II. CORPORATE FINANCIAL RISK ASSESSMENT AND ROLE OF BIG DATA; NEW PERSPECTIVE USING FUZZY ANALYTIC HIERARCHY PROCESS

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Abstract

Technological progress can help in the systematization of information linked with customer sentiments regarding the enterprise and products. This information can help incorporate decision-making and reduces financial risk. This study puts forward the theory of the impact of big data on corporate financial risk assessment, integrates big data public opinion indicators into the traditional corporate financial risk assessment index. The empirical outcomes are obtained using the Fuzzy Analytic Hierarchy Process. The results show that big data indicators, especially negative sentiment index have a more profound effect on corporate financial risk. In addition, profitability got the highest weightage in our case. A risk assessment model built with big data indicators can effectively correct the original assessment model's shortcomings and improve risk assessment results. Therefore, the financial risk assessment model that incorporates big data indicators shows better performance.

Keywords: Corporate Financial Risk; Big data; Fuzzy Analytic Hierarchy Process; Public Opinion

JEL Classification: G32, C55, D81

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1. Introduction

The growing global competition and the availability of unstructured and structured information have fundamentally changed the production and organizational processes. Therefore, to compete in the global environment, firms to upgrade conventional management and data analysis methods (Vasarhelyi et al., 2015). Systematization of knowledge through the right assessment methods, the building of archives, management, and data analysis generated in large quantities with speed in various formats, should be considered to get value from the information (Big Data analytics [BDA]). This is the first step towards developing business intelligence via the deployment of information processing systems, services to incorporate emerging technology with current systems. Moreover, infrastructural capacity, with an increase in data computational and storage capabilities through which new levels of knowledge could be derived (Dicuonzo et al., 2019). Therefore, companies around the world are focusing on the assessment and processing of big data to improve decision-making (Khurshid et al., 2020), get a competitive advantage (Elgendy & Elragal, 2014) reduce the financial risk (Florio & Leoni, 2017), and enhance the company's value (Saggi & Jain, 2018).

In the current background of big data, companies are facing a more complex social and economic environment. The explosive growth of information makes some potential factors that positively or negatively affect the firms and market economy both inside and outside. Internet technology is developing rapidly and is widely used in production and business activity can provide an opportunity to study enterprises from a big data perspective (Mao et al., 2003). Simultaneously, the network public opinion derived from internet technology also profoundly impacts the development of enterprises (Khurshid *et al*., 2016). Financial risk is inevitable in an enterprise's operation process and economic activities (Ahmed & Manab, 2016). The evaluation and measurement of financial risk is the key content of the fundamental research on financial risk management (Nayak & Akkiraju, 2012). Several factors can create uncertainty for enterprises that eventually affect their financial and operation situation (Grace et al., 2015). The resulting risks often drive them towards bankruptcy (Hoyt & Liebenberg, 2011). Therefore, identifying the financial risk of enterprises, measuring and evaluating the size of financial risk, and using appropriate methods to reduce and avoid risk has always been important research content in firms' financial risk management.

The current literature mainly focused on the early warning of the financial crisis and discussed the index and model construction of early financial warning but pays little attention to evaluating and measuring financial risk, especially in the big data context. By adopting big data's concept and technology, enterprises can better carry out the financial risk assessment and innovate content and form. Therefore, to reduce the risk of financial distress, it is necessary to build a financial risk assessment model through big data information to improve its scientificity, accuracy, and efficiency that will help in the development of enterprises.

Risk is a comprehensive reflection of the possibility of deviation between the actual and the expected results. Risk can reflect the probability of a specific situation and evaluate the degree of the result. For the relationship between financial risk and financial distress, different scholars also have different points. Some scholars believe that there is no essential difference between financial risk and financial distress. The management and research of enterprise financial risk is the research of financial distress (or financial crisis), but others have a different viewpoint. By analyzing the relationship between corporate governance, financial risk, and financial distress, Kahya and Theodossiou (2012) found that the failure of risk management is the direct cause of financial distress. The lack of risk identification, evaluation, and control often leads to financial distress.

