Dr Vijay Prakash Srivastava. (2012). An analysis of management of manpower- with special impact on it sector. *International Journal of Economic Perspectives*, 6(1), 1-11.
Retrieved from: https://ijeponline.org/index.php/journal/article

AN ANALYSIS OF MANAGEMENT OF MANPOWER- WITH SPECIAL IMPACT ON IT SECTOR

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ABSTRACT

This paper explores what role human resource (HR) analytics plays in organizational efficiency and how well will be comprehended in a central analytics function, surpassing individual HR functions for sustainableperformance. In recent days there is a trend towards data-driven decision across myriad business areas and HR is not an exception. As human capital has been an ever knowing important element in determining organizational effectiveness. The focus of this study is to explore the relationship between HR analytics practices and power of decision making and organizational efficiency. Using a sample of 214 practitioners of HR analytics of Indian IT organizations, the authors investigated what is the function, significance and configuration, of HR analytics and its contribution to organizational efficiency. In this study pre-established questionnaire was adopted to collect responses related to the study constructs. All the three scales were enumerated in five point Likert scale. Further, we applied structural equation modelling (SEM) technique using SPSS 20 and AMOS 24 software to examine the proposed relationships the findings suggest that, HR analytics is having a tremendous scope acting as a change catalyst inimprovingbusiness efficiency, and perceived as a more methodological data drivendecision making.

Keywords*:* HR Analytics, Sustainable Performance, Data-driven Decision-making, Organizational Efficiency

INTRODUCTION

HR analytics are in the embryonic stage and having hidden potential to enhance multidisciplinary growth of every organization in using data for better decision making, as reflected in the rapid growth of data science. As another example of the guarantee of HR analytics when it comes to improving organizational outcomes, some have shown that when looking at large, publicly-traded companies, executive leaders often attribute the data-driven decisions made by its HR analytics team to business success, although such companies do not openly share the direct return on investment as a result of its people decisions (Davenport et al., 2007; Sullivan,2009)

The term “HR analytics” has different meanings to different people (Bassi, 2011, p. 15). In a recent article, HRA is defined as “the systematic identification and quantification of the people drivers of business outcomes, with the purpose to make better decisions” (van den Heuvel `in a systematic way to make better business decisions. HRA is currently one of the biggest buzzword in the field of human

***Corresponding author**:* Dr Vijay Prakash Srivastava
Submitted: 26April 2012, Revised: 09 May 2012, Accepted: 15Juner 2012 Published 30 June 2012

resource management. Commenting on the phenomenon of HRA, it is noted that there is a lot of hype and buzz, and that it is generally seen as something organizations "must have" (Platanou&Mäkelä, 2007; van den Heuvel &Bondarouk, 2007). However, despite the entire buzz, academics have largely been absent from the debate and have only to a very limited extent examined the HRA phenomenon (van den Heuvel, 2007; van den Heuvel &Bondarouk,2007).

This paper explores what role human resource (HR) analytics plays in organizational efficiency and how well be comprehended in a central analytics function, surpassing individual HR functions for sustainable performance. In recent days there is a trend towards data-driven decision across myriad business areas and HR is not an exception. As human capital is an ever knowing important element in determining organizational effectiveness. It can play a key role in developing a highly valued part of an organization. Falleta (2010) conducted a survey to determine the use of HR analytics across Fortune 1000firmswithasampleof220firms,Falleta(2010)reportedthatonly15%of

respondents claimed HR analytics played a central role in determining or implementing HR strategy. Furthermore, HR analytics primarily consisted only of analyzing employee survey data.

Lawler et al. (2004) and Lawler and Boudreau (2006) reported results of a survey of over 100 Fortune 500 companies suggesting less than a third of these companies have HR analytics that measures the relationship between HRM processes and people and business impact. The present paper in this context investigates the scope of HR analytics and role as a change catalyst that is quintessential for better decision making and increasing efficiency of the organization.

