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FACTORS IMPACTING ADOPTION OF PEOPLE ANALYTICS – APPLICATION OF INTERPRETIVE STRUCTURAL MODELLING

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Abstract

People Analytics has transformed the way the human resources of an organization are utilized and managed. The fast-changing field of technology has also contributed to the advancement of the people analytics evolution. The pace of adoption and application of people analytics across organizations has, however, not matched the initial expectations. Though the reasons for this slow adoption have been discussed on some platforms, there have not been many comprehensive analyses of the same. The factors are intricate and the interrelationships, complex. In this paper, Interpretive Structural Modelling (ISM), a qualitative technique has been applied to gain clarity on the prioritization and categorization of factors and also define their interrelationships. The categorization of factors as driving factors, dependent factors and linking factors can help organizations design effective strategies for smoother adoption and implementation of people analytics. This can result in improved performance of organizations not only in terms of people management but also in enhancing business performance.

Keywords: *People Analytics, HR Analytics, Factors, Interpretive Structural Modelling, MICMAC Analysis*

Introduction

People Analytics has immense potential to transform and radically change people management in organizations (Bersin et al., 2016). Early adopters, including Google, believed that it is a ground-breaking tool and that people management in organizations worldwide would be revolutionized. They believed and argued that people analytics is that magic wand that can resolve many people management issues and make life easier for HR people. It was also widely believed that people analytics will put HR at the strategic table along with other organizational functions, to contribute strategically to organizations' growth and performance (Lavastorm, 2013). It has been almost a decade since people analytics gained recognition as a powerful tool to improve business performance.

While some organizations have made great strides and have actually managed to transform their people management system with the application of people analytics for predicting and improving performance, there are still around 60% of them worldwide who haven't taken that important step yet (Bersin, 2018). Although these organizations acknowledge the importance of People Analytics, there seems to be a hesitation to initiate the process at an early stage. What are the factors that have been affecting adoption of People Analytics in organizations? What determines the application or non-application of People Analytics? This paper is an attempt to understand these factors, the factors that have been impacting organizations' adoption of people analytics.

People Analytics

Talent has never been more critical to business performance. Organizations acknowledging their people as non-replicable resources, undertake various initiatives to attract, engage and retain their talent. In multiple surveys of business leaders, organizations felt that they need more talent-related insights to make better business decisions (Bersin, 2017). Historically, HR function has been known to base decisions on the intuition and gut feeling of its members. While they would have been right on most occasions, they lacked precision, objectivity and logical proof (Vulpen, 2016).

People Analytics, whether it is called Talent Analytics or HR Analytics or Workforce Analytics, is not merely an analysis of data. Analytics employs technology to collect data from multiple platforms in various forms; filters it, and then applies statistical tools to the pertinent data. It throws light on organizational processes for better evaluation and improved business performance (McKinsey Report, 2017). People analytics helps unearth the real reasons behind current people-related issues and also predicts glitches that may arise in the future (TCS Whitepaper, 2017). It also provides insights on the organizational performance from the HR perspective. This would help in redesigning the HR systems and processes for improved performance. In other words, HR Analytics correlates business data and people data and eventually provides vital insights (CIPD, 2019). The HR managers, equipped with these insights, get to visualize the future in greater detail and also get to design more effective strategies. This would conclusively put HR in a position of strength where it can add immense value to the business processes of an organization (Bersin, 2016).

More and more organizations are trying to embrace People Analytics as a strategic tool for enhancing organizational performance. Data of all kinds and forms is in abundance with organizations; the problem is to differentiate between what is important and what is not. Also important is the uniqueness and reliability of the data (Davenport, Harris & Shapiro, 2010). Transforming this data into valuable information by employing the right metrics is the next logical step as organizations look to gain meaningful insights. This can help, not only resolving existing problems, but also in enhancing business performance.

