitioners in the ongoing effort to improve HR analytics tools and impacts (Rasmussen and Ulrich, 2015; Chamorro-Premuzic *et al.*, 2017; Strohmeier, 2018).

Table IV presents the implications of HR analytics for organizations as well as practical implementation tools. Specifically, it offers a summary overview of eight major HR tasks and activities that organizations are faced with, including their corresponding sample challenges (Srinivasan and Chandwani, 2014; Bamber *et al.*, 2017), practical implementation tools and the expected ROI. The expected ROI is categorized into three levels – low, medium and high – in accordance with the complexity of data-handling procedures that are relevant to the HR analytics research (Fitz-Enz, 2009; Rasmussen and Ulrich, 2015; Ghosh and Sengupta, 2016). The results documented in Table IV yield two notable conclusions. The two areas of HR tasks that yield the highest ROI are workforce planning and recruitment and selection because both rely on predictive analytics tools (Fitz-enz, 2009).

| Human resources task | Sample challenges | Tool[a] | Expected ROI |
| --- | --- | --- | --- |
| Industry analysis | Macro-market effect on turnover | Descriptive | Low |
| Workforce planning | High-demand jobs and attrition Person-Organization Fit | Predictive | High |
| Job analysis | Robustness of job components | Descriptive | Low |
| Recruitment and selection | Person-Job Fit | Predictive | High |
| Training and development | ROI in training | Descriptive and Predictive | Medium |
| Compensation | Total compensation scenarios | Descriptive and Predictive | Medium |
| Performance management | Performance management cycle scenarios | Descriptive | Low |
| Retention | Can retention be predicted | Descriptive and Predictive | Medium |

**Notes:** [a]Descriptive analytics tools may include: descriptive statistics, graphs and plots, benchmarking tools, KPIs-based methods (scorecards), business intelligence (BI) dashboards and advanced survey analytics. Predictive analytics tools may include: regression and parametric modeling (including logistic regression), time series analysis, classification methods (e.g. decision trees, SVM, discriminant analysis, neural networks, deep learning), clustering (*K*-nearest neighbors, *K*-means) anomaly detection, profiling, association rules, link-analysis, causality modeling (Bayesian networks), text analysis and NLP and Attrition modeling

Table IV.
HR analytics'
implications for
organizations:
practical
implementation tools
and expected ROI

As presented in Table IV, the first task of HR focuses on industry analysis. This task ensures the analysis of basic HR parameters in an organization's specific industry (e.g. retail, financial, technology). Empirical research tools are descriptive analytics that use BI and benchmarking to analyze government data, consulting firms' data, census data and macro-industry data. Our observations suggest examining macro-market effects on specific constructs, such as turnover. Relevant ratios include industry average job turnover, average cost per hire and job-specific retention budget, among others. Accordingly, the ROI for performing an industry analysis utilizing these HR analytics tools is expected to be low.

Workforce planning is the second task of HR, and we call for extended empirical analytics on this task because we believe it entails a high ROI. Workforce planning ensures the use of a continual process to align the needs and priorities of the organization with those of its workforce to ensure that it can meet its legislative, regulatory, service and production requirements as well as long- and short-term organizational objectives (Huselid, 2015). Empirical research tools include predictive analytics that use various analysis techniques based mostly on internal data (e.g. ERP, headcount, product mapping, financials, budget) and external data (e.g. surveys, salary tables, syllabuses and training program materials). Our observations suggest that certain challenges to test are person-organization fit and the connection between high-demand jobs and attrition. Accordingly, the ROI for performing workforce planning using these HR analytics tools is expected to be high.

The third task of HR focuses on job analysis, which is a process to identify and determine in detail a given job's duties, requirements and interfaces as well as its relative importance. This is a process in which judgments are made about data collected for a job (Levenson, 2005). Empirical research tools include descriptive analytical tools (e.g. financial ERP, organizational structure and headcount). Our observations suggest that some specific challenges to test are the robustness of job components and their effect on satisfaction and retention. Accordingly, the ROI for performing job analysis using these HR analytics tools is expected to be low.