RESEARCH PROBLEM AND STUDY OBJECTIVE

The objective of this study is to explore the relationship between HR analytics practices and power of decision making and organizational efficiency. Through data analytics, the goal is to transform huge complex bundle of data into knowledge and, in this way, help the decision-making process of retaining human capital by helping to make more accurate and data-driven decisions and also to make a forecast about the future, not just describe the past (Rasmussen & Ulrich, 2006). According to Rasmussen & Ulrich (2006), HR analytics is supporting value creation and the business strategy is quite slim and many organizations are still at the embryonic stages of HR analytics (Roberts, 2009). However, there also can be found some examples to the converse. Companies like Google and IBM have already taken superior steps to get a head start in the area of analytics. Still, these are just a few examples and more research is still needed relating HR analytics practices which may likely to have a positive impact on the power of decision making and organizational efficiency in the context of Indian ITindustries.

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LITERATURE REVIEW

The key objective of this literature review is to provide a comprehensive overview of the academic literature about HR analytics and data-driven HRM as well as describe the way these two concepts link together on the basis of the academic studies. Many successful companies such as Google, Facebook, and Apple are able to measure and evaluate the

effects of hr analytics practices and, in turn, make data-driven decisions to justify their returns on business performance. Human resource (HR) analytics refers to the practice of using data to support decisions pertaining to HR systems, policies, and practices.

The need for a cultural shift in the HR community is also stressed by Pease (2006). Managers should accept that HRA is possible, and it can be relied upon: this could be achieved by gradually showing the power of analyses to match existing mental models, and by education and training, seen as good ways to increase acceptance and usage (Cascio & Boudreau 2010).Only a minority of companies currently reports usage of HRA (Deloitte, 2006; 2007; 2008); on the other hand, organisations are seen as more ready to introduce and utilise HRA, as compared to the past: new specialist staff is recruited, HRA offerings are purchased and efforts to increase data quality are put in place (Deloitte, 2007). MNCs worldwide are lifting HRA higher up in their agenda, spreading it to more HR practices than before: previously performed in small technical groups in specific HR areas, HRA usage is becoming more systematic (Deloitte,2008).

In a world where top management often looks to the figures before making decisions, HR analytics represents a growing trend amongst the management field (Pfau & Cohen, 2003; Rasmussen & Ulrich, 2010), as the practice offers a useful framework and set of tools for measuring and evaluating the efficacy of HR systems, programs, and interventions. For instance, senior leaders who are paying close attention to the rise of big data and its impact on the field of human resources have potential to advance their organizations' productivity and profitability by up to 6% higher than their peers (Barton & Court, 2012).

According to Mondore, Doutitt& Carson (2011), there are significant differences between those talent metrics that organizations consider important and the data to which they have access. A legacy of disparate technology systems and a focus on measuring efficiency rather than effectiveness are the primary reasons for the lack of recent analytics and talent intelligence among many businesses. There was a growing need for more efficient and effective ways to process employee information. The computer technology was evolving as well, improving the product functionality while lowering the prices. In the 1980s, the first stand alone software packages, referred to ashumanresourceinformation systems(HRIS),were developed (e.g. Hendrickson, 2003; Stone &Dulebohn, 2009). These systems allowed organisations to collect, stock and utilize data to support HRM and facilitate HRM functions, for example recruiting, training and development, although human resource professional were dependent on IT experts on the use of these HRIS systems (Stone &Dulebohn,2009).

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Bigger change was seen in 1980 (e.g. Schuler & Jackson, 2005; Guest, 2011). The role of HR began to change and HR was seen more as a part of the core business that could have an effect on the efficiency and effectiveness of organisations (Ferris et al., 2007). In order to achieve this, human resources needed to be managed more systematically and also the capabilities and competencies of HR professionals needed to be developed (Schuler & Jackson, 2005).

