Salud, Ciencia y Tecnología. 2022;2(S2):245
doi: 10.56294/saludcyt2022245

ORIGINAL ARTICLE

Unlock the Art of People Analytics through Workforce Competency Management

Descubra el arte de la analítica de personal mediante la gestión de las competencias del personal

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Citar como: Babu GR, Govindappa S. Unlock the Art of People Analytics through Workforce Competency Management. Salud Cienc. Tecnol. 2022;2(S2):245. https://doi.org/10.56294/saludcyt2022245

Submitted: 16-11-2022 **Revised:** 09-12-2022 **Accepted:** 22-12-2022 **Published:** 31-12-2022

Editor: Fasi Ahamad Shaik

ABSTRACT

Data application in organizations has shifted its focus to meeting the legal requirements of employment. This shift in data use gradually altered the dynamics of the Human Resource Management (HRM) role, and organizations now expect high-quality analysis from HR professionals.
Various studies suggested that the use of Human Resource Analytics (HRA) would assist HR professionals in developing diverse viewpoints on their contribution to the financial targets of organizations through the creation of suitable measurements. Still, not many researchers have explored the role of HRA in increasing the business outcomes of Indian organizations. In this study, we analysed the role of HRA competencies in determining business outcomes as well as examined the gap existing in the expected and existing competencies of HR analysts in Indian organizations.
Our in-depth literature review prepared a conceptual framework based on Capability Motivation and Opportunity (CMO) model. A quantitative methodology was adopted to gather the data as it integrates the components of HRA competency and measures their impact on business outcomes. A structured questionnaire was designed and distributed to 230 HR professionals, including HRA users as well as HR managers who work in different organizations in the city of Bengaluru. The data were analysed using various statistical tools and SPSS software. Overall, our study provides a significant depiction of the role of HRA in determining business outcomes, as well as the gap between the competencies demonstrated by HR analysts and the competency levels expected of them.

Keywords: Human Resource Management; Human Resource Analytics; Decision-making; LAMP; COM; HRA; Competency Model; BASP; HR Analytics.

RESUMEN

La aplicación de datos en las organizaciones ha desplazado su centro de atención hacia el cumplimiento de los requisitos legales de empleo. Este cambio en el uso de los datos ha alterado gradualmente la dinámica de la función de Gestión de Recursos Humanos (GRH), y las organizaciones esperan ahora análisis de alta calidad por parte de los profesionales de RRHH.
Diversos estudios sugieren que el uso de la Analítica de Recursos Humanos (ARH) ayudaría a los profesionales de RRHH a desarrollar diversos puntos de vista sobre su contribución a los objetivos financieros de las organizaciones mediante la creación de mediciones adecuadas. Sin embargo, no son muchos los investigadores que han estudiado el papel de la HRA en el aumento de los resultados empresariales de las organizaciones indias. En este estudio, analizamos el papel de las competencias de la ARH en la determinación de los resultados empresariales y examinamos la brecha existente en las competencias esperadas y existentes de los analistas de RRHH en las organizaciones indias.
Nuestra profunda revisión bibliográfica preparó un marco conceptual basado en el modelo de Capacidad, Motivación y Oportunidad (CMO). Se adoptó una metodología cuantitativa para recopilar los datos, ya que

integra los componentes de la competencia de los ARH y mide su impacto en los resultados empresariales. Se diseñó un cuestionario estructurado y se distribuyó a 230 profesionales de RRHH, entre los que se encontraban usuarios de la ARH y directores de RRHH que trabajan en diferentes organizaciones de la ciudad de Bengaluru. Los datos se analizaron utilizando diversas herramientas estadísticas y el software SPSS. En general, nuestro estudio ofrece una descripción significativa del papel de la ARH en la determinación de los resultados empresariales, así como de la brecha existente entre las competencias demostradas por los analistas de RRHH y los niveles de competencia que se esperan de ellos.

Palabras clave: Administración de Recursos Humanos; Analítica de Recursos Humanos; Toma de Decisiones; LAMP; COM; ARH; Modelo de Competencias; BASP; Analítica de Recursos Humanos.

