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A Model to Evaluate the Organizational Readiness for Big Data Adoption

M. Nasrollahi, J. Ramezani

Mahdi Nasrollahi
Imam Khomeini International University (IKIU)
Qazvin, IRAN
m.nasrollahi@soc.ikiu.ac.ir

Javaneh Ramezani*
1. NOVA University of Lisbon, Faculty of Sciences and Technology
Campus da Caparica, 2829-516 Monte Caparica, Portugal
m.ramezani@campus.fct.unl.pt
2. UNINOVA-CTS
Campus da Caparica, 2829-516 Monte Caparica, Portugal
*Corresponding author: ramezanijavaneh@gmail.com

Abstract

Evaluating organizational readiness for adopting new technologies always was an important issue for managers. This issue for complicated subjects such as Big Data is undeniable. Managers tend to adopt Big Data, with the best readiness. But this is not possible unless they can assess their readiness. In the present paper, we propose a model to evaluate the organizational readiness for Big Data adoption. To accomplish this objective, firstly, we identified the criteria that impact organizational readiness based on a comprehensive literature review. In the next step using Principal Component Analysis (PCA) for criterion reduction and integration, twelve main criteria were identified. Then the hierarchical structure of criteria was developed. Further, Fuzzy Best-Worst Method (FBWM) has been used to identify the weight of the criteria. The finding enables decision-makers to appropriately choose the more important criteria and drop unimportant criteria in strengthening organizational readiness for Big Data adoption. Statistics-based hierarchical model and MCDM based criteria weighting have been proposed, which is a new effort in evaluating organizational readiness for Big Data adoption.

Keywords: organizational readiness, big data adoption, industry 4.0, fuzzy best-worst method, principal component analysis.

1 Introduction

The transformation of industrialized economies from a manufacturing base to a service orientation is an ongoing phenomenon. Contemporary, developments in information and communication technology helped organizations to access information about their market, competitors, customers, partners and . . . more easily and quickly, and this can positively impact their business processes. Furthermore, due to the rise of ever-tougher challenges in the ever-changing business environments characterized by high complexity and uncertainty, there is a clear need to respond in almost real-time to upcoming business challenges and opportunities [3]. Besides, one of the most important outcomes of the emerging Fourth Industrial Revolution (Industry 4.0) paradigm empowered by the integration of Internet of Things (IoT) technology into industrial value creation is the large generating volumes of data [19]. For these reasons, con-temporary developments in information and communication technology, and growing competitiveness have led to the emergence of the real-time Big Data analytic as a new enabler of sustainable development and sustainable competitive advantage [11].

Knowledge is a fundamental source of competitive advantage. Therefore, mining data to extract useful information about competitors, customers, suppliers, etc. and also to observe and track trends and changes in the business environment is becoming extremely beneficial for making intelligent business decisions. Big Data and its associated technologies are now relevant across industries and economic sectors [11], [22], [24].

While the term "Big Data" has been defined in different ways in the related literature sources, there is still no concrete definition to this term itself. The first concepts predominantly associated with Big Data are far from new and relate to data storage and data analysis. This is in part due to the role of digital data– available in fast-growing amounts - being produced by data-intensive organizations [22]. The fundamental notion primarily describes Big Data using the "3 Vs": Volume (referring to the amount of data), Velocity (relating to speed by which data is generated and delivered), and Variety (referring to diversity of data sources and formats) [5]. Soon the idea evolved to "5 Vs" by adding Veracity (referring to data quality) and Value (relating to the benefits from the use of data) to the former "3 Vs" [4]. Recently, Big Data has been characterized "by 7 Vs: Volume, Velocity, Variety, Veracity, Variability Visualization, and Value [12]. These characteristics of Big Data have been explained in a recent literature review [18]. In a nutshell, Big Data, as identified by [6], is a combination of architectures and innovative technologies designed to capture the value and vital information from vast volumes of data in different variety, resulting in data analysis and high-velocity capture.

