The HR analytics cycle: a seven-step process for building evidence-based and ethical HR analytics capabilities

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Abstract

Purpose – The purpose of the paper is to explore the meaning of Human Resources (HR) analytics and introduce the HR analytics cycle as a proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives.

Design/methodology/approach – Conceptual review of the current state and meaning of HR analytics. Using the HR analytics cycle as a framework, the authors describe a seven-step process for building evidence-based and ethical HR analytics capabilities.

Findings – HR analytics is a nascent discipline and there are a multitude of monikers and competing definitions. With few exceptions, these definitions lack emphasis on evidence-based practice (i.e. the use of scientific research findings in adopting HR practices), ethical practice (i.e. ethically gathering and using HR data and insights) and the role of broader HR research and experimentation. More importantly, there are no practical models or frameworks available to help guide HR leaders and practitioners in doing HR analytics work.

Practical implications – The HR analytics cycle encompasses a broader range of HR analytics practices and data sources including HR research and experimentation in the context of social, behavioral and organizational science.

Originality/value – This paper introduces the HR analytics cycle as a practical seven-step approach for making HR analytics work in organizations.

Keywords HR analytics, HR strategy, Evidence-based practice, Ethics, Workforce decisions

Paper type Conceptual paper

The human resource (HR) profession is abuzz with talk among scholars, practitioners, thought leaders and technology vendors of the potential of HR analytics – or what is synonymously referred to as workforce, talent, human capital or people analytics. Despite the hype and flurry of interest in HR analytics (e.g. Bassi, 2011; Boudreau, 2017; Boudreau and Casio, 2017; Falletta, 2014; Guzzo *et al.*, 2015; Strohmeier and Piazza, 2015; Huselid, 2018; Marler and Boudreau, 2017), there is little agreement on the meaning of HR analytics; nor do we know much yet about the processes and capabilities through which HR analytics enables HR strategy, smarter workforce decisions or individual and organizational performance outcomes.

In this article, we briefly discuss the meaning of HR analytics, share several recent definitions from extant literature and attempt to bring these definitions together in a meaningful way. We also introduce a process approach to build evidence-based and ethical

HR research and analytics capabilities – namely the *HR analytics cycle*. Moreover, we present the *HR strategy axis* as a simple and complementary framework for organizational leaders to think through key strategic HR choices in terms of HR strategy creation and competitive advantage. After all, the key outcomes associated with HR analytics work include HR strategy creation, smarter HR decisions and the adoption of evidence-based HR practices, to name a few. Lastly, we share implications and guidelines for practice for establishing an *HR analytics and strategy* function in organizations.

The meaning of HR analytics

HR analytics means different things to different people. For some, HR analytics simply refers to descriptive HR metrics while for others it means sophisticated predictive modeling procedures (Bassi, 2011). More recently, Levenson and Fink (2017) suggest that HR analytics has unfortunately become synonymous with anything related to numbers, data collection and measurement in the context of HR.

In 2014, Falletta conducted a study that explored the meaning of HR analytics by those who perform HR research and analytics work in 220 distinct Fortune 1,000 firms. Respondents were asked to rank order statements that best described what HR analytics means (see Table 1).

In addition to the multitude of monikers and descriptors used to characterize HR analytics, several competing definitions (see Table 2) have emerged in the literature. Some of these definitions refer to metrics, external benchmarks, decision-making and value creation while others emphasize the role of technology, advanced statistical analysis and data visualization. As early as 2004, Lawler, Levenson and Boudreau distinguished between HR metrics and HR analytics. More recently, Marler and Boudreau (2017) performed an evidence-based review using an integrative synthesis approach and made the case that HR analytics goes beyond HR metrics and uses a more sophisticated analytical tool set to inform HR strategy and evidence-based decision-making.

Interestingly, these definitions describe HR analytics as a process (McIver *et al.*, 2018; Mondare *et al.*, 2011). Using a process perspective, HR analytics can be thought of as both a systematic approach and journey (see Figure 1, *the HR analytics cycle*). As mentioned, HR analytics is a nascent discipline in terms of the scholarly literature and these definitions reflect the authors' disciplinary backgrounds and serve to mark the boundaries of the field.

Rank	The meaning of HR analytics
1	Making better human capital decisions by using the best available scientific evidence and organizational facts with respect to "evidence-based HR"
2	Moving beyond descriptive HR metrics (i.e. lagging indicators – something that has already occurred) to predictive HR metrics (i.e. leading indicators – something that may occur in the future)
3	Segmenting the workforce and using statistical analyses and predictive modeling procedures to identify key drivers (i.e. factors and variables) and cause and effect relationships that enable and inhibit important business outcomes
4	Using advanced statistical analyses, predictive modeling procedures and human capital investment analysis to forecast and extrapolate "what-if" scenarios for decision-making
5	Standard tracking, reporting and benchmarking of HR metrics
6	Ad-hoc querying, drill-down and reporting of HR metrics and indicators through an HRIS and/or HR scorecard/dashboard reporting tool
7	Operations research and management science methods for HR optimization (i.e. what's the best that can happen if we do XYZ or what is the optimal solution for a specific human capital problem?)