In the researches related to financial risk assessment, most scholars identified and elaborated the financial indicators for financial risk assessment. Few study the impact of different indicators on financial risk through the case analysis method (Kotane & Kuzmina-Merlino, 2012; Khalikov, Maximov & Shabalina, 2018; Kumar, Jindal & Velaga, 2018; Kim *et al*., 2019; Qinag *et al*., 2019). Zhongming et al. (2019) and Kotane & Kuzmina-Merlino (2012) used financial indicators and ratios to check the financial risk and business performances. In contrast, Goldberg & Drogt (2018) believe that income and cash flows forecast can address the future uncertainties in the banking sector. Boiko (2019) discussed the problems associated with financial risk assessment; however, they only use financial indicators such as financial stability, exchange rate, and sales in the study.

Along with financial indicators, Jin (2012) used characteristics of the board of directors and executive incentives as non-financial variables in the financial risk measurement index, and case analysis results verify the rationality and effectiveness of this method. Zhongming et al. (2019) selected 11 financial and non-financial indicators that can reflect the company's operating characteristics, such as asset quality and market sensitivity, to analyze its financial risk status. He and Lu (2018) discuss the risk management process for SMEs using both financial and non-financial variables for risk management and control. Whereas, Ertugrul, Ozun and Kirikkaleli (2019) examine the role of economic and political stability on the financial stability of the emerging markets and find positive linkages between them. Suyuan & Khurshid (2015) used the entropy-weighted and TOPSIS method to study listed companies' financial risk in China's offshore engineering equipment manufacturing industry. They found that the development and cash ability in the financial risk evaluation system have a large weight.

In recent years, some scholars begin to link big data with enterprise financial management. Ostrom (2009) has pointed out that trust, reputation, and mutual benefit mechanisms come from the interpersonal network. The enterprise risk and crisis come from the interaction of related people in the social network. The emergence of big data technology makes it more comprehensive and convenient to obtain detailed information about enterprises from the social network's perspective. Therefore, some scholars put their research perspective on the impact of big data on enterprise development. Hasnat (2018) proposed building an enterprise financial risk management system based on big data to address its existing problems. Regarding big data technology and enterprise financial risk early-warning needs, Hassani et al., (2018) constructed a multi-dimensional enterprise financial risk warning mechanism that enriched the theoretical basis of big data technology applied in the field of financial risk warning. They suggested that online information can be used for analyzing emotional polarity. Du, Liu & Lu (2021) come out with similar outcomes using BP neural network algorithm. Liang et al. (2020) focus on the problems of financial risk early-warning systems in a big data context. They explore corresponding financial management strategies and provide suggestions for promoting the effective management of enterprise financial risk in big data background. Kim, K. and Ryu, D., 2020 examine the role of investors sentiments on the stock market outcomes and suggested that it can swing the market in both ways.

Recent studies are more focused on the procedure and processing of big data. We find similarities in the choice of financial variables; however, there is no consensus regarding non-financial variables, especially customer sentiments regarding the enterprise and product. Several studies ignore the non-financial variables due to a lack of clarity about their choice, inflow mechanism, processing, and usage. Therefore, there is no systematic conclusion on the research of enterprise financial risk assessment. Hence set of recognized and complete enterprise financial risk assessment index systems has not been established. This paper attempts to improve the financial risk assessment index system, which will have practical significance for the financial risk assessment of enterprises.

It is imperative to select indicators that can accurately assess the financial risk of the firm. A complete set of financial risk assessment indexes includes both financial indicators and non-financial indicators. The traditional financial indicators are profitability, solvency, operating capacity, and development capacity indicators based on the enterprise's financial report. Extracting enterprise network public opinion information from big data will play a significant application value in non-financial indicators. In the era of big data, people have different social functions, which cause various impacts on enterprises, such as customer satisfaction with products, investor attitude, enterprise credit evaluation, etc. The dissemination and evolution of netizens' comments on enterprises form the network public opinion. Therefore, this paper's network public opinion index includes five parts and is classified according to netizens' emotional polarity on enterprises. This study will check financial and big data variables weights in overall financial risk assessment and explain them with a practical case study. The public opinion index is divided into the following parts; (i). Positive emotion index, (ii) Neutral emotion index, (iii) Negative emotion index, (iv) Mixed emotion index and (v) Information frequency index. In addition, this study exemplified it in a case study.

