Journal of Contemporary Issues in Business and Government Vol. 28, No. 03, 2020
https://cibgp.com/
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

An Empirical Study of Confirmatory Factor Analysis Successful Adoption of Human Resource Analytics in Indian Organizations

SAAEMAAKHTAR[1]
Research Scholar (PhD)
Email id: saaemaakhtar@gmail.com, contact no.: 8318928820

DR. RAJESH KUMAR SHASTRI[2]
Associate Professor
Email Id: rkshastri@mnnit.ac.in, Contact No: 91-532-2271283

Department of Humanities and Social Sciences
Motilal Nehru National Institute of Technology, Allahabad, Prayagraj 211004

Abstract

The Main purpose of this research is to assess the extent of awareness of Human Resource Analytics among HR Managers at various levels in various firms in India.

Design/methodology/approach:-

To collect data a combination of quantitative and qualitative research methodologies is used. Data is gathered specifically from various levels of management in selected organizations. Descriptive data analysis is presented in relation to the level of awareness, and a causal research approach is used to identify the major aspects that raise personnel' consciousness of HR Analytics.

Findings:-

This study gives current information about HR Analytics through the practice of HR Analytics in India which is minimal. The findings show that HR Analytics expertise is influenced by a variety of factors.

Practical implications:-

The study determined the level of HR Analytics understanding among managers from various sectors in India. To attain outstanding organizational performance, enterprises need implement the necessary HR Analytics.

Originality/value:-

The importance of the current study stems from the fact that just a few studies have looked into employee knowledge levels in the hands-on human resource analytics in India.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Furthermore, the study makes an important contribution to the ongoing development of this field of study.

Keywords- HR Analytics, Awareness Level of analytics, HR professionals, HR Analytics adaptation, Confirmatory factor analysis.

Introduction

HR analytics can be traced back to 1978 when Jac Fitz-enz wanted to link HR activities with the profit of the organizations. It is a data-driven tool to increase HR-related choices. HR analytics is dependent on the accuracy of the data gathered through HR measurements. .HR Analytics is gaining popularity now a day because of its accuracy as it is data based decision. HR Analytics is one of the ways used to produce and analyse perspectives into the workforce in order to determine the contribution of each employee to producing income and saving costs. . It analyses the data of every employee and predicts the future of the organization's success. HR Analytics is the use of analytics in the human resource department of a company with the goal of increasing employee discharge. In the other words HR Analytics is commonly known as people analytics and describe with workforce analytics and talent analytics, is essential in evaluating customers' concerns using data to answer key concerns about businesses. This paper will check the awareness level of HR Analytics among HR professionals of various organizations. As the need of HR analytics is growing day by day but due to the novelty of the concept people are lacking knowledge about HR analytics. HR Analytics does not seek information as to how your personnel function at workplace conversely, its main purpose is to have detailed knowledge into one of the human resource processes by collecting associated data and then use this data to make better decisions about how to enhance these practices. . An organization should adopt HR Analytics to become successful and competitive and to be proactive. Organizations must increasingly link their Hr policies with their corporate strategy in order to maintain a strong edge over its competitors. As a result, Human Resource Management is the component of the organisation dealing with "people." (DeCenzos and Robbins, 1996).Every organisation is basically comprised of its people and ensuring their productivity so that it remains profitable to the organisation is the job of the Human Resource Management. Application of HR Analytics in various organizations will give better support in delivering improved HR services and all connected process. Big data even now springing up in several discrete HR areas like employee recruitment, selection, on boarding, training and development, HR reporting, competency

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

management, talent acquisition, succession management, rewards. On the basis of historical and current data HR analytics predicts future outcomes. HR Analytics can be applied to all the various department of an organization. It starts from the prediction of failure/success of new employees to adapt organization culture to predict an employee's next career step or when an employee can leave the organization.

Literature review

HR Analytics definition can help clarify the concept, and the phrase has been used interchangeably with advanced analytics, talent analytics, and workforce analytics. HR Analytics is defined as the implementation of a technique and an associate example to improve the effectiveness of employees' decisions in order to increase individual and/or corporate success.' (Laurie Bassi , Mc Bassi & Company). Nowadays Human Resource functions has been recognized as a strategic partner of the organizations .Years back HR department lacks data based decision to influence any strategies. With the help of HR analytics, management of people becomes easy (Handa, Dimpy, Garima2014). It helps in reduction of cost of the organizations by predicting the decision in advance. HR has embraced the use of technology, which has had a significant impact on HR practises and processes. As a result, HR Analytics has emerged as a reliable business management model that employs analytics capabilities to make decisions.(Jabir, B., Falih, N., & Rahmani, K. (2019)The attention towards HR Analytics is very good but the adoption rate is yet not that magnificent. (Keerthi, L., & Reddy, P. R. (2018) it further discusses that technology is an instrument which reduces uncertainties and produce desired outcomes. To adopt HR Analytics successfully issues should be solved at data level, individual level and organizational level. By linking HR activity to business outcomes, it is possible to understand how HR contributes to the firm's performance. This strategy succeeds by adding activities with business decisions — not just validating prior evidence in reality, but also by teaching how to maximize the wealth of shareholders that intervene and promote productivity and profitability. . (Reddy, P. R., & Lakshmikeerthi, P. (2017).) High-performing enterprises utilize analytics to make evidence-based decisions. However, many firms' human resource (HR) functions have been slow to implement this innovation.

