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AN EXPLONATORY ANALYSIS OF HR ANALYTICS MODEL OVER BIG DATA PROCESS IMPACT ON THE DECISION-MAKING PROCESS IN THE ORGANIZATIONS

RAVI KUMAR BOMMISETTI[1*], ARUP ROY CHOWDHURY[2], ABDULLAH A. AL-ATAWI[3], BHAVANA RAJ KONDAMUDI[4], SINH DUC HOANG[5], and GIRISH BAGALE[6]

[*1]PG Department of Business Administration and Dean – R&D Cell, Maris Stella College, Vijayawada, Andhra Pradesh. E-mail: ravi9949418650@yahoo.com, Orcid ID - 0000-0003-1675-2058.
[2]School of HRM, XIM University, Bhubaneswar – 752050. Email: aruproychow8@gmail.com Orcid ID – 0000-0001-8177-1875.
[3]Department of Computer Science, Applied College, University of Tabuk, Tabuk 47512, Saudi Arabia. Email: a.alatawi@ut.edu.sa, ORCID: 0000-0001-9968-8092.
[4]Department of Management Studies, Institute of Public Enterprise, Hyderabad–500 101, Telangana, India. Email: bhavana_raj_83@yahoo.com, ORCID ID: 0000-0002-0789-3070.
[5]International University, National University of Vietnam, Quarter 6, Linh Trung Ward, Thu Duc District, HCM City, Vietnam. Email: hdsinh@hcmiu.edu.vn.
[6]SBM's Pravin Dalal School of Entrepreneurship and Family Business Management, SVKM's NMIMS University, Mumbai, India. Email: girishbagale08@gmail.com.

Abstract

By generating pertinent indicators, Human Resource Analytics (HRA) can provide HR personnel with a broader perspective on their contribution to the organization's financial objectives. There is a scarcity of research, however, regarding the impact of HRA on business outcomes, specifically in the context of organisations based in India and Vietnam. Within this particular framework, the current study investigates the impact of HRA big data capabilities on business outcomes. The study also investigates the discrepancy between the actual and perceived levels of big data expertise possessed by human resources analysts in Indian and Vietnamese organisations. The current study constructs a conceptual framework in order to examine the hypotheses formulated for assessing the interconnections between the variables being investigated. Utilising the Capability, Motivation, and Opportunity (CMO) framework, it accomplishes this. The data were collected using a quantitative approach, which entailed integrating the various components of HRA expertise and assessing their influence on business outcomes through the utilisation of big data. A systematic questionnaire was developed and distributed to 230 human resources professionals employed by various organisations located in Ho Chi Minh City, Vietnam, and Hyderabad, India. In addition to HR administrators, users of HRAs comprised the participants. A variety of statistical methods were applied to the data to assess the disparity between HRA's anticipated and realised big data capabilities, as well as the impact of HRA on business outcomes. It appears, based on the data that offering incentives and opportunities to employees with HR analytical skills could result in enhanced performance for the organisation. Research has demonstrated that providing opportunities and incentives to skilled employees is crucial for encouraging the development of their analytical abilities. Possessing these types of analytical abilities significantly influences the outcomes of an organisation.

Keywords: Human Resource Management, Human Resource Analytics, Big Data, Decision-Making Process.

1. INTRODUCTION

With the passage of time and situations human resource practices have changed from mere management of the legal and other obligatory functions to a dependable advisor for entrepreneurs with business strategy creation and applications [1]. From the very early phase of the 20th century, the Human Resource Management (HRM) has been playing a pivotal role in rationalizing the data accumulated from the relevant processes for business entrepreneurs [2]. The manner in which data is utilised has evolved; initially collected for the purpose of monitoring employee information, its subsequent application centred on fulfilling the legal obligations of the employment. [3]. Gradually, more diverse data were accumulated with increasing understanding about employee efficiency and their positive contribution in bringing dynamism in the HRM role [4]. It is an established fact that rapid development in the information technology sector has been considered as the major driving force to promote this new evolution.

Research suggests that the role of the Human Resource (HR) functioning has progressed from being driven by need to be driven by opportunities and capabilities [5]. In the need-driven tradition, the role of HR was to evaluate and deal with deficits in skills of the organisations on the other hand, in the opportunity-driven tradition, the role of HR was to focus on the potential of employees to learn with particular emphasis on skills which would be beneficial in active participation in the strategic planning of the organisation such as systematic thinking. In the capability-driven tradition, the focus of the HR is to deliver executive and managerial capabilities which can significantly contribute to the performance of the organisation [6]. This evolution of the HR function has caused an increased use of metrics and analytics, although it has been pointed out that this has often been ignored by HR professionals.

Decision-making in HR is a matter of significance to organisations as is the need for a robust link between HR and other areas of the organisation. In order to provide HR professionals with the means to enhance organisational relationships and decision-making, a substantial amount of research has been devoted to determining the value and efficacy of HR operations. This frequently entails the usage of numerical models [7]. It appears that the functions of the HR professionals are experiencing mounting pressure to prove their usefulness to the organisation. This need must be translated into a novel notion or subject which characterises one of the principal movements of the present day with regard to decision-making and strategy from an HR perspective.