INTRODUCTION

A general analytics discipline has been described by Mortenson et al.[1] It involves the intersection of evolved technologies, decision-making and quantitative methods. In other words, analytics includes tools for efficiently processing data, quantitative methods for analyzing business data, and theories, tools, and practices for facilitating and becoming aware of the decision-making process.

The evolution of Human Resources Analytics (HRA) has grown due to three significant advancements that pertain to the functioning of organisations currently. First, the global environment in which organisations function has resulted in increasing competition. This has been accompanied by advances in technology. Consequently, there was a need for the HR function to acclimatise to the unfamiliar competitive conditions by transforming itself.[2,3,4]

Second, the globalisation of organizations has resulted in a recognition of its relevance in terms of human capital competitiveness and superior human capital management.[5,6] Third, with the advent of Big Data came the rise of business analytics as a means to deal with huge amounts of data, a trend that has entered HR as well.

Human Resource Management (HRM) administrators have been able to collect more efficient data for processing and subsequent storage for future use by utilizing this new technology. As a result, the entire process ultimately saves time in engaging administrators for new roles. During its early phase, HRM was considered as an administrative-oriented practice while keeping employee management as its focal point. Because employees were essentially identified as business expenses, HRM administrators emphasized performing these functions with maximum proficiency. This very primitive idea evolved over time and situation as employees were increasingly viewed as a workforce that provides competitive advantages for the organization in the marketplace. As such, in recent times, employees were considered more of an important asset to the organization than a mere expense. HRM practices have also shifted from being an administrative functional tool to a strategic one as a result of the new modified perspective.[7]

Strategic HRM has evolved critical Human Resources (HR) practices to assist entrepreneurs in achieving the necessary business goals and, ultimately, increasing profitability.[8] However, it is observed that despite its crucial efforts, the strategic HRM has not yet been able to accomplish the target of fitting into the role of a strategic partner. The major drawback behind this failure lies in not receiving accurate information about issues relating to its workforce.[9]

In spite of making some considerable advancements and progress regarding its usage in business strategy preparation and application, HR practices are still difficult in respect of data delineation and measurement. Besides, in the past, the data accumulation process has been considered more operational than HRM concentrated. As a result, it does not assess the impact on business entrepreneurs as a whole.[9]

To address this challenge, data-driven HRM is considered the most appropriate method.[10] This new method is solely based on the data and facts hence it does not consider feedback based on any intuition or experience.[11]

Aside from data-driven measurement and decision-making activities, experts advocated for an outside-in approach to improve the effectiveness of HRM practices. Based on these findings, it is possible to conclude that HR should emphasize its role as a strategic partner. By doing this, they not only involve themselves in data-driven decision-making processes, but also are engaging in outside decision-making activities. These activities must include important business perspectives as well as external stakeholders, particularly customers.

The main obstacle to creating any HRM devices and tools that add value to any company is the gap in the literature between studies of HR approaches and those that look into the function of the HR department and the propensity to monitor corporate governance. Extensive literature is available on the performance of HRM, in order to make the task feasible and economical; selective studies will be incorporated so as to make the study selective.

Renowned scholars such as Guest[7] have emphasized the need for an integrated review of literature, whereas,

Wright et al.[12] suggested that the instance of the "elephant and the blind men", implies that no experience completely exemplifies a phenomenon, but only suggests that when all blind people had to inform each other about a particular part, their combined details would approximately sound like the elephant.

HRA is a subset of analytics that deals with employee analysis and, by applying analytical processes to human capital in the organization, obtains significant results on employee retention and improves employee performance. Therefore, data analytics play a significant role in managing HR functions. Enterprises can soar high and reach the zenith of success by improving and enhancing the performance of their employees using HR analytics. For the purpose of institutional success, an organisation needs to recognize these human drivers. ABN Amro, for example, has worked with their HR analytics team since 2013.[13]

Acito et al.[14] suggested that the efficiency and effectiveness of a business are improved by the operation of data analytics. It is achieved by having an impact in operational fields like accounting, organizational or managerial networks such as supply chains and in commercial divisions, e.g. health management and wellness programs.[15] On the bandwagon of data analytics, HRM is a novice department, but the management recognizes its worth while acknowledging apprehension about their own institutional willingness for adoption.

