

A STUDY FOR IDENTIFICATION OF LEVEL OF ADOPTION OF HR ANALYTICS

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ABSTRACT

In this paper, the identification of level of adoption of HR analytics is exhibited based on analysis of the data collected through primary sources. Various statistical techniques are applied to analyse the responses appropriately. In this paper, item-wise descriptive attributes of study variables are represented. Descriptive statistics are presented using per cents, means, and modes as per the type of data following a general convention of analysing nominal and ordinal data as observed by Velleman and Wilkinson,[1] and Sarle[2]. Adoption levels of HR analytics among the IT professionals respondents is assessed based on the four constructs presented in the theoretical model. The four constructs are performance expectancy, effort expectancy, social influence, and facilitating conditions. The items under the constructs are measured using a five-point scale.

Keywords:- HR analytics, adoption of HR analytics, Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions

INTRODUCTION

Analytics is rapidly evolving as a subject that integrates computer expertise with qualitative methodologies to solve numerous management difficulties in modern enterprises.[3]

The complexity of today's business landscape and its demands need complicated judgments involving several dimensions, necessitating businesses to embrace innovative processes and approaches that have the natural capacity to assess facts and figures required to make such decisions. The necessity for companies to adapt to and respond to changing circumstances has become critical for survival. [4]

The notion of HR Analytics may be traced back to Fitz-work Enz's in the early 1990s .[5] He attempts to apply the quantitative method to the usually qualitative subject of Human Resource Management in his book "How to Measure Human Resource Management." [6]

Though Human Resource (HR) Analytics is frequently regarded as a passing fad, Ramussen and Ulrich[7] contend that HR Analytics brings "evidence-based initiatives, data-driven decisions, and a focus on HR investments" as well as scientific rigor and objectivity to HR decision making, transforming the function from a mere staff or even a line function to a strategic function.

Ram Charan[8] in his article "It's time to split HR" published in the Harvard Business Review is considered to have initiated a huge debate by advocating splitting the function of HR into two. According to him, the role of the Chief Human Resource officer (CHRO) can be eliminated to create two roles one wherein the HR Manager called HRA (Administration) takes care of the compensation function and reports to the Chief Financial Officer (CFO) and the other where the HR has to play High Leadership Role (HRLO) who reports directly to the Chief Executive Officer (CEO) and is involved in leading and developing HR of the organization. These developments point to a shift in the function of human resources, necessitating a more in-depth examination of the nature and features of HR's strategic role. Because of its strategic approach, HR Analytics necessitates a detailed investigation.

The use of metrics and measurements in HR may be dated back to 1978, when Jac Fitz-Enz J.,[9] proposed that HR activities should be quantified. The 1980s saw the automation of essential HR activities such as payroll administration.[10] Because of the necessity for automation and computerization, the Human Resource Information System (HRIS) was developed as an outgrowth of the Management Information Systems (MIS).[11] Throughout the 1990s, the emphasis changed to seeing people as a valued corporate resource and capacity capable of creating competitive advantage.[12]

As a result, Human Intellectual Capital has become a popular term in both academic and business research. Organizations boosted their use of Decision Support Systems (DSS) and Business Intelligence (BI) technologies, merging them with HRIS, to make critical human resource decisions more efficiently and quickly. The HRIS was viewed as a technique for reducing administrative delays in human resource processes. The year 1990 saw an increase in the use of technology in HR processes. The era witnessed the advent of Enterprise Resource Planning (ERP) software, which could readily combine HR systems with other business data to make more comprehensive choices.[13]

LITERATURE REVIEW

Angrave et al.,[3] believe that these techniques are not being implemented by corporate organizations since most companies continue to limit their reach to the use of standard HRIS. The role of ERP systems in HR metrics is described by Bondarouk and Parry et al.,[14]. Heuvel and Tanya Bondarouk[10] believe that the terms "label workforce analytics" and "HR Analytics" should not be used interchangeably, and they find a strain of "exploitative association." To support their point of view, the authors cite Google, which employs people analytics as an employee-friendly name but refers to the department as "People Operations Department" rather than "HR Department." Hence, the authors raise concern over the HR department's essential identity being lost in the wild drive for analytics to explain its activities and functions.