Literature review

David Green (2019) as a part of his study, listed out six factors for the willingness to adopt people analytics. The six factors are Capability, Confidence, Culture, Mindset, Training and Organizational structure. According to a McKinsey report (2016), only 20-30% companies in the manufacturing sector progressed to capture value from data and analytics. Scepticism of organizational leadership was one of the two reasons for this. Another path-defining report by McKinsey (2017) emphasises the importance of reliable data and the essential support of IT departments. It also talks about the need for functional (HR) experts who have analytics proficiency. As per the report, leadership has to take the lead and make a commitment to analytics. It talks about the importance of a data-driven culture too. Vendor's value proposition impacts the HR outlook and decision making (Tursunbayeva, De Lauro &

Pagliari, 2018). Organizations have started taking necessary actions to address the problems of data quality and integration (Bersin, Josh 2017).

Objectives

The application of analytics for Human Resources Management in organizations has been gaining ground over the last decade. There are some common factors that impact or influence the adoption of people analytics in organizations. These factors are quite complex in terms of their level of impact and their interrelations. There are no comprehensive models / systems explaining the factors and their interdependencies. The objectives of this study are:

• To develop a comprehensive model that helps identify the different factors that impact the adoption of people analytics

• To categorize these factors as driving factors, dependent factors, autonomous factors and linking factors

• To sequence and prioritize the factors and to understand their importance and the strength of their contribution

Scope & methodology

Factors that majorly impact the adoption of people analytics have been identified based on the literature review. Inputs were also taken from HR heads and people analytics experts of Indian organizations in finalizing the ten factors. Interpretive Structural Modelling (ISM) has then been applied to establish their impact on people analytics adoption and define their complex interrelationship.

The expert inputs have been taken from HR heads and analytics experts from Indian organizations. 14 companies from Hyderabad, India that have been using people analytics for at least the last 3 years were chosen. The HR heads of these companies were interviewed on the process of people analytics and their adaptation to understand their challenges. The factors that aided them in rolling out and implementing people analytics were also captured. Inputs were also sought from 20 people analytics experts from various companies like Aon, Concentrix, TCS, Tech Mahindra, Eaton, BCG and Cargill. The analytics experts shared their ideas in an online group chat, contributing richly to the information gathered already. The final model, post ISM was shared with the HR heads for their approval. Slight modifications were made to the model based on their feedback.

Interpretive Structural Modelling

Identification of Factors / Variables

Based on literature review and inputs from the HR experts, the following factors have been identified as those impacting the adoption/application of People Analytics:

1. Leadership's perspective (Davenport, Harris & Shapiro, 2010)
2. Return on Investment assurance (Lawler III, Levenson & Boudreau, 2004)
3. Technological ease and compatibility (Vyas, 2017)
4. Data security (Agarwal, Bersin, Lahiri & Others, 2018)
5. HR attitude and outlook (Lawler III, Levenson & Boudreau, 2004)
6. In-house people analytics expertise (Bassi & Bassi, 2018)
7. Vendor's value proposition (Tursunbayeva, De Lauro & Pagliari, 2018)
8. Data reliability (Davenport, Harris & Shapiro, 2010)
9. IT collaboration (Bassi & Bassi, 2018)
10. Data-driven culture (Green, 2019)

With the 10 factors identified, the SSIM (Structural Self-Interaction Matrix) is designed (Khan & Haleem, 2015). This matrix describes the inter-relationship between pairs of different factors or variables.

SSIM (Structural Self-Interaction Matrix)

The different factors are tabled and coded in the following manner, based on the interpretation of relationship between two factors. The relationship is defined based on literature review and expert opinion.

i leads to j: V
j leads to i: A
i & j lead to each other (mutual): O
i & j are unrelated: X

i, j vary from1to10 and represent the ten factors. Based on the experts' opinion on how the factors are interrelated, and the literature review, the different cells are marked V, A, O & X. Table 1 represents the SSIM.