HRA has been defined in many ways, but in simple terms it signifies the system of utilising data to corroborate decisions related to HR procedures, systems, and policies. HRA, thus, reinforces the existence of a progressive learning amongst organisational management to review numbers prior to decision-making [8]. This is supported by the fact that HRA provides a valuable framework and tool set for quantifying and appraising the effectiveness of practices, interventions and programs related to HR [9]. The present study investigates the analytical characteristics of human capital management within an organisational context and its significance in attaining effective business resolutions. Moreover, the study identifies the existing gaps between the expected and actual HRA big data competencies in Vietnam and Indian organisations. Also, the study endeavours to provide recommendations for academia and industry on the way these gaps can be addressed. In addition, the study also throws light on how the capability, motivation and opportunities of the HR professionals can be utilised to increase the productivity and efficiency of the organisations. The need for companies to have an analytical reference point (HRA) for deriving constructive decisions that has a positive impact on the business results is also examined. Thus, it is expected that our study may contribute to theoretical inferences on the basis of the existing HR analytics parameters. It is also expected that the present study finds new prospective job criteria with good HR analytics practice.

This paper concentrated on the evaluation of the HR competitiveness in the decision-making process using big data. The big data comprises of the vast range of information about the organizations through that HR analytics able to improve the business management strategies. The data for analysis is collected from the 260-sample population those are HR professionals in the cities of Ho Chi Minh and Hyderabad. Through the framed hypothesis the big data competitiveness over the HR analytics is examined. The contents of the article are structured in such a way that the relevant studies on HR analytics are provided in section 2. The research methodology adopted for the evaluation of HR analytics using big data is evaluated in section 3. In section 4 and section 5 the analysis of results and findings are presented. Finally, the overall conclusion about HR analytics with the big data is presented.

2. RELATED WORKS

Recently, human resource management (HRM) has witnessed the emergence of human resource (HR) analytics as a trend. HR analytics is anticipated to provide solutions to a multitude of HR challenges in the near future.

In [10] analysed the role of huge data in the assessment and selection of talent. Two case studies were presented by the authors to illustrate the types of big data encountered in different cases and their impacts on talent acquisition. It was found that the role of large data was significant in HR processes like assessment and selection of worthy candidates. Author in [11] explained the relationship between high rate of attrition and low talent retention and examined the role of predictive analytic domain within HRA. It was found that some HRM metrics that were viable for predictive modelling could be recognized and proposed for generating extensive effects of HR predictive analytics. Consequently, organizational performance was improved, and execution costs related with HR interferences were reduced. Additionally, the relationship between high attrition rate and low talent retention was explicated in the study.

In [12] analysed the role of analytics for enabling a proper functioning of HRM in organizations. The study gathered data from secondary sources including scholarly articles, books, Internet, and white papers. The findings of the in-depth review of these articles and reports suggested that four levels of existing analytics had their impact in yielding a better business outcome. However, lack of solid empirical evidence was the major factor, which limited the scope of outcomes.

Research conducted in [13] re-examined an in-depth study of the significance of huge data for supply chain management. The author gathered the required data by interviewing a sample of executives selected from 300 firms. In the wake of the review, the author arrived at three conclusions regarding the role of data analytics in HRM. The first was the utilization of big data for inquiry, wherein scholars and practitioners were able to explore the queries and issues by accessing quality data, which was not possible before. The second was the utilization of big data for varying the nature of query, wherein conventional queries were swiftly answered by big data. The third was the utilization of big data for altering the experimentation, wherein it was established that big data enabled HR professionals to use the commonly occurring experiments in each organization.

In [14] explored the association between data driven HRM and HRA. The required data was gathered through HR professionals ‘blogs posted during the period of 2009-2015 on five online HR communities in Europe and the US. A dedicated software called Leximancer was used to analyse the data in the first phase, which was further quantitatively analysed in the second phase for identifying the most striking impact of HR analytics on HRM. The results revealed that HR professionals had not begun to adopt HR analytics. However, the study established that strategic role can be attained through HR analytics, which enables HR to create organizational value and act in a decisive manner. Further, the study also stated that HR analytics and data driven HRM should be scheduled and used in accordance with organizational circumstances and strategies. In other words, the capabilities of individuals using HRA are directly influenced by its efficient execution.

In [15] used the basic concepts of workforce analytics for formulating a HR model, specifically for recruitment. Initially, the definitions of recruitment and workforce analytics were studied. Subsequently, the researchers examined the changes in organizational operations and the factors that influence employees ‘selection and recruitment. It was found that HR analysis played a role in keeping a consistent strategic partner by giving proper directions to HR actions. However, the study pointed out that strategic analytics ability and data-based decision-making was found to be lacking in HR.

In [16] conducted a review on ROI-based HR analytical tools identified some of the challenges associate with HRA as a strategic management tool/ decision making tool/ as management fad. Based on the review, the study reported that management-HR interface, adoption of correct technological tool and analytical techniques, and HRA not being a part of HRM challenge the adoption of HR analytics by organizations.

