

# Bridging the gap: why, how and when HR analytics can impact organizational performance

HR analytics  
and  
organizational  
performance

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## Abstract

**Purpose** – Despite the growth and adoption of human resource (HR) analytics, it remains unknown whether HR analytics can impact organizational performance. As such, this study aims to address this important issue by understanding why, how and when HR analytics leads to increased organizational performance and uncover the mechanisms through which this increased performance occurs.

**Design/methodology/approach** – Using data collected from 155 Irish organizations, structural equation modeling was performed to test the chain mediation model linking HR technology, HR analytics, evidence-based management (EBM) and organizational performance.

**Findings** – The study's findings support the proposed chain model, suggesting that access to HR technology enables HR analytics which facilitates EBM, which in turn enhances organizational performance.

**Originality/value** – This research contributes significantly to the HR analytics and EBM literature. First, the study extends our understanding of why and how HR analytics leads to higher organizational performance. Second, the authors identify that access to HR technology enables and is an antecedent of HR analytics. Finally, empirical evidence is offered to support EBM and its impact on organizational performance.

**Keywords** Human resource (HR) analytics, People analytics, Evidence-based management, Organizational performance, Human resource management, Human capital analytics

**Paper type** Research paper

## Introduction

The concept and application of data and analytics in management have seen increasing attention as researchers and professionals aim to understand how data can be transformed into actionable insights leading to improved organizational performance (Chierici *et al.*, 2019; Ferraris *et al.*, 2019; Santoro *et al.*, 2019; Singh and Del Giudice, 2019). Consequently, this interest has transcended various management disciplines, including human resources management (HRM), which is evidenced by the growing number of HR departments implementing HR analytics to improve decision-making (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; McCartney *et al.*, 2020). Despite its increased popularity, HR analytics is not an entirely new concept (Huselid, 2018). Rather, HR analytics has emerged from previous research on the impact of HR practices such as selection, training

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and performance management, which has a long history in social sciences, including industrial and organizational psychology, HRM and organizational behaviour [1]. What is new, however, is that HR analytics in contemporary organizations has shifted from “*assessing the levels associated with a particular workforce attribute (e.g. what is our cost per hire?) to understanding the impact of the workforce on the execution of firm strategy (e.g. how might an increase in the quality of our project managers affect our new product cycle time?)*” (Huselid, 2018, p. 680). In other words, HR analytics not only centers on investigating and improving elements of human capital but also applying analytical techniques coupled with people data to inform organizational strategy and improve performance.

Furthermore, the significant growth of access to HR technology, including human resource information systems (HRISs), cloud platforms and apps, has offered HR departments the ability to collect, manage and analyze large volumes of employee data, compared to earlier legacy IT systems (Bondarouk and Brewster, 2016; Marler and Boudreau, 2017; Kim *et al.*, 2021). Such shift has also acted as a driver of HR analytics and increased its adoption within HR departments. For example, through the use of advanced HR technology to gather and analyze candidate and employee data, Google’s HR analytics team has developed an evidence-based approach to improve its recruitment and selection process by identifying several elements of high performance that could predict a candidate’s likelihood of success (Harris *et al.*, 2011; Shrivastava *et al.*, 2018). Similarly, in addition to recruitment and selection, HR analytics offers organizations the ability to address various other HR challenges, including employee engagement, diversity and inclusion, and turnover (Harris *et al.*, 2011; Andersen, 2017; Buttner and Tullar, 2018; Levenson, 2018; Simón and Ferreiro, 2018).

To date, the extant HR analytics literature has focused on many areas, including the current limitations and challenges facing the development of HR analytics (Boudreau and Cascio, 2017; Levenson and Fink, 2017; Huselid, 2018; Minbaeva, 2018; Jeske and Calvard, 2020), best practices in developing and utilizing HR analytics (Green, 2017; Falletta and Combs, 2020), and the impact and importance of analytical skills (Kryscynski *et al.*, 2018; McCartney *et al.*, 2020). In addition, several reviews have been published offering a holistic view of the current state of HR analytics research (Marler and Boudreau, 2017; Tursunbayeva *et al.*, 2018; Fernandez and Gallardo-Gallardo, 2020; Margherita, 2020). Despite the advancement of HR analytics literature and the number of case studies claiming that HR analytics allows organizations to improve their performance (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; Margherita, 2020), research investigating how and to what extent HR analytics impacts and influences organizational performance remains scarce (Huselid, 2018; Minbaeva, 2018). On this basis, this study seeks to understand *how* and *why* HR analytics influences organizational performance by theorizing and testing its underlying mechanisms.

This study draws on evidence-based management theory (EBM, Rousseau and Barends, 2011; Baba and HakemZadeh, 2012; Bezzina *et al.*, 2017), the resource-based view of the firm (RBV, Barney, 1991) and dynamic capabilities (Teece *et al.*, 1997; Winter, 2003) as the underlying frameworks linking access to HR technology, HR analytics, EBM and organizational performance. These theoretical frameworks are justified as EBM is concerned with incorporating and deploying scientific and organizational facts coupled with expert and stakeholder judgment to make managerial decisions (Rousseau and Barends, 2011; Baba and HakemZadeh, 2012). At the same time, HR analytics contributes to organizational evidence creation through acquiring and translating high-quality workforce data into information, resulting in critical organizational insights (Marler and Boudreau, 2017; Minbaeva, 2018; Coron, 2021). Further, in line with previous studies exploring the performance impact of HR (Delaney and Huselid, 1996; Guthrie, 2001; Fu *et al.*, 2017), this study integrates an RBV (Barney, 1991) and dynamic capability (Teece *et al.*, 1997) perspective to propose a chain model demonstrating that access to HR technology enables HR analytics (resource) which facilitates EBM (capability) which in turn enhances organizational performance.

By theorizing the chain model between access to HR technology, HR analytics, EBM and organizational performance, this study extends our understanding of why and how HR analytics leads to higher organizational performance. Additionally, this study addresses the conditional effect of HR technology as an antecedent of HR analytics. Finally, the study adds empirical evidence linking EBM to organizational performance, which at present is rare (Baba and HakemZadeh, 2012). Together, these contributions offer a solid foundation for the strategic importance of HR analytics and EBM.

This paper's subsequent sections are structured as follows: First, the literature review and hypotheses section will summarize existing research in HR analytics, outline the five hypotheses tested within the paper and present the theoretical model. Second, the research methodology will describe the data collection process and offer a detailed explanation of the survey measures. Third, the research findings are presented, providing analysis and support for each of the hypotheses tested. Lastly, the paper's theoretical contributions to HR analytics and EBM are presented, implications for practice, limitations and areas for future research are discussed.