Table 1.
The meaning of HR analytics (rank order)

Source(s): Adapted from Falletta (2014)

Authors	Definition
Lawler *et al.* (2004)	HR analytics (is a process) ...to understand the impact of HR practices and policies on organizational performance. Statistical techniques and experimental approaches can be used to tease out the causal relationship between particular HR practices and such performance metrics as customer satisfaction, sales per employee and, of course, the profitability of particular business activities (p. 29)
Bassi (2011)	HR analytics is an evidence-based approach for making better decisions on the people side of the business; it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modeling (p. 16)
Mondare *et al.* (2011)	HR analytics (is defined) as demonstrating the direct impact of people data on important business outcomes (p 21)
Strohmeier (2015)	HR intelligence and analytics. . . refer to the overall process of information technology-based provision of management information for the domain (of) human resources. (p. 3)
Economist Intelligence Unit and SHRM Foundation (2016)	Workforce analytics uses statistical models and other techniques to analyze worker-related data, allowing leaders to improve the effectiveness of people-related decision-making and human resources strategy (p. 10)
Marler and Boudreau (2017)	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 (p. 15)
van den Heuvel and Bondarouk (2017)	HR analytics is the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions (p. 129)
CIPD (2018)	HR analytics, also known as people analytics, is the use of people data in analytical processes to solve business problems. HR analytics uses both people data, collected by HR systems and business information. At its core, HR analytics enables HR practitioners and employers to gain insights into their workforce, HR policies and practices, with a focus on the human capital element of the workforce, and can ultimately inform more evidence-based decision-making (Source: CIPD Website)
Tursunbayeva *et al.* (2018)	People analytics is an area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualization tools for generating actionable insights about workforce dynamics, human capital and individual and team performance that can be used strategically to optimize organizational effectiveness, efficiency and outcomes and improve employee experience (p. 231)
Huselid (2018)	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?) (p. 680)
Falletta and Combs, (in this paper)	HR analytics is a proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives

Note(s): Countless definitions of HR analytics can be found in books, reports, white papers, as well as on various websites and blogs. The definitions included in this review were limited to those found in the academic literature and on the websites of *CIPD* and *SHRM* – which are the two largest HR professional associations in the world
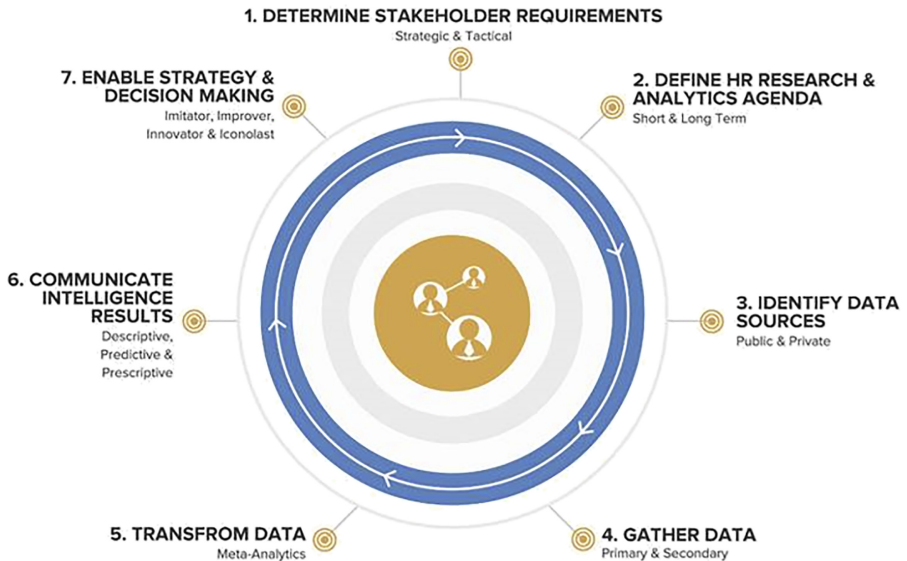
Table 2.
HR analytics definitions

With few exceptions, the definitions lack emphasis on evidence-based practice (i.e. the use of scientific research findings in adopting HR practices), ethical practice (i.e. ethically gathering and using HR data and insights) and the role of broader HR research and experimentation as part of an overall HR analytics agenda (i.e. internal HR research or partnership research conducted in the context of social, behavioral and organizational sciences).

Rethinking and redefining HR analytics

Leading organizations are performing a broad range of HR research and analytics practices that extend beyond simple metrics, scorecards and SaaS-based human capital technology platforms (Falletta, 2014; Fink, 2010; Schiemann *et al.*, 2018). Levenson and Fink (2017) assert that the HR analytics tent is too big in terms of potential data sources and the dizzying array of possible measurement activities. They suggest that the discipline needs to be more strategically focused on generating meaningful insights in support of the business strategy and execution (Levenson and Fink, 2017). We agree that HR analytics should play a central role in strategy execution and decision-making. Angrave *et al.* (2016) argue that HR analytics should facilitate active research and experimentation to identify the underlying causes of individual and organizational performance and other important outcomes. Hence, we shouldn't restrict our HR analytics capabilities and priorities to a handful of projects that are focused on a predetermined strategic mandate or human capital decisions that were already made. Ideally, insights derived from a variety of HR research and analytics practices should inform an organization's HR strategy and critical workforce decisions and subsequently align to and support the execution of the overall business strategy.