TABLE 1. STRUCTURAL SELF-INTERACTION MATRIX

j

i

	1	2	3	4	5	6	7	8	9	10
1		A	A	A	A	A	A	A	A	A
2			A	X	V	A	A	A	A	A
3				X	V	A	A	X	A	A
4					V	A	A	X	A	V
5						A	A	A	A	O
6							X	V	O	O
7								V	A	O
8									O	O
9										O
10										

Initial Reachability Matrix

TABLE 2. INITIAL REACHABILITY MATRIX

j

i

	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	0	1	0	0	0	0	0
3	1	1	1	0	1	0	0	0	0	0
4	1	0	0	1	1	0	0	0	0	1
5	1	0	0	0	1	0	0	0	0	1
6	1	1	1	1	1	1	0	1	1	1

7	1	1	1	1	1	0	1	1	0	1
8	1	1	0	0	1	0	0	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	1	1	1	0	1	1	1	1	1	1

Once the SSIM is complete, the Initial Reachability matrix is designed by populating the cells with either 0 or 1. These binary values are assigned to describe the relationship between each pair of variables as shown below.

If (i,j) in SSIM is V, then (i,j) =1 and (j,i) =0 in the initial reachability matrix

If (i,j) in SSIM is A, then (i,j) =0 and (j,i) =1 in the initial reachability matrix

If (i,j) in SSIM is O, then (i,j) =1 and (j,i) =1 in the initial reachability matrix

If (i,j) in SSIM is X, then (i,j) =0 and (j,i) =0 in the initial reachability matrix

Once the Initial Reachability Matrix is ready, the next step is to provide for the principle of transitivity and design the final reachability matrix. The principle of transitivity simply states that if A leads to B and B leads to C, then, A leads to C. Wherever transitivity is established, 0 changes to 1 and it is marked with an asterisk sign (*). Based on the final reachability matrix, the reachability and the antecedent factors are identified for each factor. Reachability set for a factor is the set of factors that lead to it and the antecedent set is the set of factors that this factor contributes to. In the next step, level partitioning is done for all the factors.

TABLE 3. FINAL REACHABILITY MATRIX (INCORPORATING TRANSITIVITY)

	1	***2***	***3***	***4***	***5***	***6***	*7*	***8***	***9***	***10***
1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	0	1	0	0	0	0	**1***
3	1	1	1	0	1	0	0	0	0	**1***
4	1	0	0	1	1	0	0	0	0	1
5	1	0	0	0	1	0	0	0	0	1
6	1	1	1	1	1	1	0	1	1	1
7	1	1	1	1	1	0	1	1	0	1
8	1	1	0	0	1	0	0	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	1	1	1	**1***	1	1	1	1	1	1

Level Partitioning

The reachability set and the antecedent set are identified for each factor/variable and are placed in a table as shown in Table 4. The variables or factors, for which the reachability and the intersection sets overlap, are placed and closed at that level. In this case, the first factor, 'leadership perspective' has the same reachability and intersection sets and is therefore in Level 1 (Table 4).

For Level 2, the process is repeated after removing the first level variables. In this case, 'leadership perspective' is removed and the process is repeated. Factors numbered 5 and 10 (HR attitude and outlook and data-driven culture respectively) are placed at Level 2 (Table 5). Thus, each of the variables is placed into different levels till the process is complete and all the levels are partitioned as shown from Table 4-9. The levels indicate the level of significance and impact of each factor on the adoption of people analytics.