It is popularly known by numerous terms: workforce, talent, HR, or people analytics. The above-mentioned analytics have many things in common. Enterprises are concerned with the analysis of data related to human resource departments, amalgamation of the data from different internal departments and even from internal sources. Infotech departments help in the accumulation, manipulation, interpretation, and broadcasting of a variety of data, which may be either structured or unstructured. All the analytics are used to reinforce decision-making, which is relevant to people in any organization, and then associate HR decisions with better results, such as a better performance of employees in any organisation.[16]

During the 1940s, some large corporations used analytics to improve and upgrade selection and talent management.[17] Nonetheless, with the advent of information technology, data collection, analysis, and interpretation have become far more convenient, and as a result, workforce analytics has become practically attainable and employable for any organization.

Furthermore, data collected from various new sources such as wearable technology, email, and calendars create more favorable conditions for understanding workers' or employees' behaviors and improving performance, which is difficult in the other case. This progression of analytical and evidence-based decision-making has tremendously promising opportunities for enhancing the effectiveness and productivity of the organisation. Regardless of ample propaganda and hype, there still remains a challenge with the organisation in terms of successful accomplishment and execution of workforce analytics. Many organizations attempt strategic intuitiveness and awareness from their employee data by forming workforce analytics teams, which has delayed other tasks and frequently falls short of prediction.[11]

For instance, in a study that involved over 10,000 business and HR heads, Deloitte[18] concluded that despite the fact that over 70 % of those within the organisation believe that workforce analytics is a key factor to enhance the performance of the employees and give a boost to the business, merely 8 % of the firms reported having any form of useful data, while 9 % opined that they know the types of talents in their workforce resulted in good performance, and 15 % decided that three are talent indices or talent rosters for their managers.

Our study aims to investigate whether there are competency-related gaps in HRA prevailing among the HR professionals of the organisations and its impact on usage of HRA.

Research Hypotheses

Based on the objectives, the following hypotheses have been formulated:

$H_0$1: There exists no significant gap between the expected and existing HRA competency.

H_a1: A significant gap exists between expected and existing HRA competency.

METHODS

Study Area

This study was conducted in Bengaluru, Karnataka, India. Bengaluru was selected due to the presence of a broad spectrum of organisations from different sectors. Since it has the highest number of small and big IT and ITES industries in India, this city is known as the Silicon Valley of India. Apart from that, a number of electronics and electrical manufacturing units and numerous other private financial and business-oriented organisations are also operating in this city. The majority of these organizations are medium or large level organisations and are presumed to apply various HR techniques to understand the nature, talent, and productivity of the employees, which in turn can help these companies design their policies to achieve the best outcome. Furthermore, this city is also largely cosmopolitan in nature, as people from various parts of India and abroad are working in parallel in the same organisations.

Study Samples

The universe for this study was HR professionals, including HRA users as well as HR managers who work in different organisations in the city of Bengaluru. The sample for the study was drawn from this population. The sampling size was selected using the formula described below,

$$n = \frac{z^2 s^2}{d^2}$$

Where n = Sample size, z = Standard score associated 95 % of Level of confidence, s = estimate of standard deviation in the population, d = Acceptable margin of error for the mean being estimated. As a result of the calculations, a sample size of 230 was considered for our study, well above the estimated count of 169 respondents (with a confidence level of 95,0 % and a margin of error of 0,05 %). These respondents were selected using random sampling. The study opted for this sampling technique because of its convenience and ability to yield satisfactory results in a short period of time. Further, the sampling method was also cost effective and provided flexibility in the selection of sampling units.

Pilot Study

A pilot study, using a small sample of data, was conducted to pre-test the scale used in the study as it is an important step in the research to validate the items used in the questionnaire. With the help of these data, the reliability and validity of the research instrument were tested. A sample population of 50 HR professionals from various organizations in Bengaluru was chosen. The study carried out a reliability analysis with the help of Cronbach's alpha and performed a factor Analysis using Principal Component Analysis (PCA) with varimax rotation to test the correlation between the items and the validity of the concepts. According to the reliability studies, the pilot test results were found to be reliable and robust enough to be kept, analyzed, and statistically inferred from. All the items in the study variables were found to exhibit satisfactory factor loadings ranging from 0,5 to 0,9, indicating their significance in explaining the factors for HR analytics present in the existing organisations. The KMO value of the variables was acceptable and moderately desirable for factor analysis. Along with that, Bartlett's test of Sphericity for the factors showed that the pilot data were acceptable for factor analysis.

