Assessment of Data Sophistication in HR functions by Applying Ridit Analysis

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http://doi.org/10.26782/jmcms.2019.10.00031

Abstract

The wealth of organizations is being determined by the amount of quality data they possess. Organizations across the globe have recognised this phenomenon. With abundance of data along with advanced analytic tools and technologies, many organizations have embraced business analytics into their essential strategic and operational decision-making tools. Heart of business analytics is the data. The quality and value of decision-making outcomes lie with the data inputs supplied. Big data and social media analytics have given impetus to the expansion of business analytics into all critical functional areas of the organization. Though a little late, the domain of HR has also caught up the trend of applying analytics. This new area is termed as people analytics or HR analytics. In this paper, an attempt is made to understand the extent of data availability and usage in analytics, termed as data sophistication in HR analytics in the organizations. As there are no definite ways to determine the data sophistication levels, a response sheet with a set of 20 items is developed based on previous literature. Data is collected from HR professionals. This data is subjected to exploratory factor analysis to capture the important dimensions from the items. Using structural equation modelling, confirmatory factor analysis was carried out to assess the model fit. Based on the resultant model, data is subjected to ridit analysis to interpret the treatment effect intuitively. The findings of the study add to the field of study in the area of data analytics, HR analytics, and decision-making domains. New approaches and study opportunities in related areas can be explored in this area due to its fast-emerging nature.

Keywords: Data analytics, Data sophistication, HR analytics, ridit analysis
I. Introduction

The emergence of new data capturing, storage, and processing technologies has led the organizations into a new era of data analytics. Much popularly, this area of knowledge is being termed as data science. Organizations always want to have more in-depth insights into their business performance as well as the other factors affecting their business. Right data inputs would enable the organizations to decide on various strategic and operational issues. For realising the value of data, analytics is being implemented by organizations. Analytics is employed widely by top-performing organizations (LaValle et al., 2011). Organizations that could not catch up on the analytics pace are turning down themselves as low performers. Heightened global competition and significant transformation in the data handling capabilities has made the Human Resource (HR) domain to advance into the analytics area (Fink, &Sturman, 2017). Big data applications have furthered the momentum of using robust analytical applications in organisations. Technology has always been expanding the horizons to become even more sophisticated in HR functions (Davenport, Harris & Shapiro, 2010). Earlier too organisations were deploying the big data technologies, yet, the value leveraged from big data has multiplied in recent times. Organisations that are leveraging value from big data are doing it at a very sophisticated level (Russom, 2011). Data thus is the vital instrument that needs to be of high-level precision to leverage the best value. In terms of HR analytics, the data being consumed should be sophisticated, ensuring clear understandability and being user-friendly (Molefe, 2014).

In this context, the present study investigated the utility of HR data in organizations in terms of the data sophistication in organizations to take various HR-related decisions. Literature related to big data, data analytics, business analytics, and business intelligence are reviewed first. Through the study, an attempt is made to identify the key areas where HR data is used in the organizations. Also, the maturity level of data sophistication is assessed. The broad functions of HR are brought together to identify the sub-groups of HR functions, where data sophistication is essential. It is attempted to understand the extent of value placed on the HR functions’ data sophistication by the HR professionals. The present study will contribute to understanding the various functions in HR that are to be measured. The data sophistication level at which the organisations are operating is also known through the present study.

II. Literature Review

In this section, research works in the context of big data, data analysis, and data sophistication are briefly reviewed.
Sahay and Ranjan (2008) in their study on business intelligence in supply chain analytics have opined that it is a challenging task to bring together data from multiple sources and consolidate into a unified source of data. In their conceptual paper, they discussed the issues related to business intelligence and supply chain analytics.

Kohavi, Rothleder, and Simoudis (2002) recommend using data mining techniques in analytics that would enable users to get the right form of data without requiring to apply analytic expertise each time the data is used. Refined data can be presented to business users with the help of several data mining techniques on board. As analytics become an enterprise-wide application, collection, refinement, and processing of data also tend to become a part of the larger enterprise system.

Lahrmann et al. (2010) presented different maturity models of business intelligence and compared their contributions. The central idea of all the maturity models is to gauge the progress of the organisations on the analytical capabilities based on the data processing and utility in the organisation.

Phillips-Wren et al. (2015) reviewed the research in the area of big data analytics. In their work, they presented a framework that enables organisations to deploy and understand their state of big data analytic progress. The authors discuss the challenges faced in big data storage, processing, and merging streams of data based on the academic and practitioner expert opinions.

