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"An Empirical Study On Hr Analytics Adoption And Its Impact On Hr Performance"

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ABSTRACT

In today's world managing employees in organization is not a one-man task. With the evolving business and advancement in technologies managing employees and tracking their performance can be performed online with the help of HR analytic tools. The use of HR analytics has improved employee performance and increased efficiency in business like, improvement of quality of recruitment, talent management, employee productivity and decreasing employee turnover. In this paper we are going to study about HR analytics, its tools, and its application in different organizations. In this paper we study various use of HR Analytics in different organisations and the benefits of the use of HR Analytics. With the help of analytical tools the organisations can recognise the issues like performance, employee turnover and retention employee behaviour, etc by using the data available with the organisation. This research is conducted because of the lack of use of HR in many organisations. The use of HR is undermined in many organisations but in this modern technological world various analytical tools have been developed which are used by huge corporations. In this paper we are going to see such uses of HR Analytics in 5 different organisations and their how the use of HR Analytics helped the organisation as well as the employees in monetary ways and change the business strategy around people - centric way.

Keywords: HR Analytics, HR analytics tools, Data Metrics, Employee Attrition, Organizations.

1. INTRODUCTION:

The concept and application of data and analytics in management have gained 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 expanded across various management disciplines, including human resource management (HRM), as evidenced by the growing number of HR departments implementing HR analytics to enhance decision-making (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; McCartney et al., 2020).

Despite its rising popularity, HR analytics is not an entirely new concept (Huselid, 2018). Rather, it has evolved from previous research on the impact of HR practices such as selection, training, and performance management, which have long been studied in social sciences, including industrial and organizational psychology, HRM, and organizational behavior. What is new, however, is the shift in contemporary organizations from merely assessing workforce attributes (e.g., "What is our cost per hire?") to understanding the broader impact of the workforce on business 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 now goes beyond evaluating human capital elements—it integrates analytical techniques with workforce data to inform organizational strategy and drive performance improvements.

Furthermore, the significant advancements in HR technology, including human resource information systems (HRISs), cloud platforms, and apps, have enabled HR departments to collect, manage, and analyze vast amounts of employee data more efficiently than earlier legacy IT systems (Bondarouk and Brewster, 2016; Marler and Boudreau, 2017; Kim et al., 2021). This technological shift has also acted as a catalyst for the adoption of HR analytics within HR departments. For instance, by leveraging advanced HR technology to gather and analyze candidate and employee data, Google's HR analytics team has developed an evidence-based approach to enhance its recruitment and selection process by identifying key performance indicators that predict a candidate's likelihood of success (Harris et al., 2011; Shrivastava et al., 2018). Similarly, beyond recruitment and selection, HR analytics enables organizations to address other HR challenges, such as 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 existing HR analytics literature has focused on various areas, including the limitations and challenges associated with its development (Boudreau and Cascio, 2017; Levenson and Fink, 2017; Huselid, 2018; Minbaeva, 2018; Jeske and Calvard, 2020), best practices for implementing HR analytics (Green, 2017; Falletta and Combs, 2020), and the significance of analytical skills (Kryscynski et al., 2018; McCartney et al., 2020). Additionally, several reviews have provided a comprehensive overview of the current state of HR analytics research (Marler and Boudreau, 2017; Tursunbayeva et al., 2018; Fernandez and Gallardo-Gallardo, 2020; Margherita, 2020). Despite these advancements and the increasing number of case studies suggesting that HR analytics enhances organizational performance (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; Margherita, 2020), there remains a gap in research investigating the extent and mechanisms through which HR analytics influences organizational performance (Huselid, 2018; Minbaeva, 2018).

Building on this gap, the present study aims to explore how and why HR analytics impacts organizational performance by theorizing and testing its underlying mechanisms. This study is grounded in evidence-based management (EBM) theory (Rousseau and Barends, 2011; Baba and HakemZadeh, 2012; Bezzina et al., 2017), the resource-based view (RBV) of the firm (Barney, 1991), and dynamic capabilities theory (Teece et al., 1997; Winter, 2003). These theoretical frameworks are well-justified: EBM emphasizes the integration of scientific and organizational facts with expert and stakeholder judgment for informed managerial decision-making (Rousseau and Barends, 2011; Baba and HakemZadeh, 2012), while HR analytics contributes to organizational evidence creation by transforming high-quality workforce data into meaningful insights (Marler and Boudreau, 2017; Minbaeva, 2018; Coron, 2021).

Furthermore, in line with prior studies examining the impact of HR on performance (Delaney and Huselid, 1996; Guthrie, 2001; Fu et al., 2017), this study integrates the RBV (Barney, 1991) and dynamic capabilities perspective (Teece et al., 1997) to propose a conceptual framework. This framework suggests a sequential model in which access to HR technology enables HR analytics (resource), which in turn facilitates EBM (capability), ultimately leading to enhanced organizational performance.