In this regard, the field of Big Data adoption looks at how we can analyze, systematically extract information from, or in other words, deal with Big Data [22], [24]. The foremost opportunity and benefit Big Data adoption presents is resourcefulness in terms of cost, productivity, and competitiveness. Big Data adoption in enterprises soared from 17% in 2015 to 59% in 2018, reaching a Compound Annual Growth Rate (CAGR) of 36% [26]. Nevertheless, according to a comprehensive Big Data analytic study, only 14% of enterprises have put Big Data projects into production [27]. Again, according to [26], "there is a strong upward trend in adoption and a corresponding drop in those with no plans." Against this background, Big Data adoption decisions involve high levels of uncertainty and complexity that most are related to the sophisticated technology and infrastructural requirements for organizations. Therefore, there is a need for a more systematic and appropriate study of tools for assessing the potential of organizations to develop Big Data implementation. Accordingly, this paper has attempted to develop a model to measure the level of organizational readiness for Big Data adoption following the objectives listed below:

(1) Identifying the criteria that are involved in evaluating the organizational readiness for Big Data adoption.

(2) Reduction and integrating of criteria using factor analysis and developing the hierarchical structure.

(3) Determining the weights of criteria using the fuzzy BWM method.

(4) Establishing hierarchy among criteria.

The remainder of this paper is organized as follows. Section two briefly describes the design and methodology of the research. Section 3 highlights the critical criteria for evaluating organizational readiness. Section 4 provides an overview of fuzzy BWM and highlights the detailed procedure for determining the importance of criteria using fuzzy BWM; describing the fuzzy-ISM and using it for modeling criteria is discussed in section 5. The last section presents the conclusion and further research directions.

2 Research methodology

Research methods are the strategies, processes, or techniques utilized in the collection of data or evidence for analysis in order to uncover new information or create a better understanding of the topic. The main purpose of this study is to identify and rank the organizational readiness criteria for Big Data adoption. To fulfill this objective, we applied field data with a focus on large scale organizations and experts with experience or expertise in this field. We need to perform a preliminary factor analysis and item reduction of evaluation criteria to achieve this purpose. Completing the factor analysis and modification of items is essential for several reasons. First, the number of identified criteria is 50 items and is too long, and some criteria have repetitive meaning. Second, several criteria required consistent clarification.

For factor analysis, a principal component analysis (PCA) was selected to consolidate the criteria. We applied an internet-based questionnaire to gather data from a sample of experts around the world. The questionnaires were sent to respondents through an email process and messages on LinkedIn. From 5th-10th September 2019, a questionnaire was sent to 2120 experts. The limited available space does not allow to provide more details about questionnaires and experts. A total of 246 answers from experts were received over 30 days. 39 answers were eliminated as not being correctly completed. Finally, only answers from 207 experts that completed the survey were kept for an analysis. Thus, data from 207 experts were included in the data set yielding a valid response rate of 9.8 percent. All data were analyzed with version 25.0 of IBM SPSS. Table 1 shows the demographics of the sample.

Table 1: Sample demographics

Item		N	%
Job title	Managing Director	34	16/4
	Vice president	20	9/7
	Consultant	33	15/9
	University Professor/Lecturer	45	21/7
	Information system manager	27	13/0
	Researcher	38	18/4
	Other	10	4/8
Education	Bachelor's degree	4	1/9
	Master's degree	76	36/7
	Professional degree	8	3/9
	Doctorate	106	51/2
	Postdoctoral	13	6/3
Age	Under 24	3	1/4
	25–34	92	44/4
	35–44	76	36/7
	45-54	31	15/0
	Over 55	5	2/4
Work experience	1-5	43	20/8
	6-10	82	39/6
	11–15	29	14/0
	16–20	44	21/3
	Over 21	9	4/3
Total	207	100	

Figure 1 shows various steps of research process.

