TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

Exploring the factors of HR Analytics Competency and its impact on Business outcomes

Gayathri R; Research Scholar, Dayananda Sagar University
Dr. Revathy Shivashankaran, Assistant Professor, Dayananda Sagar University

Article Info
Volume 82
Page Number: 2949 - 2960
Publication Issue:
January-February 2020

Abstract:
Research Background: In the past few decades the Human Resource Management (HRM) practices have tremendously evolved and with technological development came the innovative data-driven approach largely known as HR analytics. HR analytics applies various statistical tools on the collected data to create interventions, propose strategies and assess their effectiveness in the organizational performance of various departments such as marketing, finance, etc. Though the HR analytics is not less known but has been remained relatively less explored. This article attempts to explore the factors of HR analytics competency and its impact on business outcome. **Methodology:** The hypothesis was framed to test the influence of data-based HRA competencies in different processes in the organization and the business outcome. A well-structured questionnaire was used to collect the data from HR analytics professionals (n=180) working in the Bangalore city, India. The mean score, Pearson correlation and MANOVA analysis were performed. **Major findings and conclusion:** The study revealed a strong, positive and significant correlation between the sub factors of HR capability, motivation and opportunity. Our study suggests that HR capability and level of opportunities can affect the HR analytics competency outcome like process performance and strategies. Further, the results support the positive impact of HR analytics competencies on business outcome involving Return on Investments (ROI) and decision-making process. Our study emphasizes on the implementation of effective HR analytics.

Article History
Article Received: *14 March 2019*
Revised: *27 May 2019*
Accepted: *16 October 2019*
Publication: *18 January 2020*

Keywords:*HRA,HR Analytics, Competency,HRM,Human resource Management.*

I. INTRODUCTION

The Human Resource (HR) has evolved from basic administrative responsibilities to evidence and data-driven decision-making and has potentially evolved in their new strategic role in organizations (Jensen-Eriksen, 2016). Simultaneously, the technological advancements have exponentially increased the data collection, storage and processing. Currently, companies are accumulating lots of data on employees from various sources such as interviews, emails, etc. and it has remained as a challenge to analyse all the accumulated data and to draw the reliable interpretation. The data analysis on employees, their working pattern and other related activities is essential to increase the organization's effectiveness, productivity and performance (Guest, 2004). In the field of Human Resource Management (HRM), HR analytics is a new area and involves application of analytical approaches to HR owing to technology and data availability. This helps to understand the employer-employee relationship and improvement in the employee performance. HR analytics, which is also popularly known as workforce analytics, talent analytics or people analytics meticulously uses the information technology to integrate the data based on extrinsic and intrinsic function and efficiently analyse the HR data. Van Den Heuvel & Bondarouk (2016) has defined HR analytics as "the systematic identification and quantification of the people drivers of business outcomes".

Currently, the technological advancements and integration of computerized system have simplified the HRM practices (Pfeffer and Sutton, 2006). The

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

HR of any organization uses various aspects like HR metrics, HR scorecards, workforce economics, utility analysis, evidence based management, HR return of investment etc (Rasmussen and Ulrich, 2015). Levenson et al. (2005) differentiated HR Analytics as a different entity from HR metrics. The HR metrics refers to the efficient, effective, and impactful HR practices adopted by an organization's, whereas HR analytics constitutes ‘evidence-driven program’ (Bassi, 2011) which utilizes the data and applies scientific methods such as prognosticative and explanatory analytics and empirical programs to formulate the policies and take necessary steps to enhance the quality of service, persuasive decision making and increase the company’s competitive threshold (Lawler, 2004; Levenson, 2015).

HR analytics uses various terminologies of the HR department such as selection, recruitment, compensation, in-house and external training and development, employee commitment, sequential planning to measure different HR aspects such as number of people appointed/promoted, how many took training or leaves, calculation of depreciation rate, etc. (Fitz-Enz, 2010). This helps to access the condition of the employees and to take initiative for the improvement of the company’s productivity both in terms of quality and quantity. The HR analytics can analyze the data both qualitatively and quantitatively and it can be used in various areas such as finance, marketing or research and development (Rasmussen and Ulrich, 2015). However, application of HR analytics on a routine basis depends on knowledge and awareness of HR department. HR analytics assist the HR professionals to undertake strategic people-related decisions which give an evident result in terms of achieving business goals and performance metrics (Abrahamson and Eisenman, 2008). Thus, it can be stated that talent analytics is a strong, supportive element for every business organization process (Davenport et al. 2010). However, approximately 8% of the organization use workforce analytics to enhance performance of the employees and give a boost to the business (Deloitte, 2017). Thus, it can be inferred that still there is a considerable lack of competent HR analytic functions in HR team and the connection between analytical measures and proactive future strategies is not yet fully developed requiring a need to understand the recruitment of competent HRA professionals (Hoffmann et al., 2012).

