Unravelling the Barriers of Human Resource Analytics: Multi-Criteria Decision-Making Approach

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ABSTRACT Although Human resource analytics is considered a 'game-changer', most organisations have still not integrated analytics due to the organisational-related, job-related and finance-related barriers. Existing literature has focused on addressing the barriers and contributing to the literature through systematic literature review and structural equation modeling. However, little has been researched on the barriers and their degree of magnitude in the organisation. Multi-criteria decision-making (MCDM) techniques find a solution in complex scenarios that include multiple factors and criteria. This study aims to measure the magnitude of the barriers and determine the ranking of the retail & e-commerce, IT, BFSI, FMCG, and travel & transport sectors based on the adoption and implementation of analytics using quantitative techniques of MCDM. In the first phase of the study, the entropy weight method (EWM) and criteria importance through inter-criteria correlation (CRITIC) techniques are used to derive the objective weights of the barriers. In the second phase, rankings are derived for the five sectors using TOPSIS and Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS) techniques.

INDEX TERMS Human resource analytics, barriers, MCDM, TOPSIS, MARCOS, Entropy Weight Method, CRITIC.

I. INTRODUCTION

Research Background

There is no distrust that digitalization or digital transformation has changed the economy, society, and industry [1]. With Digitization, companies are evolving the design, manufacturing and delivery of their product and service with smart mobile devices, 3D printing, cognitive computing, virtual reality, and the internet of things [2]. However, human resource analytics in businesses is at an intriguing stage in its development. While interest and investment are great, it appears that progress is modest. As the difficulties of performing effective talent analytics become apparent, the expectation that the proper algorithm will rapidly and effortlessly uncover strong insight is waning. As per Deloitte's global survey 2016, only 8 percent of corporations indicate that they are fully capable of making predictive models, let alone to say nothing of fully prescriptive models that outline every single action to be taken. Sixty percent of firms specify organisations are not prepared to perform prescriptive or predictive analysis. This disparity is striking considering that only two years ago, 78 percent of major organizations evaluated HR and talent analytics as significant, placing it among the top three most critical developments (Deloitte Global Human Capital Trends 2014). Evidently, something is not functioning properly. In this study, we propose that a range of variables impede the swift advancement of effective HRA abilities.

Integration of data-driven methods and techniques to assess HRM is not a recent development [3], but the reality is that analytics in HR management—also known as workforce analytics, HR analytics (HRA), talent analytics, and people analytics (PA)—has gained popularity since 2016 as shown in Fig. 1.

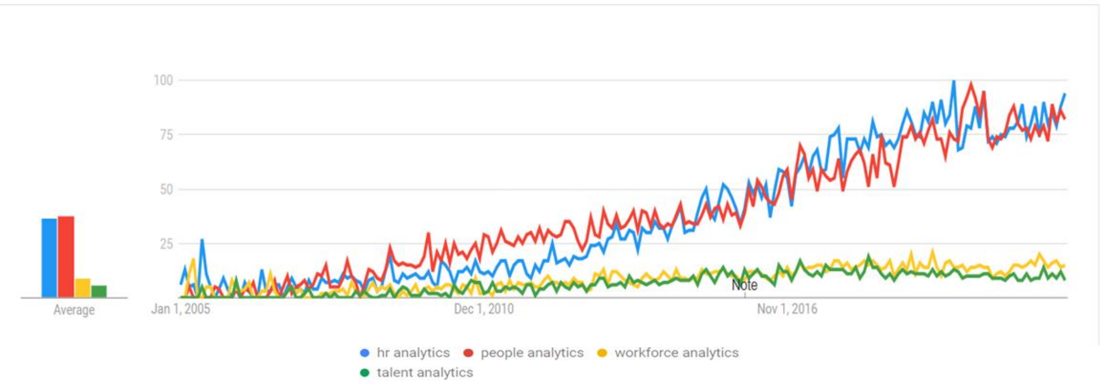

Figure 1: Google trends

Although HR analytics is regarded as a game-changer in business, its adoption is 'shallow' [3] [4]. Based on a survey by KPMG (2019) [5] of more than twelve hundred HR executives state that most HR executives (70%) recognise the necessity for workforce transformation; however, merely 37 percent feel “very confident” for analytical capabilities and skills of HR professionals to transform. More significantly, only 12% of HR leaders say analytics is their top management concern, and only 20% of HR leaders think analytics will be a major HR endeavour over the next two years.