Malladi (2013) assessed various factors affecting the adoption of business intelligence systems in organisations using the TOE framework. The study highlighted that along with data related infrastructure and sized of the data; specific industry-related issues also affect the adoption of business intelligence systems.

LaValle et al. (2011) argued that the information agenda is a critical facilitator for the progress in analytics for any organisation. Information agenda comprises several essential ideas related to data and its management. Organisations increase their analytical capabilities as they progress through the information agenda.

Ransbotham, Kiron, and Prentice (2016) emphasise that besides developing skills and culture towards analytics, the strategy should also focus more on data management. In organizations that have progressed in analytics, data is distributed and positioned well to respond to the needs of the organization.

Kaisler et al. (2013) have researched on various issues and challenges faced in the implementation of big data analytics in the organisation. The amount of data being collected is growing enormously high. Identifying data that could leverage decision making is a crucial challenge. Also, processing the data to the highest refinement and its visualization for better representation are the other vital issues.

Earley (2015) believes that enhancing the business value and facilitating new business models is possible only when the organisations have their internal data hygiene and required infrastructure capabilities in place. Without the foundational data management and integration, it is not possible to ensure analytic benefits.
Banerjee, Bandyopadhyay, and Acharya (2013) have investigated whether data analytics is a created hype, or it has the real potential to give value. They argue that big data poses a challenge to extract the meaningful patterns of data from complex sets. Even experienced data analytics professionals have to face the challenge of combining the new data sources with the traditional ones.

The review of the literature points towards focusing on data related aspects as a foundation for deploying analytics in the organisation. As HR analytics tends to progress from its nascent stage, it is imperative that organizations need to assess their data capabilities and readiness to adopt HR analytics. In the present study, it is attempted to propose ways to assess the levels of data sophistication being implemented in organizations to take various HR decisions. The method followed to study the data sophistication levels is presented in the next section.

III. Methods

In this section, the approach followed in formulating the study instrument, data collection, and analysis is presented.

There are not many studies in particular reference to measuring the sophistication levels of HR data available in the organisation. Levenson (2011) assessed certain HR functions in various organizations to understand the level at which data is being used in the organizations. In the present research, the functions considered by Levenson, 2011 are taking into consideration and are slightly modified for assessment.

III.i. Instrument Development

From the literature on the data analysis and business intelligence related works, a set of 20 items were developed to understand the data sophistication levels in organizations in terms of HR data (Levenson, 2011). A slightly adjusted Likert’s five-point scale is defined with the range of basic, exploratory, predictive, prescriptive, optimisation on which the sophistication levels of data analysis is measured (Poreca, 2018). This 20-item questionnaire was reported to experts in HR and data sciences. After language revisions and modifications made according to the expert opinion, the questionnaire was finalised. The 20 items were given labels from DS1 to DS20 for quick reference in the data analysis. The questionnaire was sent to HR professionals of various industries to capture responses. A total of 390 responses were received. It is considered that this sample is adequate to perform any multivariate analysis techniques and structural equation modelling (SEM) as advocated by Hair et al. (2013) and Tabachnick & Fidell (2013).

III.ii. Analysis methods

The scale was first tested for reliability; to this extent, Cronbach alpha coefficients were calculated. To understand the factor structure underlying the data
items in the study, first exploratory factor analysis (EFA) was performed. After EFA, the measurement model was determined using confirmatory factor analysis (CFA). To estimate the factors present in the scale, Principal components analysis (PCA) was used. After varimax rotation, the data was assessed to verify the number of factors using a) Kaiser's criterion, b) scree plot, and c) parallel analysis (Horn, 1965). Using AMOS (Ver. 24), confirmatory factor analysis was carried out. The factors confirmed in the subgroups were labelled accordingly as per the items represented under the factor. The model fit statistics were obtained and compared with the recommended threshold values.

III.iii. Ridit analysis

In the present paper, ridit analysis as defined by I. Bross is adopted. Ridit analysis has no assumption about the population distribution under study. Suppose that there are m items and n ordered categories listed from the most favored to the least favored in the scale, then, RIDIT analysis goes as follows (Wu C H, 2007) below.

Step 1: Calculating ridits for the reference data set
The total population study data can be applied as reference data when exact reference data is not available for Likert scale data.

Calculate $g_j$ for each class of responses, where $j=1,2,...,n$.

Calculate mid-point accumulated frequency $K_j$ for each class of response.

$K_1 = \frac{1}{2} g_1$

$K_j = \frac{1}{2} g_1 + \sum_{k=1}^{j-1} g_k$, where $j = 2, 3, ..., n$

- Calculate $C_j$ for each class of response in the reference data set.