## Literature review and hypotheses

### *HR analytics: definition and development*

As a result of the ongoing digital transformation, many HR departments have begun to engage with workforce data to make data-driven decisions in areas such as recruitment and selection, performance measurement, diversity and inclusion and workforce planning (Harris *et al.*, 2011; Kane, 2015; Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017; Hamilton and Sodeman, 2020; Tursunbayeva *et al.*, 2021). This application of using workforce data to improve decision-making has been synonymously referred to by scholars as HR analytics (Aral *et al.*, 2012; Rasmussen and Ulrich, 2015; Angrave *et al.*, 2016; Marler and Boudreau, 2017; McCartney *et al.*, 2020), people analytics (Kane, 2015; Green, 2017; Nielsen and McCullough, 2018; Tursunbayeva *et al.*, 2018; Peeters *et al.*, 2020), talent analytics (Harris *et al.*, 2011; Sivathanu and Pillai, 2020), human capital analytics (Andersen, 2017; Boudreau and Cascio, 2017; Levenson and Fink, 2017; Minbaeva, 2018) and workforce analytics (Huselid, 2018; Simón and Ferreiro, 2018).

Regardless of the term used, consistency exists in both academia and practice for the strategic importance of HR analytics as it provides organizations with data, information and insights to effectively make informed data-driven decisions (Huselid, 2018; Minbaeva, 2018). For example, according to van den Heuvel and Bondarouk (2017), HR analytics is the systematic identification and quantification of the people drivers of business outcomes to make better decisions. Equally important is the notion that these insights can be generated at varying levels of technological sophistication (Margherita, 2020; Sivathanu and Pillai, 2020). For example, according to Margherita (2020), HR analytics follows a linear three-stage maturity model. At its lowest level, "descriptive," HR analytics focuses on using HR technology to generate reports and dashboards to answer questions concerning what has happened. Next, the "predictive" stage utilizes statistical techniques, advanced algorithms and machine learning to anticipate what might happen in the future and why. Lastly, the "prescriptive" stage centers on determining the optimal action that should be taken in response to the analysis.

This study adopts the HR analytics definition proposed by Marler and Boudreau (2017), where HR analytics is "*an 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). In light of this definition, this paper operationalizes HR analytics through the adoption of the human capital analytics framework (Minbaeva, 2018), where HR analytics comprises of three dimensions: high-quality data, analytical competence

and strategic ability to act. According to the human capital analytics framework, the dimension of high-quality data suggests that the data used for analytics needs to be accurate, consistent, timely and complete. For instance, organizations need to ensure that the data being used to conduct HR analytics is accurate. Without accurate data, the insights gained from the analytics will be unreliable and offer no benefit to the organization (Minbaeva, 2018; Wamba *et al.*, 2019; Peeters *et al.*, 2020). Alternatively, inaccurate data could lead to implementing solutions that do not address the business's actual challenges. HR analytics also requires a high degree of analytical competence, referring to the analytics team's ability to apply statistical analysis and techniques to workforce data to transform data into valuable insights (McCartney *et al.*, 2020). For example, the analytics team needs to frame relevant research questions and answer them through developing causal models and performing sophisticated statistical analysis (Minbaeva, 2018). Moreover, the team needs to translate the insights gained into a compelling analytics narrative or story (Andersen, 2017; Minbaeva, 2018; McCartney *et al.*, 2020). Lastly, the strategic ability to act refers to having the required managerial support to make decisions and implement solutions based on the data, information and insight gathered from HR analytics.

Furthermore, we regard HR analytics as a valuable, rare, inimitable and non-substitutable resource for organizations based on the data, information and insights generated by HR analytics. This argument is justified by the many parallels that can be drawn and have been indirectly implied by scholars when it comes to HR analytics as an organizational resource (Marler and Boudreau, 2017). For example, researchers and practitioners have discussed the value offered by HR analytics through its ability to allow HR to identify and address workforce challenges (Marler and Boudreau, 2017; Huselid, 2018; Kryscynski *et al.*, 2018; McIver *et al.*, 2018; Minbaeva, 2018). In addition, the HR analytics literature has also referred to the rarity of high-quality HR analytics programs suggesting that many organizations struggle to utilize workforce data only offering basic reporting and descriptive statistics (Angrave *et al.*, 2016; King, 2016; Andersen, 2017; Green, 2017; Levenson and Fink, 2017; Minbaeva, 2018). As such, effective HR analytics programs are rare at present. Concerning the imitability of HR analytics, according to Minbaeva (2018), to utilize and conduct value-adding HR analytics, organizations need to have high-quality data, analytical capabilities and the strategic ability to act. However, it is difficult for HR departments to have all three elements given the low levels of technology, poor data quality, few resources, lack of analytical competencies and a lack of buy-in from senior management (Andersen, 2017). Finally, HR analytics is its own stand-alone practice, meaning no available alternatives or substitutes can gain similar insights (Falletta and Combs, 2020). Taken collectively, HR analytics meets the requirements set out by RBV, suggesting that HR analytics and the data, information and insight it creates, is a valuable resource for organizations with the potential to generate competitive advantage.

#### *Linking HR analytics to EBM*

The data, information and insights generated from HR analytics are not enough to generate competitive advantage alone. Instead, organizations must also deploy and incorporate the evidence effectively (Sirmon *et al.*, 2007; Lin and Wu, 2014; Fu *et al.*, 2017). This idea is consistent with dynamic capabilities, which suggests that competitive advantage depends on an organization's capacity to successfully incorporate, develop and reconfigure its resources (Teece *et al.*, 1997). Similarly, according to Baba and HakemZadeh (2012), EBM is a dynamic process where evidence is first gathered and then interpreted, forming the foundation of managerial decision-making. Accordingly, this study adopts EBM theory to argue that the evidence and organizational facts generated by HR analytics can be used to make strategic decisions and facilitate EBM.