With this aim in mind, we offer a definition that explicitly includes the notion of evidence-based and ethical HR analytics as well as the role of broader HR research and experimentation:

> *HR analytics is a proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives.*

The HR analytics cycle

There has been recent and increasing interest on building HR analytics capabilities for purposes of strategy alignment and execution, organizational effectiveness and strategic competitive advantage (Boudreau, 2015; Levenson, 2018; Levenson and Fink, 2017; Minbaeva, 2018). We approach this challenge by introducing the *HR analytics cycle* – as a proactive and systematic approach for building HR analytics capabilities. In our view, HR analytics enables human capital decisions that are based on insightful HR analytics, which are largely predictive and supported by a synthesis of the best available scientific evidence with respect to evidence-based HR. The notion of evidence-based HR is consistent with the aims of HR analytics in terms of enabling fact-based and data-driven workforce decisions that are supported by a synthesis of (1) scientific literature (i.e. theoretical and empirical studies), (2) internal organizational data and facts, (3) practitioners' professional expertise and judgment and (4) stakeholders' values, concerns and expectations (Barends and Rousseau, 2018; Briner and Barends, 2016).

The *HR analytics cycle* involves seven steps (refer to Figure 1) to help organizations develop HR research and analytics capabilities (Falletta, 2014). More importantly, it serves as a proactive and systematic process for establishing a comprehensive portfolio of strategic HR analytics practices, projects and priorities that enable HR strategy, evidence-based decision-making and the execution of the overall business strategy.

Step 1: determine stakeholder requirements

Determining stakeholder requirements is vital to the overall success of any HR research and analytics initiative. It is much more than meeting with a few influential or vocal stakeholders each year to formulate the annual HR research and analytics agenda. It is about establishing and cultivating a partnership and becoming a legitimate player by adding value to the business. With respect to the *HR analytics cycle*, an ongoing and proactive partnership with key stakeholders is an essential role to ensure trust and upfront legitimacy to obtain an accurate picture of the most pressing organizational problems.

Who are the stakeholders? A stakeholder in the broadest sense is anyone who is directly or indirectly affected by HR analytics work. Stakeholders in the context of HR analytics include executives, line managers, senior HR leaders, HR business partners, employees and, in some cases, human capital technology vendors. Each stakeholder has a different perspective and set of concerns regarding HR analytics practices and activities. Whereas line managers are usually most interested in the data visualization and reporting of key metrics and analytical insights, executives and senior HR leaders are generally more interested in how HR analytics enables HR strategy and execution, critical workforce decisions and other important business outcomes.

During this step, many interesting questions are likely to arise. Carl Sagan, in his book, *The Demon-Haunted World: Science as a Candle in the Dark*, explains "There are naive questions, tedious questions, ill-phrased questions, questions put after inadequate self-criticism. But every question is a cry to understand the world. There is no such thing as a dumb question" (Sagan, 1996, p. 323). While this is a very popular axiom and largely true, we've encountered a fair share of unusual and potentially unethical questions by some well-intended stakeholders in our work. To be fair, well-intended stakeholders are also bombarded with the latest management fads and trends (Barends and Rousseau, 2018; Rice and Boudreau, 2015). Hence, those leading HR analytics in organizations have an important role and responsibility in assisting stakeholders with framing HR research and analytics questions that are realistic, measurable, valued added and more importantly – evidence-based and ethical. Determining stakeholders' requirements is important to formulate and frame HR research and analytics questions, identify strategic and tactical

HR research and analytics priorities, secure stakeholder commitment and support and provide communication on the ongoing progress of key HR research and analytics initiatives.

Step 2: define HR research and analytics agenda
Once the stakeholder needs and expectations are identified, it is time to define the HR research and analytics agenda. An HR research and analytics agenda may be long term or short term. The constantly evolving nature of business and the "future of work" are redefining what is considered long term versus short term. In our age of on-demand data aggregation and visualization, algorithms, artificial intelligence and automation – long term is no longer 3–5 years out. One year is considered the long-term norm currently in virtually all industries. Conversely, short-term requirements tend to coincide with the organization's quarterly results, sometimes monthly. It important to note that short term doesn't necessarily mean tactical or reactive, nor is long term equated with strategic. Short-term and long-term research requirements can be both strategic and tactical in nature.

Tips for establishing the HR analytics and research agenda

(1) Organize the general stakeholder requirements by theme or major topic;

(2) Pose broad research questions for each theme or major topic and use stakeholders' language and terminology to the extent possible;

(3) Under each of the broad research questions, begin generating more targeted questions and hypotheses that lend themselves to measurement and consider the ethicality of the questions and hypotheses;

(4) Identify both the long-term and short-term requirements of the overall HR research and analytics agenda;

(5) Share the HR research and analytics agenda with key stakeholders and go through an iterative process of refinement; and

(6) Lastly, strive for a balanced HR research and analytics agenda in terms of reactive and proactive work. A relatively recent HR analytics study conducted across Fortune 1,000 firms revealed that on average nearly 40% of HR analytics priorities were determined by the HR research and analytics team while approximately 60% were driven by stakeholders (Falletta, 2014). Hence, the HR analytics team should devote some resources to research projects that are strategic in nature, aside and apart from what was generated during the stakeholder requirements step.