The objective of the present study is to determine the following: i) the correlation between HR capability, level of motivation and level of opportunity; ii) the role of Capability, Motivation and Opportunity (CMO) in HRA professional to practice HRA in their organisations; iii) the impact of utilisation of data-based HRA competencies on the business outcome.

II. REVIEW OF LITERATURE

With time the HR function has evolved and there has been an increase use of HR metrics and analytics, which is often ignored by HR professionals. (Vargas, 2015). Human resource analytics HRA is an effective tool to quantify the organizational data and to reinforce the strategies to increase the effectiveness of programs or interventions adopted by the HRM (Lydgate, 2018). The globalization, increased competition, penetration of advance technologies, management of workforce and innovation of Big Data has led the way to business analytics to analyze the data and extract the necessary information (Bassi et al., 2012).

A. 2.1 HR analytics

Green (2017) pointed out that Big Data analytics and their directive focus on projects which matters for business can enhance the HR value and contribution. Similarly, Fred (2018) reported that HR analytics is a strategic partner of HR and their directions to HR influences the selection and recruitment of employees by HR, suggesting that a lack of proper data-based decision making and analytical ability will strongly influence the HR strategies. Sanders and Ganeshan (2018) study on supply chain management executives emphasizes on the Big Data collection and associated aspects of it such as

TEST Engineering & Management
January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

opportunity and changing the nature of inquiry, changing the nature of experimentation which allows the exploration of wide range of questions and possible experimentation. According to Vardi et al (2018) talent analytics helps to identify the strategic position, talent pool, monitoring of talent performance and management of recruiting the employees and talent retention. According to Nocker and Sena (2019) talent analytics aid the senior management team to align HR strategies and issues such as retention, planning, etc. which can be personalized support the individual.

B. 2.2 Factors influencing HR analytics

According to Sparrow et al (2015) the strategic insight of HR professionals and their perspective on the contribution of HR analytics and Joahnnik's (2015) utilization of the Delphi method demonstrated that logical thinking of data analytics and the target application influence the implementation and application of HR analytics. According to Vargas (2015) factors such as social influence, quantitative self-efficacy, tool availability and effort expectancy of HR professionals had a positive influence on HRA's organizational performance and competitive advantage, whereas fear appeals, data availability, and general self-efficacy were not of significant importance. Witte's (2016) exploratory study demonstrated that organizational size and the nature of business environment influences the performance of HR analytics.

C. 2.3 Competency of HRA

In 2011, Levenson designed a capability (ability), Opportunity and Motivation (COM) model to aid HR managers to gain awareness of employee's behavior, performance, motivation, etc. and to undertake strategies to enhance the organizational outcome. Krysinsky et al. (2017) found that opportunity and job roles had a mediating effect on the performance of HR professionals with higher analytical skills.According to Minbaeva (2017) different dimensions of analytics such as data quality, analytical competencies, and strategic ability compete at individual (capabilities), process (job role design) and structure (culture of inquiry and evidence-based decision) level to provide a competitive advantage. According to Schiesmann et al. (2018) inclusion of talent analytics in an HR team played as a motivating factor and positively impacted the employee satisfaction and turnover. Thus, we propose:

Hypothesis 1: CMO has a significant impact on utilization of data-based HRA competencies in process performance and strategies.

D. Impact of HRA on business outcome

The survey conducted by Deloitte (2017) showed that 70% of the analytics workforce agreed with the key role of HRA in employee performance and positive impact on business, however, 8% cast their doubt on the quality of data, thus the usefulness of analytics and 9% were aware about the nature of talent which can result in good performance. Lochab et al (2018) in their exploratory study used a secondary source and found that the majority of the organization structure has incorporated HR analytics, however, due to non-numerical data; the study was not able to generate the output of the company. A quantitative study conducted by Van der voort et al (2019) resulted in a conclusion that the Big Data analysis provides opportunities for decision makers and analysts to improve their performance and an individual to pursue their interests, suggesting a broader application of HRA in the organizational outcome. Thus, we propose:

Hypothesis 2: Utilization of data-based HRA competencies by the organization for different processes has a significant impact on business outcome.