The idea of making decisions based on several sources of information, including organizational facts such as analytics, is a foundational element in evidence-based practice

(Walshe and Rundall, 2001; Briggs and McBeath, 2009; Rousseau and Barends, 2011; Baba and HakemZadeh, 2012; Coron, 2021). This decision-making methodology originated within the healthcare profession to better use scientific research to inform decision-making concerning patient care (Walshe and Rundall, 2001; Pfeffer and Sutton, 2006; Briggs and McBeath, 2009; Baba and HakemZadeh, 2012; HakemZadeh and Baba, 2016). More recently, this approach to decision-making has been advocated for by various scholars suggesting that management decisions should be based on the combination of critical thinking coupled with the best sources of evidence (Rousseau, 2006). These sources of information include scientific evidence found in peer-reviewed academic papers, organizational facts such as metrics and analytics, professional experience and judgment, and considering the outcome on affected stakeholders (Rousseau, 2006; Rousseau and Barends, 2011; Baba and HakemZadeh, 2012; Bezzina *et al.*, 2017; Cassar and Bezzina, 2017). Moreover, according to Barends *et al.* (2014), EBM comprises of six activities, including asking, acquiring, appraising, aggregating, applying and assessing. For example, organizations must translate an issue or problem into an answerable question (asking), systematically search for and retrieve the best available evidence (acquiring), critically judge the trustworthiness and relevance of the evidence (appraising), weigh and pull together the evidence (aggregating), incorporate the evidence into the decision-making process (applying) and evaluate the outcome of the decision (assessing).

As indicated previously, HR analytics generates evidence through organizational facts allowing managers and senior leaders to make more informed decisions (Kapoor and Sherif, 2012; Ulrich and Dulebohn, 2015; Marler and Boudreau, 2017; Levenson, 2018; McIver *et al.*, 2018; Shrivastava *et al.*, 2018). For example, according to Coron (2021), evidence-based human resource management relies on using people data and metrics to increase knowledge and, in turn, improve HR decision-making. Similarly, according to van der Togt and Rasmussen (2017), it is the individual experience, beliefs, intuition and facts acquired through HR analytics that serves as another source of evidence HR professionals can use to enhance decision-making capabilities and better organizational results. Accordingly, we argue that HR analytics contributes to evidence creation by generating organizational facts from workforce data and anticipate a positive relationship between HR analytics and EBM. Therefore, we hypothesize:

*H1.* HR analytics is positively associated with organizational EBM.

#### *Linking EBM to organizational performance*

Every day, managers and senior executives are faced with making critical decisions to improve the success of their organizations. Although some decision-makers will utilize a wide range of evidence to support their decisions, many justify their decisions based on gut feeling, outdated information, personal experience or a combination of the three (Rousseau and Barends, 2011; Baba and HakemZadeh, 2012). As such, management scholars have urged for a shift in management decision-making, placing considerable emphasis on promoting EBM (Pfeffer and Sutton, 2006; Rousseau, 2006; Briner *et al.*, 2009; Morrell and Learmonth, 2015; Rynes and Bartunek, 2017). This comes as a result of significant developments being made in healthcare toward the performance impact of EBM; specifically, the literature centered on healthcare quality and patient and hospital outcomes (Melnyk *et al.*, 2014; Aloini *et al.*, 2018; Janati *et al.*, 2018; Roshanghalb *et al.*, 2018).

In a review conducted by Roshanghalb *et al.* (2018), they identify 20 empirical studies that demonstrate the effect of EBM on various patient outcomes. For example, in a study conducted by Grundtvig *et al.* (2011), two sources of evidence (patient data and expert experience) were used in making medical decisions surrounding patients with chronic heart failure. As a result, hospitalization rates and the number of days spent in hospital were



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significantly reduced (Grundtvig *et al.*, 2011). Based on this review and evidence from the healthcare literature supporting that EBM enables better decision-making leading to better performance outcomes, we hypothesize:

*H2.* Organizational EBM is positively associated with organizational performance.

Building on this notion, HR analytics also generates evidence in the form of organizational facts, providing managers and executives with actionable insights which can be used as evidence in decision-making. Similarly, when organizations use and deploy the insights derived from HR analytics coupled with other sources of evidence to make decisions, it is likely to improve decision-making effectiveness, leading to higher organizational performance. This is evidenced in various case studies that have focused on how HR analytics facilitates evidence-based decision-making to improve HR and business performance (Harris *et al.*, 2011; Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017; Buttner and Tullar, 2018; Gelbard *et al.*, 2018; McIver *et al.*, 2018; Minbaeva, 2018). For example, a recent case study conducted by Simón and Ferreiro (2018) describes developing and implementing an HR analytics program at Inditex, a large Spanish multinational fashion retail group. In collaboration with the authors, Inditex developed key performance indicators centered around workforce analytics. Doing so led HR managers at Inditex to gain and apply critical evidence to make more informed decisions around their workforce, resulting in higher overall store performance (Simón and Ferreiro, 2018). Similarly, Bank of America, working in collaboration with Humanyze (an HR analytics software provider), used HR analytics to improve HR and business outcomes (Kane, 2015). To do so, Humanyze designed and developed ID badges for Bank of America employees, adding microphones, Bluetooth and infrared technology to facilitate workforce data collection (Kane, 2015). Their findings determined that how employees interacted with their coworkers was the most significant factor in predicting productivity (Kane, 2015). Based on this evidence, Bank of America implemented solutions to the working environment that led to increased team cohesion by 18%, a reduction in stress by 19% and a 23% increase in productivity (Kane, 2015).

As shown in the above examples, HR analytics “uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making” (Marler and Boudreau, 2017, p. 15). As such, we propose a mediating role of organizational EBM in the HR analytics and organizational performance link. Therefore, we hypothesize:

*H3.* Organizational EBM mediates the relationship between HR analytics and organizational performance.

#### *Access to HR technology enabling HR analytics*

The rapid advancement of information technology has sparked a digital revolution, with organizations taking advantage of big data to address previously unknown opportunities (Wamba *et al.*, 2015; Wamba *et al.*, 2017; Dubey *et al.*, 2019; Kim *et al.*, 2021). This is no exception for HR, as departments have shifted toward a more technology-enabled HR department (Boudreau and Cascio, 2017; Marler and Boudreau, 2017; van den Heuvel and Bondarouk, 2017; McCartney *et al.*, 2020).