Step 3: identify data sources
Once the HR research and analytics agenda is established, the next step is to identify the sources of data that will help to answer the HR research and analytics questions and hypotheses. Data sources may be either public or private. Public data reside in university libraries and governmental databases (e.g. UK's Office of National Statistics, U.S. Department of Labor Statistics). Private data includes an organization's internal employee data housed in its HRIS as well as external benchmarking data from "best-in-class" organizations. Research reports and results gathered by membership-based consortia (e.g. Global Centre for Work-Applied Learning, Centre for Evidence-Based Management, Gartner CEB, The Conference Board and the i4CP) and academic think tanks (e.g. Institute for Employment Studies in the UK, Cornell's Center for Advanced Human Resource Studies, University of Southern

California's Center for Effective Organizations) are credible sources of private data and information. Sources of data may or may not exist depending on your organization's current HR research and analytics practices.

While reviewing data sources (refer to Table 3), questions may arise as to whether the organization's HR research and analytics practices are still useful to the business (e.g. some practices may have become institutionalized over the years). Therefore, some tough decisions may need to be made with respect to modifying existing HR research and analytics practices, discontinuing outmoded or symbolic practices and adopting new ones.

In terms of adopting new HR analytics practices and solutions (refer to Table 4), we caution organizations to do their homework before plowing into uncharted territory or chasing the next human capital management (HCM) technology or artificial intelligence (AI) platform. Too often, HR practitioners are too enamored with HCM technologies designed to select, manage, measure, track, monitor, quantify, nudge, engage and coach people in the workplace. These novel technologies, while promising, typically rely on a proprietary algorithm and unexplainable "black box" without fully understanding the underlying mechanisms at work (i.e. showing which factors or reasons led to human capital prediction or decision and how). According to Angrave *et al.* (2016), analytics must be rooted in an understanding of the data to be used and the context under which data were collected if any meaningful insight is to be gained.

In our view, if an HCM technology vendor is unwilling to crack open the proverbial "black box" – don't work with them. Although HR analytics does involve the use of technology to collect, manipulate and report data (Marler and Boudreau, 2017), it is critically important to weigh the potential rewards and risks including the legal and ethical implications associated with various HCM technologies.

Step 4: gather data
This step of the *HR analytics cycle* involves the actual collection of data through primary research, secondary research or mining the organization's internal data in the HRIS. Primary

(1) Employee/organizational surveys
(2) Employee/talent profiling (tracking and modeling individual data on critical talent or high-potential employees)
(3) HR metrics including scorecards and dashboards
(4) Partnership or outsourced research including membership-based research consortia
(5) Workforce forecasting (e.g. workforce supply/demand and segmentation analysis to forecast and plan when to staff up or cut back)
(6) Ad hoc HRIS data mining and analysis
(7) HR benchmarking
(8) Learning measurement/analytics
(9) HR program evaluation
(10) Return-on-investment (ROI) projects
(11) Labor market, talent pool and site/location identification research
(12) Advanced organizational behavior (OB) research and modeling
(13) Selection research involving the use of validated personality instruments that measure various employee traits, states, characteristics, attributes, attitudes, beliefs and/or values
(14) Talent supply chain (analytics to make decisions in real time for optimizing immediate talent demands in terms of changing business conditions)
(15) 360 degree or multirater feedback (360-degree leadership and management assessments or performance appraisal/evaluations)
(16) Sentiment analysis (interpretation and classification of emotions whether positive, negative and neutral within text data using text and/or thematic analysis techniques)
(17) Using organizational network analysis (ONA) tools

Table 3.
Common data sources

(1) Datafication of personal, and often trivial, characteristics, preferences and behaviors that have little relevance to job performance
(2) Surveys that explore a job applicant or employee's attitudes, preferences and values on seemingly innocuous aspects of their personal life (e.g. "what magazines do you subscribe to?" and "what pets do you have?") as a proxy measure of personality, intelligence, cultural fit, performance and attrition, to name a few (Hansell, 2007)
(3) Identifying a job applicant's "hometown" as a relatively accurate predictor of attrition (Ganguly, 2007)
(4) Private data obtained from social media websites (e.g. Facebook) – whereby the employer asks a job applicant or employee to furnish his/her user-id and password
(5) Vendor platforms that troll, scrap and analyze public social media data (e.g. changes made to *LinkedIn* profile, summary, tagline as an indicator of job seeking/attrition)
(6) Third-partner consulting firms that predict the health risks of employees (Silverman, 2016)
(7) Technology that takes photos of employees at their desks and/or their computer screen every 10 min to manage productivity and office presence
(8) Sociometric sensors that measure team dynamics and collaboration and monitor whereabouts, etc.
(9) Monitoring nonexecutive employees who "dump" their stock as an accurate indicator of disloyalty and imminent attrition
(10) Making hiring decisions based on where employees live with (e.g. the closer employees reside to the office, the less likely they are to leave than those who live farther away)
(11) Screening job candidates with integrity data, such as credit ratings, arguing that it's an effective way to assess personal responsibility
(12) Using voice analysis software to determine whether a job candidate is being truthful and honest
(13) Using micro-expression analysis (e.g. measuring unconscious employee reactions to various stimuli – change readiness, employee engagement)
(14) Analysis of e-mail content, metadata, subject line, CC/BCC
(15) Analyzing calendar data (e.g. topic, accepting/declining meeting invites participants)
(16) Using wellness data (e.g. wellness portals and now wearables such as *Fitbit*)
(17) Using biodata (fingerprint scans) to monitor usage and whereabouts
(18) Using RFID (badge scans) to monitor usage and whereabouts
(19) Microchip implants in the workplace (e.g. a microchip is implanted in an employee's hand, which permits the employee to access their office building, computer, etc.)