Recruitment and selection of talent is the fourth task of HR, and we call for extended empirical research on this task because we believe it entails a high ROI. Practical research tools include predictive analytics. Our observations suggest that specific challenges to test are methods of classifying the talent pool according to available organizational resources; text analysis of interviews and profiling of vacant roles and organizational requirements; and logistics regression or other parametric models that predict recruitment probability of success, satisfaction and person-job fit. Accordingly, the ROI for the recruitment and selection of talent using these HR analytics tools is expected to be high.

The fifth task of HR refers to training and development, which is primarily concerned with organizational activity aimed at improving the performance of individuals and groups in the organization. The recommended empirical research tools include both descriptive and predictive analytics. Our observations suggest that some specific challenges to test are the analysis of training ROI (through BI), whereas classification methods may assist in improving the training investment per job class. Accordingly, the ROI for performing training and development using these HR analytics tools is expected to be at a medium level.

The sixth task of HR refers to compensation and benefits. This management challenge assists in the execution of organizational strategy and may be adjusted according to business needs, goals, and available resources. Empirical research tools are descriptive (e.g. BI, scorecards or other KPI-based methods) and predictive analytics. Our observations suggest that some specific challenges are total compensation scenario testing; Monte Carlo simulations assess various compensation plans and regression analyses and their interplay with selected organizational phenomena. Accordingly, the ROI for performing compensation research using these HR analytics tools is expected to be at a medium level.

The seventh task of HR refers to performance management. This task is an ongoing process of communication between a supervisor and an employee that occurs throughout the year in support of accomplishing the organization's strategic objectives (Huselid, 2015). Future empirical research tools are based on descriptive analytics. Our observations suggest that some specific challenges to explore are performance management cycle scenarios mainly through BI, dash boarding and KPI-based methods. Additionally, various levels of performance are clustered for the purpose of performance evaluation. Accordingly, the ROI for performing performance management using these HR analytics tools is expected to be low.

Finally, the eighth task of HR that is illustrated in Table IV is retention of talent. The recommended empirical research tools are based on descriptive and predictive analytics. We call for a specific challenge to test and believe that further research on the topic of whether retention can be predicted is required. This challenge can be addressed by the profiling of key jobs, the classification of various talent retention scenarios, logistic regression, anomaly detection and attrition modeling for various job groups. Accordingly, the ROI of performing talent retention using the proposed HR analytics tools is expected to be at a medium level.

Our observations documented above apply to both scholars and practitioners when planning their future HR analytics priorities. Furthermore, the ROI-based approach, which is the focus of this study, underscores the call for a more systematic approach for researchers and decision makers to use evidence-based information as a guide to the adoption of HR analytics and to understand its effectiveness (Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017).

The challenge for future research in HR analytics is to reach beyond general studies in order to identify important contextual variables of HR analytics and to consistently add value to existing HR systems on both the contextual and practical levels. As emphasized earlier, we believe that much of this potential added value lies within the empirical and conceptual research in HR analytics. Therefore, fertile avenues for future research contributions should focus on both empirical and conceptual studies in HR analytics since these are the noticeable directions where the highest return rates are expected. Enhancing and developing empirical and conceptual knowledge in HR analytics and state-of-the-art tools may serve as adequate future contributions to the field of HR analytics.

If decision makers have ROI information to guide the adoption of HR analytics, a more focused and systematic research approach must evolve. Macro-organizational theoretical frameworks can add to the ROI-based approach by proposing different perspectives. For example, the contextual approach (Johns, 2006) may offer a basis for understanding the organizational context in which specific ROI is to be found in line with new scholarly insights in the HR analytics field. Additionally, further theory development may integrate the LAMP framework (Boudreau and Ramstad, 2006) with contextual elements (Johns, 2006), which may also offer an appealing framework for testable hypotheses. Future rigorously constructed research questions may focus on the various tasks of HR from a holistic point of view while challenging the recommended analytical approach presented in this paper. Finally, future research may propose a new methodology that differs from the ROI-based approach to systematically analyze the scholarly and practical field of HR analytics.

## Contributions: ROI model to guide the way forward

This section answers *RQ3*. It also reiterates the study's contributions and emphasizes the ROI approach as a model to guide the way forward in HR analytics research.