In the conducted literature review it was found that despite the essential role of HR analytics, relatively the empirical research on HR analytics is very limited especially in the context of India. There is a dearth of studies exploring the role of demographics, organization's programs on the working attitude and behavior of HR analytics. Also, the existed studies

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

provided very less insight into the impact of HR analytics competencies such as competency to analyse the data, analytical, interpretation and application skills on the HRM practices.

III. METHODOLOGY

The study design involved exploratory and descriptive analysis with a cross-sectional time frame. For this study, 180 employees employed in HR analytics department of different companies in Bangalore city, India were selected and administered with a well-structured questionnaire. The questionnaire involved different sections like demographic profile, utilization of analytical skill in process performance and strategies, and the potential business outcome in terms of Return on Investments (ROI) and decision-making process. Each response was scored on a 5-option Likert Scale ranging from 1-5, where 1=strongly disagree, 2=disagree, 3=no idea, 4=agree, and 5=strongly agree. The collected data was subjected to statistical analysis. Exploratory Factor Analysis (EFA), multivariate analysis (MANOVA) was conducted to verify the hypothesis. The correlation between sub factors of HR capability, motivation and opportunity was evaluated using Pearson correlation coefficient. All the test results were considered statistically significant at $p<0.05$. All data analysis was performed using the Statistical Package for the Social Sciences (SPSS) program, version 24.0.

IV. RESULTS

4.1 Demographics

In the present study, out of 180 respondents, 55% were males, 47.2% were between 31-40 years and 80.6% had a PG degree. Professionally, 39.4% were working in MNC followed by 34.4% in large companies with more than 1000 employees and department wise 51.7% were from IT sector and 25.6% from services. The majority of HR analytic professionals (76.6%) had more than one but less than 10 years of experience as an HRA and abut 45.6% were from organization which had a team for HRA (Table 1).

Table 1. Demographics of the respondent

Demographics	**Categories**	**Frequency**	**Percent**
Gender	Male	99	55
	Female	81	45
Age (years)	21-30	74	41.1
	31 -40	85	47.2
	41- 50	21	11.7
Educational Qualification	UG	34	18.9
	PG	145	80.6
	PhD	1	0.6
Currently Working	MNC	71	39.4
	Small Indian Company (≥100 employees)	29	16.1
	Medium size company (100-1000 employees)	18	10
	Large companies (>1000 employees)	62	34.4
Types of Sector	IT	93	51.7
	Manufacturing	20	11.1
	Services	46	25.6
	Others	21	11.7
Total Experience as an HRA	1 - 5	80	44.4
	6 -10	58	32.2
	11 - 15	22	12.2

	16 - 20	20	11.1
Team for HRA in the Organization	Yes	82	45.6
	No	98	54.4
	Total	**180**	**100**

4.2 Exploratory Factor Analysis

Principal component analysis was used to perform an exploratory factor analysis (EFA) and to extract the factors for data-based HRA competencies and business outcome. The exploratory factor analysis (Table 2) resulted in the extraction of two factors for different processes. The Kaiser-Meyer-Olkin (KMO) value of 0.734 indicated sampling adequacy and Bartletts test of sphericity ($p<0.00$) supported the use of a factor analysis. Virtually all the items under process performance (9 items) and strategies (3 items) yielded factor loadings in the range of 0.60-0.84 with a total percentage variance of 71.82%, with process performance explaining 48.55% and strategies making up 23.26% of the variance.