HR analytics is additional mechanism apart from collecting data and conducting analyses; it can be used as an advance to quantify the effects of HR initiatives, influence executive decision, and enable cross-functional interface amongst departments (Bates, 2003; Chadwick, Super & Kwon, 2006; Mondore et al., 2011). HR analytics is a generally new articulation and mirrors a multidisciplinary drift toward utilizing information to rely on data centric decision. As needs be, for a few organizations, the ascent of HR analytics has brought about a reshaping of a current capacity, though in different sectors, an altogether new capacity waspresented.

Information theory (e.g., Blackwell, 1953) and the information-processing view of organizations (e.g. Galbraith 1974) suggests that more precise and accurate information should

Facilitate greater use of information in decision making and therefore lead to higher firm performance. There is a growing volume of case evidence that this relationship is indeed true, at least in specific situations (e.g., Davenport and Harris 2007; Ayres 2008; Loveman 2003). Loveman (2003), the CEO of Caesar's Entertainment, states that use of databases and decision science- based analytical tools are the key to his firm's success.

Davenport and Harris (2007) have listed many firms in a variety of industries that gained competitive advantage through the use of data and analytical tools for decision making such as Proctor and Gamble and JC Penney. They also show a correlation between higher levels of analytics use and 5-year compound annual growth rate from their survey of various organizations. A more recent study (Lavalle et al. 2010) has reported that organizations using business information and analytics to set apart themselves within their industry are twice as likely to be top performers as lowerperformers

In spite of the unavoidable need of HR analytics and the evidence-based review about the role that HR analytics can be incorporated into the effectiveness of the organization, relatively few empirical studies have directly investigated whether companies with a defined HR analytics function enhances the power of data-driven decision making which in turn improves organizational efficiency. There is scarcity in the literature, and more research is needed to identify with how HR analytics is adopted across organizations and under what situation a well-defined HR analytics function contributes to an organization 's sustainable performance and efficiency. Empirical research on HR analytics isinadequate, and studies on function, significance and configuration in HR analytics are limited. This research focuses on to have a say to a better understanding of the development of HR analytics, to facilitate business and gainsustainable performance by enhancing power of data driven decision making which in turn leads to organizationalefficiency.

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A research framework has been proposed based on the previous theoretical underpinnings. Prior literature was retraced to find out the linkages among study constructs and several hypotheses were formulated.

H1: Data driven decision making positively relates to improving organizational efficiency H2:

Adaptations of HR analytics significantly influence power of decision making.

H3: Increased use of HR analytics positively relates to the organizational efficiency

H4: HR analytics practices mediate the relationship between decision making and efficiency of theorganization

DESIGN/METHODOLOGY/APPROACH

Using a sample of 25 practitioners of HR analytics of Indian IT organizations, the authors investigated what is the function, significance and configuration, of HR analyticsand its contribution to organizationalefficiency.

In this study pre-established questionnaire were adopted to collect responses related to the study constructs. All the three scales were enumerated in five pointlikert scale. Further, we applied structural equation modelling (SEM) technique using SPSS 20 and AMOS 20 software to examine the proposed relationships. First, exploratory factor analysis (EFA) was conducted to extract the factors (Hair *et al*, 2010). After that reliability and validity was examined. Confirmatory factor analysis (CFA) was done using maximum likelihood technique (MLE) on all the extracted factors (Brown, 2006) to assess the measurement model fit. Further, path analysis was conducted to examine the hypotheses and model specification using structural equation modelling (SEM) technique comprised of two-stage model building approach (Anderson and Gerbing's, 1988; Joreskog, 1993).PROCESS macro was used to analyse the proposed mediation linkages. Further, study results were presented to elucidate the researchfindings.