HR analytics is a fascinating, dynamic discipline (Levenson, 2011; Huselid, 2015). The dynamic role of HR analytics enables it to focus both on the operational tasks of HR functions and on organizations' long-term and strategic objectives. The growing field of HR analytics enables HR scholars and executives to execute a broader approach, which may increase their strategic contribution (Kazakovs *et al.*, 2015; Strohmeier, 2018). By taking

advantage of the enriched environment of HR analytics, HR can position itself as an essential, value-adding department in an organization (Hou, 2016). Data analytics in general, and more specifically in the field of HR, can aid in making informed decisions based on knowledge extracted from the available data and options (Sharma *et al.*, 2015).

Our unique synthesis of the literature underscores the importance of two important fields within the HR analytics research, namely, the empirical and the conceptual research. Our observations that we analyze and discuss in this study offer an ROI-based perspective to the HR analytics field. Moreover, the ROI-based approach on the topic of HR analytics presented in this paper provides theoretical and practical contributions. As a result, it provides a model to guide the way forward in HR analytics research. From a theoretical perspective, this paper assists data analytics and HR scholars who may find the ROI-based framework useful when fine-tuning their theoretical contributions in the field. From a practical perspective, this paper clarifies the dilemma associated with the HR analytics field and assists practitioners regarding the expected ROI of HR analytics initiatives within their organizations.

In conducting our ROI-based review of the literature on HR analytics by integrating the analysis above, several major conclusions emerge. First, there is a need for more scientific empirical research in HR analytics. Focusing on the development of such research might increase the potential for action-oriented, data-driven research, which can assist HR and management professionals. Second, as with the previous conclusion, and in light of notable deficiencies in the existing HR analytics literature (Boudreau and Ramstad, 2006; Marler and Boudreau, 2017), there emerges a need to focus on an ROI-based approach, which is our proposed model to guide the way forward.

We have taken a step toward systematically explaining some notable questions in the HR analytics field. Not only does a focus on an ROI-based approach improve the adoption of HR analytics as an important field in HR, but the context in which it is being adopted and implemented also matters, both practically and theoretically speaking.

## Notes

1. Databases included for the review: Business Source Premier; EconLit; Regional Business News; SocINDEX; ERIC; Library, Information Science and Technology Abstracts; Historical Abstracts; Communication and Mass Media Complete; GreenFILE; Political Science Complete; PsycARTICLES.

2. Additional search terms included: "workforce analytics", "people analytics", and "human capital analytics".

3. The literature on performance management analytics focuses on business, sales and individual performance. This review includes the last.

## References

Aral, S., Brynjolfsson, E. and Wu, L. (2012), "Three-way complementarities: Performance pay, human resource analytics and information technology", *Management Science*, Vol. 58 No. 5, pp. 913-931.

Bamber, G.J., Bartram, T. and Stanton, P. (2017), "HRM and workplace innovations: formulating research questions", *Personnel Review*, Vol. 46 No. 7, pp. 1216-1227.

Baron, A. (2011), "Measuring human capital", *Strategic HR Review*, Vol. 10 No. 2, pp. 30-35.

Bassi, L. (2011), "Raging debates in HR analytics", *People and Strategy*, Vol. 34 No. 2, p. 14.

Becker, G.S. (2009), *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, University of Chicago press, Chicago.

Bondarouk, T. and Ruël, H. (2013), "The strategic value of e-HRM: results from an exploratory study in a governmental organization", *The International Journal of Human Resources Management*, Vol. 24 No. 2, pp. 391-414.

Bontis, N. and Fitz-enz, J. (2002), "Intellectual capital ROI: a causal map of human capital antecedents and consequents", *Journal of Intellectual Capital*, Vol. 3 No. 3, pp. 223-247.

Bose, M.T. (2015), "Growing impact of human capital analytics on modern economy: a generic overview", *Journal of Business and Management*, Vol. 17 No. 1, pp. 11-13.

Boudreau, J. (2014), "Will HR's grasp match its reach? An estimable profession grown complacent and outpaced", *Organizational Dynamics*, Vol. 43 No. 3, pp. 189-197.

Boudreau, J.W. (2006), "Talentship and HR measurement and analysis: from ROI to strategic organizational change", *People and Strategy*, Vol. 29 No. 1, pp. 25-33.

Boudreau, J.W. and Ramstad, P.M. (2006), "Talentship and HR measurement and analysis: from ROI to strategic organizational change", *People and Strategy*, Vol. 29 No. 1, pp. 25-33.