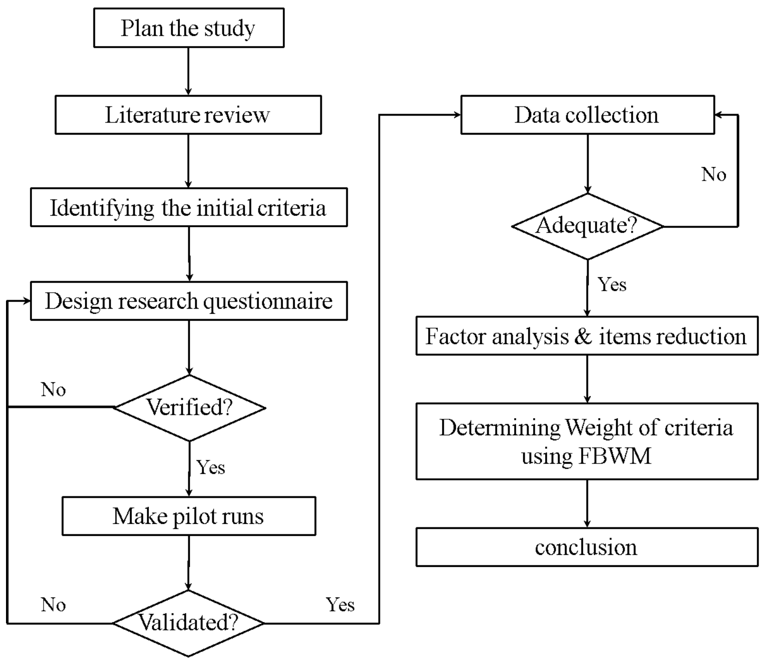

Figure 1: Research process

3 Identification of Organization Readiness Criteria

Although organizations invest in Big Data for its recognized benefits, the actual realization of Big Data benefits lies in the complete readiness of organizations to adopt Big Data. Based on a comprehensive review of the relevant literature, 50 initial criteria for evaluating organizational readiness for Big Data adoption have been identified (Table 2).

An initial sample of 30 experts was completed the questionnaire's 50-item draft version. Cronbach's alpha was applied to verify the internal consistency of the constructs and to measure the scale reliability. The results in Table 3 show that the alpha value is above 0.7, and constructs are consistent accordingly. Data normality must be evaluated before running the statistical tests. The normality of the data was tested at a meaning level of 5% using the K-S test. The level of significance for all constructs was greater than 5 percent, so the data had a normal distribution.

The adequacy of the data set was determined by the use of Bartlett's test for sphericity and the "Kaiser Meyer Olkin" measure of sampling adequacy. As specified in Table 4, Bartlett's test for sphericity was significant ($P < 0.05$), and the KMO index was 0.916; therefore, the sample was determined to be adequate for further analysis.

Principal component analysis (PCA) is a method of consolidating mutually correlated criteria to a smaller number of criteria [9]. After the PCA is run, Eigenvalue is analyzed to aid in selecting the number of factors that have to be extracted as part of the next step. Table 5 aid in deciding the number of criteria to be obtained. From Table 5, it is seen that criterion 12 has a variance of 1.326; and variance of 1.0 and above shows that there is considerate variability in the criterion. Thus, it leads to con-ducting a 12-criterion extraction.

In an attempt to propose the underlying theme or criterion within each domain, the research team, grouped the items from the matrix of pattern correlation using the varimax rotation on these 12 domains. Rotation optimizes the criterion structure and improves the interpret ability of the criterion solution. The unrotated and varimax rotation factors were analyzed, and the variables were categorized under criteria based on their maximum absolute value. The result was a decrease from 50 criteria in the initial study to 12 criteria. A name was selected for each criterion according to the type and structure of the criteria. Figure 2 shows the hierarchical structure of organizational readiness evaluation criteria for big data adoption.