2. Research Methodology

Saaty (1977) initially develops the analytic hierarchy process (AHP). It held an important place in the field of operation research while selecting the best alternatives. The analytic hierarchy process (AHP) is a multi-criterion technique used to solve and analyze complex problems and helps in decision making by providing alternatives options (Saaty, 1980). AHP has various steps; in the first step, the problems are structured for clear understanding. This order is based on a particular pattern; it consists of the goal, decision-making criteria, sub-criteria, and in the last, all accessible alternatives. When the hierarchy is structured, the decision-makers construct pair-wise comparison matrices. The scale that is used to measure criteria is called Satty's scale (Saaty, 1987). Based on the measurement, the alternative is first determined and then ranked. The AHP can predict both qualitative and quantitative elements. This quality is widely used in multi-criteria decision-making techniques. In practical life, the decision criterion is habitually hazy, complicated, and conflicting. In uncertain situations using the non-fuzzy value in a decision matrix sometimes leads to wrong decisions (Saaty, 1986). This is also a factor in the way of accuracy. Many researchers started to use a new theory called the fuzzy set theory (Zadeh, 1996). However, there were some drawbacks in that theory that it only considers truth membership degree. The first time, Van Laarhoven and Pedrycz (1983) introduced fuzzy AHP. The membership is taken in terms of fuzzy triangular numbers and used a logarithmic least squares method to obtain the fuzzy weight fuzzy concert scores for ranking the alternatives. This method can help in controlling indeterminacy, inconsistency, and inaccuracy. Then Buckley (1985) extended the classical AHP with the trapezoidal fuzzy number. It gets the fuzzy weight and fuzzy concert scores using the geometric mean method. After that, Chang (1996) used the row mean method to derived priority for similarity ratio in the perspective of fuzzy triangular numbers. The Chang method is comparatively easier than the other fuzzy AHP approach. The researcher and policymakers are using the fuzzy AHP in different fields, for instance, public administration (Ju, Wang & Liu, 2012), airlines industry (Rezaei, Fahim & Tavasszy, 2014), manufacturing industry (Duran & Aguilo, 2008), textile industry (Cebeci, 2009), electronic industry (Chang, Wu, & Chen, 2008), oil industry (Hsu, Lee & Kreng, 2010), the entertainment industry (Lu & Wen, 2010), and transportation industry (Kulak & Kahraman, 2005).

The stepwise criteria used for the estimation is as under;

Step1: First, we construct the hierarchy structure of the problem. This hierarchy structure consists of four stages;

(i). To choose the desirable goal.

(ii). Criteria

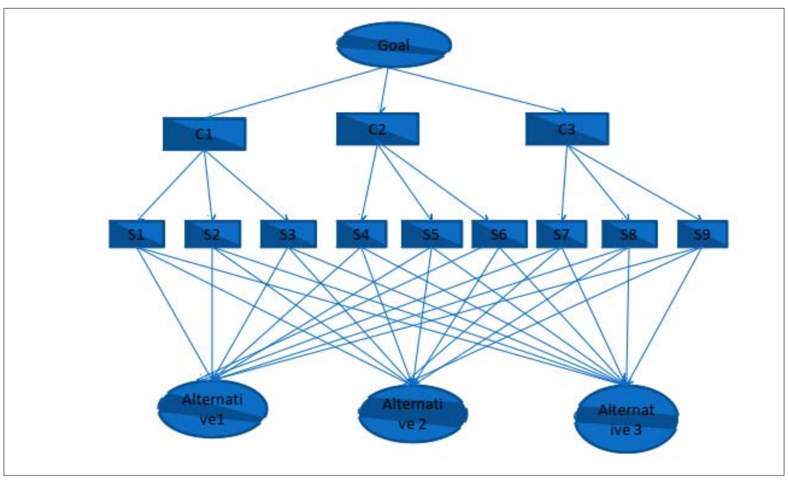
(iii). Sub-criteria's

(iv). Ranking of alternatives evaluated.