Table 4.
Novel and potentially dubious data sources

research is new or original research that addresses a specific research question or set of questions (e.g. a research project or experiment to identify which factors enable or inhibit employee engagement and performance, selection research using validated personality instruments for leadership succession, employee and organizational surveys for action planning and change, organizational network analysis to determine the level of collaboration by specific jobs and roles). Primary research can be done in-house if an organization has the HR research and analytics capabilities or in partnership with credible think tanks or universities (Simón and Ferreiro, 2018). Secondary research is data and information available through existing sources (e.g. literature review of journal articles and reports from credible institutes, HR benchmarking, labor market databases). The most reliable and trustworthy secondary sources of information for evidence-based decisions and practice come from scientific research studies (e.g. systematic reviews, meta-analyses, literature reviews) (Briner and Barends, 2016). Theory-driven (deductive) and data-driven (inductive) approaches to mining and modeling data from the organization's HRIS, SaaS-based platforms (e.g. data aggregation and visualization products, employee engagement tools, social or organizational network technologies) and other external data sources are another way to gather, query and analyze data about the workforce, provided it is done ethically and responsibility.

Step 5: transform data
Transforming data into useful and meaningful insights is arguably the most important, yet most challenging, step. Many advancements and innovations have been made by leading-

edge software firms (e.g. Oracle, Salesforce, SAP, SAS, Workday) that incorporated HR analytical capabilities within their suite of products such as predictive analytics, process analytics, text and sentiment analytics and real-time analytics, to name a few (Strohmeier *et al.*, 2015). Similarly, several promising data aggregation and visualization platforms have entered the market. However, none of these enterprise platforms and SaaS-based tools can magically codify, analyze, visualize and interpret all the disparate "Big Data" at our disposal (Angrave *et al.*, 2016). This is especially true for evidence-based findings and insights derived through scholarly research as well as applied HR research and experimentation projects performed in organizations.

In the context of HR strategy, much of this work is still done manually by qualified HR researchers, analysts and data scientists (Falletta, 2014). It is suggested that organizations start small and build their HR analytical capabilities overtime. Organizations should perform a meta-analysis (i.e. an analysis of analysis) across a handful of targeted data sources. We refer to the term meta-analysis loosely and not in the traditional sense in which scholars use advanced statistical procedures to combine the results and examine the effect sizes of multiple scientific studies (Barends and Rousseau, 2018). Therefore, meta-analysis in the context of HR analytics is a practical approach to explore and understand multiple data sources in relation to each other. For example, to what extent are the results from individual 360-degree assessments consistent with your employee survey data, exit survey data, or actual turnover? Are high-potential, emerging leaders leaving the organization for the same reasons year over year (e.g. little to no advancement and promotion opportunities, few organizational leadership opportunities, lack of decision rights, low base pay relative to the market)? Performing a meta-analysis enables you to answer these questions and, more importantly, codify and make sense of disparate data sources to glean critical workforce insights. Performing the meta-analysis can be simple or complex. This largely depends on the nature of the data gathered, sophistication and competency of the HR researcher, analyst or data scientist and the amount of resources and time to conduct the analysis.

Step 6: communicate intelligence results
The sixth step of the *HR analytics cycle* involves communicating intelligence results. Real HR analytics capabilities place more effort and emphasis on telling a story about the data and visualizing the data in the context of the organization's most pressing problems and successes (Minbaeva, 2018). Storytelling can be a powerful approach in communicating data-driven insights, both in words and visually, because it stimulates emotions (i.e. the brain processes emotions differently than facts and data) (Waters *et al.*, 2018; Welbourne, 2015). Storytelling, however, Should not be a guise or pretext for telling executives what they want to hear or "cherry-picking" the data and insights. For example, Rasmussen and Ulrich state that "HR analytics can be misused to maintain the status quo and drive a certain agenda (i.e. when you know what story you want to tell, and you then go look for data to support same" (2015, p. 237). Moreover, we need to consider the "veracity of the story" and the ethicality of the way in which data-driven insights are derived, communicated and used (Rotolo and Church, 2015). The dissemination of inaccurate or misleading insights will invariably lead to bad workforce decisions and big organizational consequences (Church and Dutta, 2013). Hence, communicating and reporting HR analytical insights involves not only some ethical interpretation on the part of HR analytics team, but also speaking truth to power.

Considerable advances have been made in linking HR to the business strategy and organizational performance (i.e. a value creation framework) through the use of the *balanced scorecard* (Kaplan and Norton, 1992), *HR scorecard* (Becker *et al.*, 2001) and the *workforce scorecard* (Huselid *et al.*, 2005). However, as alluded to earlier, not all forms of internal and external data and information can be expressed in terms of a simple metric or indicator. For

example, some HR research and analytics activities (e.g. advanced research in the context of social, behavioral and organizational sciences) require advanced statistical analysis, meta-analytic, multivariant or causal modeling procedures as well as expert interpretation and insight. Nonetheless, scorecards and dashboards are effective means to communicate strategic metrics and are best used as communication and reporting tools for strategy execution once an agreed-upon strategy is in place.