Framework Analysis

This section shows the tools used for performing structural equation modelling (SEM) as well as other statistical analyses. Using SPSS statistical software, the collected data was statistically analyzed, and meaningful inferences were drawn from the results. The questionnaires were tested for reliability and construct validity. The demographic data points and other variables were computed using descriptive analysis such as frequency, percentage, mean, and standard deviation. The dimensions of HRA competency were explored using the correlation matrix and Eigenvalue of the Exploratory Factor Analysis (EFA) technique. The parameters of the distribution were estimated using Maximum likelihood estimation and the interpretation was done using an Oblimin rotation of factor analysis. Furthermore, using the Psych software, derived factors were named in the context of the literature studies. Hypothesis testing was performed using path analysis, and the influence of independent variables on the dependent variables was analysed using Hayes process or regression analysis. The testing of significant differences on various study constructs and the verification of hypothesis was also performed using t-test and ANOVA. Structural Equation Modelling (SEM) was used to confirm the theoretical framework created for this study using Lavaan software. The outcome of the theoretical model was evaluated with the help of good and bad indices: GFI, CFI, TLI, NNFI, RMR, SRMR, and RMSEA respectively. 1st order and 2nd order Confirmatory Factor Analysis (CFA) were performed to assess the higher order of the construct.

Conceptual Framework of the study

The framework provides the relationship between the variables adopted by the study. It integrates the existing and expected competency characteristics with four sub-variables each, namely, understanding of data, Analytical, and Interpretation skills and Capability, Motivation and Opportunity of the HR professionals with the utilisation of competency outcomes by the organisation for different processes on business outcomes of the various organisations where they are currently working. The measurement of Return on investments (ROI) and Decision-making process formed the business outcomes of the organisations located in Bengaluru, Karnataka. The significance of the relationship between the variables was analysed using the hypotheses which were formulated with respect to the objectives of the study (Fig. 1).