Accordingly, access to HR technology such as HRISs and other forms of electronic HRM (e-HRM) platforms have been a driving force in the implementation and growth of HR analytics (Ashbaugh and Miranda, 2002; Dulebohn and Johnson, 2013; McIver *et al.*, 2018; Schiemann *et al.*, 2018; Kim *et al.*, 2021; Zhou *et al.*, 2021). For example, HRIS allows for capturing, storing, manipulating, retrieving and distributing HR data and are equipped with the functionality to generate reports on key performance indicators (KPIs)

(Hendrickson, 2003; Stone *et al.*, 2015). Furthermore, these systems can add more advanced analytics and reporting modules to predict short- and long-term workforce trends by incorporating big data, business intelligence and statistical applications (Kapoor and Sherif, 2012; Stone *et al.*, 2015; van den Heuvel and Bondarouk, 2017; McIver *et al.*, 2018; Garcia-Arroyo and Osca, 2019; Mikalef *et al.*, 2019). More recently, advancements in HR technology platforms have led to integrating artificial intelligence (AI) solutions, including chatbots, for streamlining HR processes (Buck and Morrow, 2018; van Esch and Black, 2019; Black and van Esch, 2020). As can be seen, HR technology evolves along a continuum from basic data collecting and storage (i.e. HRIS) to more robust platforms with AI and analysis capabilities. Although it is essential to distinguish among these differences, this study does not focus on the sophistication level of HR technology. Instead, this study aims to understand whether HR departments that have access to HR technology at any point on the continuum can adequately leverage it to enable HR analytics. As such, this study defines access to HR technology as an HR department that invests in and implements an HR software tool that allows for the recording, storage and perform analysis of data surrounding an organizations human resources that can be used by members of the department (Aral *et al.*, 2012; Stone *et al.*, 2015; Marler and Boudreau, 2017; Kim *et al.*, 2021; Maamari and Osta, 2021).

Building on that notion, this study argues that access to HR technology is a driving force in HR analytics adoption and enables and acts as an antecedent to HR analytics. The justification for this is two-fold. First, HR technology serves as the foundation for HR analytics as it allows HR professionals timely access to workforce data that can be used to make more informed and data-driven decisions (Lengnick-Hall and Mortiz, 2003; Johnson *et al.*, 2016; King, 2016; McIver *et al.*, 2018). For example, according to McIver *et al.* (2018), HR technology enables the collection, cleaning and manipulation of various data types from several data sources that can be used to aid organizational decision-making. Thus, meeting the first element of the HR analytics framework high-quality data (Minbaeva, 2018).

Second, HR technology facilitates the process of transforming workforce data into information, where executives, HR professionals and line managers can make strategic workforce decisions through its ability to conduct statistical and predictive analysis (Aral *et al.*, 2012; Fernandez and Gallardo-Gallardo, 2020). According to van der Togt and Rasmussen (2017), insights derived from HR analytics are enabled by HR technology as they can perform sophisticated statistical analyses such as regression on longitudinal and cross-functional data. Moreover, HR technology allows HR professionals to aggregate and perform predictive analytics, which would otherwise not be possible without HR technology (Ulrich and Dulebohn, 2015). Current HR technology platforms also offer a wide range of functionality, allowing HR professionals to translate data into meaningful insights through their ability to generate dashboards, scorecards and data visualizations (Ulrich and Dulebohn, 2015; Angrave *et al.*, 2016; Marler and Boudreau, 2017; McIver *et al.*, 2018). For instance, according to Ulrich and Dulebohn (2015), dashboards and scorecards are descriptive analytics that HR professionals can utilize to compare and visualize various HR metrics over time. Similarly, McIver *et al.* (2018) suggest that dashboards offer HR professionals a way to efficiently illustrate workforce trends to help drive questions and take advantage of emerging workforce opportunities. Thus, meeting the two final elements of the HR analytics framework (analytical competence and strategic ability to act) (Minbaeva, 2018).

As can be seen, access to HR technology plays a critical role in offering HR professionals the ability to gather, analyze and visualize data, enabling senior management to make more informed decisions (Kapoor and Sherif, 2012; Ulrich and Dulebohn, 2015; Marler and Boudreau, 2017; McIver *et al.*, 2018). Therefore, this study argues that access to HR technology will enable HR analytics by acting as a facilitator for transforming workforce data into organizational knowledge and insights.

H4. Access to HR technology is positively associated with HR analytics.

As suggested above, access to HR technology enables HR analytics through its ability to collect and analyze workforce data. Building on this notion, and drawing upon the RBV of the firm (Barney, 1991) and dynamic capabilities (Teece *et al.*, 1997), this study proposes that HR analytics (i.e. high-quality data, analytical capabilities and strategic ability to act) is an organizational resource that can transform data into evidence in the form of organizational facts which is deployed through the organizational EBM capability leading to improved organizational performance.

Therefore, we hypothesize a chain model linking HR technology, HR analytics, EBM and organizational performance.

H5. Access to HR technology is positively linked with HR analytics which in turn facilitates organizational EBM, ultimately leading to organizational performance.

Figure 1 presents the theoretical model.

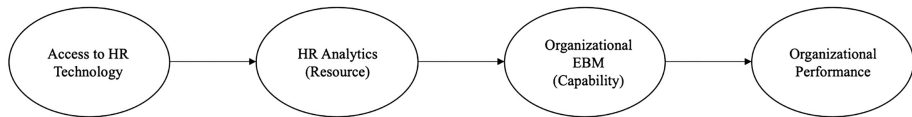


Figure 1.  
Theoretical model

## Research methodology

### Data collection

An online survey focusing on HR analytics and organizational performance was developed in collaboration with a large professional recruitment agency in Ireland. The survey was pilot-tested among several HR managers and senior managers with significant knowledge of the organization's performance metrics to ensure face validity. Some questions were minorly revised to achieve face validity. The survey was then distributed online to HR managers, business partners and senior management teams in 8,116 organizations. The organizations surveyed covered several sectors, including accounting, legal, banking and financial services, marketing, ICT, human resources and insurance sectors. After the initial email invitations were distributed, 51 organizations bounced back and 117 organizations chose to opt out of the survey, leaving 7,948 as the final population. Overall, a total of 260 responses were received, generating an overall response rate of 3%. After removing incomplete responses and organizations that completed less than one-third of the survey, the valid sample size was 155. The low response rate in this study was not surprising given that the response rate at the organizational level is much lower than that at the individual level and has been declining over time in management research (Baruch and Holtom, 2008).

To examine the representativeness and detect the difference between the valid sample and the deleted responses, a one-way analysis of variance (ANOVA) was carried out. Similarly, a comparative analysis of early responses and late responses was conducted to determine the sample's representativeness (Wilcox *et al.*, 1994). This is consistent with existing studies that have checked non-response bias by comparing demographic and contextual variables between early and late respondents (Armstrong and Overton, 1977; Guthrie *et al.*, 2009; Fu *et al.*, 2017).