Data analysis

To ensure that measures are free from the error and therefore yields consistent results, during the process of purifying of constructs, reliability of questionnaires have to be measured (Peterson, 1994). Furthermore, in order to validate reinforcement of the scales by data, exploratory factor analysis (EFA) was conducted. Based on EFA, indicators of Kaiser-Mayer-Olkin (KMO) for all questionnaires were greater than 60% that endorsed (Kaiser, 1974). Based on results of test of Bartlett of Sphericity for total variables shows that correlation indicator between items is greater than 30% and was appropriate for exploratory factor analysis (Hair, 2009). According to analysis of responses amount of sum up variance among constructs was greater than 0.60 (Hair, 2009).

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Cronbach"s α Value of the Instruments

Table 1

Variables	**Number of Items**	**Cronbach's α**	**KMO**	**Bartlett's test Sphericity**	**Variance Explained**
HRA	*10*	*0.921*	*0.876*	*0.000*	*67.062*
DDM	*12*	*0.875*	*0.754*	*0.001*	*65.606*
OE	*8*	*0.812*	*0.813*	*0.000*	*66.033*

Validation of the Measurement Model

The SEM process contains two phases: validation of measurement model and fitness of structural model. The validation of the measurement model, as the first phase of SEM process, was done principally via Confirmatory Factor Analysis (CFA), after that the test of fitness of structural model was done mainly by path analysis of latent variables. By measurement model researcher can examine the reliability of observed variables. Observed variable measures the unobserved one. A weak or strong fitness of the data is presented by measurement model, as well as the unreliability of observed variables.

Reliability Measurement (Construct-Level)

The reliability of construct-level ensures items that assigned to similar variables disclosed higher relationship with each other. Despite the fact, former reliability items calculated in individual-level was sufficient enough. As respects it is recommended observing reliability of constructs measured jointed by a group of items in the same construct (Bagozzi, 1984). In the present research, reliability of constructs level was examinedusing

Measuring the Convergent Validity

In general, the validity determines that to what extent a group of measurement item signifies the concepts of the proposed conceptual framework (Hair *et al.*, 2012). Specially, convergentvalidityclarifiesthecorrelationsamonganswerersachievedbydifferentways

signify the same constructs (Niedergassel, 2011). Convergent validity in this study was examined by AVE (average variance extracted). Table 2presents the AVE that adapted for each construct, was greater than defined amount 0.5 (Fornell and Larcker, 1981).

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Table. 2: *Measuring the Convergent Validity*

Variables	**AVE**	**Cronbach's α**	**Composite reliability**
HRA	*0.567*	*0.911*	*0.906*
DDM	*0.574*	*0.876*	*0.894*
OE	*0.532*	*0.815*	*0.813*

Measuring the Discriminant Validity

Discriminant validity at construct-level was examined by means of Fornell and Larcker (1981) standard. This indicator at item-level was examined by means of Chin (1998) measures. Fornell and Larcker norm proposes that square-root of the average variance extracted for every variable should be more than another correlation of construct with each other, for instance inter-construct correlation. As shown in Table 3 none of correlation of inter-construct amount is greater than square-root of AVE. Chin (1998) recommended examining the cross loading inside factor loading at item level discriminant validity.

Table 3: Results of Discriminant Validity

	HRA	**DDM**	**OE**
HRA	*0.767*		
DDM	*0.574*	*0.776*	
OE	*0.232*	*0.215*	*0.713*

Structural Model Evaluation

Hypothesis testing

The SEM model was employed to examine the relationship between constructs developed by study. Hence SEM analysis was performed by AMOS 24 version and analyses simultaneously goodness-of-fit indices.

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Table 3. Model Fit.

Goodness of fit indices	**Constructs**
χ^2/degree of freedom	2.146
CFI (comparative fit index)	0.975
TLT (Tusker–Lewis fit index)	0.943
IFI (incremental fit index)	0.984
RMSEA (root mean square error)	0.24
GFI (goodness fit index)	0.930
SRMR (root mean square residual)	0.45

Table 4 shows all path were significant. The relationship between DM -> OE was the first hypothesis. The results indicated that DM and OE are related positively and significantly (β = 0.335; t = 7.760) it implies DM has direct effect on OE.The second hypothesis expressed the relationship between HRA -> DM. The results of the hypothesis recognized a significant and positive relationship between to constructs (β = 0.790; t =27.133). The third hypothesis suggests that the relationship between HRA -> OE. The results of the hypothesis publicized a positive and significant relationship between HR analytics and organizational effectiveness (β= 0.651 and t =16.467).