[17] By conducting an extensive review of the literature encompassing publications from 2010 to 2019, we have discerned fourteen pivotal factors that exert an impact on HR analytics. The aforementioned elements were categorised into the following four groups: management, software and technology, personnel, and data and models. Numerous data and model-related issues were brought to light by the evaluation, including inadequate data and metrics, insufficient data and sharing, the absence of standards for HR and data metrics, substandard HR data quality, and a failure to prioritise strategic HR in complex models. The analysis brought to light numerous software and technology-related challenges, such as the absence of advanced HR Analytics software tailored to the typical characteristics of HR professionals and incompatibilities between systems when attempting to combine data from different departments. The evaluation uncovered three human-related issues: an absence of analytics-related knowledge, skills, and big data competencies; a deficiency in strategic business perspective; and a deficiency in narrative abilities. The evaluation identified several management-related rationales, such as maintaining HR Analytics within the HR department, underestimating the significance of culture, substituting HR Analytics for management discussions, and concentrating on intriguing subjects instead of business challenges.

In [18] attempted to define HR analytics based on a comprehensive review of 71 studies. Based on these reviews, the author presented an opportunity to comprehend the role enacted by analytics in the formulation and implementation of strategy across businesses. Further, the study scrutinized nine case studies to analyse its practicability and effect on US-based organizations. The findings based on in-depth reviews demonstrated that real-life business cases were influenced by HR analytics. Nevertheless, the study failed to prove the competency of analytics in providing favourable business outcomes.

A study was done, referred to as [19], to quantitatively examine the influence of big data on decision-making inside organisations. The study analysed two prominent instances of big data utilisation processes to explore the collaboration between data analysts and decision makers. The study findings from these case studies indicate that big data offers several opportunities for decision makers and analysts. Additionally, it allows actors to follow their own objectives.

The HRA strategic practice has accumulated a lot of hype and buzz in the business field. However, the contribution of the academic sector towards the formal discussion on this aspect of the HR management is very limited [20]. Although there are studies concerning the effect of the HRA on organizational performance conducted extensively in the international forum, not much has been researched about the same in the Vietnam and Indian milieu [21]. In spite of the considerable amount of emphasis on HRA in the last ten years, there is still a complexity regarding which aspect the people should be attentive. Studies have shown that HR team members focused less on the strategic needs and more on the exchange needs [22]. Although the relationship of HRA related capabilities, motivation, opportunities (COM) and Business outcomes has been studied earlier and has been considered to contribute to the debate of HRA practices [23], further exploration is required to study its role in enhancing the competency of HRA. Accordingly, the current research maintains that the COM might be a potential aspect to reflect the demand of the HRA practice. Though HRA is a much-anticipated concept in the Indian perspective, it is still lagging in the contextualization of its strategic regulation in most of the companies and has been limited only to the primary levels [24]. The HRA driven prospects for management of HR have been recognized by companies, but there still exists tremendous scope of progress in the relevant field of analytics for corporate growth. Again, this study examines HRA's influence and potential on business capability and results in selected Vietnamese and Indian cities.

3. RESEARCH METHODOLOGY

The term "research methodology" encompasses all the techniques and procedures involved in doing research. These stages include the identification of the research philosophy, methodology, strategy, selection of research methods, time horizon, and the approaches and processes used in the study. The methodology may be defined as the theoretical foundation and philosophical assumptions that provide the framework for doing research. The study use empirical research methods to generate concepts and assess their validity using statistical analysis. The research approach used in the study may be characterised as deductive. The study used a deductive method, focusing on identifying the elements that influence business results. To do this, the study first examined existing ideas and used them to construct a conceptual framework. This framework consisted of various hypotheses, which were then tested and either confirmed or refuted using research data.

3.1 Research Design

In this investigation, the researcher employed a 79-survey design and collected data through the use of a survey questionnaire. Concurrently, the research questionnaire and sample selection were carried out. In the following sections, the questionnaire design and sample strategy will be discussed. After the development of the research instrument, assessments of its validity and reliability were performed. Following the elimination of variables or inquiries that lacked validity and reliability, the ultimate questionnaire was employed to collect data from the samples. A process of data cleansing and screening was employed to detect any anomalies or instances of missing information. Coding, processing, and loading the cleansed data into statistical software for additional analysis. From the data, significant conclusions were derived. The progression of the investigation is illustrated in Figure 1.