The ANOVA findings showed no significant difference in organizational size, organizational age, and sectors between the complete and incomplete respondents and no significant difference among early and late respondents. Therefore, we concluded our sample to be valid and continued our analysis with the 155 respondents representing 155 organizations.



### Sample profile

Among the respondents, 53% were male, with 76% of respondents holding positions of HR managers/directors or senior managers. The average work tenure of respondents was nine years ( $SD = 8$ ). Most organizations surveyed represented private organizations, with 88% of the respondents identifying as private. Concerning the industries represented, 30% of organizations belonged to the ICT industry, 25% were financial service firms and 13% were professional services, including accounting, architecture, and consulting and law firms. The remaining organizations represented industries, including construction, transport and communications.

### Measurements

*Organizational performance.* To measure organizational performance, seven items were adopted from [Delaney and Huselid \(1996\)](#). Respondents were asked to rate their organization's performance relative to their competitors using a five-point Likert-type scale (1 = much weaker to 5 = much stronger). Example measures include "Ability to attract essential employees," "Ability to retain essential employees," "Quality of services" and "Customer service." The reliability was assessed, showing a Cronbach's alpha of 0.87.

While concerns about the use of subjective performance data can be raised, several previously published studies examining HR and firm performance research have used self-reported performance measures ([Delaney and Huselid, 1996](#); [Youndt et al., 1996](#); [Sun et al., 2007](#); [Takeuchi et al., 2007](#); [Chuang and Liao, 2010](#); [Fu et al., 2018](#)). As the previous studies have shown, the rationale for using subjective performance data is partly due to the difficulty and inability to access the objective performance measures ([Gupta and Govindarajan, 1984, 1986](#); [Gupta, 1987](#)). Similarly, the comparative method allows for more participants' responses rather than requiring respondents to provide exact figures ([Tomaskovic-Devey et al., 1994](#)). Finally, as evidenced by [Wall et al. \(2004\)](#), subjective and objective measures of company performance are positively linked at 0.52.

Along with difficulty collecting objective performance, the organizations involved in this study represent several different service industries; therefore, financial performance, i.e. fee income, might not be the best indicator for firm performance. To validate the organizational performance measure, the authors conducted a second round of data collection six months later. Among the 155 organizations, only 36 responses were received. Respondents answered the same questions on organizational performance. The correlation between organizational performance at two-time points was significant ( $r = 0.36, p < 0.05$ ). Although the correlation was significant, the coefficient was not large. Upon reflection, we believe there might be a few factors influencing the low correlation coefficient. First, this study involves multiple industries, and industry-wide economic changes might be one factor [2]. Due to the limited sample, we would not be able to test this. Second, the relatively long-time lag (6 months) may also explain the changes as, within the last six months, organizations may have undergone several changes that have influenced their performance.

*Organizational EBM.* To measure organizational EBM, six items were developed based on EBM's definition in [Rousseau \(2006\)](#) and [Barends et al. \(2014\)](#). Respondents were asked to indicate to what degree they agree or disagree with the following statements: "We translate an issue or problem into an answerable question" (asking), "We systematically search for and retrieve the best available evidence" (acquiring), "We critically judge the trustworthiness and relevance of the evidence we collect" (appraising), "We weigh and pull together the evidence" (aggregating), "We incorporate the evidence into the decision-making process" (applying) and "We evaluate the outcome of the decision" (assessing). Each item was evaluated on a five-point Likert scale (1 = strongly disagree, and 5 = strongly agree). The Cronbach's alpha was 0.93.

*HR analytics.* Given that no valid scale has been developed to measure HR analytics, this study applies the theoretical framework proposed by [Minbaeva \(2018\)](#) and adopts questions from established scales to reflect the theoretical definition. For the first dimension, high-quality data, we adopted five questions from [Pipino et al. \(2002\)](#), which include: “The HR data we have is correct and reliable” (accuracy), “The HR data we have is sufficiently up to date” (timeliness), “The HR data we have is presented in the same format” (consistency), “The HR data we have is complete and no necessary data is missing” (completeness) and “The HR data we have is collected on a regular basis” (data process). The Cronbach’s alpha for data quality was 0.91.

For the second dimension, analytical competency, we adopted five items from [Kryscynski et al. \(2018\)](#). Example items include “Our HR Department translates data into useful insights”, “Our HR department identifies problems that can be solved with data” and “Our HR Department effectively uses HR analytics to create value for my organization.” The Cronbach’s alpha for analytical capability was 0.95. Finally, the strategic ability to act was operationalized through three questions adopted from [Minbaeva \(2018\)](#), including “Our HR Department has success stories to justify HR analytics projects”, “Our HR Department inspires relevant organizational stakeholders (e.g. senior management teams and line managers) to take action on the basis of their findings” and “The data-driven insights that we provide are used by our organization’s stakeholders.” The Cronbach’s alpha for analytical capability was 0.86.

Each of the three dimensions of the HR analytics’ measure was evaluated based on a five-point Likert scale (1 = strongly disagree and 5 = strongly agree). We conducted a second-order confirmatory factor analysis (CFA) for the HR analytics measure to examine the new scale’s validity. The model fit indexes indicated an acceptable model fit for the second-order CFA with three first-order dimensions ( $\chi^2/df = 171.65/72 = 2.38, p < 0.001$ ; comparative fit index [CFI] = 0.95; Tucker–Lewis Index [TLI] = 0.93; root-mean-square error of approximation [RMSEA] = 0.09; and the standardized root mean square residual [SRMR] = 0.05). Considering HR analytics as a theorized higher-order concept in this study and the CFA’s support for the higher-order factor structure, we treated HR analytics as one overall concept with three dimensions in the model test.

*Access to HR technology.* Three items were adapted from measures previously used by [Aral et al. \(2012\)](#). The three items developed were “My organization has the necessary tools to conduct HR analytics,” “My organization invests in the tools needed to conduct HR analytics” and “My organization has the appropriate tools for performing HR analytics.” Respondents evaluated these statements based on a five-point Likert scale (1 = strongly disagree and 5 = strongly agree). The Cronbach’s alpha was 0.93.