The hierarchal structure is shown in Figure 1.

Figure 1

Fuzzy hierarchy structure



Step 2: In this step, we construct the pair-wise comparison matrix of criteria, sub-criteria, and alternatives and their linguistic triangular scale, as shown in Table 1. Besides, Saaty nine-point scale is shown in Figure 2.

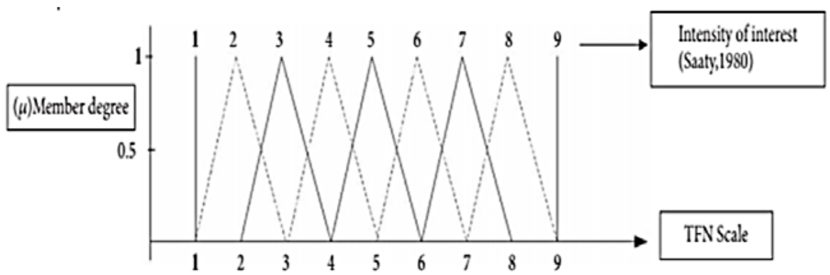
Table 1

Fuzzy linguistic triangular scale

Saaty Scale	*Explanation*	*fuzzy AHP linguistic triangular scale*
1	Identical	$\hat{1}=(1,1,1)$
3	Important	$\hat{3}=(2,3,4)$
5	Very important	$\hat{5}=(4,5,6)$
7	Very very important	$\hat{7}=(6,7,8)$
9	Perfect	$\hat{9}=(9,9,9)$
2		$\hat{2}=(1,2,3)$
4	*middle value b / w*	$\hat{4}=(3,4,5)$
6	*two closest scales*	$\hat{6}=(5,6,7)$
8		$\hat{8}=(7,8,9)$

Figure 2

Saaty nine-point scale



The fuzzy linguistic triangular scale based on expert's opinion, the pair-wise comparison matrix of criteria, sub-criteria, and the alternative is as follows,

$$A=\begin{bmatrix} a_{11}^{\sim} & a_{12}^{\sim} & . & . & a_{1n}^{\sim} \\ a_{21}^{\sim} & a_{22}^{\sim} & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ a_{n1}^{\sim} & a_{n2}^{\sim} & . & . & a_{mn}^{\sim} \end{bmatrix} \quad \text{(A)}$$

Where a $_{ji}^{\sim}=a_{ij}^{\sim-1}$ is a triangular q-rung ortho pair, fuzzy numbers are used to measure the indeterminacy in the decision.

Step 3: Check the consistency of the expert's judgment.

If the pair-wise comparison matrix is consistent, then we have $a_{ik} = a_{ij}\, a_{jk}$ for *i, j, k*. The lower, upper, and middle-lower values are important in the triangular fuzzy number of the comparison matrix.

Step 4: We use a pair-wise comparison matrix to analyze the weight of alternatives, criteria's and sub-criteria. The values of fuzzy synthetic extend concerning criteria *i* is represented as

$$w_j = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}} \tag{1}$$

Where

$$\sum_{j=1}^{n} a_{ij} = \left(\sum_{j=1}^{n} a_{ij}, \sum_{j=1}^{n} b_{ij}, \sum_{j=1}^{n} c_{ij} \right) \tag{2}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij} = \left(\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}, \sum_{i=1}^{m}\sum_{j=1}^{n} b_{ij}, \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij} \right) \tag{3}$$

and $(i = 1, 2, 3 \ldots m), (j = 1, 2, 3 \ldots n)$

Step 5: The degree of possibility of *Mi* > *Mj* is used to compare the fuzzy number by the following equations