Step 7: enable strategy and decision-making

The final step of the *HR analytics cycle* is to enable HR strategy creation and evidence-based decision-making. We have heard the proverbial mantra that behind every successful organization is a strategy that works. But what exactly is strategy? Strategy is a multidimensional concept that can be defined in many ways. Mintzberg describes strategy is terms of a plan, ploy, pattern, position and perspective. As a plan, strategy relates to leaders establishing the overall direction for the organization. As a ploy, strategy is all about maneuvering and outwitting competitors. As a pattern, strategy involves engaging in specific behaviors and consistent action to effectively implement the strategy. Strategy is also a position in terms of how an organization differentiates itself in the competitive marketplace. Lastly, strategy is a perspective that reflects an organization's culture and character (i.e. does the organization see itself an imitator, improver or innovator when it comes to its people, products and services) (Mintzberg *et al.*, 2005). In summary, strategy involves asking intelligent questions, identifying strengths, weaknesses, opportunities and threats (SWOT), knowing the right things at the right time, scenario planning, evidence-based decision-making, establishing priorities and goals and effectively managing execution. Despite these various methods and processes, strategy in the context of HR "refers to the processes, decisions, and choices organizations make regarding how they manage their people" (Cascio and Boudreau, 2014, p. 79). A human resource strategy tends to focus on aligning people policies, practices and processes with the overall business strategy in order to achieve the organization's goals and objectives. In a perfect world, HR strategy creation should be done in concert with the overall business strategy, although this rarely occurs in practice.

A human resource strategy also involves making smarter HR decisions, and there are no shortage of models, frameworks and guidelines on the topic of HR decision-making. For example, Boudreau and Ramstad (2007) introduced their HR decision science approach to improve human capital decisions in organizations. Similarly, evidence-based HR involves making HR decisions through the conscientious, explicit and judicious use of the best available evidence from multiple sources of information (Briner and Barends, 2016). Another intriguing approach is Dulebohn and Johnson's (2013) classification framework for HR decision-making in the context of HR information systems and analytics that is based on the seminal work of Gorry and Scott Morton (1971). The framework is organized by two dimensions: (1) management decision-making level (i.e. strategic planning, management control and operational control) and (2) decision-making structure (i.e. structured, semistructured and unstructured). Their framework describes the data needs, decision characteristics and concomitant metrics across the operational, managerial and strategic levels. Specifically, this framework is a useful decision support tool for categorizing a wide range of HR practices, activities and choices in a meaningful way (Dulebohn and Johnson, 2013).

In short, these models and frameworks represent a complementary approach for enabling HR strategy and decision-making in the context of HR analytics. In our view, the primary purpose of HR analytics is to enable HR strategy and decision-making. The resultant data and insights derived from HR analytics play a central role in influencing HR strategy, decision-making and the strategic choices organizational leaders make when it comes to adopting evidence-based HR practices (Falletta, 2014). Further, we introduce the *HR strategy axis* as a useful framework to guide strategic HR choices with respect to human capital decision-making and investments in organizations.

A framework for strategic HR choices

We use the term strategy creation to distinguish it from traditional strategic planning. Strategy creation involves the formulation of something creative, innovative or new. Conversely, strategic planning tends to focus on analyzing and evaluating all the consequences associated with selecting and implementing proven solutions or best-known methods. While there is nothing wrong with adopting best-in-class solutions from other companies, exclusively copycatting and leveraging what everyone else does rarely leads to competitive advantage in terms of differentiation. Instead, HR should drive an appropriate level of innovation as part of their overall HR strategy to differentiate their organization for competitive advantage (*see* Figure 2).