The majority of HRA literature is more promotional than descriptive. Specifically, the vast majority of research papers are qualitative case studies that depend upon well-acknowledged management theories, albeit often at a relatively generic level [3]. In addition, there was a lack of defined HR indicators, which prevented us from having clear courses to follow, as is the case in finance and operations [6] [7]. All of these considerations can explain why HR professionals lack confidence in using HR analytics in their departments.

Existing literature has focused on addressing the barriers that have fully affected the embracing of HR analytics. The authors of this paper have used a quantitative approach to know the magnitude of each barrier using Multi-Criteria Decision Making (MCDM) techniques. Studies have focused on using MCDM in various fields, such as supply chain management, logistics, and retail, but pay little attention to its application to human resource management. MCDM assists in evaluating different real-world circumstances based on criteria in a particular or unpredictable environment to make judgments, policies, and strategies, as well as in making decisions based on many contradictory criteria. Researchers have focused on dimensions of human resource analytics, importance, and factors that prompt the adoption of HRA. As per a recent scenario, the adoption of HRA has not reached the optimum level due to the various barriers that organisations have to deal with. This paper focuses on this research gap and aims at:

- Summarising the barriers that are hindering the adoption and implementation of HR analytics.
- Assessing the barriers to implementing and integrating HRA using the MCDM techniques: EWM and CRITIC.
- Ranking the selected industry/sectors based on adopting and implementing analytics using TOPSIS and MARCOS.

II. RELATED WORK

After the first quarter of 2009, the term "HR Analytics" (HRA) became widely used.

TABLE 1 EXISTING LITERATURE REVIEW

Authors	Techniques used
Niharika & Vijay (2019) [16]	Interpretive Structural Modelling
Roslyn et al. (2018) [17]	Partial least squares path modelling (PLS PM)
Brigid et al. (2021) [18]	Systematic literature review
Tobias et al., (2020) [19]	Comprehensive literature review
Vicenc & Eva (2020) [20]	Comprehensive literature review

Researchers were actively studying the idea under the labels HRA and PA in the decade beginning in 2010. HRA domain was granted independent status from data analytics in 2004 [8]. Authors define HR analytics as an approach enabled by information technology that employs statistical, graphic, and descriptive analysis of data on organisational performance, human capital, and other macroeconomic standards to assess the business impact [3].

HRA is regarded to have the ability to revolutionise what HR does and the influence HR has on organisations [9]. Analytics is considered to be "a game-changer for the future of HR." [10].

In the automotive and industrial industries, which were the first to automate, the beliefs and attitudes of employees about technological change are still being examined [11]. However, current advances in emerging technologies like artificial intelligence (AI), robotics, and cloud computing are upending a wide range of industries, including healthcare [12], hospitality [13], wholesale and service sectors [14], banking and financial services, and education [15]. Past studies have explored the barriers based on a systematic literature review; structural equation modelling is shown in Table 1.

As shown in table 1, the current studies have focused on human resource analytics and identifying barriers. However, MCDM methods have not been used for studies in HRM. MCDM techniques have been used in blockchain evaluation systems [21], logistics [22], e-commerce recommender systems [23], financial performance [24], 5G industry evaluation [25], employee categorisation [26].

Regardless of the data type employed, its quality is essential. Academics acknowledge that HRA outcomes are contingent on the quality of the input data. Therefore, data quality is one of the most essential prerequisites for HRA success [27]. Vargas [17] cites culture as an additional leading obstacle to HR analytics implementation. Utilizing enormous volumes of data and more complicated models is a characteristic of HR analytics [7]. The outputs of such models are difficult to comprehend and analyze, making the development of tools (or new methods) to make the results and their consequences clear to executives one of the greatest obstacles in the application of analytics [28]. The legitimacy and trust of these results among executives is a second problem posed by the application of complicated models. Considering the prerequisite to leverage HR data and organizational results like financial data, inconsistencies across systems and the associated data integration challenges hinder the development of new HRA. Technology and software are insufficient. Having the necessary analytical skills is required. It has been proven that the lack of HR personnel with analytical skills is a significant obstacle to the implementation of HRA within firms. Certainly, HR executives do not feel "very confident" in HR's ability to adapt and propel their organizations forward using essential competencies such as analytics and AI [29]. Other barriers to HRA implementation include the effectiveness and efficiency of data collection and analysis [6]. HRA implementation is impossible without correct data; hence, the data must be synchronized and made accessible for the HRA. Insufficient quality data and adequate data are significant challenges to HRA adoption. [9].