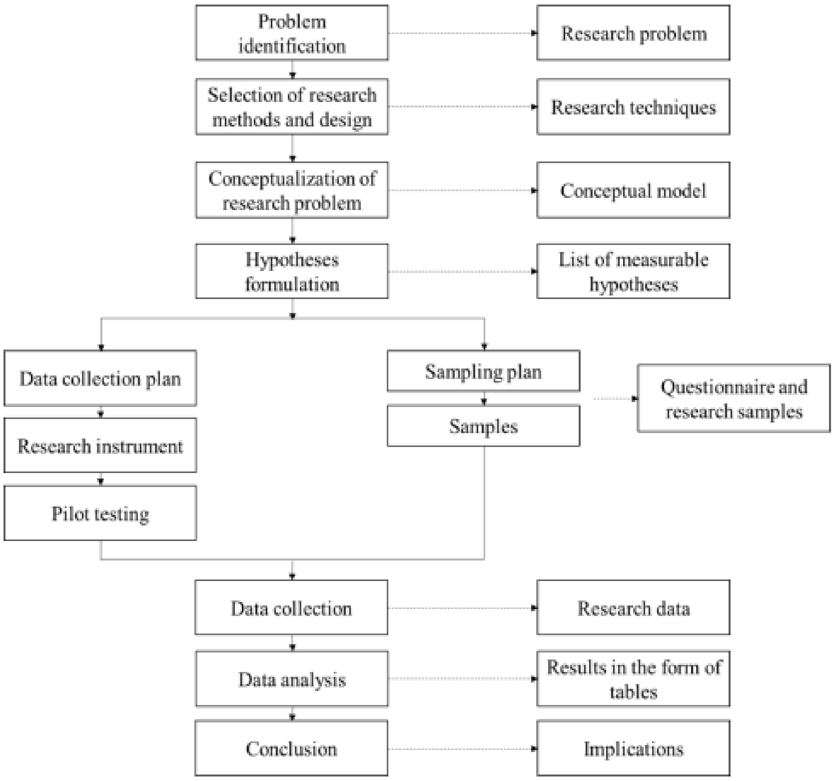

Figure 1: Overall Flow of Conceptual Model

3.2 Research Instrument

A research instrument is used to gather information from study participants during data collecting. When it comes to survey technique, the most often used research tool is the questionnaire. To meet its goals, the research collected information from primary and secondary sources. The research participants, in this case HR experts from different organisations, completed the questionnaire in order to provide primary data. Through an examination of the relevant literature, secondary data were acquired. Literature was evaluated for this research from a number of sources, including EBSCO Host, Google Scholar, Scopus, and others. Human Resources The organization's scale for analytical big data capabilities was 1 (totally absent), 2 (rarely present), 3 (sometimes present), 4 (present most of the time), and 5 (fully present). The utilisation of HRA competence objectives, on the other hand, was evaluated using the following Likert scale: 1 (not at all present), 2 (present to a little amount), 3 (present to some extent), 4 (present to a large level), and 5 (present to a great extent). The sub-constructs and principal constructs used to evaluate the research constructs covered in this section are shown in Table 1.

Table 1: Construct in HR Analytics Competitiveness in Big Data

Main construct	Sub-constructs	No. of items
Existing Human Resources Analytic big data competencies	Comprehension of data	4
	Analytical competencies	11
	Proficient interpretation abilities	5
Expected Human Resources Analyticbig data competencies	Comprehension of data	4
	Analytical competencies	11
	Proficient interpretation abilities	5
Utilization of HRA competency outcomes	Process Performance	10
	Strategies	4

Components of the survey were formulated to evaluate employees' proficiency in utilising human resources data, alongside the recognition and prospects provided by their HR managers. The statements were assessed utilising a Likert scale comprising of five points: 1 (complete absence), 2 (minimal presence), 3 (some presence), 4 (moderate presence), and 5 (significant presence) with regard to HRA capability and level of motivation, respectively. Opportunity levels are as follows: 1 denotes never, 2 represents rarely, 3 signifies occasionally, 4 signifies very frequently, and 5 signifies frequently. In Section VI, respondents were asked to evaluate the impact of HR analytics on perceived business outcomes. These inquiries were also scored using a five-point Likert scale: 1 (strongly disagree), 2 (disagree), 3 (no notion), 4 (agree), and 5 (strongly agree). The sub-constructs and primary constructs utilised to assess the research constructs discussed in this section are presented in Table 2.

Table 2: Construct measures in HR analytics with Big Data

Main construct	Sub-constructs	No. of items
Capability towards Human Resources Analytic	Knowledge	6
	Skills	6
	Behavior	5
Opportunity towards Human Resources Analytic	Organization infrastructure	3
	Job design/Job responsibility	3
	Cross-functional dynamics	5
Motivation towards Human Resources Analytic	Organization fit/Job fit	6
	Creative analytics	5
	Job Satisfaction	4
Business outcomes	Return on Investments (ROI)	7
	Decision-making process	16

3.3 Sample Design

Sampling is the procedure by which research subjects are selected for a study, given the inherent difficulty in investigating the entire globe. The data for this study were provided by human resources professionals in the private sector located in Hyderabad, Telangana, India, and Ho Chi Minh City, Vietnam. The identification of the working populations in Hyderabad, India and Ho Chi Minh City, Vietnam is necessary in order to ascertain the sample size for the study. The investigation must ascertain the quantity of personnel utilising business analytics software in order to assess its impact on the performance of the organisation. Nevertheless, limited public information exists regarding the matter. Consequently, the research conducted an analysis on a sample size of 230, significantly surpassing the initial estimate.

3.4 Reliability of Data

A scale is said to be reliable when consistent results can be obtained in performing repeated measurements of the same construct. The reliability of the questionnaires used for HR analytics and managers was tested using Cronbach alpha. This value varies from a scale of zero to one. When the value of Cronbach alpha is close to 1, itindicates to the greater internal consistency of the scale and that the number of items exhibiting covariance is high. This implies that with an increase in the value of Cronbach alpha, the correlation between the several items also enhances.