Boyd, N. and Gessner, B. (2013), "Human resources performance metrics: methods and processes that demonstrate you care", *Cross Cultural Management: An International Journal*, Vol. 20 No. 2, pp. 251-273.

Briggs, H. (2011), "How to use a data-focused approach to embed good HR practices", *Strategic HR Review*, Vol. 10 No. 2, pp. 18-23.

Bukhari, H., Andreatta, P., Goldiez, B. and Rabelo, L. (2017), "A framework for determining the return on investment of simulation-based training in health care", *Inquiry: The Journal of Health Care Organization, Provision, and Financing*, Vol. 37 No. 2, pp. 679-712, 34.

Burdon, M. and Harpur, P.D. (2014), "Re-conceptualising privacy and discrimination in an age of talent analytics", *University of New South Wales Law Journal*, Vol. 37 No. 2, p. 679.

Carlson, K.D. and Kavanagh, M.J. (2011), "HR metrics and workforce analytics", Human resource information systems: Basics applications and future directions, pp. 150-174.

Chamorro-Premuzic, T., Akhtar, R., Winsborough, D. and Sherman, R.A. (2017), "The datafication of talent: how technology is advancing the science of human potential at work", *Current Opinion in Behavioral Sciences*, No. 18, pp. 13-16.

Charlton, K. and Osterweil, C. (2005), "Measuring return on investment in executive education: a quest to meet client needs or pursuit of the holy grail?", *Ashridge Journal*, pp. 6-13.

Chong, D. and Shi, H. (2015), "Big data analytics: a literature review", *Journal of Management Analytics*, Vol. 2 No. 3, pp. 175-201.

Church, A.H., Ginther, N.M., Levine, R. and Rotolo, C.T. (2015), "Going beyond the fix: taking performance management to the next level", *Industrial and Organizational Psychology*, Vol. 8 No. 1, pp. 121-129.

Cuozzo, B., Dumay, J., Palmaccio, M. and Lombardi, R. (2017), "Intellectual capital disclosure: a structured literature review", *Journal of Intellectual Capital*, Vol. 18 No. 1, pp. 9-28.

Davenport, T.H. (2006), "Competing on analytics", *Harvard Business Review*, Vol. 84 No. 1, pp. 98-107.

Davenport, T.H., Harris, J. and Shapiro, J. (2010), "Competing on talent analytics", *Harvard Business Review*, Vol. 88 No. 10, pp. 52-58.

Del Angizan, S., Navid, B.J. and Soratiyan, G. (2014), "Modeling the impact of data integration on the functional elements of human resources management", *International Research Journal of Applied and Basic Sciences*, Vol. 8 No. 7, pp. 926-932.

Delbridge, R. and Barton, H. (2002), "Organizing for continuous improvement: structures and roles in automotive components plants", *International Journal of Operations & Production Management*, Vol. 22 No. 6, pp. 680-692.

Ding, C. and Zhang, J. (2014), "Diagnosis for effectiveness: performance assessment from a diagnostic measurement perspective with big data", *International Journal of Business and Social Research*, Vol. 4 No. 6, pp. 1-11.

Dulebohn, J.H. and Johnson, R.D. (2013), "Human resources metrics and decision support: a classification framework", *Human Resources Management Review*, Vol. 23 No. 1, pp. 71-83.

Fernández-Delgado, M., Cernadas, E., Barro, S. and Amorim, D. (2014), "Do we need hundreds of classifiers to solve real world classification problems?", *The Journal of Machine Learning Research*, Vol. 15 No. 1, pp. 3133-3181.

Fink, A.A. (2010), "New trends in human capital research and analytics", *People and Strategy*, Vol. 33 No. 2, p. 14.

Fitz-enz, J. (2000), *The ROI of Human Capital*, Amacom, New York, NY.

Fitz-enz, J. (2009), "Predicting people: from metrics to analytics", *Employment Relations Today*, Vol. 36 No. 3, pp. 1-11.

Frigo, M.L., Ubelhart, M.C., Eccles, R.G. and Youmans, T. (2015), "CFO+ CHRO = Power pair", *Strategic Finance*, Vol. 97 No. 5, p. 26.

Fulmer, I.S. and Ployhart, R.E. (2014), "Our most important asset: a multidisciplinary/multilevel review of human capital valuation for research and practice", *Journal of Management*, Vol. 40 No. 1, pp. 161-192.