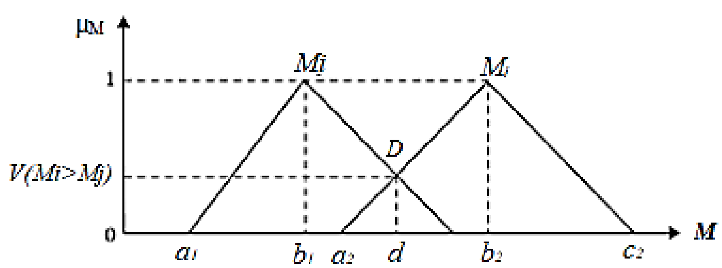
$$\mathrm{V(Mi > Mj)} = sup_{y \geq x}[\min\left(\mu_{M_{i(x)}}, \mu_{M_{j(y)}}\right] = hgt(M_i \cap M_j) = \mu_{M_{j(d)}} \tag{4}$$

$$= \begin{cases} 1 & if \quad M_i \geq M_j \\ 0 & a_1 \geq c_2 \\ & \frac{(a_1 - c_2)}{(b_2 - c_2) - (b_1 - c_1)} \end{cases} \tag{5}$$

Where Mi = (a1, b1, c1) and Mj = (a2, b2, c2) and D is the highest interaction point as shown in the Figure 3.

Figure 3

Interaction between both Mi and Mj



Step 6: The degree of fuzzy numbers to be greater than k is defined as

$$d'(A_i) = \min V\,(S_i \geq S_k), i, k = 1,2, \dots, n; i \neq k \quad (6)$$

Then vector weights are specified by

$$W' = (d'(A_1), d'(A_2), \dots., d'(A_n))^T \quad (7)$$

Step 7: In the normalized form

$$W = (d(A_1), d(A_2), \dots., d(A_n))^T \quad (8)$$

3. Empirical Outcome

The financial Risk Evaluation Index construction is based on the principles of comprehensiveness and applicability. This study selected nine secondary valuation indexes, including financial index and big data index, to establish an enterprise financial risk evaluation index system. The constructed financial risk assessment index system is shown in Table 2.

Table 2

Firms financial risk assessment system

Objective	Criteria	Scheme
The corporate financial risk assessment system	Financial Indicators R1	Profitability F1
		Operating capacity F2
		Solvency F3
		Development capacity F4
	Big Data Index R2	Positive emotion index D1
		Neutral emotion index D2
		Negative emotion index D3
		Mixed emotion index D4
		Information frequency D5

3.1. Case Study

This Capital Spinning Mills Ltd, a listed manufacturing group from Pakistan, involves textile, power generation, footwear manufacturing, and leather garments as the object of empirical analysis. The fuzzy comprehensive evaluation method evaluates the weights of financial and non-financial factors that can contribute to the financial risk assessment. The criterion is based on the interviews conducted from the 12 top-level managers from the sales, finance, customer services departments and assigned weights as per their response.

3.1.1 Financial Risk Assessment Index Weight

According to the financial risk assessment index system established above, the Fuzzy analytic hierarchy process is used to determine the weight of each index. Firstly, the judgment matrix is constructed, representing the relative importance of all factors in this layer to a specific factor in the upper layer. In this paper, a fuzzy linguistic triangular scale is used to construct the judgment matrix. The evaluation criteria are summarized in Table 3.

Table 3

Evaluation criteria

<table>
<tr><th>Scale</th><th>Fuzzy triangular numbers</th><th>Reciprocal values</th><th colspan="2">Definition</th></tr>
<tr><td>1</td><td>(1, 1, 1)</td><td>1, 1, 1</td><td>Equal Important</td><td>The 2 factors are equally important</td></tr>
<tr><td>3</td><td>(2, 3, 4)</td><td>1/4, 1/3, 1/2</td><td>Moderate Important</td><td>The former indicator is slightly important than the later</td></tr>
<tr><td>5</td><td>(4, 5, 6)</td><td>1/6, 1/5, 1/4</td><td>Strong Importance</td><td>The former indicator is important than the later</td></tr>
<tr><td>7</td><td>(6, 7, 8)</td><td>1/8, 1/7, 1/6</td><td>Very Strong Importance</td><td>The former indicator is much more important than the later</td></tr>
<tr><td>9</td><td>(9, 9, 9)</td><td>1/9, 1/9, 1/9</td><td>Extreme Strong Importance</td><td>The former indicator is absolutely more important than the later</td></tr>
<tr><td>2, 4, 6, 8</td><td colspan="2" rowspan="2">A similar method using Upper and lower bounds of triangular fuzzy number</td><td>Intermediate</td><td>Represent the intermediate degree of importance of the two indicators</td></tr>
<tr><td>1, 1/2, 1/3, ., 1/9</td><td colspan="2">If the ratio of the importance of factor i to factor j is Zij, then the ratio of the importance of factor j to factor i is Zji = 1 /Zij</td></tr>
</table>