The *HR strategy axis* depicts four types of strategic HR choices (e.g. *HR imitator, HR improver, HR innovator and HR iconoclast*) in a Cartesian fashion in terms of business value and an organization's tolerance for disruption. In our experience, organizations tend to operate as an *HR imitator* but strive for incremental improvement (i.e. *HR improver*) that is aligned with and responsive to their overall business strategy. Over the past two decades, HR has showed little change in terms of implementing innovative HR strategies (i.e. high-involvement HR policies, practices and processes), which has been characterized as a sort of "stubborn traditionalism" affecting the profession (Boudreau and Lawler, 2014). While some extol the value of imitation and copying other organization's ideas and practices (e.g. Shenkar, 2010), Cascio and Boudreau (2014) suggest that organizations should engage in prudent risk-taking and innovation and use practical frameworks to help explore and balance HR risk mitigation and uncertainty with HR risk optimization and opportunity. It stands to reason that a business strategy that seeks competitive advantage (i.e. differentiation relative to cost) necessitates an evidence-based and HR analytics-driven innovation strategy. Therefore, organizations committed to differentiating their HR practices, policies and processes to attract and retain top talent for strategic competitive advantage need to weigh the potential rewards and risks associated with their strategic HR choices and human capital investments. To reiterate, the *HR strategy axis* represents the
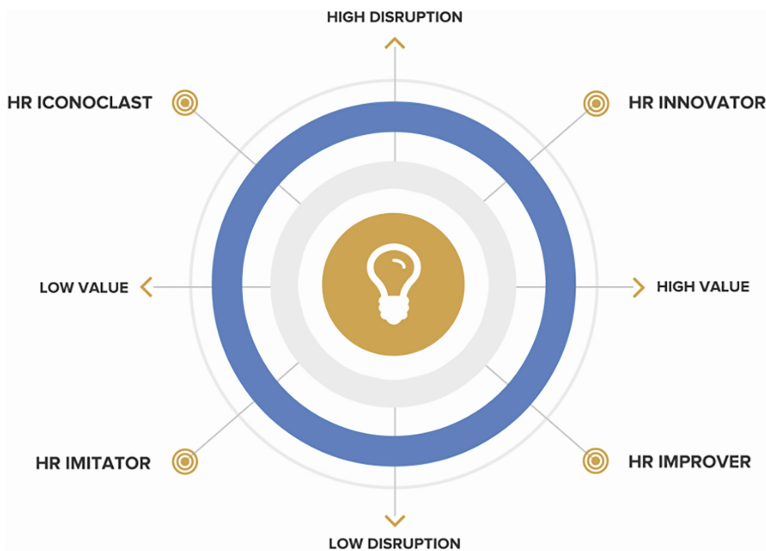

Figure 2.
HR strategy axis

strategic HR choices organizational leaders must make as part of the final step in the *HR analytics cycle*.

Implications and guidelines for practice

The following questions are likely to arise as the field of HR analytics continues to evolve and organizations develop their HR analytics capabilities. We expect some of our responses to be provocative, but our intent is to stimulate a broader conversation about the critical success factors for making HR analytics work in organizations.

Is HR analytics a new, revolutionary idea or evolutionary capability?

Arguably, HR analytics is nothing new. Yes, the data are bigger, and the technology, tools and toys are much more sophisticated and abundant. However, the use of data to understand organizational phenomena and inform HR strategy and decision-making is nothing new. In terms of historical roots, there are numerous HR research and measurement practices that have led to the emergence of HR analytics; for example:

(1) Over 100 years of workforce and HR research (e.g. Schmitt and Klimoski, 1991 – a brief history of research on people at work)

(2) Action research (Argyris *et al.*, 1985; Lewin, 1946)

(3) Assessment centers (e.g. Bray and Grant, 1966)

(4) Data-driven methods for change (e.g. Nadler, 1977; Waclawski and Church, 2002)

(5) Employee and organizational surveys (e.g. Gallup, 1988; Kraut, 1996)

(6) Evaluation/ROI (e.g. Edwards *et al.*, 2003; Kirkpatrick, 1998; Phillips, 1997; Russ-Eft and Preskill, 2009)

(7) Evidence-based practice (e.g. Pfeffer and Sutton, 2006; Rousseau, 2006; Rynes *et al.*, 2002)

(8) HR decision science (e.g. Boudreau and Ramstad, 2007)

(9) HR benchmarking (e.g. Glanz and Dailey, 1992; Fitz-enz, 1992)

(10) Human capital measurement and metrics (e.g. Fitz-enz, 1984)

(11) Personnel/employee/talent selection (e.g. Schmidt and Hunter, 1998)

(12) Scorecards (e.g. Becker *et al.*, 2001; Huselid *et al.*, 2005; Kaplan and Norton, 1992)

(13) Workforce forecasting and analysis (e.g. Bryant *et al.*, 1973; Khoong, 1996)

These same HR research and measurement practices are widely used currently and will likely continue to serve as a significant data source in the future in terms of HR analytics work. Moreover, we shouldn't forget the social, behavioral and organizational scientists who paved the way long before the "Big Data" and "analytics" monikers, data visualization tools and data science revolution came into vogue. What is new are the availability of new technological and analytical resources and the renewed interest in analytics by organizational leaders looking for novel ways to leverage such data sources to improve HR's impact on organizational effectiveness and other important business outcomes (Putka and Oswald, 2016). This renewed interest has created a cottage industry for HR analytics products and services (e.g. SaaS-based platforms, data aggregation and visualization, apps, chat-bots, AI, deep or machine learning). Therefore, HR analytics should be characterized as an evolutionary rather than revolutionary capability with a rich history and promising future.

What is the best way to get started with HR analytics?
In terms of getting started and building HR analytical capabilities, organizations tend to be enticed into procuring *R*, *Python* and the latest HCM technology platforms with novel data visualization tools and subsequently hire a low-level HR analyst to operate these tools without clarity about their HR analytics vision, strategy and the capabilities and outcomes they hope to achieve. Hence, we suggest that organizations bring in a well-qualified HR analytics leader with the right disciplinary background and skill set before investing in any technological or analytical resources. A highly trained HR analytics leader with a strategic HR perspective can pave the way by establishing the overall HR analytics vision, strategy and capabilities for success.