Garcea, N., Isherwood, S. and Linley, A. (2011), "Do strengths measure up?", *Strategic HR Review*, Vol. 10 No. 2, pp. 5-11.

Ghosh, A. and Sengupta, T. (2016), in Fitz-enz, J. and Mattox, J. II (Eds), *Predictive Analytics for Human Resources*, Vol. 2014, John Wiley and Sons, Hoboken, NJ, pp. 1-149, available at: https://books.google.co.il/books?hl=en&lr=&id=PunoAwAAQBAJ&oi=fnd&pg=PP13&dq=Predictive +Analytics+for+Human+Resources,&ots=WnHRuRhoop&sig=3CF7-D07ufaf7NNxeTk_ kVkUIx4&redir_esc=y#v=onepage&q=Predictive%20Analytics%20for%20Human%20 Resources%2C&f=false

Gilbert, B.A., McDougall, P.P. and Audretsch, D.B. (2008), "Clusters, knowledge spillovers and new venture performance: an empirical examination", *Journal of Business Venturing*, Vol. 23 No. 4, pp. 405-422.

Guszcza, J. and Richardson, B. (2014), "Two dogmas of big data: understanding the power of analytics for predicting human behavior", *Deloitte Review*, Vol. 15, pp. 161-175.

Handa, D. and Garima, A. (2014), "Human resources (HR) analytics: emerging trends in HRM", *International Journal of Research in Commerce & Management*, Vol. 5 No. 6, pp. 59-62.

Harris, J.G., Craig, E. and Light, D.A. (2011), "Talent and analytics: new approaches, higher Roi", *Journal of Business Strategy*, Vol. 32 No. 6, pp. 4-13.

Harrison, J.L. and Getz, C. (2015), "Farm size and job quality: mixed-methods studies of hired farm work in California and Wisconsin", *Agriculture and Human Values*, Vol. 32 No. 4, pp. 617-634.

Hausknecht, J.P. (2014), "Collective data on collective turnover: what factors most affect turnover rates?", CAHRS Research Link No. 4, ILR School, Center for Advanced Human resources Studies, Cornell University, Ithaca, NY.

Heuvel, S. and Bondarouk, T. (2016), "The rise (and fall) of HR analytics: a study into the future applications, value, structure, and system support", *Article submitted for the 2nd HR Division International Conference*, Sidney, February 20-22.

Holsapple, C., Lee-Post, A. and Pakath, R. (2014), "A unified foundation for business analytics", *Decision Support Systems*, Vol. 64, pp. 130-141.

Hota, J. and Ghosh, D. (2013), "Workforce analytics approach: an emerging trend of workforce management", *AIMS International Journal*, Vol. 7 No. 3, pp. 167-179.

Hou, C.K. (2016), "Using the balanced scorecard in assessing the impact of BI system usage on organizational performance: an empirical study of Taiwan's semiconductor industry", *Information Development*, Vol. 32 No. 5, pp. 1545-1569.

Huselid, M.A. and Becker, B.E. (2011), "Bridging micro and macro domains: workforce differentiation and strategic human resources management", *Journal of Management*, Vol. 37 No. 2, pp. 421-428.

Huselid, M.A. (2015), "The rise of HR: wisdom from 73 thought leaders", in Ulrich, D., Schiemann, W.A. and Sartain, L. (Eds), HR Certification Institute Publisher, pp. 309-315.

Ingham, J. (2011), "Using a human capital scorecard as a framework for analytical discovery", *Strategic HR Review*, Vol. 10 No. 2, pp. 24-29.

Johns, G. (2006), "The essential impact of context on organizational behavior", *Academy of Management Review*, Vol. 31 No. 2, pp. 386-408.

Kandogan, E., Balakrishnan, A., Haber, E.M. and Pierce, J.S. (2014), "From data to insight: work practices of analysts in the enterprise", *IEEE Computer Graphics and Applications*, Vol. 34 No. 5, pp. 42-50.

Kapoor, B. (2010), "Business intelligence and its use for human resources management", *The Journal of Human resources and Adult Learning*, Vol. 6 No. 2, pp. 21-30.

Kapoor, B. (2011), "Impact of globalization on human resources management", *Journal of International Management Studies*, Vol. 6 No. 1.