Table 2: Factors affecting Big Data adoption

Criteria	References
Appropriateness	[24], [2], [23]
Availability of Big Data tools	[2], [17], [13]
Big Data awareness	[8], [16]
Business strategy orientation	[24], [2]
Change efficacy	[24], [2]
Competitive (Perceived industrial pressure)	[24], [2], [13],[14], [10], [25], [1], [15]
Complexity	[24], [2], [16], [14], [15]
Cost of adoption	[24], [2], [15]
Data control	[2], [1]
Data quality and integration	[22], [12], [2], [17], [10], [25], [1], [15]
Decision-making culture	[24], [2]
Firm size	[24], [2], [15]
Government support, laws and policy	[24], [12], [2], [13], [14], [10]
Human resources	[24], [2], [13]
Industry type	[25]
information security culture	[22]
Internal versus external technologies	[2], [17], [13]
Interpret unstructured data	[2], [1]
IS competence/IT structure (infrastructure)	[24], [2], [14], [10], [25], [15]
IS fashion	[24], [2]
IT expertise	[24], [14]
Knowledge about Big Data	[2], [17], [13]
Leaders' attitude towards change	[15]
Management support for Big Data	[22], [24], [18], [2], [10], [25], [15]
Market turbulence	[24], [2]
Marketing and inventory	[2], [13]
Network challenges	[2], [17], [13]
Observe-ability	[24], [2], [14]
Organizational (learning) culture	[22], [2], [13], [18]
Organizational data environment	[2], [25]
Perceived benefits (advantage)	[24], [2], [15], [13], [14], [10], [25], [1]
Perceived compatibility	[22], [24], [2], [25], [15]
Perceived Simplicity (Ease of use)	[22], [2], [15], [18], [13], [14], [10], [25]
Perceived cost	[2], [25]
Perceived financial readiness	[2], [13], [14], [10] , [18]
Perceived usefulness	[2], [25]
Predictive analytic accuracy	[2]
Relative advantage	[24], [2], [13], [14], [10], [15]
Risks of outsourcing	[22], [2]
Security and privacy	[22], [24], [2]
Staffing	[2], [1], [18]
Supply chain connectivity	[10]
system integration	[2], [1]
Technological capability	[2]
Technology readiness/ technology resources	[24], [2], [14], [10], [15], [18]
Trading partner adoption/ readiness	[24], [2]
Training	[2], [1], [18]
Trial ability	[24], [2]
Vendor support	[2], [17], [13]
Willingness to change	[18]
Predictive analytic accuracy	[2]

Table 3: Reliability Statistics

Cronbach's alpha	Cronbach's alpha Based on Standardized Items	N of Items
.867	.892	50

Table 4: KMO and Bartlett's test

Kaiser-Meyer-Olkin measure of sampling adequacy		.916
Bartlett's test for sphericity	Approx. Chi-Square	1628.317
	df	846
	Sig.	.000

Table 5: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	Variance (%)	Cumulative (%)	Total	Variance (%)	Cumulative (%)	Total	Variance (%)	Cumulative (%)
1	26.368	36.080	36.080	26.368	36.080	36.080	7.819	11.644	11.644
2	8.116	11.105	47.185	8.116	11.105	47.185	8.730	13.001	24.645
3	6.540	8.949	56.134	6.540	8.949	56.134	7.694	11.458	36.103
4	5.342	7.310	63.444	5.342	7.310	63.444	6.173	9.192	45.295
5	4.390	6.007	69.451	4.390	6.007	69.451	5.784	8.613	53.909
6	3.095	4.235	73.686	3.095	4.235	73.686	4.909	7.311	61.220
7	2.716	3.716	77.402	2.716	3.716	77.402	3.775	5.622	66.842
8	2.487	3.403	80.805	2.487	3.403	80.805	3.580	5.331	72.173
9	2.225	3.045	83.850	2.225	3.045	83.850	3.160	4.707	76.880
10	1.843	2.522	86.371	1.843	2.522	86.371	3.344	4.980	81.860
11	1.581	2.163	88.535	1.581	2.163	88.535	3.002	4.471	86.330
12	1.326	1.814	90.349	1.326	1.814	90.349	2.698	4.019	90.349
13	0.946	1.531	91.880						
14	0.865	1.184	93.064						
15	0.791	1.082	94.146						
16	0.733	1.003	95.149						
17	0.669	0.915	96.065						
18	0.578	0.791	96.856						
19	0.537	0.735	97.590						
20	0.492	0.673	98.264						
21	0.445	0.609	98.872						
22	0.358	0.490	99.362						
23	0.284	0.389	99.751						
24	0.182	0.249	100.000						
25	0.000	0.000	100.000						
26	0.000	0.000	100.000						
. . .	. . .	. . .	. . .						
50	0.000	0.000	100.000						