*Control variables.* In the analysis, we controlled several contextual variables with the potential to influence the use of HR analytics, EBM, HR technology and organizational performance such as organization size, organization age, organization type (multinational or domestic), sector and industries. Organization size was measured using three categories: 1 = small organizations (less than 50 employees), 2 = medium organizations (between 50 and 250 employees) and 3 = large organizations (more than 250 employees). Organization age was operationalized as the natural log of the actual organization age. Organization type (multinational or domestic) was measured using a dummy variable (1 = multinational companies; 0 = domestic companies). Sector was measured using a dummy variable (1 = private, 0 = public or semi-state). The industry was measured by four categories (1 = professional services including accounting, advertising, architecture, consulting and law firms; 2 = Information, communications and technology (ICT); 3 = financial services including banking, insurance, compliance and risk firms; and 4 = other services including education, healthcare, pharmaceutical etc.). Three dummy variables were created for the industry variable using ICT as the baseline category.

### *Common method bias*

It was necessary to check whether common method bias was present in the study since all variables were collected from a single source. To address this concern, this study follows several recommendations made by Podsakoff *et al.* (2003) and Podsakoff *et al.* (2012). For instance, before launching the survey, it was piloted with a group of HR managers and was revised and retested several times. Changes made as a result included the wording and order of the questions. Likewise, during the data analysis stage, we assessed the common method variance by carrying out a series of CFA to establish the validity of the studied variables. Likewise, we added one unrelated common factor to the CFA with enforced equal factor loadings to all items in evaluating the common method variance (Podsakoff *et al.*, 2012). The squared regression estimates indicated a common variance of 3%, indicating no significant concern for common method bias.

## **Results**

Table 1 presents the descriptive statistics of the core variables in this study, including the mean, standard deviation and correlations.

### *Measurement models*

Analysis was conducted using Mplus 8.0. A full measurement model was tested using three pre-calculated variables (data quality, analytical capability and strategic ability to act) loaded on one general factor representing HR analytics. EBM, HR technology and organizational performance items loaded on to their respective factors. The four-factor model showed a good model fit ( $\chi^2/df = 236.93/143 = 1.66$ ,  $p < 0.001$ ; CFI = 0.95; CLI = 0.94; RMSEA = 0.07; SRMR = 0.07) with factor loadings higher than 0.55 ( $p < 0.001$ ). We then carried out  $\chi^2$  difference tests that compared this full measurement model to seven alternative nested models, as shown in Table 2. The comparison results reveal that the model fit of the full measurement model was significantly better than the alternative models (all at  $p < 0.001$ ), suggesting that the study's variables are distinct.

### *Structural models*

We carried out the structural equation modeling in Mplus 8.0. Figure 2 presents the results.

Hypothesis 1 proposed that HR analytics would be positively linked to organizational EBM. Results in Figure 2 show that the standardized coefficient of organizational EBM on HR analytics was positive and significant ( $\beta = 0.30$ ,  $p < 0.05$ ). Therefore, Hypothesis 1 was supported. Hypothesis 2 proposed that organizational EBM would be positively linked to organizational performance. Figure 2 shows that the standardized coefficient of organizational performance on EBM was 0.41 ( $p < 0.001$ ). Thus, Hypothesis 2 was supported.

Hypothesis 3 proposed the mediating role of organizational EBM in the relationship between HR analytics and organizational performance. According to Baron and Kenny (1986) and Hayes (2013), three conditions need to be tested for the mediation model. The first two conditions include the significant relationships between the independent variable and the mediator and between the mediator and the dependent variable. The third condition requires the reduced relationship between the independent variable and dependent variable after including the mediator. Support for Hypotheses 1 and 2 met the first two conditions. The direct impact of organizational performance on HR analytics was 0.31 ( $p < 0.05$ ). After including the mediator—organizational EBM—the coefficient of organizational performance on HR analytics became non-significant ( $\beta = 0.20$ , n.s.), meeting the third condition. To further test EBM's mediating effect in the relationship between HR analytics and organizational performance, this study adopted a bootstrapping test recommended by

**Table 1.**  
Descriptive statistics  
and correlations of  
study variables

Variables	Mean	SD	1	2	3	4	5	6	7	8
1. Organizational performance	3.57	0.62								
2. Evidence-based management	3.68	0.68	0.44**							
3. HR analytics	3.43	0.72	0.35***	0.37**						
4. Access to HR technology	3.08	0.90	0.20*	0.22**	0.66**					
5. Organization size	1.95	0.79	0.01	-0.07	0.21*	0.07				
6. Organization age	3.10	0.99	-0.11	-0.23**	0.06	-0.03	0.44**			
7. Sector	0.89	0.32	0.05	0.00	-0.14	-0.01	-0.17*	-0.14		
8. Organization type	0.56	0.50	-0.14	-0.05	0.04	-0.07	0.06	-0.09	-0.03	
9. Industry	2.78	1.04	-0.11	-0.03	-0.06	-0.08	0.09	0.09	-0.05	0.06

**Note(s):** *N* = 134 (listwise) \*\**p* < 0.01 \**p* < 0.05

Models	$\chi^2/df$	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	$\Delta df$
Full measurement model	236.93/143	0.95	0.94	0.07	0.07		
Model A <sup>a</sup>	498.61/146	0.82	0.78	0.13	0.13	261.68***	3
Model B <sup>b</sup>	371.73/146	0.88	0.86	0.10	0.09	134.80***	3
Model C <sup>c</sup>	842.54/148	0.64	0.58	0.18	0.16	605.61***	5
Model D <sup>d</sup>	412.52/146	0.86	0.84	0.11	0.12	175.59***	3
Model E <sup>e</sup>	459.60/146	0.84	0.81	0.12	0.15	222.67***	3
Model F <sup>f</sup>	669.10/148	0.73	0.68	0.15	0.16	432.17***	5
Model G <sup>g</sup> (Harman's single factor test)	1010.77/149	0.55	0.48	0.19	0.18	773.84***	6

**Note(s):**  $N = 153$ , \*\*\* $p < 0.001$ ;  $\chi^2$  = chi-square discrepancy,  $df$  = degrees of freedom; CFI=comparative fit index; TLI = Tucker–Lewis Index; RMSEA = root mean square error of approximation; SRMR= standardized root mean square residual; = difference in chi-square, = difference in degrees of freedom. In all measurement models, error terms were free to covary to improve fit and help reduce bias in the estimated parameter values. All models are compared to the full measurement model

<sup>a</sup> = HR analytics and evidence-based management combined into a single factor

<sup>b</sup> = HR analytics and technology combined into a single factor

<sup>c</sup> = HR analytics, evidence-based management and technology combined into one factor