Kapoor, B. and Sherif, J. (2012), "Human resources in an enriched environment of business intelligence", *Kybernetes*, Vol. 41 No. 10, pp. 1625-1637.

Karasek, A. (2015), "Information technologies in human resources management-selected examples", *World Academy of Science, Engineering and Technology, International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*, Vol. 9 No. 6, pp. 1837-1842.

Kazakovs, M., Verdina, A. and Arhipova, I. (2015), "Automation of human resources development planning", *Procedia Computer Science*, Vol. 77, pp. 234-239.

Korpela, K. (2015), "Improving cyber security awareness and training programs with data analytics", *Information Security Journal: A Global Perspective*, Vol. 24 Nos 1-3, pp. 72-77.

Lawler, E.E. III, Levenson, A. and Boudreau, J.W. (2004), "HR metrics and analytics–uses and impacts", *Human resources Planning Journal*, Vol. 27 No. 4, pp. 27-35.

Lazear, E.P. (2000), "The future of personnel economics", *The Economic Journal*, Vol. 110 No. 467, pp. 611-639.

Levenson, A. (2005), "Harnessing the power of HR analytics", *Strategic HR Review*, Vol. 4 No. 3, pp. 28-31.

Levenson, A. (2011), "Using targeted analytics to improve talent decisions", *People and Strategy*, Vol. 34 No. 2, pp. 1-7.

Levenson, A. (2015), *Strategic Analytics: Advancing Strategy Execution and Organizational Effectiveness*, Berrett-Koehler Publishers.

Lipkin, J. (2015), "Sieving through the data to find the person: HR's imperative for balancing big data with people centricity", Electronic version, Cornell HR Review, ILR School, Cornell University, September 4, available at: http://digitalcommons.ilr.cornell.edu/chrr/84 (accessed April 10, 2016).

McIver, D., Lengnick-Hall, M.L. and Lengnick-Hall, C.A. (2018), "A strategic approach to workforce analytics: integrating science and agility", *Business Horizons*.

Macan, T., Lemming, M.R. and Foster, J.L. (2012), "Utility analysis: do estimates and format matter?", *Personnel Review*, Vol. 42 No. 1, pp. 105-126.

Marler, J.H. and Boudreau, J.W. (2017), "An evidence-based review of HR analytics", *The International Journal of Human Resources Management*, Vol. 28 No. 1, pp. 3-26.

Mayo, A. (2006), "Measuring and reporting – the fundamental requirement for data: what's the future for human capital?", *What's the Future for Human Capital?*, pp. 31-40.

Minbaeva, D. and Collings, D.G. (2013), "Seven myths of global talent management", *The International Journal of Human resources Management*, Vol. 24 No. 9, pp. 1762-1776.

Momin, W.Y.M. and Mishra, K. (2015), "HR analytics as a strategic workforce planning", *International Journal of Advanced Research*, Vol. 1 No. 4, pp. 258-260.

Mondore, S., Douthitt, S. and Carson, M. (2011), "Maximizing the impact and effectiveness of HR analytics to drive business outcomes", *People and Strategy*, Vol. 34 No. 2, pp. 20-27.

Newcomer, K. and Brass, C.T. (2015), "Forging a strategic and comprehensive approach to evaluation within public and nonprofit organizations: integrating measurement and analytics within evaluation", *American Journal of Evaluation*, Vol. 37 No. 1, pp. 80-99.

Pape, T. (2016), "Prioritizing data items for business analytics: framework and application to human resources", *European Journal of Operational Research*, Vol. 252 No. 2, pp. 687-698.

Perrin, B. (2015), "Bringing accountability up to date with the realities of public sector management in the 21st century", *Canadian Public Administration*, Vol. 58 No. 1, pp. 183-203.

Philips, J.J. (2012), *Return On Investment in Training and Performance Improvement Programs*, Routledge.

Ramamurthy, K.N., Singh, M., Yu, Y., Aspis, J., Iames, M., Peran, M. and Held, Q.S. (2015), "A talent management tool using propensity to leave analytics", *IEEE International Conference on Data Science and Advanced Analytics*, pp. 1-10.