https://doi.org/10.56294/saludcyt2022245

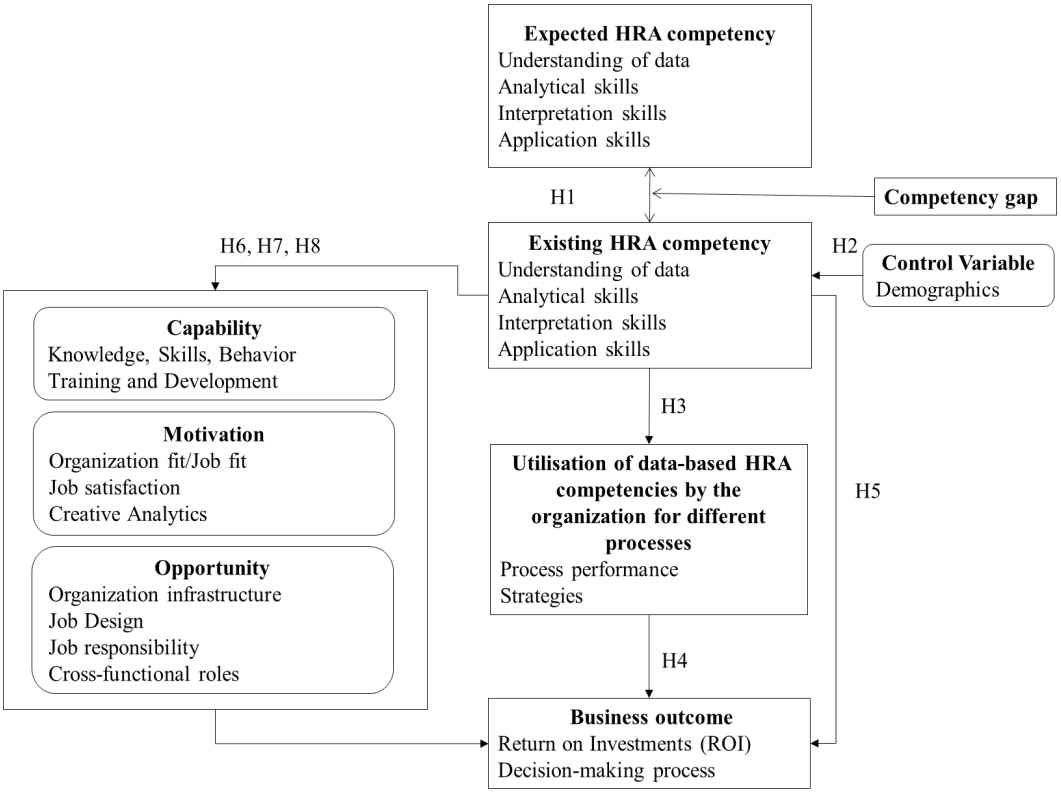

Figure 1. The conceptual framework of our study

Table 1. Factors of Existing HR Analytic Competencies

Factors	Factor Loadings	% of Variance	Cumulative %
Understanding of data		45,687	45,687
We have the skills of identifying the proper data for analysis	0,840		
We have the skills for preparing/transforming the data	0,723		
Data integration from various functions or process is very much available in our organization	0,708		
We have the skills for understanding the data for analysis	0,665		
Analytical skills		10,240	55,927
We have knowledge of software such as R, Python, Lavaan, etc. for data analysis	0,895		
We know how to use a pivot table to explore the patterns in the employee performance	0,812		
We have knowledge of lookup in the regular work to fetch the data from one sheet to another sheet in excel	0,782		
We have intermediate data analysis kills (correlation, standard deviation, statistically significant differences)	0,756		
We know how to use a Machine learning algorithm for key decision in our organization	0,662		

We know how to use the Root cause analysis technique	0,641		
We have knowledge of statistical modeling for data analysis	0,598		
We have basic multivariate analysis skills (ANOVA, regression, and factor analyses)	0,593		
We know how to use predictive and talent metric skills to predict employee attrition beforehand using a statistical model in our organization	0,572		
We have basic data analysis skills (mean, median, minimum and maximum range)	0,507		
Interpretation skills		7,683	63,610
We know how to interpret the return on investment on our training activities	0,806		
We know how to interpret our reports with graphical illustrations supported by figures using the Visualization software	0,784		
We know how to interpret the cause-effect relationship	0,782		
We know how to use the writing skills for making our statistical data understandable	0,747		
We know how to interpret dynamic dashboards to present our key performance indicators in the meeting	0,559		

Table 2. Factors of Expected HR Analytic Competencies

Factors	Factor Loadings	% of Variance	Cumulative %
Analytical skills		***35,644***	***35,644***
We have basic multivariate analysis skills (ANOVA, regression, and factor analyses)	0,843		
We know how to use the Root cause analysis technique	0,789		
We know how to use an Artificial intelligence system in our process	0,751		
We have knowledge of statistical modelling for data analysis	0,744		
We have basic data analysis skills (mean, median, minimum and maximum range)	0,696		
We know how to use a pivot table to explore the patterns in the employee performance	0,675		
We know how to use a Machine learning algorithm for key decision in our organization	0,671		
We know how to use predictive and talent metric skills to predict employee attrition beforehand using a statistical model in our organization	0,577		
We have knowledge of software such as R, Python, Lavaan, etc. for data analysis	0,558		
Interpretation skills		***13,014***	***48,658***

https://doi.org/10.56294/saludcyt2022245

We know how to interpret the cause-effect relationship	0,791
We know how to interpret dynamic dashboards to present our key performance indicators in the meeting	0,772
We know how to interpret the return on investment on our training activities	0,661
We know how to use the writing skills for making our statistical data understandable	0,574

RESULTS AND DISCUSSION

Comparison of expected and existing understanding of data within the HR Analysts

The analysts' level of data understanding was measured as part of their competency and compared to existing and expected competencies (shown in Table 3).