$C_j = \frac{K_j}{N}$, where $j = 1, 2, ..., n$.

$N$ refers to the total sample size in the study. By definition, the expected value of $C$ for the reference data set is always 0.5.

Step 2: Calculating ridits and mean ridits for comparison data sets. A comparison data set has the frequencies of responses for each category of a Likert scale item. Since there are m Likert scale items in this illustration, there will be m comparison data sets.

- Calculating ridit value $r_{ij}$ for each category of scales items.

$\gamma_{ij} = \frac{C_j \times \Pi_{ij}}{\Pi_{ij}}$, where $i = 1, 2, ..., m$.

$\Pi_{ij}$ is the frequency of category $j$ for the $i^{th}$ scale item, and $\Pi_i$ is a short form for the total of frequencies for scale item $i$ across all categories, i.e. $\Pi_i = \sum_{k=1}^{n} \Pi_{ik}$.

- Calculate mean ridit $\rho_i$ for each Likert scale item,
Calculatethe confidence interval for $P_i$, when the size of the reference data is very large relative to that any comparison data set, the 95% confidence interval of any $P_i$ is

$$P_i \pm \frac{1}{\sqrt{3\Pi_i}}$$

Verify the hypothesis using Kruskal-Wallis statistic K-W:

$H_0$: $P_i = 0.5, \forall i$

$H_1$: $P_i \neq 0.5, \forall i$

$$K-W = 12 \sum_{i=1}^{m} \Pi_i (P_i - 0.5)^2$$

K-W follows a $\chi^2$ distribution with (m-1) degree of freedom. If $H_0$ cannot be accepted, examine the relationships among confidence intervals of $P_i$.

Generally, $P$ is interpreted as:

Deviation of $P_i$ value from 0.5 implies a significant difference between the reference and the comparison data sets for the specific item. If the confidence interval of $P_i$ contains 0.5, then it is accepted that the $P_i$ value is not significantly deviate from 0.5. $P_i$ is expected to be low showing a low probability of being in a negative propensity. Overlapped confidence intervals of response patterns of $P$ show statistical differences among respondents.

IV. Results and Analysis

IV.i. Reliability

Cronbach's Alpha values were obtained to assess the reliability of the scale. All the 20 items in the study were included for reliability analysis. The results indicated that the reliability value is 0.855 (Chronbach’s Alpha), which suggests the instrument compiled for the study to be of good reliability. Reliability statistics are presented in Table 1.

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|------------------|-------------------------------------------|------------|
| .854             | .855                                      | 20         |

Table 1. Reliability Statistics
The item-total statistics were obtained to check whether the reliability of the instrument can be further enhanced by removing any items. The comparison values (Table 2) indicate that the reliability of the instrument may not further be improved by removing any of the 20 items on the scale. The 20 items related to HR functions included in the study are: DS1-Strategic planning, DS2-HR planning, DS3-Diversity, DS4-Recruitment, DS5-Selection, DS6-Compensation, DS7-Benefits, DS8-Employee training/education, DS9-Management development, DS10-Performance management, DS11-Competency/talent assessment, DS12-Promotions, DS13-Career planning, DS14-Succession planning, DS15-Employee attitude surveys, DS16-Downsizing/layoffs, DS17-Union/labor relations, DS18-Organization design, DS19-Organization development, DS20-Change management

| Item | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Squared Multiple Correlation | Cronbach's Alpha if Item Deleted |
|------|---------------------------|-------------------------------|---------------------------------|-------------------------------|---------------------------------|
| DS1  | 63.13                     | 128.156                       | .540                            | .926                          | .843                            |
| DS2  | 63.11                     | 130.158                       | .489                            | .840                          | .846                            |
| DS3  | 63.09                     | 128.898                       | .534                            | .880                          | .844                            |
| DS4  | 62.97                     | 130.958                       | .442                            | .953                          | .847                            |
| DS5  | 63.20                     | 131.781                       | .406                            | .207                          | .849                            |
| DS6  | 63.19                     | 131.494                       | .442                            | .277                          | .848                            |
| DS7  | 63.24                     | 131.414                       | .441                            | .953                          | .848                            |
| DS8  | 62.91                     | 131.518                       | .441                            | .953                          | .848                            |
| DS9  | 63.23                     | 131.087                       | .452                            | .935                          | .847                            |
| DS10 | 63.28                     | 129.824                       | .470                            | .936                          | .846                            |
| DS11 | 63.22                     | 132.343                       | .405                            | .233                          | .849                            |
| DS12 | 63.15                     | 132.014                       | .386                            | .253                          | .850                            |
| DS13 | 63.13                     | 132.513                       | .374                            | .227                          | .850                            |
| DS14 | 63.21                     | 130.302                       | .446                            | .254                          | .847                            |
| DS15 | 63.29                     | 131.499                       | .418                            | .233                          | .848                            |
| DS16 | 63.31                     | 132.034                       | .383                            | .183                          | .850                            |
| DS17 | 63.35                     | 130.959                       | .416                            | .214                          | .849                            |
| DS18 | 63.23                     | 131.506                       | .411                            | .260                          | .849                            |
| DS19 | 63.08                     | 132.463                       | .400                            | .229                          | .849                            |
| DS20 | 63.06                     | 127.929                       | .562                            | .421                          | .843                            |