Objectives

The main focus of this study is to identify the characteristics that influence human resource analytics adaption in India. This research solely looks at the adaption of human resource

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

analytics and the operating structure of the other versions. The primary research questions investigated in this study are as follows.

1. *What are the primary variables influencing the adoption of human resource analytics?*
2. *The relationship between these variables?*

Research methodology

Statistical tools for data analysis such as Structural Equation Modelling (SEM) is used for Confirmatory Factor Analysis (CFA) were employed in the study, which was conducted employing AMOS 23. The main reason of applying SEM and CFA is to assess the proposed concept based on the past and present literature review and questionnaire were adopted from various studies conducted in Indian context. This survey using study set of data. (Gefen et al., 2000).Structural modelling is done with SEM, while the measurement model is done with CFA.According to Anderson and Gerbing (1988), a two-step strategy was utilised, in which CFA was done prior to utilising SEM to assess the reliability and validity of the measuring device. Following that, SEM is performed to assess the model fit using the sample data under consideration. A standardised questionnaire was created to collect data in an organized manner.The questionnaire, in particular, is built on a seven-point Likert scale response structure.

Table 1 Respondents' profile

Demographic	Groups	Frequency	Percentage
Age	20-30	19	19
	31-40	50	50
	41-50	25	25
	51-60	06	06
	61 and above	00	00
Gender	Female	38	38
	Male	62	62
Education	Graduate	9	9
	Post graduate	57	57
	Hr professional	29	29
	PhD	05	05
	Others	00	00
Organization	Pubic	15	15
	Private	39	39
	Semi-government organization	13	12
	MNC	34	34
Hr_ experience	Less than 1 year	06	06
	1-5 years	33	33
	6-10 years	35	35
	11-15 years	14	14
	16-20 years	08	08
	21- 25 years	03	03
	26 years and above	01	01

Sources :(Primary data of respondents)

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Sample size and sampling method

According to Bentler and Chou's (1987) recommendation for a baseline subjects-to-item ratio of 10:1, a sample of 100 participants were needed for a CFA of 46 inventory items.

The sample size was raised to 512 participants to accommodate for a 10% drop-out rate. The phases and participants' gender were used as stratification variables in stratified random sampling. These strata were considered because the ratio of participants in each stratum varied throughout time.

Data Collection Procedures

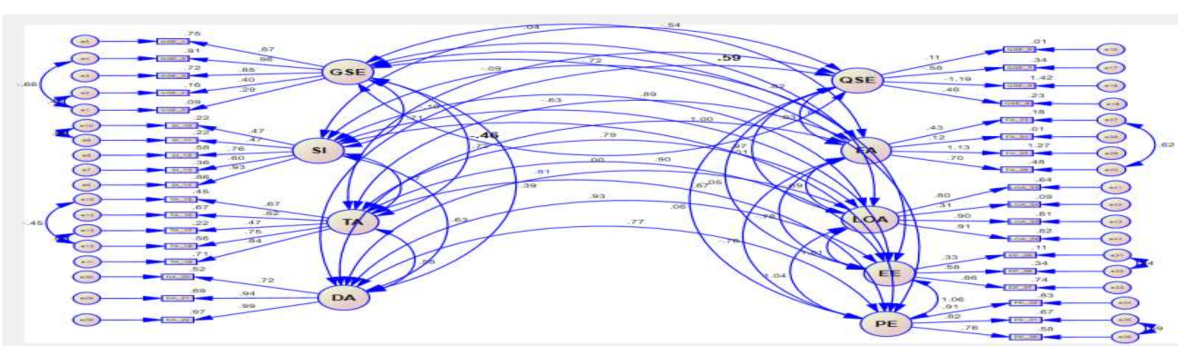
All the data were collected from the private as well as government sector of HR Adopted organisation. Informed consent was obtained from the HR of every organisation prior to the collection of forms.

The measurement model- Confirmatory Factor Analysis

Figures 1 and 2 shows a graphical representation of the measuring model's or CFA's AMOS output. The covariance link between two latent variables is indicated by the double headed arrow between them. The scores might range between -1 and 1, with higher values indicating a greater level of covariance/correlation of both parts The factor loading and the criterion's contribution to the hidden variable are shown by the single predictor arrow from the untapped variable to the indicator. The closer the value is to one, the greater the contribution.

Confirmatory Factor Analysis is carried out using SPSS Amos 23. According to Ahire, Golhar, and Waller, CFA stands for Confirmatory Factor Analysis (1996) provides greater control for analysing unidimensionality. The extent to which all elements on a scale measure the same thing is measured by its unidimensionality. CFA was performed on each of the 22 components to determine whether the 06 variables sufficiently evaluated the construct to which they were associated. Convergent validity and construct validity are two major validity tests that are commonly discussed.