The first and foremost skills required by an HR analyst are to identify, understand, integrate, and analyse the obtained data from various functions of the organization. Much improvement of the HR analytic competencies is not required pertaining to the skills of identifying the proper data for analysis. It was present most of the time, as expected as a competency (3,996 ± 1,080) as well as the existing HR analytics (3,770 ± 0,977). Similarly, the skills for understanding the data were present most of the time in the expected (4,057 ± 1,029) and existing (3,713 ± 0,965) HR analytics. Further, the skills for preparing/transforming the data were present most of the time in the expected (4,061 ± 0,870) and existing (3,709 ± 1,023) HR analytics competencies.

The existing HR analytic competencies had availability of data integration from various functions at most of the times (3,483 ± 1,192) in the organization, however, its complete presence was expected (4,204 ± 0,780). Thus, it can be inferred that most of the existing skills pertaining to the understanding of the data, such as the skills for understanding, identifying and transforming the proper data for analysis of the HRA matched the expected HRA competencies, except the data integration function.

Table 3. Comparison of expected and existing HR Analytic Competencies with respect to Understanding of Data

Understanding of data	Expected HR Analytic competencies		Existing HR Analytic competencies	
	Mean	Std. Dev.	Mean	Std. Dev.
We have the skills of identifying the proper data for analysis	3,996	1,080	3,770	0,977
Data integration from various functions or process is very much available in our organization	4,204	0,780	3,483	1,192
We have the skills for understanding the data for analysis	4,057	1,029	3,713	0,965
We have the skills for preparing/transforming the data	4,061	0,870	3,709	1,023

Comparison of expected and existing HR Analytic Competencies with respect to Analytical Skills

Analytical skills involve the ability to analyse, simplify complex problems, and draw solutions. The analytical skills can be classified into basic, intermediate, and basic multivariate analysis skills. Table 5 presents a comparison between the present and the expected HR analytics competencies with respect to analytical skills. The overall analytical skills were sometimes expressed by the existing HR analysts (3,334 ±1,176); however, the expectation was to have these analytical skills most of the time (4,092 ±695). For HR analytics, the knowledge of analytical skills such as statistical modelling, software such as R, Python, and lookup was quite essential in regular work.

The survey showed that the expected HR competency was to have complete knowledge of how to use the root cause analysis technique (4,265 ± 0,732) and how to use predictive and talent metric skills to predict employee attrition beforehand using a statistical model in the analysts(4,248 ±0,670); however, the existing HR professionals were not fully aware of these skills (3,783±1,084; 3,170±1,201, respectively).

It was also expected that there would be a complete presence of the knowledge of lookup in the regular work to fetch the data from one sheet to another sheet in excel (4,252±0,685). The use of a pivot table to

explore the patterns in the employee performance (4,209±0,804) was successful, but the existing HR analytics did not match the expectations (3,900±1,131; 3,961±1,063, respectively). The larger gap between the expected and existing competencies was evident in the competencies, such as awareness regarding the machine learning algorithm for key decision-making in the organization and awareness regarding the application of artificial intelligence in organizations. Analytics professionals were expected to have a comprehensive knowledge in the use of machine learning algorithms for key decision-making in the organization (4,148±0,602) as this helps the organization to assess productivity in order to take appropriate corrective measures. However, our findings illustrate that the existing HR professionals exhibited limited knowledge regarding the application of machine learning (2,974±1,101). Professionals were also supposed to be well versed in the application of artificial intelligence (4,030 ±0,594), however, once again our findings indicated that the reality was completely different (2,987±1,202). Overall, it can be concluded that, aside from the basic data analysis skills of HR professionals, no other analytical skills met the expected HR analytic competencies. The large gaps between expected and existing analytics competencies indicate a lack of awareness among HR professionals about the importance of analytics competencies, as well as an unwillingness on the part of organizations to provide proper training to HR professionals about modern analytical skills.