Table 2. Factors of utilisation of data-based HRA competencies by the organization for different processes

Factors	Factor Loadings	% of Variance	Cumulative %
Process Performance		**48.555**	**48.555**
Downsizing workforce assessment	0.840		
Organization design/dysfunctional aspects of work flow	0.834		
Organizational development assessments	0.812		
Employee attitude surveys	0.796		
Compensation analysis	0.780		
Employee competency assessments	0.766		
Recruitment analysis	0.741		
Employee performance assessments	0.707		
Management development assessments	0.609		
Strategies		**23.261**	**71.816**
HR manpower planning	0.840		
Succession planning for leadership development	0.818		
Change management planning	0.638		

Table 3 represents the extracted factor loadings, namely return on investments (ROI) and decision-making process of the business outcome. The ROI contained six items with a factor loading ranging from 0.58-0.91 and decision-making process contained thirteen items with a factor loading ranging from 0.61-0.85. ROI contributed 36.623% and decision-making process accounted for 29.185% of the overall variance.

Table 3. Factors ofbusiness outcome

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

Factors	Factor Loadings	% of Variance	Cumulative %
Return on Investments (ROI)		**36.623**	**36.623**
Wide application of Analytics will change the organization results drastically	0.912		
Analytics helps to link each activity to the business bottom-line very objectively	0.821		
Analytics helps to evaluate the efficiency of the operating standards	0.748		
Analytics will enhance the efficiency of the business process	0.769		
The learning curve of the organization is enhanced	0.749		
The company in the position to assess the ROI on Training	0.580		
Decision-Making Process		**29.185**	**65.808**
Point out HR programs that should be discontinued	0.852		
Link human capital practices to organizational performance	0.851		
Measure the cost of providing HR services	0.811		
Outcome of key HR activities like man power planning can be forecasted well	0.771		
Identify the area where talent has the maximum scope for strategic impact	0.770		
Measure routine HR activities (payroll, benefits, communication, etc.)	0.765		
Evaluate and track the performance of outsourced HR activities	0.732		
Getting input from analytics process key input for business decisions, especially from strategic perspectives	0.728		
Contribute to decisions about business plans and human capital management	0.698		
Analytics cuts the unnecessary opinion based decision making in the organization	0.682		
Make decisions that reflect your company’s competitive status	0.681		
Evaluate and improve the human capital strategy of the company	0.669		
Evaluate the practicality of new business strategies	0.613		

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

4.3 Correlation analysis

The correlation between the sub factors of HR capability, level of motivation and level of opportunity is demonstrated in Table 4. In the present study, statistically significant correlations at varying degrees were observed between the above mentioned variables. The correlation among the sub factors of HR capability, namely, behaviour with skills (r=0.734) and knowledge (r=0.918) was found to be highly, positive and significant. Among the sub factors of the level of motivation, job satisfaction was highly correlated to knowledge (r=0.681) and creative analytics (r=0.772). Also, organization fit was positively and highly correlated with behaviour (r=0.814), the sub-factor of HR capability. Among the level of opportunity sub factors, job design was highly correlated with cross-functional dynamics (r=0.700) and skills (r=0.864), the sub factor of HR capability.

Table 4. Correlation between capability, motivation and opportunity

	1	2	3	4	5	6	7	8	9
HR Capability									
1. Knowledge	1								
2. Skills	.811**	1							
3. Behavior	.734**	.918**	1						
Level of motivation									
4. Organization fit	.702**	.786**	.814**	1					
5. Creative analytics	.832**	.640**	.561**	.661**	1				
6. Job Satisfaction	.681**	.460**	.451**	.547**	.772**	1			
Level of opportunity									
7. Organization infrastructure	.584**	.656**	.621**	.487**	.517**	.530**	1		
8. Cross-functional dynamics	.661**	.641**	.713**	.571**	.699**	.718**	.573**	1	.
9. Job design	.700**	.797**	.792**	.632**	.711**	.623**	.708**	.864**	1

Descriptive statistics with multivariate analysis of variance

Means and standard deviations of process performance and strategies in HRA competencies are given in Table 5. Of the present CMO sub-factors, both HRA capability and level of opportunities had a significant impact on process performance and strategies (Table 6). MANOVA revealed a statistically significant difference in HRA capability (F=35.978; Wilks' Lambda=0.709; partial eta squared=0.291, p<0.01) and exerted a significant impact on process performance (F=64.121, p<0.01) and strategies (F=54.335, p<0.01). Similarly, level of opportunities (F=8.234; Wilks' Lambda=0.914; partial eta squared=0.086, p<0.01) exerted a significant impact on process performance (F=16.461, p<0.01) and strategies (F=8.231, p<0.01). The level of motivation (F=0.522; Wilks' Lambda=0.994; partial eta squared=0.006, p>0.05) did not exert any significant impact towards HRA, process performance (F=0.152, p>0.05) and strategies (F=0.950, p>0.05). Thus, the hypothesis H1 which states that CMO has a significant impact on utilization of data-based HRA competencies in process performance and strategies is accepted.