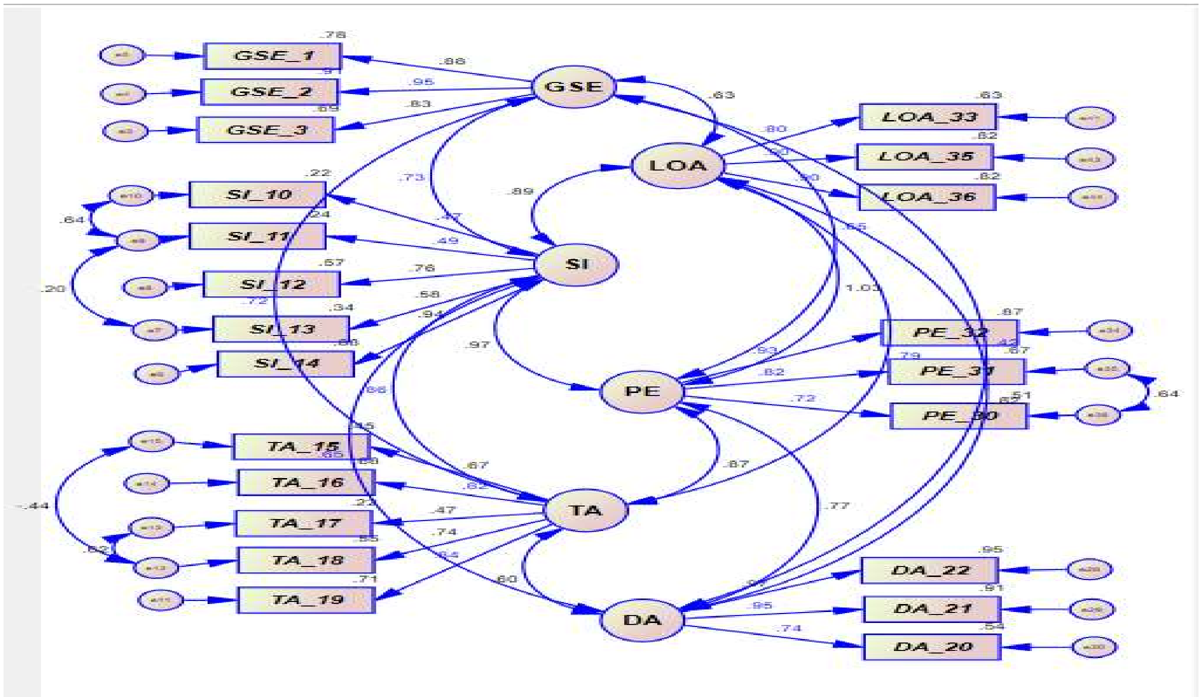
Figure 1 Confirmatory Factor Analysis



Sources :(Primary data from AMOS 23

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Figure 2 Confirmatory Factor Analysis (after deleted item)



Sources :(Primary data from AMOS 23)

Construct Validity

To test for unidimensionality in the current study, a measurement model has been proposed for each construct, and the entire structure was subjected to CFA. If the Comparative Fit Index (CFI) of the model is 0.90 or higher it indicates that there is significant indication of unidimensionality - Byrne (1994). This strongly suggests that the scale is unidimensionality.

Convergent Validity

O'Leary-Kelly and Vokurka define it as the degree to which several ways of evaluating a variable yield the same findings (1998). A coefficient known as the Bentler-Bonett coefficient can be used to establish convergent validity. In this study, the 0.924 Bentler-Bonett Normed Fit Index (NFI) produced from CFA can be utilised to determine convergent validity.

Journal of Contemporary Issues in Business and Government Vol. 28, No. 03, 2020
https://cibgp.com/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Table 2 Correlation &Co-variances

Implied Correlations (Group number 1 - Default model)