Profitability and a certain degree of solvency are important for every company to progress and ensure their operational capabilities to achieve long-term sustainable development. The big data (public opinion) have both direct and indirect impact on the firm's development. Positive public sentiment is likely to affect the company positively; however, negative public sentiment has a greater negative effect on them. The influence of neutral and mixed public opinion on the enterprises is relatively small. However, information frequency cannot be ignored. Firstly, fuzzified pair-wise comparison based on expert's response to analyzing the weight of both Financial and Big-data indexes. Equations 1, 2, 3, 6,7, and 8 are used to find the following criteria weights.

$$A = \begin{bmatrix} \tilde{1} & \tilde{2} \\ \tilde{\tfrac{1}{2}} & \tilde{1} \end{bmatrix}$$

Where, 1=(1,1,1) and 2=(1,2,3)

Here we use the geometric mean method to calculate the weight.

$$A = \begin{array}{ccc} C_1 & C_2 & r_i \\ \end{array}$$
$$\begin{bmatrix} \tilde{1} & \tilde{2} & (1, 1.41, 1.73) \\ \tilde{\tfrac{1}{2}} & \tilde{1} & (0.57, 0.70, 1) \end{bmatrix}$$

$$= \begin{bmatrix} C_1 & C_2 & r_i & w_i \\ \tilde{1} & \tilde{2} & (1,1.41,1.73) & (1,1.41,1.73)\times\left(\frac{1}{2.73},\frac{1}{1.84},\frac{1}{1.57}\right) \\ \tilde{\frac{1}{2}} & \tilde{1} & (0.57,0.70,1) & (0.57,0.70,1)\times\left(\frac{1}{2.73},\frac{1}{1.84},\frac{1}{1.57}\right) \end{bmatrix}$$

$$= \begin{bmatrix} C_1 & C_2 & r_i & w_i \\ \tilde{1} & \tilde{2} & (1,1.41,1.73) & (0.366,0.766,1.10) \\ \tilde{\frac{1}{2}} & \tilde{1} & (0.57,0.70,1) & (0.208,0.380,1.10) \end{bmatrix}$$

For further calculation, we can defuzzified to get crisp numeric values

$$= \begin{bmatrix} W_i \\ 0.7440 \\ 0.5627 \end{bmatrix}$$

The sum of weight vectors is 1.3067, which is not acceptable so we normalized the above matrix

$$= \begin{bmatrix} W_i \\ 0.5694 \\ 0.4306 \end{bmatrix} \tag{10}$$

The matrix (10) gives the corporate financial risk weights to the judgment matrix. Financial variables contribute 56.94% to financial risk, whereas information / big data can cause/avoid 43.06% risk of the firms.
The secondary financial variables based on fuzzy linguistic triangular scale and expert opinions are represented in Table 4.

Table 4

Pair-wise Fuzzy matrix for financial indicators

	F_1			F_2			F_3			F_4		
F_1	1	1	1	1.23	1.51	1.87	1.07	1.35	1.76	0.77	0.97	1.24
F_2	0.54	0.66	0.81	1	1	1	0.77	1.02	1.32	0.76	0.95	1.19
F_3	0.57	0.74	0.94	0.76	0.98	1.30	1	1	1	0.93	1.14	1.43
F_4	0.80	1.04	1.30	0.84	1.05	1.31	0.70	0.88	1.08	1	1	1

Table 5 summarizes the outcomes of fuzzy sum, synthetic, degree of possibility, weights, and normalized weights for the financial index's secondary variables. The results reveal that financial risk is mainly dependent on profitability (33.3%), solvency (23.9%), development capacity (23%), and 19.8% on operating ability. The matrix consistency is tested using the pair-wise consistency method (PCM) proposed by Saaty (1980). If CR < 0.1, the consistency of the PCM is acceptable; else, the PCM could be adjusted unless CR < 0.1, where 0.1 is the Saaty threshold. In this case, CR values 0.011 and 0.034 are <0.1, confirming the consistency of the pair-wise matrix.