Because of its distinct manner of ranking all potential criteria and figuring out the proportional weight of each criterion, MCDM methods are finding increasing utility in organisational decision-making issues [30]. MCDM is a methodical procedure for choosing the best or ideal alternative following a thorough evaluation of various contradictory criteria.

The EWM measures the level of differentiation to assess value. The significant advantage of the entropy weight method (EWM) over other subjective weighting models is the elimination of human influence with the weight of indicators, which improves the objectivity of the outcomes of the thorough review. As a result, recent years have seen an extensive application of the EWM in decision-making [31]. The EWM measures the level of differentiation to assess value [32]. The more the measured value is dispersed, the more differentiated the index is, and the more information may be gleaned [33]. The technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) depends on mathematical operations. The fundamental principle is to simultaneously measure the distances of each alternative to both positive (PIS) and negative ideal solutions (NIS) to choose the best answer. When maximising benefit criteria and minimising cost criteria, the decision-makers (DMs) favour PIS over NIS. In contrast, NIS is the least chosen option regarding these two criteria [34].

III. RESEARCH METHODS

The paper aims to identify the magnitude of the barriers to analytics in the implementation process in organisations and determine its adoption sector-wise. The questionnaire was given to the five hundred employees of IT, Retail, E-commerce, FMCG, Travel & transport, and BFSI. However, 75, 89, 67, 78, and 81 responses respectively were used for the analysis. The study is split into two phases. In the first phase, objective weights are derived for the barriers using EWM and CRITIC. In the second phase of the study, the sector-wise data is processed using TOPSIS and MARCOS to derive the ranking of the sectors based on the implementation and execution of HRA.

Based on the extensive literature study, we identified and categorised the barriers into organisational-related, data-related, and finance-related categories.

TABLE 2

BARRIERS TO IMPLEMENTATION AND EXECUTION OF HRA

Category 1	Organisational related barriers
B1	Culture does not encourage information sharing
B2	Insufficient knowledge about how to use analytics to improve the business
B3	Limited managerial capacity as a result of competing priorities
B4	Lack of executive sponsorship
B5	Lack of expertise in the industry
B6	Strategic ability to act
Category 2	Data related barriers
B7	Inaccurate data
B8	Ability to collect data
B9	Credibility and trust in the result of complex models
B10	Concern with the data
B11	Uncertainty regarding ownership of the data or inadequate governance
Category 3	Finance related barriers
B12	No case for change
B13	Actual expenses exceed anticipated advantages