Table 3: Cronbach Alpha for HR competitiveness with Big Data

Factors	Sub factors	Cronbach's Alpha	N of Items
Existing HR Analytic big data competencies	Comprehension of data	0.840	4
	Analytical competencies	0.807	11
	Proficient interpretation abilities	0.930	5

Expected Human Resources Analytic	Comprehension of data	0.751	4
	Analytical competencies	0.892	11
	Sub factors	Cronbach's Alpha	N of Items
	Interpretation skills	0.887	5
	Process Performance	0.888	10
	Strategies	0.726	4
	Knowledge	0.916	6
	Skills	0.929	6
	Behavior	0.871	5
	Organisational fit/Job fit	0.731	6
	Creative analytics	0.679	5
	Job Satisfaction	0.751	4
	Organisational infrastructure	0.671	3
	Cross-functional dynamics	0.885	5
	Job design/Job responsibility	0.900	3
	Return on Investments	0.907	7
	Decision-making process	0.926	16

Table 3 shows the Cronbach alpha test for all variables. All items measuring Understanding of data, analytical, and interpretation skills in Existing HR analytic big data competencies; Expected HR analytic big data competencies; Process performance in Utilisation of HRA competency outcomes; Knowledge, skills, and behaviour in HRA capabilities; Cross-functional dynamics and job design/responsibility in Level of opportunities, Return on investments, and decision-making process in Business outcomes from the HR professional questionnaire had Cronbach alpha values above 0.80, indicating good internal consistency. However, items measuring Understanding of data in Expected HR analytic big data competencies; Strategies in Utilisation of HRA competency outcome; Organization/Job fit and Job satisfaction in Level of Motivation had Cronbach alpha values from 0.7 to 0.8, indicating satisfactory internal consistency of the scale, and items of Creative analytics from Level of Motivation and Organizational job fit. This suggests that the pilot test findings are dependable enough for retention, analysis, and statistical conclusions.

3.4 HR Analytic Big data competencies

According to the EFA as presented in Table 4, it can be suggested that for the pilot study Understanding of data individually represented the most important factor accounting for 45.687% of the total variation within Existing HR analyticbig data competencies, followed by Analytical skills (10.24%) and Interpretation skills (7.68%).

Table 4: Big data competencies in HR Analytics

Factors	**Factor Loadings**	**% of Variance**	**Cumulative %**
Comprehension of data		**45.687**	**45.687**
We have the abilities to identify the appropriate data for analysis.	0.840		
Our talents include data preparation and transformation.	0.723		
Factors	Factor Loadings	% of Variance	Cumulative %
Data integration from diverse activities or processes is widely accessible in the organisation.	0.708		
We have the expertise to comprehend the data for analysis.	0.665		
Analytical Competencies		10.240	55.927
We are familiar with data analysis applications like R, Python, and Lavaan.	0.895		
We understand how to utilise a pivot table to analyse trends			

in employee performance.	0.812		
In our normal work, we use lookups to move data from one sheet to another in Excel.	0.782		
We have intermediate data analysis kills (correlation, standard deviation, statistically significant difference).	0.756		
We employ machine learning algorithms to make important decisions in our organisation.	0.662		
We understand how to employ the Root Cause Analysis approach.	0.641		
We understand statistical models for data analysis.	0.598		
We have fundamental abilities in multivariate analysis (ANOVA, regression, and factor analysis).	0.593		
We know how to apply predictive and talent metrics abilities to anticipate employee attrition ahead of time utilising a statistical model in the Organisation.	0.572		
We possess fundamental data analysis abilities (mean, median, minimum, and maximum range).	0.507		
Analytical Competencies		7.683	63.610
We understand how to analyse the return on investment from our training operations.	0.806		
We understand how to comprehend our reports using graphical drawings accompanied by numbers utilising the Visualisation programme.	0.784		
We can comprehend cause-and-effect relationships	0.782		
we are aware of how to utilise writing abilities to communicate statistical facts effectively.	0.747		
We can interpret dynamic dashboards and show crucial performance data during meetings.	0.559		

In summary, the explanatory power of the determinants of existing HR analytic big data capabilities exceeded 69%. With factor loadings ranging from 0.5 to 0.8, each variable adequately described the HR analytic big data capabilities observed in contemporary organisations, indicating their significance.

4. RESULTS AND ANALYSIS

The data for examination of the competitiveness in the HR analytics using big data were collected from HR professionals. The data collected from the 230-sample population are presented as follows:

4.1 Demographic Profile of Respondents

To ascertain the eligibility of the respondents to participate in the study and to find out the differences in perception of the HR professionals, the demographic data were taken into consideration for this research. The demographic details included age,gender, and educational qualification of the respondents, as well as their designation ofthe organization and the total number of years of work experience as an HR analyst.