Strohmeier et al.[15] explain how the Internet of Things has entered the field of HR Analytics, broadening its reach. In their paper with the same title, Sivathanuand Pillai (2018) explore Smart HR 4.0 - how Industry 4.0 is affecting HR. According to the author, Smart HR is most effective in talent onboarding since big data and AI aid in sifting through a stack of applications with the most simplicity and speed. Instead of generic testing, automated and tailored testing will forecast improved on-the-job performance in the future to customize socializing. As a result, the role can expand into talent management and offboarding.

According to Jensen and Ericksen[16], HR Analytics and data-driven techniques are still in their infancy in the area of HRM. HR as a function is now routine-oriented, with an emphasis on universal HR. After a thorough assessment of the works of many authors, Marler and Boudreau[17] claim to detect a lack of grounding in HR subjects connected to analytics in their review-based work. These reflect HR managers' sluggish acceptance of digital innovations in HRM. This may not be entirely true in the context of the software industry, which is primarily regulated by the methodical and analytical analysis of data in order to make or take strategic decisions.

According to Volini, Ocean, Stephan, and Walsh[18], HR can cope with a digital workforce more effectively by utilizing digital platforms. Hence, workers in the IT industry, as well as HR departments in IT firms, see it as a natural move to migrate their HR services to a digital platform and quickly integrate HR Analytics. But, given the current business requirements, there is no easy way for firms to ignore analytics. Improved productivity and efficiency are the most prevalent reasons why businesses engage in analytics for human capital management.[19] A high proportion of businesses cited increased competitive advantage and innovation as a result of their use of analytics. HR may use analytics to get from opinion to data, metrics to analysis, and eventually to an insight that leads to action. Despite the fact that 71% of firms prioritize HR analytics, relatively few have made significant headway in terms of using analytics to improve organizational performance.[20]

According to Deloitte Insights[21], there is a paradigm change in the way HR uses data to solve business challenges and drive business. HR Analytics contributes to HR optimization by providing a comprehensive knowledge of organizational strategy, structure, processes, skills, and performance metrics. HR can better shape its business choices by using more comprehensive data and analytical skills as it creates more effective workforce insights. Companies failed to use business intelligence on people to gain a competitive edge due to three types of issues: data-related, management-related, and employee-related.[22] Just 39% of business leaders say their organization has "very excellent" or "good" quality data for people-related decisions. This is despite the fact that sophisticated organizations employed seven various data collection methods, including internal and external social media, ERP systems, questionnaires, and data analysis in corporate communication tools.[23]

HR analytics, with its sophisticated tools, may assist enhance an organization's perception of the accuracy of its performance assessment system by giving more objective and accurate data on employee performance and behavior. High-performing organizations are four times more likely to report a substantial ROI from analytics. According to this Accenture and MIT analysis, both high and low performers are equally likely to confront a shortage of analytical skills. Human resource analytics is expected to increase significantly and become integrated with a centralized analytics function that spans all functional boundaries.[24]

Yet, not only is HR analytics usage now limited, but academic research and hence evidence on the issue is also minimal. One factor for the lack of information is corporations' reluctance to reveal the degree of people analytics utilization due to ethical and regulatory limitations. Predictive analytics may assist HR in retaining and engaging personnel, therefore indirectly solving staffing concerns by assisting in retention and leadership development. HR Analytics is crucial and delivers significant value if it focuses on the issues that matter and does so correctly.[25]

For example, an employee's worth is the sum of his human capital and social capital. As a result, data on both of these characteristics must be gathered in order to estimate the worth of maintaining an employee in the firm. Hence, organizational network analysis becomes a valuable complement to the HR analytics toolset. Data governance, HR analytics team competencies, core infrastructure, business alignment, user engagement, and data-driven culture are the top drivers of People Analytics Maturity. Together with other talents like as data exploration, collecting, and consumption, storytelling is an essential skill for effective analytics implementation.[26]

Feinzig [27] proposed an eight-step process for implementing HR analytics. The first stage is to frame the business questions around the business concerns or organizational goals. The hypotheses are then developed in response to these inquiries. The information is then gathered and analyzed using the relevant technologies. Insights are derived from the results, and conclusions are reached using business concepts.