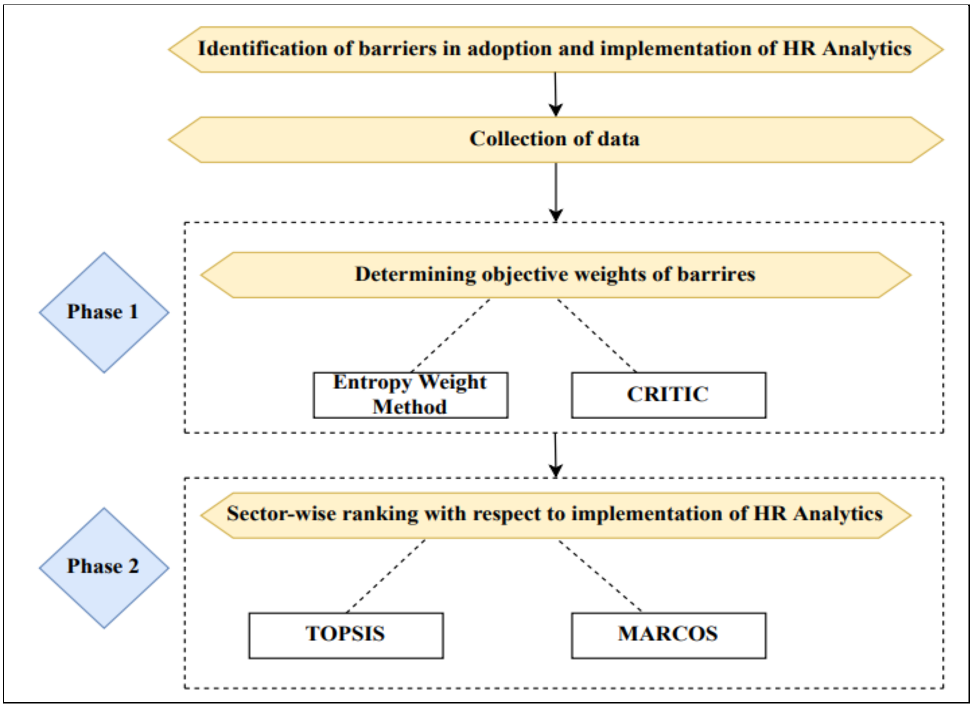

Figure 2: Research Methodology

A. *EWM and CRITIC*

Entropy weight describes the accessibility of several alternatives relative to one another in terms of a certain attribute. Shannon's Entropy is suggested to determine the criterion's weight because it is a powerful technique that improves decision-making and has minimal modelling challenges. When evaluating the weights of indexes using subjective weighting techniques like surveys, Delphi, the Analytic Hierarchy Method (AHP), etc., the weights of the indexes may deviate from these subjective considerations.

TABLE 3

STEPS OF EWM AND CRITIC METHOD

EWM	CRITIC
Step 1: Normalising the decision matrix $p_{ij} = \frac{x_{ij}}{\Sigma_{j=1}^{n} x_{ij}}$	*Step 1: Normalising the decision matrix* $x*_{mn} = \frac{x_{mn} - \min(x_{mn})}{\max(x_{mn}) - \min(x_{mn})}$
Step 2: Calculation of entropy value $E_i = \frac{\Sigma_{j=1}^{n} P_{ij}. \text{In } p_{ij}}{\text{In } n}$ $w_e(j) = \frac{1 - e_j}{\Sigma_{j=1}^{m} (1 - e_j)}$	*Step 2: Calculation of criteria weights using standard deviation and correlation* $w_n = \frac{C_n}{\Sigma_{n-1}^{n} C_n}$ $C_n = \sigma_j \sum_{n=1}^{n} p_{mn} (1 - r_{mn})$

CRITIC, proposed by Diakoulaki, is another objective weight method of MCDM that derives relative weights of the criteria/factors. The standard deviation of the criterion and the connection between the criteria and other criteria are two factors that go into defining the objective weight. Compared to the current objective determination methods, the CRITIC method somewhat approximates the subjective weight and the inner information of data transmission [35]. The sum of all derived weights is one [36].

B. TOPSIS and MARCOS

One of the well-known MCDM methods to find a solution from a finite number of points is the TOPSIS approach, which Hwang and Yoon first developed. The TOPSIS refers to a linear weighting method. Numbers and fuzzy data can both be used with TOPSIS. It is best to choose the alternative that is most similar to the ideal solution according to an additional measure that TOPSIS offers proximity to PIS and distance from the NIS. A scalar criterion that combines the two distance measurements is generated by creating the preference order according to the alternative that is closest to the PIS and farthest from the NIS.

MARCOS consist of seven simple steps. This method is based on evaluating alternatives and their ranking concerning a compromise solution. The MARCOS technique is built on specifying how alternatives and reference values relate to one another (ideal and anti-ideal alternatives). The utility functions of alternatives are established based on the defined relationships, and compromise rankings for ideal and anti-ideal solutions are created.