Who should perform HR analytics?
HR analytics is a team sport (Green, 2017; Levenson, 2015). HR analytics practitioners and scholars come from a variety of disciplines (e.g. business management, HR and organizational behavior, industrial and organizational psychology, HR development, economics, finance, statistics, data science, computer science). While a human capital technologist, econometrician, mathematician, statistician, data scientist or financial analyst might possess the technological and statistical skills to mine, model and visualize data, we believe it takes an applied researcher with a background in the social, behavioral and organizational sciences to accurately and ethically interpret the insights derived from HR analytics in the context of individual, group and organizational behavior (Falletta, 2014; King *et al.*, 2016).

Where should HR analytics reside?
Among larger Fortune 1,000 firms in the United States, research estimates that over 75% of these organizations have an individual or group dedicated to HR research and analytics. Nearly a third of these dedicated HR research and analytics groups report directly to the chief HR officer, suggesting that HR analytics capabilities are strategically positioned in terms of organizational structure (Falletta, 2014). Some argue that HR analytics should be situated in an enterprise-wide business intelligence function and report to line management outside of the HR function (Rasmussen and Ulrich, 2015; Ulrich and Dulebohn, 2015). We contend that this is a battle the HR profession cannot afford to lose and as such, HR analytics should reside squarely in the HR function and report directly to the chief HR officer. We also argue that the HR analytics function be led by someone trained in the social, behavioral and organizational sciences (e.g. strategic HRM and organizational behavior, industrial and organizational psychology) to ensure the discipline remains both evidence-based and ethical in terms of humanistic values (Church and Dutta, 2013). Human resources should collaborate with line management, business intelligence, information technology, finance and other functions – but the HR profession must be willing to lead the way in terms of its own strategic legitimacy and influence.

Should the HR analytics team be connected to HR strategy?
We recommend that HR analytics be merged with an organization's HR strategy function. In many organizations, a dedicated HR strategy function doesn't exist. Politically, some organizations prefer this arrangement in that all HR business partner groups and functional leaders have an equal role and responsibility in driving HR strategy creation and execution rather than a centralized function. Kaplan and Norton (2005) suggest that organizations should establish a dedicated Office of Strategy Management (OSM) to address the gap between strategy creation and execution. The notion of a dedicated OSM should be part of the

corporate HR function, coupled with its HR analytics capabilities. Hence, the establishment of a "HR Analytics and Strategy" function would be ideal and ensure a coordinated effort between HR analytics, strategy creation and execution, human capital decisions and the adoption of evidence-based practices.

What are the ethical and privacy implications associated with HR analytics?
The erosion of workplace privacy and ethics coupled with a clandestine "quantified employee" agenda in an age surveillance capitalism might sound like Orwellian dystopian hyperbole. Notwithstanding, ethical questions have begun to arise about the potential abuses of HR analytics with respect to technological advancements (e.g. SaaS-based platforms that scrap and analyze external social media data, electronic performance monitoring and surveillance, wearable technologies, micro-expression analysis) and datafication of personal, and often trivial, characteristics, preferences and behaviors that have little relevance to job performance (e.g. Bassi, 2011; Falletta, 2014; Karim *et al.*, 2015; Oehler and Falletta, 2015). In using such tools and insights, how much business value and competitive advantage can we hope to achieve and what are the trade-offs? While some insist that Big Data doesn't necessarily mean "Big Brother" (Young and Phillips, 2016), there have been a fair share of questionable and creepy stories that have made front page news. For example, according to a *Wall Street Journal* report, some organizations are using outside firms to predict the health risks of employees (Silverman, 2016). To what extent should employers use such data about their employees' health conditions, habits, prescription drug use and the like with respect to HIPPA and privacy laws? What about values and ethics? HR, like most professions, is built around norms, values and ethical principles. HR professionals are ethically responsible for promoting and fostering fairness and justice for all employees and their organizations as part of the Code of Ethics for the Society for Human Resource Management. Similarly, the American Psychological Association (APA) ethical principles and code of conduct require psychologists to abide by the general principle of "First, Do No Harm".

In summary, building evidence-based and ethical HR analytics capabilities that foster trust and transparency is critically important to the success of any HR analytics effort. Each member of the HR analytics team plays a vital role as ethical researcher, analyst, interpreter, translator and educator (Dekas and McCune, 2015). Lastly, organizations need to think through how their HR analytical insights are derived, communicated and more importantly – used (Illingworth, 2015). A generic HR data governance, transparency and privacy policy is not enough. Organizations must also rapidly and rightly address how HR analytical insights will be used (i.e. determining the responsible usage of Big Data and HR analytical insights) as well as the situations and circumstances in which certain technologies, practices, data and insights should never be used.

Conclusion
Human resource analytics includes a broad range of practices and data sources including HR research and experimentation in the context of social, behavioral and organizational science. Proactive HR analytics capabilities arm strategists and decision-makers with pertinent knowledge and insight to make critical decisions pertaining to human capital. Establishing an upfront HR research and analytics agenda as part of an ongoing *HR analytics cycle* can also help ameliorate reactive data fetching and the proverbial data dump by providing HR leaders with much needed insights (in a push and pull fashion) to inform HR strategy creation and smarter workforce decisions. Finally, the *HR analytics cycle* coupled with the *HR strategy axis* can help HR leaders and practitioners avoid costly missteps in terms of implementing potentially unethical or questionable HR analytics practices while thoughtfully considering their strategic HR choices when it comes to creating an evidence-based and HR analytics-driven innovation strategy for success.

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