For implementation, the findings are conveyed to high management or the parties involved. Once deployed, the last phases of HR analytics deployment include constant assessment and refinement. The four ways that HR analytics can be improved, according to a research issued by i4CP and ROI Institute (2018)[28], are by concentrating on people, integrating throughout the business, investing in tools and technology, and developing trust via tiny incremental steps. Company performance may be enhanced by bridging the gap between people and business strategy, reducing bad data, and educating HR personnel in fundamental quantitative skills. Organizational Network Analysis (ONA) is one of the analytics topics that is gaining traction. It discusses how work is done in companies by presenting a new perspective on how teams and networks communicate and behave.[29]

The topic of HR analytics crosses functional boundaries and is hampered by questions of training and ethics. According to a poll of 3852 business professionals, including 1288 HR professionals, the HR profession lacks the knowledge and confidence to engage in advanced levels of people analytics. HR analytics specialists have three sorts of skill sets: HR domain skills, business and strategic thinking skills, and data and analytics skills, and how they use these talents varies depending on the project.[30] As HR analytics matures from descriptive to predictive analytics, the projected ROI rises. The biggest reason firms fail to transition from operation reporting to human capital analytics is the analytics team's failure to build credible analytics and demonstrate its value. Data quality is crucial for gaining valuable insights from it, and this may assist reduce different biases that might influence decision-making.[31]

HR has access to the majority of untapped data, which has enormous potential. In addition to functional and strategic skills, HR analytics professionals must have statistical analysis, data engineering and warehousing skills, business intelligence skills, database management skills, big data and machine learning skills, market research and insights, and market research and insights for successful roll-out. Furthermore, it is proposed that businesses create a culture that supports data-driven insights and improve employee experiences throughout the enterprise.[32]

Analytics may influence not just the decision-making process, but also the decision-making styles, resulting in increased performance. Because of the deployment of new technology and increasing knowledge of evidence-based HRM, the role of HR as a strategic tool has grown. HR Analytics may assist firms with precise workforce planning, error-free recruiting, superior performance management, increased employee engagement, and intense leadership management.[33]

The scope and effect of HR analytics may be expanded by focusing less on individuals and more on the impact of their interactions using relational analytics. Artificial intelligence and other technical advancements have boosted the power of people analytics while also increasing the need to constantly learn and improve. The three basic building blocks of HR analytics are solving real-world business challenges, gathering relevant data, and developing people' analytical skills. HR Analytics in enterprises include gathering data, creating reports, doing analyses, constructing models, and delivering insights as one progresses along the HR analytics maturity model's continuum. HR and Finance should work together to create a suitable analytics strategy and culture by removing the hurdles or problems of skill gaps, entrenched habits and structural impediments, reluctance to change, and overconfidence. Engineering and manufacturing firms experiencing the fourth industrial revolution consider themselves technology firms implementing digital advances, and they may gain by assuring quality data and integrating across several activities.[34]

People analytics may help businesses adapt by quantifying people's behavior, measuring how a change project will affect their job, and determining how it might lead to improved financial performance. HR analytics may give valuable insights into an organization's most valuable asset, its people, and assist in better managing and engaging them.[35]

HR Analytics may assist firms boost their recruitment efficiency by 80%, their business productivity by 25%, and their attrition rate by 50%. HR Analytics at enterprises include acquiring data, producing reports, doing analyses, constructing models, and finally offering insights as we go along the HR analytics maturity curve. Companies must develop the IT capabilities to migrate data from legacy systems, adopt HR analytics, and progress up the analytics maturity ladder.[36]