TABLE 4. LEVEL 1 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1	1-10	1	**I**
2	1,2,5,10	2,3,6-10	2,10	
3	1,2,3,5,10	3,6,7,9,10	3,10	
4	1,4,5,10	4,6,7,9,10	4,10	
5	1,5,10	2-10	5	
6	1-6, 8-10	6, 9,10	6, 9,10	
7	1-5,7,8,10	7,9,10	7,10	
8	1,2,5,8-10	6-10	8,9,10	
9	1-10	6,8,9,10	6,8,9,10	
10	1-10	2-10	9-10	

TABLE 5. LEVEL 2 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
2	2,5,10	2,3,6-10	2,10	
3	2,3,5,10	3,6,7,9,10	3,10	
4	4,5,10	4,6,7,9,10	4,10	
5	5,10	2-10	5,10	**II**
6	2-6, 8-10	6, 9,10	6,9,10	
7	2-5,7,8,10	7,10	7,10	
8	2,5,8-10	6-10	8,9,10	
9	2-10	6,8,9,10	6,8,9,10	
10	2-10	2-10	2-10	**II**

TABLE 6. LEVEL 3 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
2	2	2,3,6-9	2	**III**
3	2,3	3,6,7,9	3	
4	4	4,6,7,9	4	**III**
6	2-4,6, 8-9	6, 9	6, 9	
7	2-4,7,8	7	7	
8	2,8,9	6-9	8,9	
9	2-4,6-9	6,8,9	6,8,9	

TABLE 7. LEVEL 4 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
3	3	3,6,7,9	3	**IV**
6	3,6,8,9	6,9	6,9	
7	3,7,8	7	7	
8	8,9	6-9	8,9	**IV**
9	3,6-9	6,8,9,	6,8,9	

TABLE 8. LEVEL 5 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
6	6,9	6,9	6,9	**V**
7	7	7	7	**V**
9	6,7,9	6,9	6,9	

TABLE 9 LEVEL 6 OF LEVEL PARTITIONING

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
9	9	9	9	**VI**

The Digraph

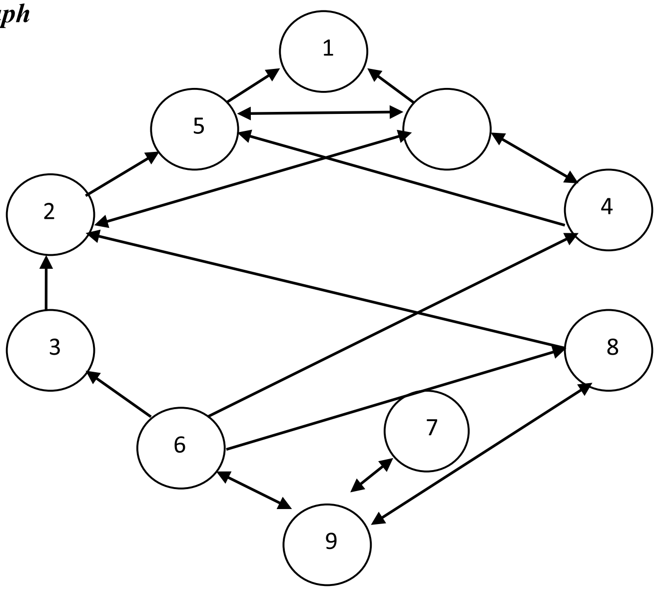

FIGURE 1. THE DIGRAPH

The digraph is a pictorial representation of the interrelationships among the different factors and the sequence of impact of the factors on the adoption of people analytics. It is the basis for the Interpretive Structural Modelling (ISM). The digraph, as shown in Figure 1 is based on the level partition wherein the factors are placed in multiple levels to make a logical step-wise structure.

The factors or variables that are in Level 1(Table 4) appear at the top and those that are in Level 6 (Table 9) appear at the bottom. So, the digraph has 6 steps/levels effectively. The interrelationships among the factors are defined using arrows, both single-pointed and double-pointed, depending on their relationships. These arrow markings are decided based on the final reachability matrix.