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

Table 5. Descriptive statistics of impact of CMO on utilization of data-based HRA competencies by the organization for different processes

Utilisation of data-based HRA competencies for different processes	Mean	SD
Process Performance	3.643	0.893
Strategies	3.668	0.939

Table 6. Test between subject effects of impact of CMO on utilization of data-based HRA competencies in process performance and strategies

CMOtowards HRA in the organization	Utilisation of data-based HRA competencies for different processes	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
HRA Capability	Process Performance[a]	14.607	1	14.607	64.121	0.000	0.267
	Strategies[b]	18.140	1	18.140	54.335	0.000	0.236
Level of motivation	Process Performance[a]	0.035	1	0.035	0.152	0.697	0.001
	Strategies[b]	0.317	1	0.317	0.950	0.331	0.005
Level of opportunities	Process Performance[a]	3.750	1	3.750	16.461	0.000	0.086
	Strategies[b]	2.748	1	2.748	8.231	0.005	0.045

a. R Squared = .719 (Adjusted R Squared = .714)

b. R Squared = .627 (Adjusted R Squared = .621)

Means and standard deviations of return of investments (ROI) and decision-making process in business outcome are presented in Table 7. MANOVA revealed a significant difference between process performance (F=10.638; Wilks' Lambda=0.892; partial eta squared=0.108, p<0.01) and strategies (F=3.851; Wilks' Lambda=0.958; partial eta squared=0.042, p<0.05) in business outcome. Of the business outcome variables, process performance had a significant impact on return on investment (F=12.688, p<0.01) and decision-making process (F=20.686, p<0.01), whereas strategies did not exert any significant impact on business outcome variable selected in this study (Table 8). Thus, the hypothesis 2 which states that utilization of data-based HRA competencies by the organization for different processes has a significant impact on business outcome is accepted.

Table 7. Descriptive for impact of utilization of data-based HRA competencies on business outcome

Business outcome	Mean	Std. Deviation
Return on Investments (ROI)	3.908	0.682
Decision-making process	3.893	0.550

Table 8. Test between subject effects of impact of utilization of data-based HRA competencies on business outcome

Utilisation of data-based HRA competencies for different processes	Business outcome	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Process Performance	Return on Investments (ROI)[a]	4.539	1	4.539	12.688	0.000	0.067
	Decision-making process[b]	4.905	1	4.905	20.686	0.000	0.105
Strategies	Return on Investments (ROI) [a]	0.000	1	0.000	0.000	0.995	0.000
	Decision-making process[b]	0.439	1	0.439	1.853	0.175	0.010

a. R Squared = .240 (Adjusted R Squared = .232)

b. R Squared = .226 (Adjusted R Squared = .217)

V. Discussion

The present study has achieved its objectives and the coupled hypothesis. A strategic HRM theory involving capability, motivation and opportunity (CMO) constructs is an established model in an HR analytics area (Delery and Shaw, 2001). It suggests that hiring an individual with analytical abilities and providing opportunity and motivation will improve the behaviour, performance and productivity of an employee. Researchers have claimed that very few HR professionals have the analytical capabilities and also there is very low sharing of data due to lack coordination between the departments (Levenson, 2005; Gale, 2015).

In this study the different sub factors of the CMO were invariably correlated to each other. Our result was in agreement with many researcher's studies which claim that HR analytics outcome can be moderated by HR professions analytical skill, managerial buy-in and information technology acumen (Marler and Boudreau, 2017). It can also be inferred that knowledge and creative analytics give better job satisfaction. Bassi (2011) elaborated that in the higher education sector, creativity and knowledge of the HR analytics elevate the HR rationality and creativity which can lead to job satisfaction.