A whopping two-thirds of business leaders polled claimed that if their organization does not further digitize by 2020, it will lose its competitiveness. According to Neeraj Tandon of Willis Towers Watson, building the proper team and procedures, using the right technologies, and investing for the long term will help firms effectively leverage the value of people analytics. Leaders must recognize the value of analytics and be the change agents in their businesses.[37]

The competence of resources, confidence, mentality toward analytics, training interventions, and organizational culture and structure are all elements that might impact the adoption of people culture. The availability of in-house knowledge and the vendor's value offer, as well as the approach of senior leadership and the HR function, all influence the adoption of HR analytics.

Hüllmann and Jana Mattern[38] continue to believe that HR Analytics need a robust theoretical foundation. Despite the fact that HR Analytics claims to have evolved from the idea of scientific management to other strong management theories, they believe that the concept's operationalization and measurement are still not extensively examined. This observed gap may be deemed to have been filled by Peters et al., (2020), who believe that despite having the greatest statistical skills, various components such as stakeholder awareness and the like may contribute to the success of people's analytics teams.

RESEARCH GAP

The review of the literature clearly brings out the existing gap in the literature. Most of the earlier studies emphasised the spread of HR analytics and their different dimensions. The major areas covered by them include factors influencing HR analytics, key metrics used in HR analytics, trust factors, strategic role etc. Studies are limited to capture progress of HR analytics. Existing studies conducted in HR analytics context were found to be having conceptual orientation and discussions that are largely motivated by divergent opinions and thoughts. The review of literature brings out many gaps in the existing literature in this context. There are very few studies which had thrown light on the readiness and perceptions of the HR professionals,

on this relatively new technique of HR management and the possible impact of the same on key HR functions in various organisations. The present study is a modest attempt to fill the existing gap in the literature by focusing on the adoption of HR analytics among IT professionals.

OBJECTIVES OF THE STUDY

The main aim of the study is to identify the level of adoption of HR analytics among IT professionals

HYPOTHESIS

H1 Adoption of HR analytics are significantly different by respondents' age

H2 Adoption of HR analytics are significantly different by respondents' work experience

H3 Adoption of HR analytics are significantly different by the training offered to respondents

H4 Adoption of HR analytics are significantly different by no. of training programmes attended within the organisation

H5 Adoption of HR analytics are significantly different by no. of training programmes attended outside the organisation

RESEARCH METHODOLOGY

The research design for the current study has exploratory and descriptive mode. The exploratory stage helped in developing better insights on exactly the defining variables that are to be studied. In the latter part, the major part of the primary study is carried based on descriptive research design. The present study collected the required data from primary as well as secondary data sources. To achieve the objectives of the present study, various statistical methods are employed in the study. Adoption levels of HR analytics among the respondents is assessed based on the four constructs presented in the theoretical model. The four constructs are performance expectancy, effort expectancy, social influence, and facilitating conditions. Each of these four constructs and the adoption is measured using the items discussed in the methodology. The items under the constructs are measured using a five-point scale with values representing 1-strongly disagree, 2-disagree, 3-neutral, 4-agree, and 5-strongly agree. For identifying univariate outliers, box plots are used with the help of SPSS. Two-tailed independent samples t-test is used to check the differences in adoption of HR analytics by gender. To test the existence of any relation between data sophistication, and adoption, where there are differences found in the analysis of variance tests, Tukey HSD post hoc test is applied for making multiple pair-wise comparisons among the means of various groups concerning a variable, to analyse the extent of differences.