TABLE 4

STEPS INVOLVED IN TOPSIS AND MARCOS METHOD

Steps	TOPSIS	MARCOS
Step 1	Development of initial decision matrix	Creation of initial decision matrix
Step 2 Development of extended initial decision matrix	$a_{ij} = \frac{1}{k}\sum_{i=1}^{n} x_{ij}$	$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \dots & x_{aan} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{22} & \dots & x_{mn} \\ x_{ai1} & x_{ai2} & \dots & x_{ain} \end{bmatrix} \end{array}$ $AAI = \min_j x_{ij} \quad if \;\; j \in B \quad and \quad \max_j x_{ij} \quad if \;\; j \in C$ $AI = \max_j x_{ij} \quad if \;\; j \in B \quad and \quad \min_j x_{ij} \quad if \;\; j \in C$
Step 3 Normalising the decision matrix.	$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}$ (i=1, …, m; j =1 ,…n)	$p_{mn} = \frac{x_{ai}}{x_{ij}} \quad if \; j \in \; C$ $p_{mn} = \frac{x_{ij}}{x_{ai}} \quad if \; j \in \; B$
Step 4		$v_{mn} = p_{mn} \times w_n$

Determining the weighted matrix.	$v_{ij} = w_j r_{ij}$	
Step 5	Determining the PIS and NIS $A^+ = \{\{v_1^+, \ldots, v_j^+, \ldots, v_n^+) = \{(\max_i v_{ij} \mid j€J1_1), \{(\min_i v_{ij} \mid j€J_2) \mid 1\ldots, m\}$ $A^- = \{\{v_1^-, \ldots, v_j^-, \ldots, v_n^-) = \{(\min_i v_{ij} \mid j€J1_1), \{(\max_i v_{ij} \mid j€J_2) \mid 1\ldots, m\}$	Deriving utility degree of alternatives (K_i) $K_i^- = \frac{S_i}{S_{aai}}$ $K_i^+ = \frac{S_i}{S_{ai}}$ $S_i = \sum_{i=1}^{n} v_{mn}$
Step 6	Calculating the separation value $D_i^+ = \sqrt{\sum_{j=1}^{n}(s_{ij} - s_j^+)2}$ i = 1 ……, m. $D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)2}$ $i = 1 \ldots\ldots, m.$	Determining the utility function of alternatives $f(K_i)$ $f(S_i) = \frac{S_i^+ + S_i^-}{1 + \frac{1 - f(S_i^+)}{f(S_i^+)} + \frac{1 - f(S_i^-)}{f(S_i^-)}};$ $f(S_i^-) = \frac{S_i^+}{S_i^+ + S_i^-}$ $f(S_i^+) = \frac{S_i^-}{S_i^+ + S_i^-}$
Step 7	Determining the closeness coefficients and ranking the sectors $CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$ Where $0 < CC_i \leq 1$, $i = 1, \ldots, m$.	Ranking the sectors

IV. RESULT ANALYSIS

This paper focuses on the barriers that hinder adoption and implementation in the various sectors. Basis of extensive literature review, the authors have acknowledged the barriers and categorised them into organisational, job-related and finance-related ones mentioned in Table 2. EWM and CRITIC are used to assign objective weights, which are then used by other MCDM techniques to assess the relative importance of the various barriers. These methods overcome the disadvantages of objective weight methods as decision-makers intervention can bias the process. The steps of the EWM and CRITIC methods are followed (mentioned in Table 3) to derive the weights of all the barriers. The total weights of all criteria equal one. The higher the weights, the higher the barrier's magnitude and likewise. As per the EWM method, the highest score is B8, followed by B12, B2 and so on. Based on the CRITIC method, the highest score is secured by barrier B6, followed by B9, B1, B10, B11 and so on shown in Table 5.

TABLE 5RESULT OF EWM AND CRITIC METHOD

Weights derived using MCDM	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B1**
Entropy weight method (w_1)	0.0791	0.0786	0.0770	0.0779	0.0745	0.0763	0.0783	0.0807	0.0777	0.0713	0.07
CRITIC (w_2)	0.0880	0.0653	0.0759	0.0693	0.0563	0.0990	0.0796	0.0653	0.0950	0.0850	0.08

The standard deviation is determined in the CRITIC method, followed by correlation based on the weights measured for each barrier. A criterion with a high standard deviation and low correlation with the other criteria is said to have a high criterion weight.