Table 5: Demographic Profile of Sample Population

Gender	**Frequency**	**Percent**
Gender	Frequency	Percent
Male	129	56.1
Female	101	43.9
Total	230	100.0
Age (years)	**Frequency**	**Percent**
21-30 Yrs	92	40.0

31 -40 Yrs	111	48.3
41- 50 Yrs	27	11.7
Total	230	100.0
Educational Qualifications	**Frequency**	**Percent**
Undergraduate (UG)	42	18.3
Postgraduate (PG)	188	81.7
Total	230	100.0
Work Experience	**Frequency**	**Percent**
1 – 5 Yrs.	100	43.5
6 -10 Yrs.	71	30.9
11 – 15 Yrs.	33	14.3
16 – 20 Yrs.	26	11.3
Total	230	100.0
Designation	**Frequency**	**Percent**
Data scientist	31	13.5
Data Analyst	37	16.1
Others	162	70.4
Total	230	100.0
Type of Organization	**Frequency**	**Percent**
Multinational Company (MNC)	90	39.1
Small scale Company (≥100)	37	16.1
Medium scale company (100-1000 employees)	25	10.9
Large companies (>1000 employees)	78	33.9
Total	230	100.0
Sector	**Frequency**	**Percent**
IT	118	51.3
Manufacturing	24	10.4
Services	58	25.2
Others	30	13.0
Total	230	100.0

Using big data analytics, the collected demographic characteristic of the respondent's competitiveness among HR professionals is evaluated in the decision-making process.

4.2 Hypothesis Testing

To evaluate the HR analytics on the big data in decision-making process of the organization hypothesis framed and tested. The analysis of the framed hypothesis is presented in this section as follows:

$H_0 1$: The existing HR competency does not influence the utilisation of competency outcome by the organization.

$H_a 1$: The existing HR competency significantly influences the utilisation of competency outcome by the organization.

The table 6 shows that within utilization of HRA competency, process performance (M=3.633, SD=0.902) had marginally lower HRA competency than the strategies (M=3.670, SD=0.953). Manova as in table 7 conducted to evaluate the influence of existing HR competency on the utilization of competency outcomes (data analysis) bythe organization showed that all the three components of existing HRA competency, namely, understanding of data ($F = 34.304$, $\eta_p^2 = 0.234$), analytical skills ($F = 23.497, \eta^2 = 0.173$) and interpretation skills ($F = 59.502$, $\eta^2 = 0.347$) had significant ($p < 0.05$) main effects with small effect size in the case of analytical skills, moderate effect understanding of data and large effect in the case of interpretation skills. The corresponding Wilk's Lambda values for data comprehension, interpretive abilities, and analytical skills are 0.766, 0.827, and 0.653, respectively. This indicates that intergroup differences do not explain approximately 82.7% of the variability in analytical capabilities, 65.3% of the diversity in the organization's utilisation of competence outcomes for different operations, and 76.6% of the variation in data interpretation.

Table 6: Existing HR Competency based on Utilization of Competency Outcomes by Big Data Analytics

Utilization of competency outcome for different processes	Mean	Std. Deviation
Process Performance	3.633	0.902
Strategies	3.670	0.953

Table 7: Multivariate Tests for impact of existing HRA Competency using Big Data Analytics

Existing HRA competency	Wilks' Lambda	F	df	Sig.	Partial Eta Squared
Comprehension of data	0.766	34.304	2, 224	0.000	0.234
Analytical competencies	0.827	23.497	2, 224	0.000	0.173
Proficient interpretation abilities	0.653	59.502	2, 224	0.000	0.347
Comprehension of data Analytical competencies Proficient interpretation abilities	0.791	29.532	2, 224	0.000	0.209

A comparison of topic effects regarding the impact of current HRA skills on the organization's utilisation of data-driven HRA big data competencies across different processes is presented in Table 8. Analysis skills and process performance interacted in a manner that yielded a negligible effect (F = 31.181, ηp2 = 0.122). Conversely, strategies and analytical skills interacted in a moderate manner (F = 47.004, ηp2 = 0.173), whereas interpretation skills and process performance interacted in a substantial manner (F = 37.644, ηp2 = 0.30). A moderate effect was observed for knowledge of data and process performance (F=56.494, ηp2 = 0.210), whereas a negligible effect was observed for knowledge of data and strategies (F=20.415, ηp2 = 0.083).

Table 8: Test of between subject effects for Impact of Existing HRA Competency on Big data analytics in decision -making process

ExistingHRA competency	Utilization of big data competencies outcome for differentprocesses	Type III Sum ofSquares	df	Mean Square	F	Sig.	PartialEta Squared
Comprehension of data	Performance of the Process	22.051	1	22.051	56.494	0.000	0.201
	Methodologies	11.516	1	11.516	20.415	0.000	0.083
Analytical Competencies	Performance of the Process	12.171	1	12.171	31.181	0.000	0.122
	Methodologies	26.515	1	26.515	47.004	0.000	0.173
Interpretation abilities	Performance of the Process	37.644	1	37.644	96.442	0.000	0.300
	Methodologies	18.958	1	18.958	33.609	0.000	0.130
Comprehension of data Analytical Competencies Interpretation abilities	Performance of the Process	21.504	1	21.504	55.092	0.000	0.197
	Methodologies	15.332	1	15.332	27.230	0.000	0.108
R Squared = .528 (Adjusted R Squared = .520)							
R Squared = .390 (Adjusted R Squared = .379)							

The results indicate that the alternative hypothesis (H_a1), which states that the utilisation of competency outcomes (data analysis) by organisations is significantly influenced by the extant HR competency, is accepted and the hull hypothesis (H_01) is rejected.