Table 1 Summary statistics

Item	Variables	
Adoption	AD1	“My organisation is putting a policy in place to use HR Analytics.”
	AD2	“I am beginning to explore using HR Analytics.”
	AD3	“I am interested in using HR Analytics.”
	AD4	“I am recommending my organisation to invest in HR Analytics.”
	AD5	“I use HR Analytics for some specific tasks.”
Performance Expectancy	PE1	“I would find HR analytics useful in my job.”
	PE2	“Using HR analytics enables me to accomplish tasks more quickly.”
	PE3	“Using HR analytics increases my productivity.”
	PE4	“If I use HR analytics, I will increase my chances of getting a raise.”
Effort Expectancy	EE1	“My interaction with HR analytics would be clear and understandable.”
	EE2	“It would be easy for me to become skilful at using HR analytics.”
	EE3	“I would find HR analytics easy to use.”
	EE4	“Learning to operate HR analytics is easy for me.”
Social Influence	SI1	“People who influence my behavior think that I should use HR analytics.”
	SI2	“People who are important to me think that I should use HR analytics.”
	SI3	“The senior management of this business has been helpful in the use of HR analytics.”
	SI4	“In general, the organisation has supported the use of HR analytics.”
Facilitating Conditions	FC1	“I have the resources necessary to use HR analytics.”
	FC2	“I have the knowledge necessary to use HR analytics.”
	FC3	“HR analytics is compatible with other systems I use.”
	FC4	“A specific person or group-is available for assistance with HR analytics difficulties.”

The responses for all the items under all the constructs are found to have a median and mode value of four, indicating good agreement by the respondents for the constructs under study.

- The mean values for all the items under the construct adoption- AD1 (3.6), AD2 (3.71), AD3 (3.6), AD4 (3.61), and AD5 (3.68) are having mean values above 3.6 indicating respondents’ agreement with the respective statements.
- The mean values for all the items under the construct performance expectancy- PE1 (3.73), PE2 (3.54), PE3 (3.61), and PE4 (3.85) are having mean values above 3.5 indicating respondents’ agreement with the respective statements.
- The mean values for all the items under the construct effort expectancy- EE1 (3.71), EE2 (3.53), EE3 (3.65), and EE4 (3.78) are having mean values above 3.5 indicating respondents’ agreement with the respective statements.

- The mean values for the items under the construct facilitating conditions- FC1 (3.6), FC3 (3.55), and FC4 (3.66) are having mean values above 3.5 indicating respondents' agreement with the respective statements. However, for the item FC2 (3.48), the mean value is slightly below 3.5.
- The mean values for all the items under the construct social influence- SI1 (3.69), SI2 (3.51), SI3 (3.54), and SI4 (3.73) are having mean values above 3.5 indicating respondents' agreement with the respective statements. The summary statistics for the items are presented in Table 2.

Table 2: Distribution of Variables of HR analytics Adoption)

Variable	M	SD	SEm	Mdn	Mode	Skewness	Kurtosis
AD1	3.6	.94	.05	4	4	-.76	.59
AD2	3.71	.88	.04	4	4	-.35	-.21
AD3	3.6	.91	.05	4	4	-.44	-.2
AD4	3.61	.88	.04	4	4	-.28	-.19
AD5	3.68	.9	.05	4	4	-.49	.15
PE1	3.73	.81	.04	4	4	-.79	1.26
PE2	3.54	.84	.04	4	4	-.21	-.3
PE3	3.61	.9	.05	4	4	-.47	.09
PE4	3.85	.78	.04	4	4	-.52	.63
EE1	3.71	.88	.04	4	4	-.75	.98
EE2	3.53	.91	.05	4	4	-.22	-.34
EE3	3.65	.9	.05	4	4	-.43	.11
EE4	3.78	.84	.04	4	4	-.75	1.11
SI1	3.39	.88	.04	4	4	-.63	.64
SI2	3.51	.95	.05	4	3	-.21	-.35
SI3	3.54	.94	.05	4	4	-.34	-.23
SI4	3.73	.87	.04	4	4	-.79	1.04
FC1	3.6	.87	.04	4	4	-.69	.44
FC2	3.48	.91	.05	4	4	-.28	-.26
FC3	3.55	.89	.05	4	4	-.4	.02
FC4	3.66	.89	.05	4	4	.69	.63