Interpretive Structural Model

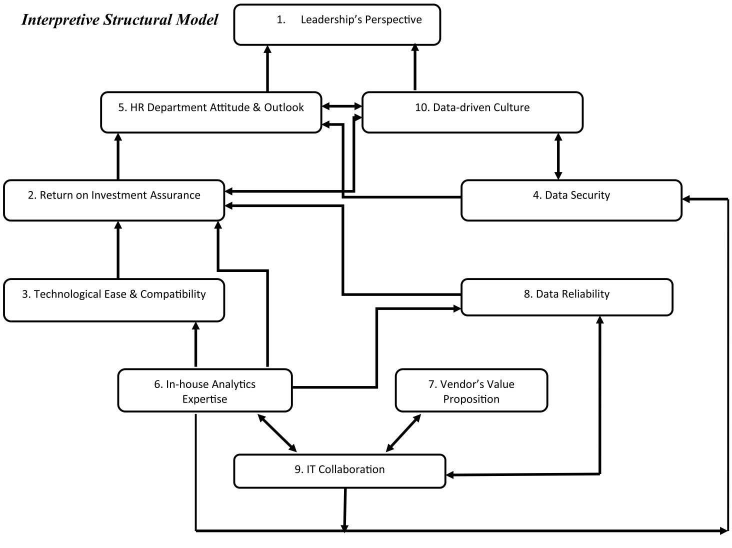

FIGURE 2. INTERPRETIVE STRUCTURAL MODEL

The ISM or Interpretive Structural Model is designed based on the digraph. The numbers in the digraph are replaced by the factual actors and the interpretive structural model is constructed as shown in Figure 2. Logically, the model aligns almost perfectly with the inputs provided by the HR heads and the analytics experts. For example, HR outlook and data-driven culture impact each other and influence the leadership's perspective. The interrelationships among the various factors, as defined by the ISM, are not only apparent but also approved by the experts.

The presence of in-house expertise impacts technical-ease and also the return on investment according to the model. Logically too, the availability of in-house expertise can help in the choice of technology for ease of implementation and for better financial benefits. The structure is thus quite extensive and helps establish the prioritization and sequencing of the factors. This structure gives a clear understanding of how each factor leads to another and how it is influenced by the other factors.

TABLE 10. THE CONICAL MATRIX

j

i

	1	***5***	***10***	***2***	***4***	***3***	***8***	***6***	*7*	***9***	***Driving Power***
1	1	0	0	0	0	0	0	0	0	0	1
5	1	1	1	0	0	0	0	0	0	0	3
10	1	1	1	1	1	1	1	1	1	1	10
2	1	1	1	1	0	0	0	0	0	0	4
4	1	1	1	0	1	0	0	0	0	0	4
3	1	1	1	1	0	1	0	0	0	0	5
8	1	1	1	1	0	0	1	0	0	1	6
6	1	1	1	1	1	1	1	1	0	1	9
7	1	1	1	1	1	1	0	1	1	0	8
9	1	1	1	1	1	1	1	1	1	1	10
Dependence	10	9	9	7	5	5	4	4	3	4	60

The conical matrix (Table 10) is based on the level partitioning exercise done earlier. The driving power and the dependence for each variable are calculated based on the final reachability matrix. These dependences and driving powers help us understand the role of each factor in the entire analysis. They also help define the coordinates for each variable in the MICMAC analysis.