	LOA_36	LOA_35	LOA_33	PE_30	PE_31	PE_32	DA_20	DA_21	DA_22	TA_15	TA_16	TA_17	TA_18	TA_19	SI_10	SI_11	SI_12	SI_13	SI_14	GSE_1	GSE_2	GSE_3
LOA_3	1																					
LOA_3	0.82	1																				
LOA_3	0.694	0.724	1																			
PE_30	0.675	0.704	0.596	1																		
PE_31	0.75	0.783	0.662	0.843	1																	
PE_32	0.842	0.879	0.744	0.68	0.756	1																
DA_20	0.487	0.508	0.43	0.426	0.473	0.532	1															
DA_21	0.633	0.66	0.559	0.554	0.616	0.691	0.703	1														
DA_22	0.643	0.671	0.568	0.562	0.625	0.702	0.714	0.928	1													
TA_15	0.459	0.479	0.406	0.402	0.447	0.502	0.29	0.377	0.383	1												
TA_16	0.608	0.634	0.537	0.532	0.591	0.664	0.384	0.499	0.507	0.52	1											
TA_17	0.36	0.376	0.318	0.315	0.351	0.394	0.227	0.296	0.3	0.308	0.408	1										
TA_18	0.559	0.583	0.494	0.489	0.544	0.61	0.353	0.459	0.466	0.272	0.633	0.723	1									
TA_19	0.628	0.655	0.555	0.55	0.611	0.686	0.396	0.516	0.524	0.537	0.711	0.421	0.654	1								
SI_10	0.373	0.39	0.33	0.327	0.363	0.408	0.236	0.307	0.311	0.222	0.294	0.174	0.271	0.304	1							
SI_11	0.386	0.403	0.341	0.338	0.376	0.422	0.244	0.317	0.322	0.23	0.304	0.18	0.28	0.315	0.72	1						
SI_12	0.629	0.656	0.555	0.55	0.612	0.687	0.397	0.516	0.524	0.374	0.496	0.294	0.456	0.512	0.351	0.363	1					
SI_13	0.474	0.495	0.419	0.415	0.461	0.518	0.299	0.389	0.395	0.282	0.374	0.222	0.344	0.386	0.264	0.421	0.445	1				
SI_14	0.764	0.797	0.675	0.668	0.743	0.834	0.482	0.627	0.637	0.455	0.602	0.357	0.554	0.622	0.426	0.441	0.717	0.541	1			
GSE_1	0.517	0.54	0.457	0.452	0.503	0.565	0.326	0.425	0.431	0.308	0.408	0.242	0.375	0.421	0.25	0.259	0.422	0.318	0.512	1		
GSE_2	0.547	0.571	0.483	0.479	0.532	0.597	0.345	0.449	0.456	0.326	0.431	0.256	0.397	0.446	0.265	0.274	0.446	0.336	0.542	0.847	1	
GSE_3	0.479	0.499	0.423	0.419	0.466	0.523	0.302	0.393	0.399	0.285	0.377	0.224	0.347	0.39	0.232	0.24	0.39	0.294	0.474	0.741	0.784	1

Standardized Residual Covariances (Group number 1 - Default model)

	LOA_36	LOA_35	LOA_33	PE_30	PE_31	PE_32	DA_20	DA_21	DA_22	TA_15	TA_16	TA_17	TA_18	TA_19	SI_10	SI_11	SI_12	SI_13	SI_14	GSE_1	GSE_2	GSE_3
LOA_36	0																					
LOA_35	0.077	0																				
LOA_33	0.309	-0.362	0																			
PE_30	-0.003	-0.114	-0.209	0																		
PE_31	0.621	-0.178	0.355	0	0																	
PE_32	-0.259	0.174	-0.119	-0.3	0.068	0																
DA_20	2.536	1.734	2.22	2.321	2.417	1.657	0															
DA_21	1.101	-0.28	0.849	1.081	1.067	-0.547	-0.273	0														
DA_22	1.171	-0.641	1.365	0.534	0.506	-0.519	-0.009	0.024	0													
TA_15	0.372	0.561	1.415	2.066	1.014	0.398	1.865	-0.009	-0.427	0												
TA_16	0.047	-0.19	0.789	0.749	0.39	0.203	1.614	1.244	0.783	0.05	0											
TA_17	-1.193	-2.049	-1.751	-1.445	-1.244	-1.764	-0.573	-1.368	-1.667	-1.275	1.338	0										
TA_18	-0.976	-1.729	-1.265	-2.686	-1.325	-0.894	0.404	-0.631	-0.892	-0.591	0.423	0.367	0									
TA_19	-0.524	0.103	-0.535	-0.738	-0.412	0.333	1.66	-1.129	-1.338	-0.478	-0.375	0.64	0.686	0								
SI_10	0.32	-0.403	-1.004	-0.292	-0.314	0.105	1.136	-0.229	0.085	-0.176	1.925	4.004	3.438	1.84	0							
SI_11	-0.292	-0.531	-1.655	-1.615	-0.531	0.161	0.192	-0.669	-1.142	-0.363	1.85	3.869	3.97	2.117	0.624	0						
SI_12	-0.187	-0.224	0.793	0.579	-0.221	-0.075	1.35	0.711	0.522	3.104	0.365	-2.029	-1.971	-0.197	-0.989	-0.854	0					
SI_13	-0.75	-0.523	-0.328	-0.775	-1.234	0.031	0.386	0.017	0.235	0.62	2.021	2.619	1.807	1.101	3.356	2.041	0.668	0				
SI_14	-0.555	0.194	-0.056	-0.203	-0.565	0.279	1.747	-0.558	-0.895	1.601	0.692	-1.662	-1.143	0.231	-0.176	0.038	0.011	-0.179	0			
GSE_1	0.791	0.691	0.184	1.659	0.969	0.255	3.188	-0.225	-0.264	3.271	1.018	-0.214	-0.262	1.313	0.151	-0.259	0.714	-0.604	1.104	0		
GSE_2	-0.119	-0.296	-0.083	0.465	-0.205	-0.283	1.924	-0.572	-0.601	3.639	0.883	-0.279	-0.467	0.768	0.519	0.14	0.864	0.214	1.142	-0.061	0	
GSE_3	-1.196	-1.402	-0.791	-1.277	-1.613	-0.841	0.844	-2.357	-1.636	2.038	0.404	1.083	0.769	0.832	2.189	1.217	-0.497	0.794	0.374	-0.036	0.124	0