Rasmussen, T. and Ulrich, D. (2015), "Learning from practice: how HR analytics avoids being a management fad", *Organizational Dynamics*, Vol. 44 No. 3, pp. 236-242.

Rivera, R.J. and Smolders, F. (2013), "Operational workforce planning is quietly transforming HR", *Workforce Solutions Review*, April/May.

Russell, C. and Bennett, N. (2015), "Big data and talent management: using hard data to make the soft stuff easy", *Business Horizons*, Vol. 58 No. 3, pp. 237-242.

Ryan, J. and Herleman, H. (2015), "A big data platform for workforce analytics. In Big Data at Work", Routledge, pp. 33-56.

Ryan, J. and Herleman, H. (2016), "A big data platform for workforce analytics. Big data at work", *The Data Science Revolution and Organizational Psychology*, p. 19.

Schläfke, M., Silvi, R. and Möller, K. (2012), "A framework for business analytics in performance management", *International Journal of Productivity and Performance Management*, Vol. 62 No. 1, pp. 110-122.

Sharif, Y.M. (2015), "Research development in human resources analytics in Malaysia", *Full Paper Proceeding*, Vol. 1, pp. 109-113.

Sharma, R., Anand, A. and Coltman, T. (2015), "Creating business value from digital data streams: the role of organizational interventions", *MIS Quarterly Executive*, available at: https://scholar.google.co.il/scholar?hl=en&as_sdt=0%2C5&q=Sharma%2C+R.%2C+Anand%2C+A.+and+Coltman%2C+T.+%282015%29%2C+%E2%80%9CCreating+business+value+from+digital+data+streams%3A+the+role+of+organizational+interventions%E2%80%9D%2C+MIS+Quarterly+Executive&btnG=

Short, J. (2009), "The art of writing a review article", *Journal of Management*, Vol. 35 No. 6, pp. 1312-1317.

Singh, N.K. and Roushan, R.K.S. (2013), "Data analytics and decision support in the context of ERP and beyond for giving CSIR a competitive advantage – two case studies from HR (Human resources) and MM (Materials Management) modules", pp. 1-11.

Snell, A. (2011), "Developing talent intelligence to boost business performance", *Strategic HR Review*, Vol. 10 No. 2, pp. 12-17.

Sparrow, P. (2012), "Globalising the international mobility function: the role of emerging markets, flexibility and strategic delivery models", *The International Journal of Human resources Management*, Vol. 23 No. 12, pp. 2404-2427.

Srinivasan, V. and Chandwani, R. (2014), "HRM innovations in rapid growth contexts: the healthcare sector in India", *The International Journal of Human resources Management*, Vol. 25 No. 10, pp. 1505-1525.

Steffi, R.S., Baranikumar, D. and Prakash, K. (2015), "Adding the shade of green to big data analytics", *International Journal of Informative & Futuristic Research*, Vol. 2 No. 10, pp. 3835-3841.

Stone, D.L. and Dulebohn, J.H. (2013), "Emerging issues in theory and research on electronic human resources management (eHRM)", *Human resources Management Review*, Vol. 23 No. 1, pp. 1-5.

Stone, D.L., Deadrick, D.L., Lukaszewski, K.M. and Johnson, R. (2015), "The influence of technology on the future of human resources management", *Human resources Management Review*, Vol. 25 No. 2, pp. 216-231.

Strohmeier, S. (2018), "Smart HRM – a Delphi study on the application and consequences of the Internet of things in human resource management", *The International Journal of Human Resource Management*, pp. 1-30.

Ulrich, D. (2016), "HR at a crossroads", *Asia Pacific Journal of Human Resources*, Vol. 54 No. 2, pp. 148-164, doi: 10.1111/1744-7941.12104.

Ulrich, D. and Dulebohn, J.H. (2015), "Are we there yet? What's next for HR?", *Human Resources Management Review*, Vol. 25 No. 2, pp. 188-204.

Van Barneveld, A., Arnold, K.E. and Campbell, J.P. (2012), "Analytics in higher education: establishing a common language", *EDUCAUSE Learning Initiative*, Vol. 1 No. 1, pp. 1-11.

Varshney, K.R., Chenthamarakshan, V., Fancher, S.W., Wang, J., Fang, D. and Mojsilović, A. (2014), "Predicting employee expertise for talent management in the enterprise", *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining ACM, August*, pp. 1729-1738.