2. Objectives:

- Assess the impact of HR analytics on organizational performance.
- Examine the moderating role of Evidence-Based Management (EBM) in HR analytics adoption.
- Evaluate the effect of HR analytics on employee satisfaction and retention.
- Analyze the role of HR analytics in workforce planning and talent management.
- Investigate the relationship between HR analytics adoption, employee engagement, and productivity.
- Identify challenges and best practices in implementing HR analytics.

3. Literature Review and Hypothesis Development

HR Analytics and Evidence-Based Management (EBM)

HR analytics has emerged as a critical tool for organizations seeking to enhance decision-making through data-driven insights. By leveraging advanced analytics, companies can optimize workforce planning, talent acquisition, employee engagement, and performance management. Evidence-Based Management (EBM) plays a complementary role by ensuring that HR decisions are based on systematic research, empirical data, and organizational context rather than intuition or tradition. Studies indicate that organizations that integrate HR analytics with EBM frameworks achieve improved efficiency, reduced biases in HR processes, and enhanced employee productivity.

Organizational Performance and HR Analytics

The impact of HR analytics on organizational performance is well-documented in academic and industry research. Organizations that systematically analyze HR data can identify workforce trends, predict employee turnover, and implement strategic interventions to enhance productivity. The use of HR analytics facilitates data-driven decision-making, leading to better alignment between HR strategies and business objectives. Empirical studies suggest that companies investing in HR analytics witness improvements in financial performance, employee satisfaction, and operational efficiency.

4. Hypothesis Development

Based on the literature review, the following hypotheses are proposed:

H1: The adoption of HR analytics has a significant positive impact on organizational performance.

H2: Evidence-Based Management (EBM) moderates the relationship between HR analytics and organizational performance.

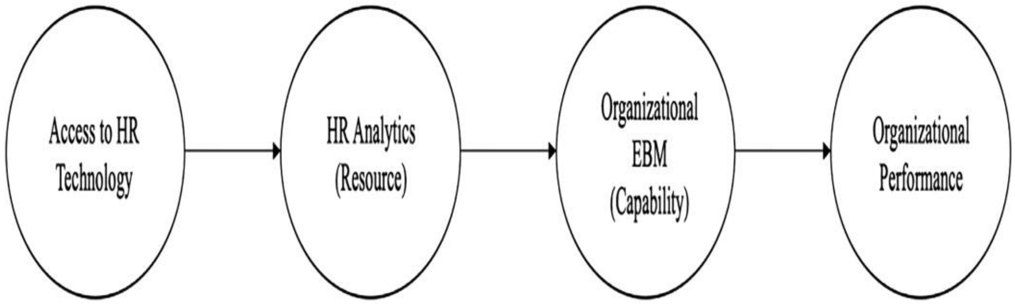
H3: Organizations that leverage HR analytics for decision-making experience higher employee satisfaction and retention rates.

H4: The integration of HR analytics in workforce planning leads to improved talent acquisition and management outcomes.

H5: HR analytics adoption is positively associated with enhanced employee engagement and productivity.

The proposed hypotheses will be tested through empirical research, utilizing quantitative and qualitative methods to validate their significance and impact on organizational performance.

Figure 1 presents the theoretical model.



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 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 as HR managers/directors or senior managers. The average work tenure of respondents was nine years (SD = 58). 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, 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 previous studies have shown, the rationale for using subjective performance data is partly due to the difficulty and inability to access objective performance measures (Gupta and Govindarajan, 1984, 1986; Gupta, 1987). Similarly, the comparative method allows for more participant 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.

Due to the difficulty in collecting objective performance data, 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. 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, 5 = strongly agree). The Cronbach's alpha was 0.93.

HR Analytics and Organizational Performance

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.

5. Descriptive Statistics

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

6. Measurement Models

The analysis was conducted using Mplus 8.0. A full measurement model was tested, incorporating three pre-calculated variables—data quality, analytical capability, and strategic ability to act—loading onto a general factor representing HR analytics. Additionally, EBM, HR technology, and organizational performance items were loaded onto their respective factors.

The four-factor model demonstrated a good model fit ($\chi^2/df = 236.93/1435.66$, $p < 0.001$; CFI = 0.95; CLI = 0.94; RMSEA = 0.07; SRMR = 0.07), with factor loadings exceeding 0.55 ($p < 0.001$). To further validate the model, we conducted χ^2 difference tests comparing this full measurement model to seven alternative nested models, as detailed in Table 2. The results revealed that the full measurement model provided a significantly better fit than the alternative models (all at $p < 0.001$), confirming that the study's variables are distinct.

Structural Models

Structural equation modeling (SEM) was conducted using Mplus 8.0, and the results are presented in Figure 2.