Table 2. Item-Total Statistics
IV.ii. Factor Analysis

In order to verify the factor structure of data sophistication scale for HR functions, factor analysis is conducted. Through this, the underlying structure of factors can be estimated. At first, principal components analysis (PCA) was carried out on the twenty items of the data sophistication levels of HR functions. The correlation statistics indicated the presence of several coefficients above 0.3 values. The KMO value computed has shown .691 and Bartlett’s Test of Sphericity also was of significance (Table 3).

| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | .691 |
|--------------------------------------------------|------|
| Bartlett’s Test of Sphericity                     |      |
| Approx. Chi-Square                                | 4074.589 |
| df                                               | 78   |
| Sig.                                             | 0.000 |

Table 3. KMO and Bartlett’s Test

PCA indicated the presence of five components with eigenvalues above 1. The scree plot (Fig. 1) also indicated a break next to the fifth component. Thus, the five-component structure was retained for further study.

![Scree Plot](image)

Fig.1. Scree Plot

The results of the parallel analysis confirmed the five-factor structure (Table 4). Only five components were found to have eigenvalues more significant than the random criterion values.
Table 4. Comparison of eigenvalues from PCA and criterion values from parallel analysis

In the next step, exploratory factor analysis was carried out on the five-components with varimax rotation. Some of the factors did not load. The final five-factor model explained 76.32% of the variance. The rotated solution had five factors with strong loadings for variables (Table 5).

Table 5. Total variance Explained
Component 1 2 3 4 5

|    | Component |
|----|-----------|
| DS1 | .961      |
| DS3 | .942      |
| DS2 | .939      |
| DS8 | .969      |
| DS4 | .968      |
| DS9 | .966      |
| DS10| .960      |
| DS12| .741      |
| DS18| .721      |
| DS15| .624      |
| DS7 | .744      |
| DS13| .739      |
| DS17| .510      |

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 6. Varimax Rotation of 5 factor Solution: Rotated Component Matrix

IV.iii. Confirmatory factor analysis

After the five-factor structure was identified, confirmatory factor analysis was carried out using the maximum likelihood estimation approach. The model achieved significantly high factor loadings. The measurement model output had 13 items mapped to five components (Fig. 2). Considering the similar nature of the items loaded on to the five factors, the factors are given labels as planning functions, talent acquisition, training & development, compensation & benefits, and employee relations.
The model fit indices (Table 6) showed that all the fit indices (CMIN/DF, CFI, GFI, RMSEA) are well above the prescribed threshold limits of structural model fit indices (Rex B. Kline, 2005).

Fig.2. Path Diagram of the Data Sophistication Measurement Model

The model fit indices (Table 6) showed that all the fit indices (CMIN/DF, CFI, GFI, RMSEA) are well above the prescribed threshold limits of structural model fit indices (Rex B. Kline, 2005).
IV.iv. Ridit Analysis

To perform ridit analysis, the data sophistication levels of HR functions with 13 items are considered. The required reference data set (Agresti, 1984 and Bross, 1958) of the sample is chosen to represent the stable ridits. The frequencies andridit values of the reference data set are presented in Table 7. Rj values in the last row refer to the ridit value of the corresponding response category. Similarly, the ridit values of the comparison data sets are calculated and presented in Table 8. From the data obtained, the Kruskal-Wallis K-W is computed. As the Kruskal-Wallis K-W (54.47) is significantly greater than $\chi^2(13 - 1) = 21.026$, it is referred to as responses having statistical differences. The confidence intervals of item DS17 vary significantly fromDS8. Among the items, a higher priority is placed on DS17 compared to other items. Very low preference is placed on item DS8.