4.2 Hypothesis -2

The next hypothesis considered for analysis is

Hypothesis 02: The impact of competency outcome utilisation on business outcomes is negligible.

Hypothesis 2: The implementation of competency outcomes has a substantial impact on business outcomes.

In table 9 presents the level of utilization of data-based HRA big data competencies by the organization for different processes based on business outcomes. It indicates that decision-making process (M=3.915 SD=0.545) has slightly lower utilization of competency outcome than the Return on investments (M=3.937, SD=0.679). To evaluate the significant influence of the utilization of data based HRA competency outcomes (data analysis) by the organization on business outcome, MANOVA was conducted. The results of Manova established the relationship of the utilization of competency outcome (data analysis) on the business outcome and showed that there was a significant ($p < 0.05$) direct influence of process performance ($F(2,225) = 18.681$), with a moderate effect size ($\eta p^2 = 0.142$) and strategies ($F(2,225) = 4.253$) with a small effect size ($\eta p^2 = 0.036$) on business outcome. The Wilk's Lambda value for process performance and strategies is 0.858 and 0.964, respectively. This means that about 85.8% of the variation in process performance and96.4% of the variation in the strategies was not accounted for by the intergroup variations.

Through analysis as presented in table 9 The interaction effect depicted that a significant interaction was observed between process performance with ROI ($F = 20.11, \eta_p^2 = 0.082$), implying medium effect size and process performance with the decision-making process ($F = 35.479, \eta_p^2 = 0.136$), also implying a medium effect size. Further, strategies showcased a significant association with ROI ($F=8.538$, $\eta_p^2 = 0.036$) and decision- making process ($F=6.681$ $\eta^2 = 0.029$) implying small impact.

Table 9: Test of between Subject Effects of Impact of Utilization of Competency Outcome by the Organization for Different Processes on Business Outcome

Utilization of competency outcomes fordifferent processes	Businessoutcome	Type III Sum ofSquares	df	Mean Square	F	Sig.	Partial ETA Squared
Process Performance	Return on	6.857	1	6.857	20.1	0.00	0.082
	Investment				12	0	
	s (ROI)						
	Decision-	7.777	1	7.777	35.4	0.00	0.136
	making				79	0	
	process						
Methodologies	Return on	2.911	1	2.911	8.53	0.00	0.036
	Investment				8	4	
	s (ROI)						
	Decision-	1.464	1	1.464	6.68	0.01	0.029
	making				1	0	
	process						
Process Performance	Return on	3.219	1	3.219	9.44	0.00	0.040
* Methodologies	Investment				1	2	
	s (ROI)						

	Decision-	3.191	1	3.191	14.5	0.00	0.061
	making				59	0	
	process						
R Squared = .270 (Adjusted R Squared = .260)							
R Squared = .271 (Adjusted R Squared = .261)							

Based on the results obtained above, the null hypothesis ($H_0 2$) is rejected and alternate Hypothesis $H_a 2$: The utilization of competency outcome (data analysis) directly affects the business outcomes, is accepted.

Hypothesis -3

$H_0 3$: The HRA competency (existing) has no impact on the business outcomes.

$H_a 3$: The HRA competency (existing) significantly impacts the business outcomes.

The table 10 shows the level of existing HRA competency based on business outcome.This indicates that decision-making process (M=3.915 SD=0.679) occurs due to lower HRA competency than the return on investments (M=3.937, SD=0.545). The relationship between existing HRA competency and business outcome was evaluated using MANOVA. The results showed that the existing HRA competency had a direct significant impact on business outcomes in terms of understanding of data ($F(2,224) = 10.511$, $\eta_p^2 = 0.086$), analytical skills ($F(2,224) = 1.40$, $\eta^2 = 0.012$) and interpretation skills ($F(2,224) = 37.214$, $\eta^2 = 0.249$). The effect size was found to be small in the case of understanding of data as well as analytical skills and large for interpretation skills.

Table 10: Test of between Subject Effects for Impact of Existing HRA Competency on Business Outcomes

Existing HRA competency	Business Outcomes	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial ETA Squared
Understanding of data	Return on Investments (ROI)	4.644	1	4.644	13.984	0.000	0.059
	Decision-making process	3.716	1	3.716	20.941	0.000	0.085
Analyticalskills	Return on Investments (ROI)	0.001	1	0.001	0.003	0.960	0.000
	Decision-making process	0.115	1	0.115	0.647	0.422	0.003
Interpretationon skills	Return on Investments (ROI)	11.112	1	11.112	33.461	0.000	0.129
	Decision-making process	12.041	1	12.041	67.852	0.000	0.232
Understanding of data * Analytical skills *Interpretation skills	Return on Investments (ROI)	2.703	1	2.703	8.139	0.005	0.035
	Decision-making process	2.734	1	2.734	15.407	0.000	0.064
R Squared = .292 (Adjusted R Squared = .279)							
R Squared = .412 (Adjusted R Squared = .402)							