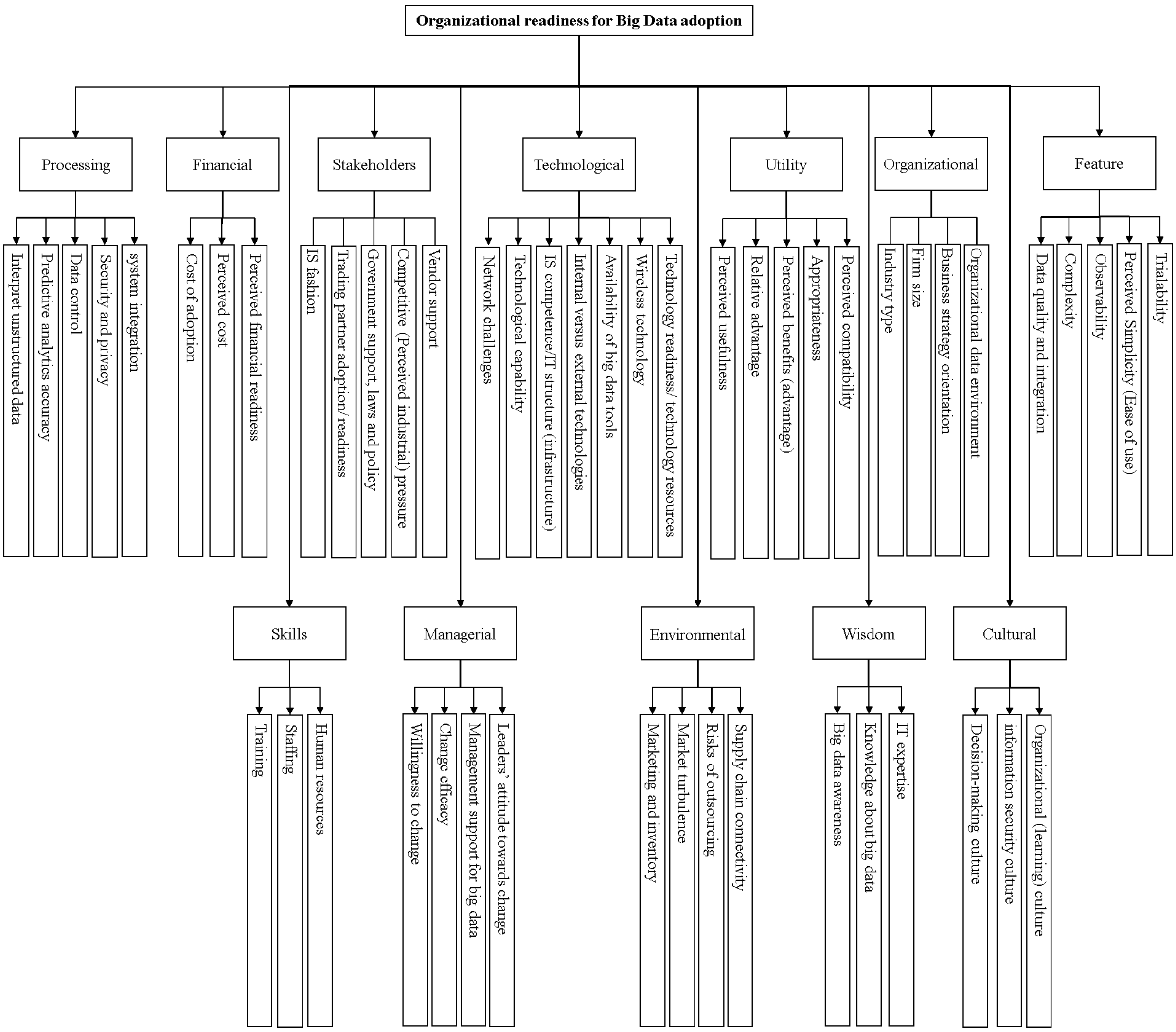

Figure 2: Hierarchical structure of organizational readiness evaluation

4 Determining the importance of criteria by FBWM

In this stage, the importance of the identified criteria will be determined. These criteria and their weights can be used to assess organizational readiness for Big Data adoption. According to Best-Worst Method (BWM) – introduced by Rezaei [21]– the best and the worst criteria are identified first by the decision-maker, followed by pairwise comparisons conducted between each of these two criteria and the other criteria [20]. A MaxiMin problem is then formulated and solved to determine the weights of different criteria. The salient features of the proposed method, compared to the existing multi-criteria decision making (MCDM) methods, are: (1) it requires fewer comparison data; (2) it leads to more consistent comparisons, which means that it produces more reliable results". Fuzzy Best-Worst Method (FBWM) is executed in 5 steps [7].