Test of the Total Effects Using Bootstrapping

Table 4

	Original sample	**Std. Error**	**T-statistics**	**P value**
DM -> OE	0.335	0.043	7.760	0.0010
HRA -> DM	0.790	0.029	27.133	0.0002
HRA-> OE	0.651	0.040	16.467	0.0102

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Mediation Effect of HRA on the relationship between DM and OE

To examine the mediating effect of the HRA on the relationship between a DDM and OE Baron and Kenny criterions was exercised as below: Table 4 indicated that requirements regarding mediation specified by Baron and Kenny have been achieved. Firstly, DDM is directly, significantly and positively related to OE. (β=0.823 and t=62.123).Second, HRA is directly, significantly and positively related to DM (β=0.815 and t=34.016). Third, HRA is directly, significantly and positively with OE (β=0.853 and t= 63.127). Finally, the absolute effect DM on OE is reduced from 0.823 to 0. 334 When the mediating variable is introduced. These consequences show that the to relationship between DM and OE is mediated by HRA. Second, because of being a relationship between [‘dependent and independent variables decreased to significant level (from 0.823 to 0. 334), partial type of mediation was alsorecorded.

Standardized Coefficient of DM on OE

The Mediating Effects of HRA on the Relationship between OE and DM

Table 4a

				DM-> OE Mediated by HRA		
	DM-> OE	**HRA-> DM**	**HRA->OE**	DM-> OE	HRA-> DM	HRA->OE
Beta	0.823	0.815	0.853	0.334	0.786	0.653
SE	0.013	0.0265	0.012	0.043	0.025	0.042
t-value	62.123	34.061	63.127	7.734	2.134	15.465

Type of mediation: Partial Standardized Coefficient of DM on OE ***FINDINGS OF THESTUDY***

The development of HR analytics will be characterized by the synergy effect of technological advancement in tapping complex task of analyzing potential human capital.

The findings suggest that, HR analytics is having a tremendous scope acting as a change catalyst in improving business efficiency, and perceived as a more methodological data driven decision making. Furthermore, the development of HR analytics will be characterized by the synergy effect of technological advancement in tapping complex task of analyzing potential human capital. The HR function is lagging behind other functional areas of management in the adoption of analytics technology and in the analysis of big data. Many in the HR profession do not understand analytics or big data, while analytics teams do not understand HR. As a result, the expensive analytics capabilities provided by the latest forms of HR metrices are failing to deliver strategic HR analytics to the fuller extent. The results of continuous upgradation may then be used to update HR practice and to develop

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meaningful day-to-day metrics, measuresand dashboards within conventional analytics packages. Academics could play a constructive role in these developments, but could also do more to elucidate the praxis of strategic HR analytics.

PRACTICAL IMPLICATIONS

The consequences of the exploration infer that HR analytics is need of any organization to maintain and it require significantly more clearness and agreement to utilize its potentiality.HR analytics can surely upgrade the believability of the capacity and the calling by enhancing the adequacy of HR arrangements and practices and adding to the upper hand of associations that create it as a center competency. The outcomes have common sense ramifications for associations. HRA have turned into a fundamental piece of modern people management all through the world. The role of HRA approved in the investigation has been observed to be critical for enhancing the efficiency of the organizations. Second, the study recommends associations may present particular and centered preparing project to improve representative abilities to utilize HR analytics, building aptitude in them, which will give winning association's focused edge. In conclusion, the present study recommends that appropriate adjustment of HR analytics may arrange such that an individual meet execution desires through better information driven decision making, which will upgrade organizational effectiveness.

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