Adoption of HR analytics by the level of age and work experience

ANOVA test was carried out to ascertain the differences among respondents' adoption of HR analytics by the levels of age and total work experience. The results are shown in Table 3. From the results, it can be observed that there are significant differences ($F(8, 381) = 2.7, p = 0.007$) in the adoption of HR analytics among the levels of age and total work experience of the respondents. Adoption of HR analytics differed significantly (at 95% confidence level, $F(4, 381) = 2.8, p = 0.027, \eta^2 = 0.03$) by age levels. Also, adoption of HR analytics differed significantly (at 95% confidence level, $F(4, 381) = 3.7, p = 0.006, \eta^2 = 0.04$) by total work experience levels.

Table 3 Adoption by level of Age and Experience using ANOVA

Variable	SS	df	F	P	ηp^2	Sig.	Hypothesis validation
Age	5.4	4	2.8	0.027	.03	P<.05	Supported
Experience	7.1	4	3.7	.006	.04	P<.05	Supported
Residuals	184.9	381					

Tukey pairwise comparisons were made for the hypothesis that yielded significance, based on an alpha of 0.05. The means of analytical competencies are compared by the levels of training offered and no. of training programmes attended outside the organisation using a t-test. However, no significant effects were found.

Adoption of HR analytics by level of Training Programmes

ANOVA test was carried out to ascertain the differences among respondents' adoption of HR analytics by the levels of whether training was offered, no. of training programmes attended within the organisation, and no. of training programmes attended outside the organisation. The results are shown in Table 4. From the results it can be observed that there are significant differences ($F(7, 382) = 3.38, p = 0.002$) in adoption of HR analytics among the levels of whether training was offered, no. of training programmes attended within the organisation, and no. of training programmes attended outside the organisation. Adoption of HR analytics differed significantly (at 95% confidence level, $F(1, 382) = 8.5, p = 0.004, \eta p^2 = 0.02$) by whether training was offered levels. But, adoption of HR analytics was not significantly different (at 95% confidence level, $F(3, 382) = 0.9, p = 0.44$) by no. of training programmes attended within the organisation levels. However, adoption of HR analytics differed significantly (at 95% confidence level, $F(3, 382) = 3, p = 0.03, \eta p^2 = 0.02$) by no. of training programmes attended outside the organisation levels.

Table 4 Adoption by level of training programmes using ANOVA

Variable	SS	df	F	p	ηp^2	Sig.	Hypothesis validation
Training was offered	4.1	1	8.5	.004	.02	P<.05	Supported
No. of training programmes attended within the organization	1.3	3	.9	.44	-	P>.05	Not Supported
No. of training programmes attended outside the organization	4.4	3	3	.03	.02	P<.05	Supported
Residuals	184	382					

Tukey pairwise comparisons were made for the hypothesis that yielded significance, based on an alpha of 0.05. The means of analytical competencies are compared by the levels of training offered and no. of training programmes attended outside the organisation using a t-test. When the effect of whether training was offered was tested, the mean of adoption for the response 'no' ($M = 3.4$, $SD = 0.7$) was significantly smaller than for the response 'yes' ($M = 3.7$, $SD = 0.7$), $p < .001$. However, no other significant effects were found.

FINDINGS

The focus area of this study is the adoption of HR analytics. Four independent variables, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, have been chosen to measure the degree of adoption of HR analytics. The respondents are asked what motivated them to adopt HR analytics. The major findings relating to the adoption of HR analytics among HR professionals is as follows.