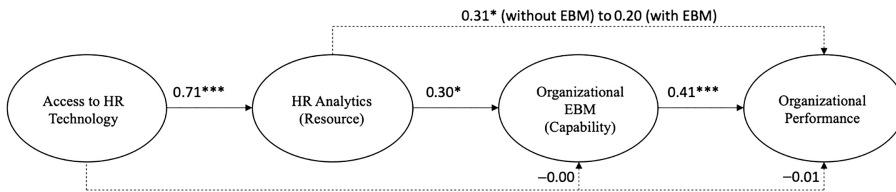
<sup>d</sup> = Evidence-based management and organizational performance combined into a single factor

<sup>e</sup> = HR analytics and organizational performance combined into a single factor

<sup>f</sup> = HR analytics, evidence-based management and organizational performance combined into a single factor

<sup>g</sup> = All factors combined into a single factor

**Table 2.** Fit statistics from measurement model comparison



	HR analytics	EBM	Organizational performance
Firm size	-0.01	-0.04	0.02
Firm age	-0.01	-0.22*	0.01
Organization type dummy (multinational)	-0.07	-0.09	-0.20**
Sector dummy (private)	-0.00	-0.01	0.07
Industry dummy 1 (professional services)	0.03	0.00	-0.20*
Industry dummy 2 (financial services)	0.01	0.07	-0.08
Industry dummy 3 (other)	0.05	0.02	-0.21*

**Note(s):** Standardized coefficients were reported. The dash lines indicate non-significant relationships. The real lines indicate significant relationships. \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$  (two-tailed tests)

**Figure 2.** SEM results

Hayes and Preacher (2014). The bootstrapping test results reveal that the indirect effect of HR analytics and organizational performance through EBM was 0.16 ( $p < 0.05$ ), with a 95% confidence interval between 0.007 and 0.321. As such, Hypothesis 3 was supported, suggesting that EBM mediates the relationship between HR analytics and organizational performance.

Hypothesis 4 proposed that HR technology is positively associated with HR analytics. It is supported by the positive and significant coefficient for HR technology on HR analytics



( $\beta = 0.71, p < 0.001$ ). [Hypothesis 5](#) proposed a chain model linking HR technology to organizational performance via the mediators of HR analytics and organizational EBM. The support for [Hypotheses 1 to 4](#) confirms the significant impact of HR technology on HR analytics ( $\beta = 0.71, p < 0.001$ ), which in turn facilitates organizational EBM ( $\beta = 0.30, p < 0.05$ ), ultimately leading to organizational performance ( $\beta = 0.41, p < 0.001$ ). In addition, the indirect impact of organizational performance on HR technology via HR analytics and organizational EBM was calculated as 0.06 ( $p < 0.05$ ) with a 95% confidence interval between 0.0013 and 0.117. Therefore, [Hypothesis 5](#) on the chain model of HR technology–HR analytics–organizational EBM–organizational performance was supported.

## Discussion

Despite the claimed importance of HR analytics, research investigating the performance impact of HR analytics on organizational performance remains underdeveloped ([Rasmussen and Ulrich, 2015](#); [Baensens et al., 2017](#); [Levenson and Fink, 2017](#); [Marler and Boudreau, 2017](#); [Huselid, 2018](#); [Greasley and Thomas, 2020](#)). As such, this study sets out the first attempt to (1) theorize and establish the relationship between HR analytics and organizational performance; and (2) understand the process for how HR analytics can influence organizational performance. Drawing upon EBM ([Rousseau, 2006](#); [Rousseau and Barends, 2011](#); [Barends et al., 2014](#)), dynamic capabilities ([Teece et al., 1997](#)) and the RBV of the firm ([Barney, 1991](#)), this study proposed a chain model where access to HR technology enables HR analytics which facilitates EBM, ultimately enhancing or improving organizational performance. Using a sample of 155 organizations based in Ireland, the structural equation modeling results provided full support for the theoretical chain model. Therefore, the study finds that HR technology enables HR analytics and acts as an antecedent to HR analytics, with HR analytics facilitating organization EBM, leading to higher organizational performance.

### *Theoretical contributions*

The findings of this study make several contributions to the fields of HR analytics and EBM. First, this study offers a very timely investigation of whether HR analytics impacts organizational performance. Due to the growing interest in HR analytics, organizations have begun to buy into HR analytics, assembling HR analytics teams dedicated to using workforce data to make strategic workforce decisions ([Rasmussen and Ulrich, 2015](#); [Andersen, 2017](#); [McIver et al., 2018](#)). However, very little empirical evidence supports the impact HR analytics has on organizational performance ([Rasmussen and Ulrich, 2015](#); [Marler and Boudreau, 2017](#); [van der Togt and Rasmussen, 2017](#); [McIver et al., 2018](#)). According to [McIver et al. \(2018\)](#), despite the great enthusiasm for adopting HR analytics in practice, there remains a misunderstanding of how organizations can leverage and use HR analytics to increase organizational performance. Furthermore, [King \(2016\)](#) argues that although the practice of conducting HR analytics has risen in popularity, organizations should only begin to invest in HR analytics programs if they can demonstrate value and increase organizational performance. This research has responded to the above calls by seeking support for the positive effect of HR analytics on organizational performance and offers evidence of the performance impact of HR analytics.

Second, this study promotes current HR analytics research by providing evidence suggesting a relationship between HR technology and HR analytics. In recent years, scholars have theorized that HR technology is critical in enabling the HR analytics process. For example, [Marler and Boudreau \(2017\)](#) and [McIver et al. \(2018\)](#) have suggested that HR analytics are enabled by HR technology as it allows for the collection, manipulation, and

reporting of structured and unstructured workforce data. Furthermore, several scholars have also begun to suggest that HR analytics are enabled by HR technology as they allow HR professionals to perform complex statistical analysis, leading to the development of predictive analytics and sophisticated people models (Levenson, 2005; Ulrich and Dulebohn, 2015; Sharma and Sharma, 2017; van der Togh and Rasmussen, 2017). Despite these claims, evidence supporting the enabling role of HR technology in HR analytics has yet to be discussed in the extant HR analytics literature. Therefore, this paper supports these claims, indicating a link between HR technology and HR analytics, where HR technology is a critical component and antecedent to HR analytics.