Sources :(Primary data)

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Table 3Standardised Factor loading

No	**Construct statements**	**Standardised factor loadings**		**Reliability Statistics**	
				Cronbach's Alpha	N of Items
	CS	***QUESTIONNAIRE ADOPTED***	***SF***		
1.	GSE1	*General Self-Efficacy: [Adapted from Davis (1989); Chau (2001)*	***0.87***	**.919**	**03**
2.	GSE2		***.96***		
3.	GSE3		***.85***		
~~4.~~	~~GSE4~~		~~**.40**~~		
~~5.~~	~~GSE5~~		~~**.29**~~		
~~6.~~	~~QSE6~~	*Quantitative Self-Efficacy: [Adapted from Bai et al. (2009)]*	~~**.11**~~	**Remove due to low factor loading**	
~~7.~~	~~QSE7~~		~~**-.68**~~		
~~8.~~	~~QSE8~~		~~**-1.19**~~		
~~9.~~	~~QSE9~~		~~**.48**~~		
10.	SI10	*Social Influence: [Adapted from Johnston and Warkentin (2010); Venkatesh et al. (2012)]*	**.47**	**.838**	**05**
11.	SI11		**.47**		
12.	SI12		***.76***		
13.	SI13		***.60***		
14.	SI14		***.93***		
15.	TA15	*Tool Availability: [Adapted from Johnston (2006)]*	***.67***	***.846***	***05***
16.	TA16		***.82***		
17.	TA17		**.47**		
18.	TA18		**.75**		
19.	TA19		**.84**		
20.	DA20	*Data Availability: [Adapted from Johnston (2006)]*	**.72**	**.910**	**03**
21.	DA21		**.94**		
22.	DA22		**.99**		
~~23.~~	~~FA23~~	*Fear Appeals: [Adapted from Johnston and Warkentin (2010); Witte et al. (1996)]*	~~**.43**~~	**Remove due to low factor loading**	
~~24.~~	~~FA24~~		~~**-12**~~		
~~25.~~	~~FA25~~		~~**1.13**~~		
~~26.~~	~~FA26~~		~~**.70**~~		
~~27.~~	~~EE27~~	*Effort Expectancy: Adapted from Venkatesh et al. (2012)*	~~**.86**~~	**Remove due to low factor loading**	
~~28.~~	~~EE28~~		~~**.58**~~		
~~29.~~	~~EE29~~		~~**.33**~~		
30.	PE30	*Performance Expectancy: [Adapted from Johnston and Warkentin (2010); Venkatesh et al. (2012)]*	**.76**	**.900**	**.03**
31.	PE31		**.82**		
32.	PE32		**.91**		
33.	LOA33	*Level of Adoption: [Adapted from Johnston and Warkentin (2010); Venkatesh et al. (2012)]*	**.80**	**.899**	**03**
~~34.~~	~~LOA34~~		~~**.31**~~		
35.	LOA35		**.90**		
36.	LOA36		**.91**		

Sources :(Primary data)

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Table 4Overall structural model fit estimation

Structural model Fit Indices	Recommended Value	Model Fit Indices	Interpretation
CMIN/df	*< 3*	*3.986*	**Acceptable**
p-value	***≥ 0.05***	*.000*	**Need DF more**
NFI	***≥ 0.90***	*0.0824*	**Acceptable**
CFI	***≥ 0.90***	*0.857*	**Acceptable**
RMSEA	***≤ 0.08***	*0.062*	**Acceptable**
P Close	***≥ 0.05***	*0.000*	**Acceptable**

Sources :(Primary data)

The unstandardized path regression coefficients and the path diagram link between unobserved and measured variables are shown. This picture depicts the standardised path regression coefficients as well as the link between unobserved and measured variables in reference to the path diagram.