Vihari, N.S. and Rao, M.K. (2013), "Analytics as a predictor for strategic and sustainable human resources function: an integrative literature review", doctoral dissertation, IIT Roorkee, Roorkee.

Webster, J. and Watson, R.T. (2002), "Analyzing the past to prepare for the future: writing a literature review", *MIS Quarterly*, Vol. 26 No. 2, pp. xiii-xxiii.

Welbourne, T.M. (2015), "Data-driven storytelling: the missing link in HR data analytics", *Employment Relations Today*, Vol. 41 No. 4, pp. 27-33.

Wiblen, S., Grant, D. and Dery, K. (2010), "Transitioning to a new HRIS: the reshaping of human resources and information technology talent", *Journal of Electronic Commerce Research*, Vol. 11 No. 4, pp. 251-267.

Xiu, L., Liang, X., Chen, Z. and Xu, W. (2017), "Strategic flexibility, innovative HR practices, and firm performance: a moderated mediation model", *Personnel Review*, Vol. 46 No. 7, pp. 1335-1357.

Yadav, R. (2014), "Managing global HR issues in today's challenging times", available at: http://works.bepress.com/rakesh_yadav/8

Zang, S. and Ye, M. (2015), "Human resources management in the Era of big data", *Journal of Human Resources and Sustainability Studies*, Vol. 3 No. 1, pp. 41-45.

Zhao, G. and Carlton, D. (2015), "Forecast competency migration by a methodology of competency analytics", *Open Journal of Social Sciences*, Vol. 3 No. 11, pp. 16-22.

**Further reading**

Aral, S., Brynjolfsson, E. and Wu, L. (2010), "Three-way complementarities: performance pay, HR analytics and information technology", *Management Science* (forthcoming).

(The Appendix follows overleaf.)

**Appendix**

| Code | Cluster/category | No. of articles | % | Example references |
|------|-----------------|-----------------|---|--------------------|
| E | Empirical | 14 | 17 | Aral *et al.* (2012), Bondarouk and Ruël (2013), Kandogan *et al.* (2014), |
| E1 | Quantitative | 4 | 30 | Harrison and Getz (2015), Hou (2016), Ramamurthy *et al.* (2015) |
| E2 | Qualitative | 6 | 40 | |
| E3 | Mixed methods | 4 | 30 | |
| C | Conceptual | 36 | 45 | Davenport *et al.* (2010), Kapoor (2010), Wiblen *et al.* (2010), Harris |
| C1 | Management tools | 10 | 28 | *et al.* (2011), Snell (2011), Minbaeva and Collings (2013), Pape (2016) |
| C2 | General | 18 | 50 | |
| C3 | Specific | 8 | 22 | |
| CB | Case based | 11 | 14 | Davenport (2006), Fitz-enz (2000), Briggs (2011), Mondore *et al.* |
| CB1 | General | 4 | 36 | (2011), Boyd and Gessner (2013), Singh and Roushan (2013), |
| CB2 | Specific | 7 | 64 | Varshney *et al.* (2014), Frigo *et al.* (2015), Russell and Bennett (2015) |
| T | Technical | 19 | 24 | Karasek (2015), Kazakovs *et al.* (2015), Korpela (2015), Momin and |
| T1 | Informative | 9 | 47 | Mishra (2015), Perrin (2015), Stone *et al.* (2015), Ulrich and Dulebohn |
| T2 | Specific | 5 | 26 | (2015), Welbourne (2015), Ryan and Herleman (2016) |
| T3 | Literature review | 3 | 16 | |
| T4 | HRA trends | 2 | 11 | |

**Table AI.**
Classification system for analyzing HR analytics articles

**About the author**
Dr Hila Chalutz Ben-Gal is an Assistant Professor at the Department of Industrial Engineering and Management, Afeka College of Engineering in Tel Aviv, Israel. She studies the changing nature of organizations in the digital era, with a focus on organizational design and the future of work. She conducts field research and consulting in a variety of organizational settings; some of her current projects include HR analytics and turnover forecasting, career moves detection in online labor markets and trust dimensions. During 2015-2017 she was a Visiting Scholar at the University of San Francisco and SJSU in California, USA. Dr Hila Chalutz Ben-Gal can be contacted at: hilab@afeka.ac.il