- A large majority of the respondents have indicated performance expectancy as the driving force behind the adoption of HR analytics.
- There are also other factors. In order of importance, effort expectancy, and social influence are the other factors. Effort expectancy was found to be an important influential factor affecting the HR professional's intention to adopt HR analytics in the study by Vargas (2015).
- Present study reiterates the same postulate. However, the present study adds that the facilitating conditions in the organisation are the strongest factor for the adoption of HR analytics at the organisational level. Facilitating conditions also include availability of appropriate tools which enable adoption (Vargas, 2015).
- Even at the individual level, an HR professional is willing to adopt HR analytics either because of performance expectancy or social influence; it is ultimately the enabling conditions that ensure adoption on a larger scale.
- The study results indicate that the adoption of HR analytics is significantly different by age, total work experience, training offered, and no. of training programs attended outside the organisation by the HR professionals.

CONCLUSIONS

The present study has been undertaken against the rising prominence of HR analytics and inadequacy of literature regarding the adoption of HR analytics. The objective of the study is to examine the levels of adoption of HR analytics. The adoption of the identified HR analytical tools is measured using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Further, the study results indicate that the adoption of HR analytics is significantly different by age, total work experience, training offered, and no. of training programs attended outside the organisation by the HR professionals.

REFERENCES

1. Velleman, P. F., & Wilkinson, L. (1993). Nominal, ordinal, interval, and ratio typologies are misleading. *The American Statistician*, 47(1), 65-72.
2. Sarle, W. S. (1995). Measurement theory: Frequently asked questions. *Disseminations of the International Statistical Applications Institute*, 1(4), 61-66.
3. 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.
4. Guest E. David (2004), Human Resource Management and Industrial Relations, *Journal of Management Studies*, Volume 24, Issue 5.
5. Fitz-Enz, J. (2000). ROI of human capital: Measuring the economic value of employee performance: AMACOM Div. American Management Association.
6. Marler. J. H & John W. Boudreau (2017) An evidence-based review of HR Analytics, *The International Journal of Human Resource Management*, 28:1, 3-26, DOI: 10.1080/09585192.2016.1244699
7. Rasmussen, Thomas, Dave Ulrich (2015), Learning from Practice: How HR Analytics avoid being a management fad, *Organizational Dynamics* 44(3), May, 2015
8. Ram Charan (2014): It's time to split HR. *Harvard Business Review*. Jun 2014
9. Fitz-Enz, J. (2010). The New HR Analytics: Predicting the Economic Value of Your Company's Human Capital Investments: AMACOM Division American Management Association
10. Van Den Heuvel Sjoerd and Tanya Bondarouk (2017), The rise (and fall?) of HR Analytics: A study into the future application, value, structure, and system support, *Journal of Organizational Effectiveness: People and Performance*, June 2017
11. Mathys and LaVan, 1982: Human resource information systems: a review and empirical analysis,2004. www.emeraldinsight.com/0048-3486.htm
12. Barney, J. B., & Wright, P. M. (1998). On becoming a strategic partner: The role of human resources in gaining competitive advantage. *Human Resource Management* (1986-1998)
13. Stone, Dianna, L. and James, H. Dulebohn (eds.) (2016), *Human Resource Management Theory and Research on New Employment Relationships (Research in HRM)*, Information Age Publishing, 2016.
14. Bondarouk, Tanya, Emma Parry and ElfiFurtmueller (2016), Electronic HRM: four decades of research on adoption and consequences, *The International Journal of Human Resource Management*, Volume, 28, 2017- Issue 1