MICMAC Analysis

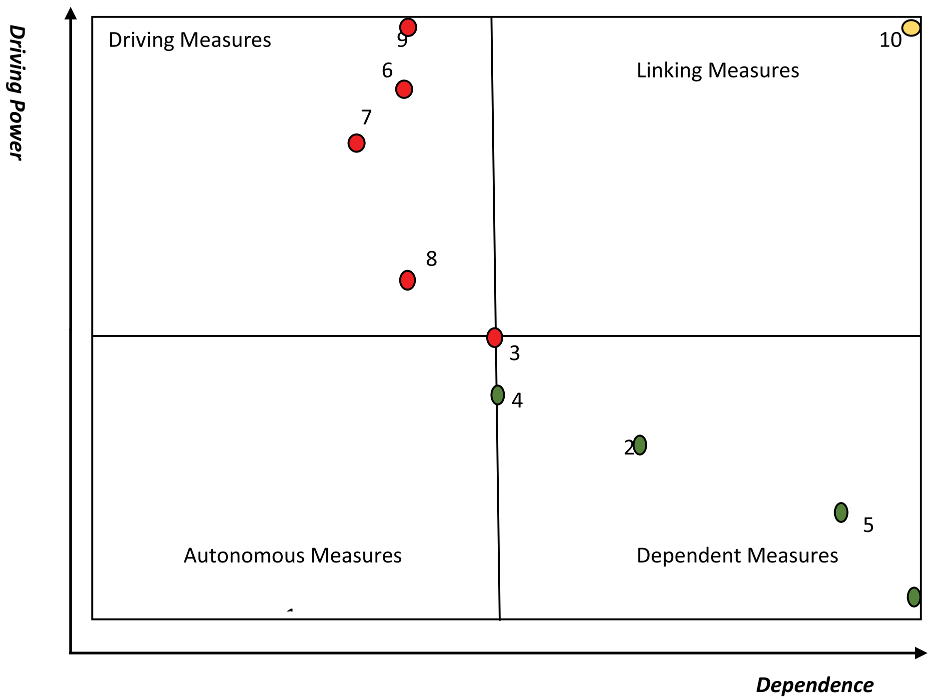

FIGURE 3. MICMAC ANALYSIS

MICMAC Analysis is based on the coordinate values (i, j) of each factor in the conical matrix. With dependence on X-axis and driving power on Y-axis, the factors are plotted as shown in Figure 3. As per the graph, the different factors can be categorised as dependent measures, autonomous measures, linking measures and driving measures.

Driving Measures are the ones that have relatively more impact or influence on the other factors. The following are driving measures and play a very significant driving role.

- Data Reliability
- In-house Expertise
- IT Collaboration
- Vendor Assurance
- Technical Ease

The linking measure is the data-driven culture. Logically, all the other factors are influenced by 'data-driven culture' and also drive the culture of the organization. It is at the core of people analytics adoption.

Dependent Measures are the ones that are driven by the driving measures. They are

- Leadership Perspective of People Analytics
- HR Attitude and Outlook
- RoI (Return on Investment) Assurance
- Data Security

Conclusion

Interpretive Structural Modelling (ISM) has been applied to establish the relationship among the different factors impacting the adoption of people analytics and also the level of impact of each of the factors. The interrelationships, including the direction of influence are clearly explained by the ISM. The ISM and the MICMAC analysis together help simplify the complex network of interrelationship among the different factors. This can provide better clarity to organizations and help them prioritize their strategies for smoother adoption of people analytics. This can also be extended to improve the effectiveness of people analytics in an organization as it provides inputs on issues that may be stunting the progress or impacting the performance of people analytics.

Future Scope

With some minor adaptive modifications, the model is universally relevant and applicable as most of the HR heads and analytics experts considered for the study are from MNCs with operations across the globe. The study can be conducted for specific sectors for improved focus and specific understanding of adoption factors of people analytics. Consulting firms and vendors can also apply the knowledge from similar studies to offer better customized solutions to client companies.

References

Agarwal, D., Bersin, J., Lahiri, G., Schwartz, J., Volini, E. (2018, March 18). People data: how far is too far? Deloitte Insights-2018 Global Human Capital Trends,

Ahmed, M. (2019, January 22). HR Analytics is a high priority in APAC but the adoption is sluggish,

Anand, A. and Bansal, G. (2017). Interpretive structural modelling for attributes of software quality. Journal of Advances in Management Research, Vol. 14 No. 3, pp. 256-269.

Attri, R., Dev, N. & Sharma, V. (2013). Interpretive Structural Modelling (ISM) Approach: An overview. Research Journal of Management Sciences, Vol. 2(2), 3-8.

Bassi, L., McBassi & Company (2011). Raging Debates in HR Analytics. People and Strategy, Vol 34, Issue 2, 2011.