Table 4. Model fit Indices for existing HR Competency

Model Fit Indices	Observed Value
Chi-square (CMIN/DF)	5,486
Normed Fit Index (NFI)	0,833
Relative Fit Index (RFI)	0,751
Incremental Fit Index (IFI)	0,859
Tucker Lewis Index (TLI)	0,787
Comparative Fit Index (CFI)	0,857
Root Mean Square Error of Approximation (RMSEA)	0,038

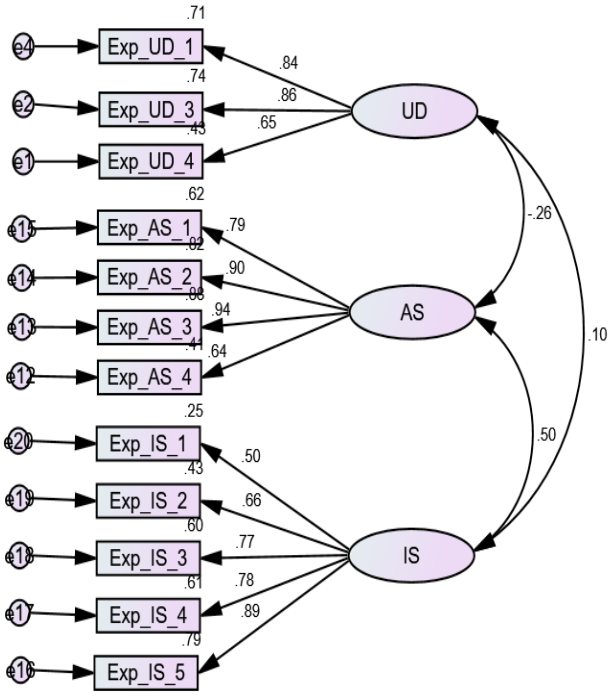

Figure 2. Measurement model for existing HR Competency

The relationship between the observed variables and the underlying constructs was studied with the help of standardized estimates, as shown in Tables 1 and 2. The factor loadings of the items measuring the reflective constructs, Understanding data (UD), Analyzing data (AD), and Interpreting data (ID) which were found to be greater than or close to 0,6 alone, were retained in the scale. The standardized factor loadings of items measuring the construct were greater than or equal to 0,5, which indicates the convergent validity of the items

on the scale, i.e., the items in the constructs that are to be related are indeed related.

Independent student's t-test was carried out to analyse the difference in existing and expected human resources analytical competencies in the organization (Table 5). It was observed that there is a statistically significant difference between existing competency (3,668 ±0,844) and expected competency (4,079 ± 0,747) of the HRA professionals with respect to understanding of data with t (*230*) =5,527, p<0,05. In addition, there is a statistically significant difference between existing competency (3,334 ± 0,724) and expected competency (4,092 ± 0,416) of the HRA professionals with respect to analytical skills with t (*230*) =13,782, p<0,05. A statistically significant variation was also observed between existing (3,357 ± 1,083) and expected competency (3,996 ± 0,728) of the HRA professionals with respect to interpretation skills with t (*230*) =7,417, p<0,05. Therefore, we demonstrate that a significant gap exists between expected and existing HRA competency.

Table 5. Gap Analysis showing Expected and Existing HRA Competency

HRA competency	Group	N	Mean	Std. Deviation	T	Sig.
Understanding of data	Expected	230	4,079	0,747	5,527	0,000
	Existing	230	3,668	0,844		
Analytical skills	Expected	230	4,092	0,416	13,782	0,000
	Existing	230	3,334	0,724		
Interpretation skills	Expected	230	3,996	0,728	7,417	0,000
	Existing	230	3,357	1,083		

CONCLUSIONS

Overall, our study provides a significant depiction of the role of HRA in determining business outcomes, as well as the gap between the competencies demonstrated by HR analysts and the competency levels expected of them. Particularly, most of the existing skills pertaining to the understanding of the data, such as the skills for understanding, identifying and transforming the proper data for analysis of the HRA matched the expected HRA competencies except the data integration function. We demonstrate that a significant gap exists between expected and existing HRA competency. Further investigations will shed light on how to minimize the gap between existing and expected competencies demonstrated by HR analysts in order to improve business outcomes.

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CONFLICTS OF INTEREST

None.

FINANCING

None.

AUTHORSHIP CONTRIBUTION:

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