15. Strohmeir, Stefan, Franca Piazza (2017) Human Resource Intelligence and Analytics, Springer Gabler, London.
16. Jensen-Eriksen, K. (2016). The role of HR analytics in creating data-driven HRM: Textual network analysis of online blogs of HR professionals. Aalto University School of Business.
17. Marler, J. H & John W. Boudreau (2017) An evidence-based review of HR Analytics, The International Journal of Human Resource Management, 28:1, 3-26, DOI: 10.1080/09585192.2016.1244699
18. Volini, Erica; Pascal Ocean, Michael Stephen, Bret Walsh (2017), Digital HR: Platform, People, and Work, Global Human Capital Trends, 2017.
19. Research, Ventana. "Human Capital Analytics Drives Strategic Business Decisions." Ventana Research Human Capital Analytics Benchmark Research, 2017. https://www.ventanaresearch.com/white_paper/human_capital_management/human_capital_analytics_drives_strategic_business_decisions/thankyou?submissionGuid=4b420191-100c-4450-8584-7165a48b2acc.
20. Collins, Laurence, David R Fireman, and Akio Tsuchida. "People Analytics: Recalculating the Route 2017 Global Human Capital Trends."
21. Deloitte Insights, 2017. <https://www2.deloitte.com/insights/us/en/focus/human-capital-trends/2017/peopleanalytics-in-hr.html>
22. Reddy, P. Raghunatha, and P. Lakshmikeerthi. "HR analytics-An effective evidence based HRM tool." International Journal of Business and Management Invention 6, no. 7 (2017): 23-34.
23. Bersin. "High Impact People Analytics: The 2017 Maturity Model." Deloitte, 2017.
24. Levi, David Simchi, Jyo Gadewadikar, Brian McCarthy, and Lynn La Fiandra. "Winning with Analytics-Accenture & MIT." accenture.com, May 2, 2017.
25. Ulrich, Dave. "Analytics on HR Analytics: What Really Works," July 13, 2017. <https://www.rbl.net/insights/articles/analytics-on-hr-analytics-what-really-works>.
26. Lee, Marianne. "People Analytics." Trend Analytics- Head HR , 2017AD.
27. Guenole, Nigel, Jonathan Ferrar, and Sheri Feinzig. The power of people: Learn how successful organizations use workforce analytics to improve business performance. FT Press, 2017.
28. Phillips, Patti, and Kevin Oakes. "Four Ways to Advance Your People Analytics." Intel, i4CP& ROIInstitute, May 31, 2018. <https://roiinstitute.net/fourways-to-advance-your-people-analytics-an-i4cp-report-in-partnership-with-roiinstitute/>.
29. Green, David. "The Role of Organisational Network Analysis in People Analytics." (2018)

30. Chensoff, Grace, Catherine Coppinger, and Pooja Chabbria. "The Rise of Analytics in HR." LinkedIn. Talent Solutions, 2018.
31. Sesil, James C. Applying Advanced Analytics to HR Management Decisions: Methods for Selection, Developing Incentives, and Improving Collaboration (Paperback). FT Press, 2018.
32. Russo, Rosario. "A Smooth Adoption Path for HR Analytics in FS Organizations." <https://financialservicesblog.accenture.com/>. Accenture, February 22, 2018. <https://financialservicesblog.accenture.com/a-smooth-adoption-path-for-hranalytics-in-fs-organizations>.
33. Atchyutuni, Niharika, and P. Vijay Kumar. "FACTORS IMPACTING ADOPTION OF PEOPLE ANALYTICS-APPLICATION OF INTERPRETIVE STRUCTURAL MODELLING." Skyline Business Journal 14, no. 2 (2019).
34. VASUDEVAN , SUSHEEL. "MANUFACTURING NEXT Intelligent, Agile, Automated, and Cloud-Enabled." hbr.org-White Paper, n.d. <https://hbr.org/resources/pdfs/comm/tcs/ManufacturingNext.pdf>
35. West, Mike. People Analytics for Dummies. 978-1-119-43476-4. Newdelhi: Wiley, 2016.
36. Nocker, Manuela, and Vania Sena. "Big data and human resources management: The rise of talent analytics." Social Sciences 8, no. 10 (2019): 273.
37. McKinsey & Company Website. "Advanced Analytics for Better Talent and Business Decisions." People Analytics, 2019.
38. Hüllmann & Jana Mattern, 2020, Three Issues With The State Of People And Workplace Analytics , 33RD BLED ECONFERENCE Enabling Technology For A Sustainable Society, University Of Maribor Press. [Http:// Bledconference.Org/](http://Bledconference.Org/)