HRA capability in terms of knowledge of company's culture and relationship with former employees (M=3.728, SD=1.103), external market and customer demands (M=3.739, SD=1.059), job design (M=3.711, SD=1.198), etc. followed by skills to engage key stakeholders and decision makers (M=3.800, SD=1.169), transfer training into practice (M=3.689, SD=0.965), assessment of internal and external environment (M=3.639, SD=1.209), to name a few and behaviour such as meeting the timeline and quality standards (M=3.761, SD=0.861), segment the employees based on performers and non-performers (M=3.822, SD=0.847) took the precedence and had a significant impact on HRA competencies such as process performance and strategies. The present study supports Jensen-Eriksen's (2016) study that the application of HR analytics strongly depends on the analytical skills of an individual who plans to use it, therefore it is essential to make a effort to develop the capabilities of HR analytics.

The second aspect of CMO model, the level of opportunities, including companies infrastructure facilities (M=3.711, SD=1.022), platform for cross-training (M=3.833, SD=1.226), leadership skill (M=3.967, SD=0.921) and analytical skill (M=3.567, SD=1.1.09) development, awareness and interaction

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

with team members on analytics and statistical tool (M=3.678, SD=0.961) significantly influence the process performance and strategy building. Opportunities enhance the competency development and improve performance and strategic decision making (Angrave et a., 2016) and this was in agreement with our study.

To list a few, the HR analytics competencies were used for process performance involving employee performance (M=4.0450, SD=1.110), employee competency (M=3.983, SD=1.217), employee attitude (M=3.756, SD=1.071) and management development (M=3.722, SD=1.426) assessments. Under strategies, planning of HR manpower (M=4.022, SD=1.123), management change (M=3.622, SD=1.260) and employee promotion strategies (M=3.639, SD=1.147) were included.

In this study, we have shown that the utilisation of data-based HRA competencies, namely the process performance will improve the ROI in terms of enhanced efficiency of the business process (M=4.056, SD=60), evaluation of operating standards (M=3.800, SD=0.924) and measure the effect of employee and company performance (M=3.894, SD=0.888). In line with this Aral et al (2012) has shown that practice of HR analytics with an inclusion of information technology (IT) in a company is positively related to the financial performance as well the individual performance. Data collection and its effective use (Levension, 2014; Pape, 2016), business understanding (Rasmussen and Ulrich, 2015) and analytical skills (Lawler et al., 2004) of HRA professionals helps to undertake evidence-based decisions. In the present study, input from analytic process helps the decision-making process involving, measurement of routine HR activities (M=3.950, SD=0.719), improvement in companies strategies on human capital (M=3.989, SD=0.685), evaluation of HR effectiveness of employee's capability, opportunity and motivation (M=3.967, SD=0.624). However, the strategies for employee promotion, manpower planning or leadership development had no influence on business outcome. Based on results, it can be inferred that HR analytics help to identify the various areas with maximum scope, points out the discontinuation of HR programs, workforce planning, avoids opinion-based decision making, etc. Thus, it can be summarized that proper usage of data by HR analytics will help to identify and develop best HR practices which will facilitate the employee and organizational performance and strategic-decision process.

VI. CONCLUSION

HR analytics is a new area and involves data collection and analysis, which is further used by different organizational departments to improve decision making, introducing new function in order to enhance the efficiency of the organization. This paper contributes to the literature by exploring different aspects of HR analytics with special reference to Indian companies. The study has explored the factors of competencies such as HR capability and level of opportunities which influences the process performance and strategies building of HRA professionals. It also shows that this impacts the business outcome in terms of ROI and decision-making process.

VII. REFERENCES

1. Abrahamson, E., and Eisenman, M. (2008). Employee-management techniques: Transient fads or trending fashions? Administrative Science Quarterly, 53, 719–744
2. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.
3. Aral, S., Brynjolfsson, E., & Wu, L. (2012). Three-way complementarities: Performance pay, human resource analytics, and information technology. Management Science, 58(5), 913-931.
4. Bassi, L. (2011). Raging debates in HR analytics. People and Strategy, 34(2), 14–18.
5. Bassi, L., Carpenter, R., & McMurrer, D. (Eds.).