Bersin, J. (2017, February 17). Big Data in Human Resources: Talent Analytics Comes of Age Retrieved from http://www.forbes.com/sites/joshbersin/2013/02/17/big-data-in-human-resources-talent-analytics-comes-of-age

Bersin, J., Collins, L., Mallon, D., Moir, J., Straub, R. (2016, February 29). People analytics gaining speed, Deloitte Insights. Retrieved from https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2016/people-analytics-in-hr-analytics-teams.html

CIPD (2019, February 20). People Analytics Fact Sheet. Retrieved from https://www.cipd.co.uk/knowledge/strategy/analytics/factsheet

Green, David. (2019, June 28). Six factors for adoption of people analytics, Retrieved from https://www.myhrfuture.com/blog/2019/6/28/six-factors-influencing-the-adoption-of-people-analytics

HCI in partnership with Oracle (2015, April 28). Insightful HR: Integrating Quality Data for Better Talent Decisions, Retrieved from http://www.hci.org/lib/insightful-hr-integrating-quality-data-better-talent-decisions.

Keerthi, L. & Reddy, P.R.. (2018, November). Adoption Issues of HR Analytics. Retrieved from https://www.researchgate.net/publication/329265118_Adoption_issues_of_HR_analytics

Khan, U. & Haleem, A., (2015, July). Improving to Smart Organization, Journal of Manufacturing Technology Management, Emerald Insight. Vol. 26, No. 6, pp. 807-829.

Lavastorm Analytics Survey (2013, October 16). Analytics is critical to day-to-day decisions, but further analytics adoption is restricted by shortage of talent. Business Wire, New York. Retrieved from www.lavastorm.com › assets › Analyst-Survey-Press-Release-10.16.2013.pdf

Lawler, E.E. III, Levenson, A. & Boudreau, J. (2004, May). HR Metrics and Analytics –Uses & Impacts, CEO Publication, May 2004

Leonardi, P. & Contractor, N. (2018, November). Better People Analytics, Harvard Business Review, Issue. Nov.-Dec., 2018 Retrieved from https://hbr.org/2018/11/better-people-analytics

Lije, G. and Kamalanabhan, T. J. (2016). A Study on the Acceptance of HR Analytics in Organizations, International Journal of Innovative Research and Development, Vol 5, Issue 2

McKinsey Global Institute (2016, December). The Age of Analytics: Competing in a data-driven world. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world

McKinsey Report (2017, July). Chun, J.K., Hagstroem, M., Libarikian, A. & Rifai, K. Advanced analytics: Nine insights from the C-suite. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/advanced-analytics-nine-insights-from-the-c-suite

Niharika, A. & Kumar, V. (2018). Applying Data Analytics for Human Resource Management: Opportunities & Challenges, Journal of Social Welfare & Management; Volume 10, Number 2, pp. 128-132

Rosario, R.. (2018, February 22). A Smooth Adoption Path for HR Analytics in FS Organizations. Retrieved from https://talentorganizationblog.accenture.com/financialservices/a-smooth-adoption-path-for-hr-analytics-in-fs-organizations

Sushil (2012). Interpreting the Interpretive Structural Modelling, Global Journal of Flexible Systems Management, Vol 13, Issue 2, pp 87-106

Davenport, T.H., Harris, J. & Shapiro, J. (2010, October). Competing on Talent Analytics, Harvard Business Review

TCS (2017). Predictive Analytics in HR: A Primer, A White Paper by TCS.

Tursunbayeva, A., De Lauro, S. & Pagliari C. (2018). People analytics-A scoping review of conceptual boundaries and value propositions, International Journal of Information Management, Volume 43, December 2018, Pages 224-247

Vulpen E. (2018). What is HR Analytics? AIHR Academy Blog. Retrieved from https://www.analyticsinhr.com/blog/what-is-hr-analytics

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