The corresponding Wilk's Lambda values for business result interpretation, analytical skills, and data comprehension are 0.914, 0.988, and 0.751, respectively. This indicates that intergroup differences failed to account for 75.1% of the variance in interpretive skills, 98.8% of the variance in analytical abilities, and 91.4% of the variance in data comprehension. The outcomes of ROI ($F=13.984$, $p<0.05$) and decision-making ($F=20.941$, $p<0.05$) were significantly influenced by data comprehension. ROI was significantly impacted by interpretive abilities (F=33.461, p0.05), as was decision-making (F=67.852, p0.05). This implies that the existing HRA big data experts possess a significant impact on the overall capabilities of data utilisation and interpretation. Based on the results obtained above, the null hypothesis ($H_0$3) is rejected and alternateHypothesis H_{a3}: The HRA competency (existing) significantly impacts the business outcomes, is accepted.

Hypothesis - 4

H_{04}: Capability and Opportunities provided to HRA do not influence the competency they possess.

H_{a4}: Capability and Opportunities provided to HRA significantly influences the competency they possess.

In table 11 depicts that the motivation showcased comparatively high impact on understanding of data (M=3.668, SD=0.844). The impact was least in Analytical skills (M=3.334, SD=0.724). The relationship between motivation and existing HRA competency was evaluated using MANOVA. The results showed that the motivation significantly and positively influenced the big data competencies possessed by the HRA ($F(3,226)=26.543$, $\eta^2=0.261, p=0.0<0.05$). The Wilk ‘s Lambda value for motivation is 0.739. This means that 73.9% of the variation was not accounted for by the intergroup variations.

Table 11: Test of between Subject Effects for Impact of Motivation on existingHR Competency

Motivation	Existing HR competency	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Motivation	Understanding of data	9.131	1	9.131	13.505	0.000	0.056
	Analyticalskills	12.920	1	12.920	27.513	0.000	0.108
	Interpretationskills	69.754	1	69.754	79.892	0.000	0.259
a. R Squared = .056 (Adjusted R Squared = .052)							
b. R Squared = .108 (Adjusted R Squared = .104)							
c. R Squared = .259 (Adjusted R Squared = .256)							

The impact of motivation on three major competency factors is depicted in Table 11.It can be observed from the table that motivation exerted a significant impact on all the three competency factors, implying low impact on Understanding of data ($F(3,226)=13.505$, $\eta_p^2=0.056$),medium effect on analytical skills ($F(3, 226)=27.313$,$\eta_p^2=0.108$) as well as interpretational skills($F(3,226)=79.892$,$\eta^2=0.259$). This indicates that motivation has a significant impact on all competency factors and hence the null hypothesis ($H_0$4) is rejected and alternate Hypothesis H_a4: Motivation provided to HRA significantly influences the competency they possess, is accepted.

5. FINDINGS

The utilisation of competency outcomes in HR professionals are measured using two factors: performance process and strategies.

1. Within the performance processes, the HR professionals are used for a high level of employee performance assessments (4.026 ± 1.243) and organizational development assessments (4.035 ± 1.129), whereas they are least bothered with downsizing workforce assessment (3.048 ± 1.326) and labor compliance (3.335 ± 1.088). Thus, the HRA are utilized to a moderate extent to improve the performance process of the organization

2. In terms of strategic processes, the HR professionals were utilized mostly in HR manpower planning (4.009 ± 1.118) and least in succession planning for leadership development (3.417 ± 1.200).

3. The opportunity of the HR analytics in an organisation can be based on the organisational infrastructure, cross functional dynamics and job prospects. Within the organisational infrastructure, the HR professionals quite often use infrastructure facilities to perform the tasks (3.717 ± 1.004), access the right data (3.670 ± 0.946) followed by the platform to use analytics in every aspect of the job (3.183 ± 1.091). The cross functional dynamics allowed the HR professionals to access opportunities for the development of leadership skills (4.009± 0.916) and provided platforms for cross training (3.865± 1.234). In terms of job prospects, the respondents agreed to a moderate extent that the opportunity to be aware of various statistical tools (3.674 ± 0.950), opportunities to use individual analytical skills (3.578 ± 1.114) and analytics from team members was provided by the organisation (3.552±1.326) was accomplished.

6. CONCLUSION

Organisational data utilisation has evolved to accommodate employment-related legal requirements. The evolution in the way data is being utilised has progressively transformed the HRM function's dynamics, and now HR professionals are expected to deliver analyses of exceptional quality. The findings indicate that the analytical big data capabilities of HR professionals fall significantly short of their expected level. The study revealed that, with the exception of fundamental data analysis skills, no other analytical abilities satisfied the criteria for the necessary HR analytic big data competencies with regard to data interpretation. The significant discrepancies between anticipated and current analytics big data competencies suggest that HR professionals are oblivious to the significance of such skills and that their employer is unconcerned with the provision of adequate training on contemporary analytical abilities.

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