In the TOPSIS method, the steps of normalising and calculating the weighted matrix are followed by determining the separation values that calculates the Euclidean distance for each row from the ideal worst and ideal best values and the ideal best and worst values.

TABLE 6

CALCULATION OF TOPSIS METHOD

Sectors	D_i^+	D_i^-	CC_i	Rank
IT	0.010402	0.042616	0.803806	1
BFSI	0.012448	0.030546	0.710468	2
Retail &E-Commerce	0.029461	0.013304	0.311093	5
FMCG	0.032817	0.02835	0.463488	3
Travel and transport	0.037172	0.023929	0.391625	4

TABLE 7

CALCULATION OF MARCOS METHOD

	S_i	S_i^-	S_i^+	f(S_i^-)	f(S_i^+)	S_i	Rank
Antiideal	0.770263	1					
IT	0.972566	1.262641	0.972566	0.435112	0.564888	0.728432	1

BFSI	0.952734	1.236894	0.952734	0.435112	0.564888	0.713578	2
Retail &E-Commerce	0.845056	1.0971	0.845056	0.435112	0.564888	0.632929	3
FMCG	0.807886	1.048845	0.807886	0.435112	0.564888	0.60509	4
Travel and transport	0.794402	1.031338	0.794402	0.435112	0.564888	0.59499	5
Ideal	1	1.298257	1				

The sector-wise collected data was analysed using TOPSIS and MARCOS to derive the ranking of the sectors. The process from Table 4 was used to generate the sector-wise ranking found in Table 8.

TABLE 8
RESULT OF RANKING DERIVED USING TOPSIS AND MARCOS

Sectors	**Ranking derived using TOPSIS**	**Ranking derived using MARCOS**
IT	1	1
BFSI	2	2
Retail & E-commerce	5	3
FMCG	3	4
Travel and transport	4	5

IT and BFSI sectors ranked 1 and 2 respectively in both the methods. However, the ranks differ for retail & e-commerce, FMCG, travel & transport. This statistical analysis is used to determine the reliability and effectiveness of the study's methodologies. MARCOS is renowned for its versatility and is capable of managing multiple criteria without hinderance. Combining the ratio approach with the reference point technique further enhances MARCOS's accuracy in providing results.

V. DISCUSSION

The preparedness and inclination of organizations to make effective decisions, particularly within the HR department, is a result of HR analytics's potential future as a measurement tool. Despite the promising nature of the usage of HR analytics in businesses, some still struggle to apply it [37]. Most HR departments cannot mix business and data to create organizational results [38]. These deficiencies manifest as a lack of HR analytics expertise, a lack of management support, and inadequate data and tool management.

Big data is viewed as the utmost major "tech" disruption to the business sector since the advent of the internet and digital economy [39]. Wamba [40] defines big data as a systematic tactic to managing, process, and analyse the five V’s, namely; volume, variety, velocity, veracity, and value of the data providing insights that can be put to use for sustained value delivery, performance measurement, and instituting competitive advantage. A massive amount is being produced continuously from various sources like smartphones, e-commerce, social networking sites, and instrumented technology) on any subject that pertains to a business. The main arguments in favour of big data adoption are the substantial declines in the cost of data storage and data-generating technology.

HRA does not meet these three requirements. It uses a wide range of data types (emails, spreadsheets, papers, reports, and evaluations), but HR data is static when compared to customer data. Similarly, the information concerning employees, recruitment, trainings, and more does not change rapidly enough to require real-time data analysis. How often does a company update information regarding its employees' performance, personality qualities, and training programs? HR analytics also fails to meet the volume requirement since HR data is insufficient in amount. Thus, we cannot use the same concepts and techniques of analysis in HRA as we do for big data.

The availability of tools for experimenting with analytics and the time to do so must be ensured. These activities can also be utilized to promote a good approach toward analytics in order to accelerate adoption and improve the number of individuals embracing HRA as well as their adoption rate. Suppose individual users are not statistically savvy but have strong subject-matter expertise. In that case, positions in cross-functional analytical teams should be arranged so that a statistician performs the statistical analysis. In contrast, the individual's knowledge of the data and possibly some modeling are utilized.