Third, this study contributes to HR analytics research by exploring the process (i.e. the mediating role of EBM) through which HR analytics influences organizational performance. As reviewed earlier, the research examining the performance impact of HR analytics is scarce within the extant literature. Likewise, evidence illustrating the process of how HR analytics can influence organizational performance is non-existent, making the analysis of intervening variables essential both theoretically and empirically. We acknowledge that this is only the first step in identifying the underlying linkage between HR analytics and organizational performance; however, this study undoubtedly contributes to this endeavor.

Lastly, this study contributes toward EBM research significantly by identifying an antecedent of EBM (i.e. HR analytics), as well as offering evidence supporting the performance impact of EBM. To date, EBM research has seen increasing attention in both research and practice. However, there has been limited attention paid to directly address EBM's performance impact within the field of management, which is "of the utmost importance" (Reay *et al.*, 2009, p. 13). Moreover, the organizational level factors which drive EBM remain unknown. Thus, this paper contributes to EBM research by offering a critical organizational factor (HR analytics) that facilitates EBM within organizations.

#### *Implications for practice*

The findings offer several implications for practitioners. First, this study offers evidence for the positive impact of HR analytics on organizational performance, suggesting that investing in HR analytics and employing EBM practices can increase organizational performance. Second, the study provides supporting evidence for the critical role that access to HR technology plays in enhancing the impact of HR analytics on EBM. In other words, this study proposes that access to HR technology significantly impacts HR analytics and, in turn, EBM. Thus, HR analysts and managers must have the necessary tools to effectively transform and translate high-quality workforce data into organizational insights.

In addition, this study is significant for organizations looking to improve their current HR technology capabilities or are starting to implement or expand their current HR analytics activities. We find that HR technology offers HR managers and business partners the ability to run reports, create dashboards, visualizations, monitor KPIs and perform predictive analytics. Thus, providing several sources of additional information enabling evidence-based decision-making.

Lastly, this study suggests that establishing and cultivating a culture focused on decision-making has significant advantages for improving organizational performance. Likewise, we find support for HR analytics' important role in facilitating EBM. For instance, HR analytics offers information through mediums such as dashboards, scorecards and predictive analytics. According to Rousseau and Barends (2011), these sources of organizational knowledge create a link between HR analytics and EBM, allowing HR managers and business partners to make more informed decisions about their workforce. Thus, we conclude that organizations should employ the organizational facts generated by HR analytics and incorporate them into their decision-making process.

*Limitations and future research*

Despite the significant implications for theory and practice in HR analytics, several limitations are evident in this study. First, this study adopted a cross-sectional design, which does not allow us to test for the causality between the studied variables. Second, the small sample size, response rate and context where it was conducted are limitations of the study. Future research is encouraged to collect longitudinal data among multi-industry, multi-sector and multi-country data sets. Doing so would allow for testing causality between the key variables and aid in the generalizability of the findings. Moreover, it would offer greater consideration to potential economic changes that may be impacting specific industries. Likewise, future studies may use more objective performance data such as return on investment (ROI), return on assets (ROA) or revenue growth rather than subjective measures to operationalize organizational performance similar to existing studies (Crook *et al.*, 2011; Singh *et al.*, 2016; Omran *et al.*, 2021). The findings on the significant correlation coefficient between HR technology and HR analytics ( $r = 0.66, p < 0.01$ ) as well as the path coefficient of HR technology on HR analytics ( $\beta = 0.71, p < 0.001$ ) is another limitation of the study and raises concerns for the validity of the measurements. Accordingly, future research should adapt cross-disciplinary measures from the big data, marketing or information technology literature to better test this relationship. Lastly, the research study may have an issue with endogeneity. For example, according to Hill *et al.* (2021) and Semykina and Wooldridge (2010), there are four causes of endogeneity, i.e. omitted variables, simultaneity, measurement error and selection. This study has addressed some sources, i.e. the omitted variables, by including control variables; and the measurement error issue at both the design (e.g. using valid scales) and analysis (e.g. addressing the CMV and using SEM) stages. However, future research should pay more attention to endogeneity in management research and adopt the recommendations and solutions proposed by previous studies (e.g. Larcker and Rusticus, 2010; Semykina and Wooldridge, 2010; Ketokivi and McIntosh, 2017; Hill *et al.*, 2021).

In addition, future research is warranted to further investigate the connection between HR technology and HR analytics. For instance, should HR technology be incorporated as a fourth component of HR analytics? Or does it only act as an enabler in the HR analytics process? Furthermore, as illustrated, organizations utilize various levels of HR technology in order to perform HR analytics. At the most basic level, HR departments rely on Excel and HRIS such as Workday, SuccessFactors, or BambooHR for reporting, generating HR metrics and dashboarding. In contrast, analytically mature HR departments will also utilize these platforms but will integrate them with more advanced forms of HR technology (e.g. business intelligence (BI) tools, AI-enabled platforms, open-source statistical packages) to enable predictive and prescriptive data analytics. This raises the question of whether the use of more advanced HR technology leads to more insightful HR analytics. And if so, how significant are these insights compared to those derived from basic level technology? Equally important is the notion that organizations currently engaging with HR analytics often rely on HR analytics teams to conduct the analytics (i.e. transforming and translating high-quality workforce data into organizational insights), rather than an individual employee (Andersen, 2017; McIver *et al.*, 2018; McCartney *et al.*, 2020; Peeters *et al.*, 2020). However, very little attention has been paid to exploring the composition of HR analytics teams or their impact on HR practices and organizational performance (McCartney *et al.*, 2020). For instance, given the complex range of skills required to transform and translate high-quality workforce data into organizational insights effectively, HR analytics teams require members to have various complimentary knowledge, skills, abilities and other characteristics (KSAOs) (Andersen, 2017; McIver *et al.*, 2018; McCartney *et al.*, 2020). As such, it is essential that research examining the complimentary KSAOs and synergies among specific team members that enable the emergence of highly effective HR analytics teams be explored. Likewise, a significant way to

move HR analytics research forward would be to explore how HR analytics teams can help develop or enhance HR practices and their effect on organizational performance.

## Conclusion

While HR analytics is gaining increasing interest as a field of study, HR analytics is still a relatively new concept. As a result, scholars and practitioners are poised to conduct research highlighting how HR's digitalization and the growing amount of people data can impact HR decision-making and organizational outcomes. The present study sheds light on HR analytics research by identifying the impact of HR analytics on organizational performance. By doing so, we hope to see more research aiming to better understand how HR analytics adds value to organizations in the future.

## Notes

1. The authors would like to thank one of the reviewers for this point.
2. Thanks are given to one of the reviewers who raised this point.

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