Table 5 Regression Weights

			Estimate	S.E.	C.R.	**P**	Label
GSE_3	**<---**	**GSE**	***1.000***				
GSE_2	<---	GSE	*1.133*	*.091*	*12.483*	***	par_1
GSE_1	<---	GSE	*1.053*	*.094*	*11.168*	***	par_2
SI_14	**<---**	**SI**	***1.000***				
SI_13	<---	SI	*.636*	*.098*	*6.477*	***	par_3
SI_12	<---	SI	*.805*	*.080*	*10.027*	***	par_4
SI_11	<---	SI	*.740*	*.144*	*5.158*	***	par_5
SI_10	<---	SI	*.771*	*.157*	*4.913*	***	par_6
TA_19	**<---**	**TA**	***1.000***				
TA_18	<---	TA	*1.082*	*.130*	*8.323*	***	par_7
TA_17	<---	TA	*.576*	*.125*	*4.627*	***	par_8
TA_16	<---	TA	*.966*	*.100*	*9.685*	***	par_9
TA_15	<---	TA	*.857*	*.124*	*6.918*	***	par_10
DA_22	**<---**	**DA**	***1.000***				
DA_21	<---	DA	*.937*	*.041*	*22.697*	***	par_11
DA_20	<---	DA	*.730*	*.072*	*10.167*	***	par_12
PE_32	**<---**	**PE**	***1.000***				
PE_31	<---	PE	*1.128*	*.092*	*12.266*	***	par_13
PE_30	<---	PE	*.971*	*.103*	*9.430*	***	par_14
LOA_33	**<---**	**LOA**	***1.000***				
LOA_35	<---	LOA	*.795*	*.074*	*10.797*	***	par_15
LOA_36	<---	LOA	*.887*	*.081*	*10.956*	***	par_16

Sources :(Primary data)

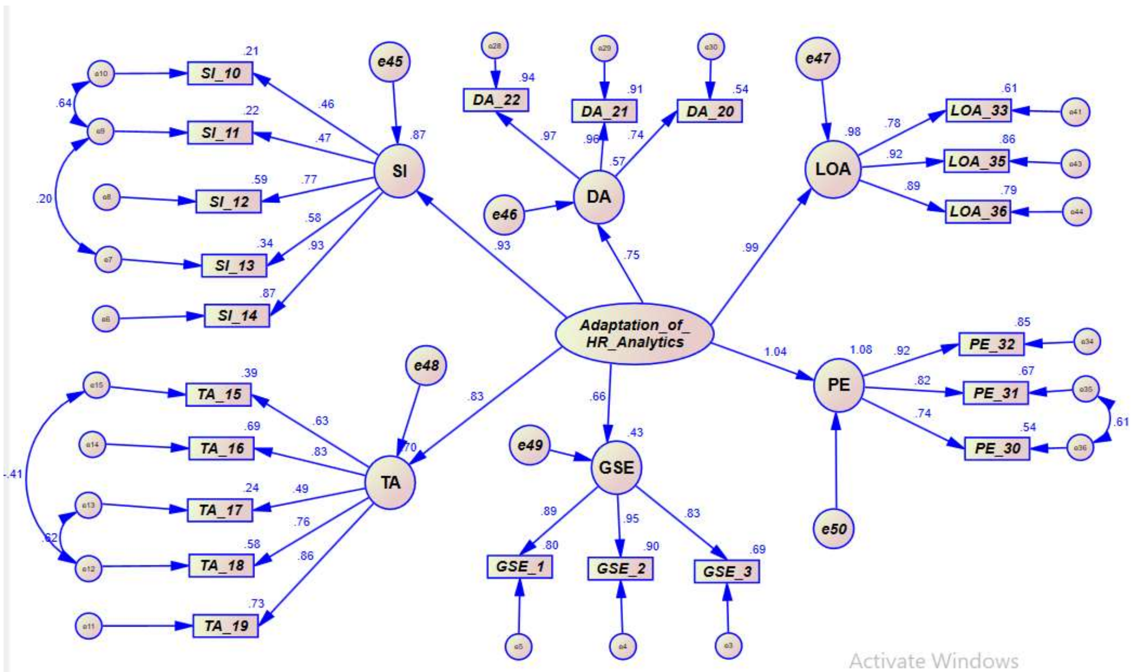
Structure Equation Model

The Structural Equation Model is used to perform confirmatory factor analysis with the SPSS Amos 23 software (SEM). The model has 50 variables in total, including 22 observable variables and 18 unknown variables. The data contains no null values. The structure is over-identified, which is beneficial to SEM. The data is not regularly distributed, as per the

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

univariate and multivariate normality tests. The Maximum likelihood (ML) estimate method is performed once the data has been standardised. ML seeks to optimise the possibility that the qualifying variable values acquired will be properly anticipated. Based on the Structure Equation Model, It is determined that Chi-square (CMIN) = 753.330, Degree of freedom (DF) = 189, and probability level is close to 0.000, indicating that support against the null hypothesis is not significant at the 0.05 level. The minimal discrepancy is known as CMIN/DF, and it is 3.986. Wheaton et al. (1977) proposed that a model is fair fit if the smallest discrepancy is less than 5.