| Measure | Estimate | Threshold | Interpretation |
|---------|----------|-----------|----------------|
| CMIN    | 71.254   | --        | --             |
| DF      | 55       | --        | --             |
| CMIN/DF | 1.296    | Between 1 and 3 | Acceptable |
| CFI     | 0.996    | >0.95     | Acceptable     |
| GFI     | 0.973    | >0.95     | Acceptable     |
| TLI     | 0.994    | >0.90     | Acceptable     |
| NFI     | 0.983    | >0.90     | Acceptable     |
| AGFI    | 0.955    | >0.80     | Acceptable     |
| SRMR    | 0.038    | <0.08     | Acceptable     |
| RMSEA   | 0.028    | <0.05     | Acceptable     |
| PClose  | 0.989    | >0.05     | Acceptable     |

Table 6. Model Fit Summary

* Rex B. Kline. (2005) recommend values.
Table 7. Ridits for the Data Sophistication Levels of HR Functions reference data set

|        | Descriptive | Exploratory | Predictive | Prescriptive | Optimization | \( P_i \) | Lower Bound \( * \) | Upper Bound \( * \) | Priority Rank |
|--------|-------------|-------------|------------|--------------|--------------|---------|----------------|----------------|--------------|
| DS1    | 0.0035      | 0.0319      | 0.0471     | 0.3113       | 0.1202       | 0.5140  | 0.485          | 0.543          | 9            |
| DS2    | 0.0026      | 0.0336      | 0.0557     | 0.3096       | 0.1131       | 0.5147  | 0.485          | 0.544          | 10           |
| DS3    | 0.0028      | 0.0323      | 0.0529     | 0.3130       | 0.1179       | 0.5188  | 0.490          | 0.548          | 11           |
| DS4    | 0.0021      | 0.0275      | 0.0769     | 0.2399       | 0.2003       | 0.5468  | 0.518          | 0.576          | 12           |
| DS7    | 0.0050      | 0.0280      | 0.0894     | 0.1837       | 0.1791       | 0.4852  | 0.456          | 0.514          | 6            |
| DS8    | 0.0018      | 0.0236      | 0.0807     | 0.2535       | 0.2003       | 0.5600  | 0.531          | 0.589          | 13           |
| DS9    | 0.0025      | 0.0345      | 0.1086     | 0.1991       | 0.1343       | 0.4790  | 0.450          | 0.508          | 4            |
| DS10   | 0.0036      | 0.0350      | 0.0971     | 0.1974       | 0.1367       | 0.4697  | 0.440          | 0.499          | 3            |
| DS12   | 0.0032      | 0.0297      | 0.0923     | 0.2127       | 0.1650       | 0.5028  | 0.474          | 0.532          | 7            |
| DS13   | 0.0026      | 0.0315      | 0.0990     | 0.1957       | 0.1768       | 0.5054  | 0.476          | 0.535          | 8            |
| DS15   | 0.0035      | 0.0332      | 0.1067     | 0.1974       | 0.1249       | 0.4656  | 0.436          | 0.495          | 2            |
| DS17   | 0.0048      | 0.0297      | 0.1057     | 0.1905       | 0.1249       | 0.4557  | 0.426          | 0.485          | 1            |
| DS18   | 0.0035      | 0.0315      | 0.0961     | 0.2144       | 0.1367       | 0.4821  | 0.453          | 0.511          | 5            |

Kruskal-Wallis K-W=54.47; \( \chi^2 (13-1)=21.026 \)

Table 8. Ridits for the Data Sophistication Levels of HR Functions comparison data sets.

Note: * indicates 95% confidence interval of mean ridit \( P_i \).
V. Conclusion

Through the present study, an attempt is made to assess the levels of data sophistication in various HR functions in organizations in the context of applying HR analytics. To take the HR analytics implementation forward, it is important to ensure a higher level of data sophistication across all these HR functions. There is limited literature available to this extent of understanding data analytics in the context of HR analytics. The 20-item scale developed for the study is processed using structural equation modelling and ridit analysis. The model presented attained good reliability. The measurement model was well identified with 13-items. Through confirmatory factor analysis, the model was found to have achieved required threshold limits for the goodness of fit. A five-factor model was confirmed through the analysis. The five sub-functions of HRM are recognised and labelled accordingly. By applying ridit analysis scores to the response data, the priority placed on the items was obtained through ranking.

Due to slow progress in adopting, HR analytics has not reached higher levels of implementation in an organization. The background problem lies with the available data and the form in which it is processed to make it useful for the decision-makers. Thus, understanding the extent of data sophistication available in HR functions in organizations would help in assessing the readiness to make use of HR analytics. The scale used in the present study would help in extending the future research area in this context. Further studies can be carried out to understand the data analytics in the HR functions and implementation levels towards HR analytics.

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