- **Hypothesis 1** proposed that HR analytics would have a positive relationship with organizational EBM. The results in Figure 2 indicate that the standardized coefficient of organizational EBM on HR analytics was positive and significant ($\beta = 0.30$, $p < 0.05$), supporting Hypothesis 1.
- **Hypothesis 2** suggested that organizational EBM would positively impact organizational performance. The analysis showed that the standardized coefficient of organizational performance on EBM was 0.41 ($p < 0.001$), confirming Hypothesis 2.
- **Hypothesis 3** examined the mediating role of organizational EBM in the relationship between HR analytics and organizational performance. Based on the mediation framework proposed by Baron and Kenny (1986) and Hayes (2013), three conditions needed to be met:

1. A significant relationship between the independent variable (HR analytics) and the mediator (organizational EBM).
2. A significant relationship between the mediator (organizational EBM) and the dependent variable (organizational performance).
3. A reduction in the direct relationship between the independent and dependent variable when the mediator is included.

The first two conditions were met with the support for Hypotheses 1 and 2. The direct effect of HR analytics on organizational performance was initially significant ($\beta = 0.31$, $p < 0.05$). However, after including the mediator (organizational EBM), the coefficient became non-significant ($\beta = 0.20$, n.s.), meeting the third condition for mediation.

To further validate the mediating effect of EBM, a bootstrapping test, as recommended by Hayes (2013), was conducted.

Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
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	0.9	0.20*	0.22**	0.66**	—					
5. Organization Size	1.95	0.79	0.01	-0.07	0.21*	0.07	—				
6. Organization Age	3.1	0.99	-0.11	-0.23**	0.06	-0.03	0.44**	—			
7. Sector	0.89	0.32	0.05	0	-0.14	-0.01	-0.17*	-0.14	—		
8. Organization Type	0.56	0.5	-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	—

Models	χ^2/df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf
Fullmeasurementmodel	*236.93/143*	*0.95*	*0.94*	*0.07*	*0.07*		
ModelA[a]	498.61/146	0.82	0.78	0.13	0.13	261.68***	3
ModelB[b]	371.73/146	0.88	0.86	0.1	0.09	134.80***	3
ModelC[c]	842.54/148	0.64	0.58	0.18	0.16	605.61***	5
ModelD[d]	412.52/146	0.86	0.84	0.11	0.12	175.59***	3
ModelE[e]	459.60/146	0.84	0.81	0.12	0.15	222.67***	3
ModelF[f]	669.10/148	0.73	0.68	0.15	0.16	432.17***	5
ModelG[g](Harman'ssinglefactor test)	1010.77/149	0.55	0.48	0.19	0.18	773.84***	6

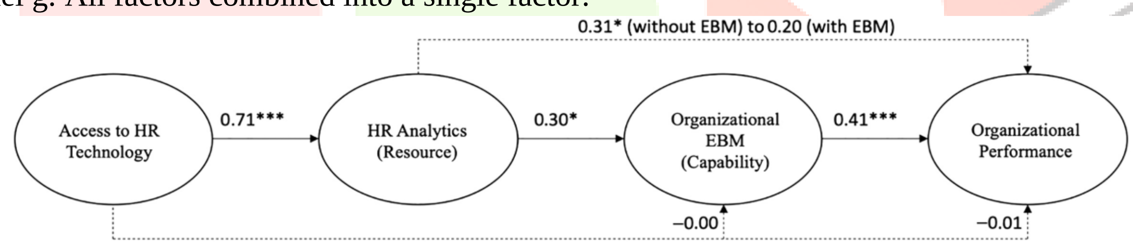
Model Comparisons and Fit Indices

Square discrepancy (χ^2), degrees of freedom (df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) were used to evaluate model fit. The difference in chi-square ($\Delta\chi^2$) and the difference in degrees of freedom (Δdf) were also considered.

In all measurement models, error terms were allowed to covary to improve model fit and help reduce bias in the estimated parameter values. All models were compared to the full measurement model.

Alternative Measurement Models:

- Model a: HR analytics and evidence-based management combined into a single factor.
- Model b: HR analytics and technology combined into a single factor.
- Model c: HR analytics, evidence-based management, and technology combined into one factor.
- Model d: Evidence-based management and organizational performance combined into a single factor.
- Model e: HR analytics and organizational performance combined into a single factor.
- Model f: HR analytics, evidence-based management, and organizational performance combined into a single factor.
- Model g: All factors combined into a single factor.



	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)

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; Baesens 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 by which 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 organizational 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 invest in 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 offering 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 Togt and Rasmussen, 2017). Despite these claims, evidence supporting the enabling role of HR technology in HR analytics has yet to be discussed in the existing 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, research examining the performance impact of HR analytics is scarce within the existing 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) and 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 addressing 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 that drive EBM remain unknown. Thus, this paper contributes to EBM research by offering a critical organizational factor (HR analytics) that facilitates EBM within organizations.

Conclusion

While HR analytics is gaining increasing interest as a field of study, it 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.

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