Figure 3 Empirical Model



Sources :(Primary data)the path diagram with standardized parameters estimate

Findings

CMIN/df, p-value, Goodness of Fit (GFI), Adjusted Goodness of Fit (AGFI), NFI, Comparative Fit Index (CFI), Root Mean Square Approximation (RMSEA), and P Close are used to assess structural model fit. Concept fit indices for the constructions were discovered, and a summary of the results is presented in the table, where the obtained Model fit indices are compared to the prescribed threshold. We did not consider the actual chi square value because the likelihood of model refusal increases with sample size. As a result, we divided the chi square value by the degrees of freedom to overcome the sample size issue. The p-value calculated is 0.000, indicating that further degrees of freedom are necessary. The

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038
calculated NFI value of 0.0824 is quite close to the intended value of 0.90. The obtained CFI value is 0.857, which is higher than the suggested value of 0.90. The discovered RMSEA value is 0.062, which is the same as the recommended value of 0.08. The discovered P-close value is 0.000, which above the suggested threshold of 0.05. As a result, we can conclude that the overall model fit indices are within the researchers' recommended levels and that the hypothesised model fits the sample data. All eight elements met all of the other acceptable criteria for validating the Model's fitness. As a result, we can conclude that the Model is completely appropriate.Figure 1 is an SPSS Amos Graphics path-diagram that depicts the link between both the observed red variables and the unobserved variables. The structural model is the component of the model that describes how the unobserved variables are related to each other. The relative relevance is determined by the estimation of regression weights. The estimations with the highest values represent the most significant aspect in terms of its impact on HR Analytics awareness level. Table4 summarises the results of the regression weights estimates. According to the findings of the study, the level of awareness of HR Analytics among HR professionals is affected more by Level of Adoption (0.99) than by Social Influence (0.93), Tool Availability (0.83), Data Availability (0.75), and General Self-Efficacy (0.75). (0.66).

Discussion:-

The study looks into the elements that influence HR analytics awareness among HR professionals, as well as the relationships between them. The empirical data is broken down into nine components that influence HR analytics consciousness: common self-efficacy, quantitative self-efficacy, social impact, apparatus accessibility, information accessibility, fear requests, exertion desire, execution desire, and level of appropriation. Based on the statistics, it is possible to deduce that the level of adoption has a stronger impact on HR Analytics awareness among Indian HR professionals (0.99). The degree to which an innovation is accepted is measured by its level of adoption, which consists of five stages: knowledge, persuasion, choice, execution, and confirmation. When and how early adopters appear is influenced by the rate of adoption. The most important factor influencing the rate of adoption is the type of society in which innovation is introduced. It examines how new technologies and inventions spread throughout society and why they are favoured over prior methods.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Conclusion:-

The Structured Equation model was employed in this study to evaluate the impact of numerous elements on HR analytics awareness among Indian HR practitioners. There is currently very little research available to study the elements impacting HR analytics awareness levels. According to the findings of this study, the amount of adoption has the most influence on HR Analytics awareness among HR professionals, while general self-efficacy has the least. The outcomes of this study give an overview of the link between nine latent variables. The study's findings, in particular, can assist practicing and academics comprehend the extent of influence that these elements have on HR Analytics knowledge among HR professionals in India, as well as the correlation between these aspects.

Conflict of Interest
There is no conflict of interest to be declared

References:-

Fitz-enz, J. (n.d.). Toward Analytics and Prediction. The New HR Analytics, 8–44. doi:10.5848/amacom.978-0-814416-44-0_3

Sattelberger, T. (1996). Human Resources Management in der flachen Organisation: Zwischen blinder Anpassung und proaktivem Management of Change. Human Resource Management Im Umbruch, 80–113. doi:10.1007/978-3-322-87093-3_5

Hamilton, R. H., & Sodeman, W. A. (2020). The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources. Business Horizons, 63(1), 85–95. doi:10.1016/j.bushor.2019.10.001

Vargas, R., Yurova, Y. V., Ruppel, C. P., Tworoger, L. C., & Greenwood, R. (2018). Individual adoption of HR analytics: a fine grained view of the early stages leading to adoption. The International Journal of Human Resource Management, 29(22), 3046–3067. doi:10.1080/09585192.2018.1446181

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038
Reddy, P. R., & Lakshmikeerthi, P. (2017). HR analytics-An effective evidence based HRM tool. International Journal of Business and Management Invention, 6(7), 23-34.

Jabir, B., Falih, N., & Rahmani, K. (2019). HR analytics a roadmap for decision making: case study. Indonesian Journal of Electrical Engineering and Computer Science, 15(2), 979. doi:10.11591/ijeecs.v15.i2.pp979-990

Kremer, K. (2018). HR analytics and its moderating factors. Vezetéstudomány-Budapest Management Review, 49(11), 62-68.

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. The International Journal of Human Resource Management, 28(1), 3-26.

HANDA, D. (2014). Human resource (HR) analytics: Emerging trend in HRM (HRM). CLEAR International Journal of Research in Commerce & Management, 5(6).

Keerthi, L., & Reddy, P. R. (2018). Adoption issues of HR analytics.

Bassi, L. (2011). Raging debates in HR analytics. People and Strategy, 34(2), 14.

Fitz-Enz, J. (2010). The new HR analytics. American Management Association.

Rasmussen, T., & Ulrich, D. (2015). Learning from practice: how HR analytics avoids being a management fad. Organizational Dynamics, 44(3), 236-242.

Mondore, S., Douthitt, S., & Carson, M. (2011). Maximizing the impact and effectiveness of HR analytics to drive business outcomes. People and Strategy, 34(2), 20.