Step 1. Build the decision criteria system. In this step, we consider the criteria $\{C_1,\ C_2,\ \ldots,\ C_n\}$ that should be used to arrive at a decision.
Step 2. Determining the best (e.g., most important) and the worst (e.g., least important) criteria. In this step, the decision-maker identifies the best, and the worst criterion in general and no comparison is made at this stage.
Step 3. Execute the fuzzy reference comparisons for the best criterion. The resulting fuzzy Best-to-Others vector would be $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn})$ where $\tilde{a}_{Bj}$ indicates the fuzzy preference of the best criterion over criterion j and it is clear that $\tilde{a}_{BB} = (1, 1, 1)$.
Step 4. Execute the fuzzy reference comparisons for the worst criterion. The resulting

fuzzy Others-to-Worst vector would be $\widetilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW})$, where $\tilde{a}_{iW}$ indicates the preference of the criterion j over the worst criterion and it is clear that $\widetilde{a}_{WW} = (1, 1, 1)$.
Step 5. Finding the optimal fuzzy weights $(\widetilde{\mathrm{W}}_1^*, \widetilde{\mathrm{W}}_2^*, \ldots, \widetilde{\mathrm{W}}_\mathrm{n}^*)$. The optimal fuzzy weight for the criteria is the one where, for each pair of $\frac{\tilde{W}_B}{\widetilde{\mathrm{W}}_j}$ and $\frac{\tilde{W}_j}{\widetilde{\mathrm{W}}_w}$, we have $\frac{\tilde{W}_B}{\tilde{W}_j} = \tilde{a}_{Bj}$ and $\frac{\tilde{W}_j}{\tilde{W}_w} = \tilde{a}_{jw}$. To satisfy these conditions for all j, we should find a solution where the maximum absolute differences $\left|\frac{\mathrm{W_B}}{\mathrm{W_j}} - \mathrm{a_{Bj}}\right|$ and $\left|\frac{\mathrm{W_j}}{\mathrm{W_w}} - \mathrm{a_{jw}}\right|$ for all j is minimized. The optimization problem to determine the optimal weight of the criteria $(W_1^*, W_2^*, \ldots, W_n^*)$ is presented as the model (1):

$$\begin{gathered} Min\ \ Max\ _j \left\{ \left|\frac{W_B}{W_j} - a_{Bj}\right|,\ \left|\frac{W_j}{W_w} - a_{jw}\right| \right\} \\ s.t: \\ \textstyle\sum_{j=1}^{n} W_j = 1 \\ W_j \geq 0\ ,\quad for\ all\ j \end{gathered} \tag{1}$$

Then, model (1) turns into the following optimization problem with nonlinear constraints:

$$\begin{gathered} \text{Min } \widetilde{\wp} \\ s.t: \\ \left|\frac{\widetilde{\mathrm{W}}_\mathrm{B}}{\widetilde{\mathrm{W}}_\mathrm{j}} - \widetilde{\mathrm{a}}_\mathrm{Bj}\right| \leq \widetilde{\wp}\ ,\ \text{for all j} \\ \left|\frac{\widetilde{\mathrm{W}}_\mathrm{j}}{\widetilde{\mathrm{W}}_\mathrm{w}} - \widetilde{\mathrm{a}}_\mathrm{jw}\right| \leq \widetilde{\wp}\ ,\ \text{for all j} \\ \textstyle\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{R}(\widetilde{\mathrm{W}}_\mathrm{j}) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ \mathrm{j} = 1, 2, \ldots, \mathrm{n} \end{gathered} \tag{2}$$

Where $\widetilde{\wp} = (l_j^w, m_j^w, u_j^w)$. Considering $l_j^w \leq m_j^w \leq u_j^w$, we suppose $\widetilde{\wp}^* = (k^*, k^*, k^*)\ ,\quad k^* \leq l^{\wp}$, then nonlinear model (2) can turn into the model (3):

$$\begin{gathered} \text{Min } \widetilde{\wp}^* \\ s.t: \\ \left|\frac{(l_B^w, l_B^w, l_B^w)}{(l_j^w, l_j^w, l_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj})\right| \leq\ (k^*, k^*, k^*)\ \ ,\ \text{for all j} \\ \left|\frac{(l_j^w, l_j^w, l_j^w))}{(l_W^w, l_W^w, l_W^w)} - (l_{jW}, m_{jW}, u_{jW})\right| \leq\ (k^*, k^*, k^*)\ \ ,\ \text{for all j} \\ \textstyle\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{R}(\widetilde{\mathrm{W}}_\mathrm{j}) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ \mathrm{j} = 1, 2, \ldots, \mathrm{n} \end{gathered} \tag{3}$$

By solving model (3), the optimal weights $(\mathrm{W}_1^*, \mathrm{W}_2^*, \ldots, \mathrm{W}_\mathrm{n}^*)$ are obtained.