(2012). HR Analytics Handbook. Amsterdam: Reed Business
6. Delery, J. E., & Shaw, J. D. (2001). The strategic management of people in work organizations: Review, synthesis, and extension. In Research in personnel and human resources management (pp. 165-197). Emerald Group Publishing Limited.
7. Deloitte (2017). Rewriting the rules for the digital age: 2017 Deloitte global human capital trends. New York, NY: Deloitte
8. Fred, M. O. (2018). A Study on Role of Analytics in Human Resource Decision Making With Reference To Recruitment Process for Business Process Outsourcing Bpo Sector.
9. Hoffmann, C., Lesser, E. L., and Ringo, T. (2012). Calculating success: How the new workplace analytics will revitalize your organization. Harvard Business Press
10. Gale, S. (2015). Predict (still in) the future. Human Resource Management Systems, 44-47.
11. Green, D. (2017). The best practices to excel at people analytics. Journal of Organizational Effectiveness: People and Performance, 4(2), 137-144.
12. Guest, D. E. (2004). The psychology of the employment relationship: An analysis based on the psychological contract. Applied psychology, 53(4), 541-555.
13. Jensen-Eriksen, K. (2016). The role of HR analytics in creating data-driven HRM: Textual network analysis of online blogs of HR professionals.
14. Johannink, R. J. (2015). The future of HR Analytics: A Delphi method study (Bachelor's thesis, University of Twente).
15. Lawler III, E. E., Levenson, A., & Boudreau, J. W. (2004). HR metrics and analytics–uses and impacts. Human Resource Planning Journal, 27(4), 27-35.
16. Levenson, A. (2005). Harnessing the power of HR analytics. Strategic HR Review, 4(3), 28-31.
17. Levenson, A. (2015). Strategic analytics: Advancing strategy execution and organizational effectiveness. Berrett-Koehler Publishers.
18. Levenson, A. (2014). The promise of big data for HR. People and Strategy, 36(4), 22.
19. Lochab, A., Kumar, S., & Tomar, H. (2018). Impact of Human Resource Analytics on Organizational Performance: A Review of Literature Using R-Software. International Journal of Management, Technology and Engineering, 8(10), 1252-1260.
20. Lydgate, X. K. M. (2018). Human Resource Analytics: Implications for Strategy Realization and Organizational Performance. (Undergraduate honors thesis, Portland State University).
21. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. The International Journal of Human Resource Management, 28(1), 3-26.
22. Minbaeva, D. (2017). Human capital analytics: why aren't we there? Introduction to the special issue. Journal of Organizational Effectiveness: People and Performance, 4(2), 110-118.
23. Nocker, M., & Sena, V. (2019). Big Data and Human Resources Management: The Rise of Talent Analytics. Social Sciences, 8(10), 273.
24. Pfeffer, J., & Sutton, R. I. (2006). Evidence-based management. Harvard business review, 84(1), 62.
25. Rasmussen, T., & Ulrich, D. (2015). Learning from practice: how HR analytics avoids being a management fad. Organizational Dynamics, 44(3), 236-242.
26. Sanders, N. R., & Ganeshan, R. (2018). Big Data in Supply Chain Management. Production and Operations Management, 27(10), 1745-1748.
27. Schiemann, W. A., Seibert, J. H., & Blankenship, M. H. (2018). Putting human capital analytics to work: Predicting and driving business success. Human Resource Management, 57(3), 795–807.
28. Sparrow, P., Hird, M. and Cooper, C. (2015). Do We Need HR? Repositioning People Management for Success, Basingstoke: Palgrave Macmillan
29. van der Voort, H. G., Klievink, A. J., Arnaboldi, M., & Meijer, A. J. (2019). Rationality and politics of algorithms. Will the promise of big data survive

January - February 2020
ISSN: 0193 - 4120 Page No. 2949 - 2960

the dynamics of public decision making?. Government Information Quarterly, 36(1), 27-38.
30. Van Den Heuvel, S., & Bondarouk, T. (2016). The rise (and fall?) of HR analytics: The future application, value, structure, and system support. In Academy of Management Proceedings (Vol. 2016, No. 1, p. 10908). Briarcliff Manor, NY 10510: Academy of Management.
31. Vardi, S., Minbaeva, D., & Rabbiosi, L. (2018). The Effect of Talent Management on Individual Performance. In 7th Workshop on Talent Management.
32. Vargas, R. (2015). Adoption factors impacting human resource analytics among human resource professionals. (Doctoral dissertation, H. Wayne Huizenga School of Business & Entrepreneurship, Nova Southeastern University).
33. Witte, L. (2016). We have HR analytics! So what?: an exploratory study into the impact of HR analytics on strategic HRM (Master's thesis, University of Twente).