Data-related obstacles are the most obvious obstacles to HRA implementation. Large-scale uniformity of existing talent practices, the development of a data governance framework, the realignment of data ownership, the reduction of security and privacy issues, the integration of HR data with other datasets within the organization, and appropriate data analysis, management, and visualization can assist in overcoming these challenges. HR professionals must develop a compelling argument for exploiting data insights to attract investments; however, there is a paucity of literature on how to leverage such data. In the case of HRA, this issue is more tough to resolve because it is frequently impossible to comprehend the core behavior and decision-making processes.

Certain industries have led the way in terms of investment in this subject. Businesses in these industries tend to have clear expectations of HRA teams based on their shared experience and use the results to guide their strategic talent strategies. Due to the presence of a supportive environment, resources with expertise in managing data infrastructure, investments in strong technology to handle HR operations, and a data-driven culture, these industries have made significant advancements in this field. Thus, HRA teams can benefit both the critical management knowledge for an analytics function from other teams as well as their experience in functions such as establishing a data dictionary, documenting SOPs, and tracking productivity.

Our paper highlights the barriers in adoption of HRA and also makes an effective use of MCDM techniques to rank the sectors based on level of acceptance and implementation of HR analytics. Methodologically, the analysis is completed in two phases divulging the thirteen barriers identified based on existing literature.

VI. CONCLUSION

Due to the swift development of new technologies, such as innovative technology, AI and automation, robotics, cloud computing, and the IoT, the nature of work is primarily altering which raises apprehensions about the future of organisation and jobs [41]. Organisations need to adapt and transform their business models to stay competitive and keep up with the rapid disruption. Incorporating analytics into human resources will aid in analysing, anticipating, and diagnosing organisational challenges and in making better decisions regarding employees.

Because of its complexity, HR Analytics combines technical tools and data analysis. HR analytics go beyond just being sophisticated algorithms for data analysis. Their results are as helpful as they are regarded. Therefore, it is essential to research data visualisation for non-data scientists to include managers in the implementation and development of HRA. Few issues that must be addressed are: Which visualisations work best with each HR analysis (and possibly for each type of management profile)? What degree of complexity and depth best fits the characteristics of these managers? Furthermore, how can these managers be trained in the application and analysis of the outcomes of HRA? These fundamental issues pose a barrier if not addressed by the organisation.

As per Deloitte survey 2021 [42], access to appropriate data, skills & knowledge, and capacity are the significant barriers preventing the adoption and implementation of analytics. Risks can be assessed using analytical techniques mentioned in figure 3. Regarding analytics applications across risk areas, regulatory & compliance, operations, conduct, culture, and strategy hold a significant share in risk factors, and analytical tools can help identify and rectify these associated risks.

Past studies have explored the barriers based on a systematic literature review; structural equation modelling is shown in Table 1. However, we have used MCDM methods to identify the magnitudes of various barriers and rank the sectors based on adopting HR analytics. EWM and CRITIC methods are used to identify the barriers serving as the major setback for the adoption. TOPSIS and MARCOS methods are devised to derive the ranking of the sectors that have adopted HRA. The proposed framework provides insight into the barriers. It gives a quantitative view of measuring the magnitude of the barriers, which provides the decision-makers with the fundamental base to frame strategies accordingly. MCDM methods have been used by researchers in operations, supply chain management, and logistics majorly, but no application in human resource management. This paper has increased the horizon of MCDM into HRA [43]-[46].

HR analytics study is not at a fully developed state. Despite the increased interest in HR analytics over the past few years, there continues to be confusion about what HR analytics entails, let alone its application. Unfortunately, scholarly study provides little assistance in locating the correct solutions. In reality, HR analytics research needs to catch up to what businesses are doing in this area in terms of vision and leadership. Various lexemes (such as HR analytics, talent analytics, workforce analytics, and PA) have also referred to this issue, which can be viewed as evidence of its infancy.

VII. LIMITATIONS AND FUTURE SCOPE OF THE STUDY

The authors have devised MCDM methods for five sectors, however, more sectors can be examined using MCDM techniques other than EWM, CRITIC, TOPSIS, and MARCOS. The questionnaire was sent to five hundred respondents; however, the sample size can be increased in future studies to get insights of more people of the concerned sectors.

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