Edwards, M. R., & Edwards, K. (2019). Predictive HR analytics: Mastering the HR metric. Kogan Page Publishers.

Ben-Gal, H. C. (2019). An ROI-based review of HR analytics: practical implementation tools. Personnel Review.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Baesens, B., De Winne, S., & Sels, L. (2017). Is your company ready for HR analytics? MIT Sloan Management Review, 58(2), 20.

Kremer, K. (2018). HR analytics and its moderating factors. Vezetéstudomány-Budapest Management Review, 49(11), 62-68.

About the authors

Saaema Akhtar: She is pursuing a PhD in human resource management from Department of Humanities and Social Sciences, Motilal Nehru National Institute of Technology, Allahabad, since 2019. She has also cleared UGC-NET in Commerce and Human resource management. She has done B.ed as well.

Dr. Rajesh Kumar Shastri: He is presently working as the associate professor (human resource management and public policy) in Department of Humanities and Social Sciences, Motilal Nehru National Institute of Technology, Allahabad, Prayagraj, UP, India 211004. He has also worked on various projects funded by ICCSR (India). His research area includes human resource management, public policy.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Appendix

No	Construct statements	Standardised factor loadings
1.	HR Analytics is easy to use	*0.87*
2.	HR Analytics is convenient to use	*.96*
3.	I am able to use HR Analytics without much effort	*.85*
4.	~~I can solve most problems if I invest the necessary effort~~	~~.40~~
5.	~~When I am confronted with a problem, I can usually find several solutions~~	~~.29~~
6.	~~I find using mathematical and/or statistical measurements interesting.~~	~~.11~~
7.	~~I worry about my ability to solve mathematical and/or statistical problems.~~	~~-.68~~
8.	~~I get nervous when I use mathematics and/or statistics~~	~~-1.19~~
9.	~~I enjoy working with mathematical and/or statistical measures.~~	~~.48~~
10.	~~People who influence my behaviour think that I should use HR Analytics.~~	~~.47~~
11.	~~People who are important to me think that I should use HR Analytics.~~	~~.47~~
12.	The senior management of this business has been helpful in the use of HR Analytics.	*.76*
13.	In general, the organization has supported the use of HR Analytics	*.60*
14.	Because of my use of HR Analytics, others in my organization will see me as a more valuable employee.	*.93*
15.	I have a full array of HR Analytics tools available at work if I choose to use them	*.67*
16.	My company has invested heavily in HR Analytics tools.	*.82*
17.	~~Before deciding whether to use any HR Analytics applications, I am able to properly Try them out.~~	~~.47~~
18.	I have had a great deal of opportunity to try various HR Analytics applications	.75
19.	I know where I can go to satisfactorily try out various uses of HR Analytics	.84
20.	My organization's database has all the data I need to use HR Analytics software	.72
21.	My organization's HR system collects data from all HR interactions.	.94
22.	My organization uses the same system/platforms for all HR activities	.99
23.	~~If I were forced to use HR Analytics, it would have a negative effect on my Organizational commitment~~	~~.43~~
24.	~~It is unlikely I would be forced to try or use HR Analytics to keep my job~~	~~-12~~
25.	If I were required to use HR Analytics, it would have a significant negative impact on My job performance	1.13
26.	If I were mandated to use HR Analytics, it would have a negative effect on my job Satisfaction.	.70
27.	. It would be easy for me to become skilful at using HR Analytics.	.86
28.	Learning to use HR Analytics is easy for me.	.58
29.	~~I would find HR Analytics easy to use.~~	~~.33~~
30.	I would find the use of HR Analytics propitious for my job	.76
31.	Using HR Analytics enables me to accomplish tasks more quickly	.82
32.	Using HR Analytics increases my job performance	.91
33.	. My organization is putting a policy in place to use HR Analytics.	.80
34.	~~. I am beginning to explore using HR Analytics.~~	~~.31~~
35.	. I am interested in using HR Analytics.	.90
36.	I am recommending my organization invest in HR Analytics.	.91

Model Fit Summary
CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	86	753.330	189	.000	3.986
Saturated model	275	.000	0		

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Model	NPAR	CMIN	DF	P	CMIN/DF
Independence model	44	2733.340	231	.000	11.833

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.724	.663	.778	.724	.774
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.818	.593	.634
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	564.330	483.632	652.584
Saturated model	.000	.000	.000
Independence model	2502.340	2337.648	2674.397

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	7.609	5.700	4.885	6.592
Saturated model	.000	.000	.000	.000
Independence model	27.609	25.276	23.613	27.014

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.174	.161	.187	.000
Independence model	.331	.320	.342	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	925.330	977.383		
Saturated model	550.000	716.447		

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2022.28.03.038

Model	AIC	BCC	BIC	CAIC
Independence model	2821.340	2847.971		

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	9.347	8.532	10.238	9.873
Saturated model	5.556	5.556	5.556	7.237
Independence model	28.498	26.835	30.236	28.767