To determine the weights of the criteria (using FBWM), first, a customized questionnaire was devised and distributed among 18 experts. Next, based on the opinions of the respondent experts, the most and the least essential criteria were established. In the next step, the Best-to-Others preference vector was determined. To do this, all 18 experts were asked to specify their most preferred criterion compared with the other criteria. Afterward, the Others-to-Worst preference vector was also determined. The process of determining the latter was the same as that of the Best-to-Others vector. In the end, the optimization problem was expanded based on Model (3) of the FBWM. After solving the model above using the computer software MATLAB, the final weights of the criteria were calculated (Table 6) and depicted in a diagram (Figure 3).

Table 6: Criteria weights for organizational readiness assessment

Criterion	Technological	Wisdom	Feature	Cultural	Financial	Skills
weight	0.126	0.028	0.206	0.035	0.063	0.058
Criterion	Stakeholders	Managerial	Utility	Environmental	Organizational	Processing
weight	0.122	0.091	0.154	0.029	0.031	0.056

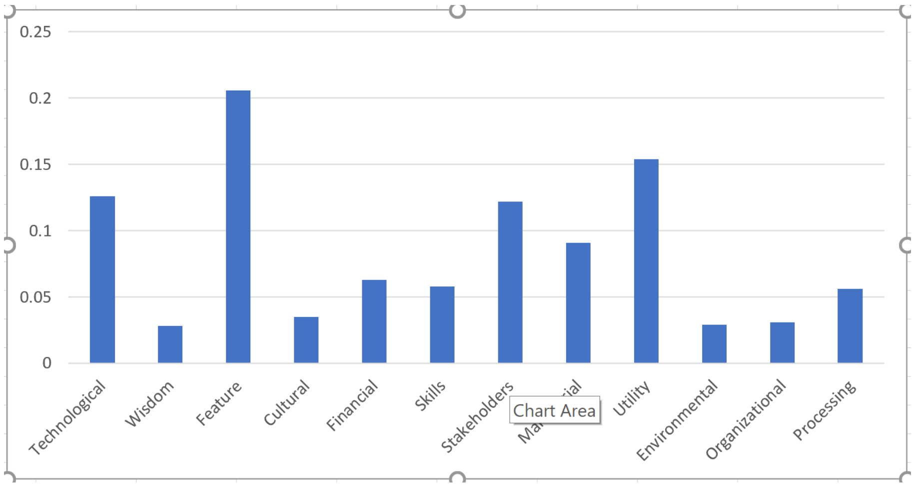

Figure 3: Criteria weights

5 Conclusion

Big Data is one of the issues that are considered by practitioners and scholars due to the high volume and speed of data exchange in today's world. The study investigates the prospects of developing frameworks for Big Data adoption on well-established methodologies. In this paper, a proper Procedure applied to identify effective criteria to evaluate organizational readiness for Big Data adoption and determine the relative importance of decision-making criteria. Here, in this study, fifty initial criteria are taken up for the present work based on a comprehensive literature review. The SPSS software has been utilized for ease of analysis, reduction of items, and examining the interrelations among the variables. Finally, fifty initial criteria are classified into12 criteria and used for further analysis. The hierarchical leveling of these criteria have been established.

In further research, the implications of the calculated weights will be analyzed. This work developed an MCDM approach using the FBWM for the assessment of organizational readiness. Results showed that Big Data features criterion (Including Trail ability, Observe-ability ...) is the most critical criterion for Big Data adoption. The methodology developed in this paper helps the decision-maker in identifying organization weaknesses for adopting Big Data by considering both conflicting quantitative and qualitative evaluation criteria in real-life applications. Researchers can use more quantitative methods such as ISM, (fuzzy) MICMAC, (fuzzy) DEMATEL, and FCM to model the inter-relationships between criteria.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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