Table 5

Estimated Results for financial indicators

	Fuzzy Sum of Each Row			**Fuzzy Synthetic Extent**			**Degree of Possibility of Mi > Mj**				**Degree of Possibility (Mi)**	**Norm. (W_1)**
F_1	4.06	4.83	5.87	0.21	0.30	0.43		1	1	1	1	0.333
F_2	3.06	3.64	4.32	0.16	0.22	0.32	0.596		0.920	0.880	0.596	0.198
F_3	3.25	3.85	4.68	0.17	0.24	0.34	0.690	1		0.962	0.690	0.239
F_4	3.34	3.96	4.70	0.17	0.24	0.34	0.717	1	1		0.717	0.230
	Consistency Ratio				**CR_m =**		0.011		**CR_g =**		0.034	

Note: Norm. is an abbreviation for normalization

Table 6 represents the fuzzy linguistic triangular scale matrix based on interview results for big data variables, whereas Table 7 summarizes the empirical outcomes based on methodological steps from 2 to 7. The results show that after normalization, negative sentiments got the highest Mi value of 0.417, followed by positive sentiments, 0.351, data intensity, 0.125, mixed emotions, 0.072, and natural emotions, and 0.035. The Consistency Ratio values (0.013, 0.038) confirm the consistency in this case. This study also checks the consistency from defuzzified and upper-lower limit matrix (see Appendix A) that confirms the outcomes for robustness.

Table 6

Fuzzy Comparison Matrix for big data variables

	A			**B**			**C**			**D**			**E**		
D_1	1.00	1.00	1.00	1.11	1.36	1.64	0.82	1.00	1.22	1.84	2.38	2.83	0.88	1.20	1.60
D_2	0.61	0.74	0.90	1.00	1.00	1.00	0.48	0.60	0.76	0.79	1.00	1.27	0.61	0.81	1.10
D_3	0.82	1.00	1.22	1.31	1.68	2.09	1.00	1.00	1.00	1.74	2.17	2.63	1.53	1.97	2.47
D_4	0.35	0.42	0.54	0.79	1.00	1.27	0.38	0.46	0.57	1.00	1.00	1.00	0.87	1.07	1.30
D_5	0.62	0.83	1.13	0.91	1.23	1.63	0.40	0.51	0.65	0.77	0.93	1.15	1.00	1.00	1.00

Table 7

Empirical results for big data variables

	Fuzzy Sum of Each Row			**Fuzzy Synthetic Extent**			**Degree of Possibility of Mi > Mj**					**Degree of Possibility (Mi)**	**Norm. (W_2)**
D_1	5.66	6.93	8.28	0.17	0.25	0.37		1	0.84	1	1	0.841	0.351
D_2	3.49	4.15	5.03	0.11	0.15	0.22	0.33		0.17	1	0.89	0.173	0.072
D_3	6.4	7.82	9.41	0.19	0.29	0.42	1	1		1	1	1	0.417
D_4	3.39	3.95	4.69	0.1	0.14	0.21	0.25	0.93	0.08		0.82	0.085	0.035
D_5	3.71	4.51	5.57	0.11	0.16	0.25	0.46	1	0.3	1		0.300	0.125
Consistency Ratio					**CR_m**		**= 0.013**			**CR_g =**		**0.038**	

To sum up, the final weight of each index of financial risk assessment is estimated and summarized in Table 8.

Table 8

Financial Risk Assessments- Weights

Criteria	%age	Scheme	Index Values	Final %age
Financial Indicators	56.94	Profitability	0.333	18.96
		Operating capacity	0.198	11.27
		Solvency	0.239	13.61
Big Data Index		Development capacity	0.230	13.10
	43.06	Positive emotion index	0.351	15.11
		Mixed emotion index	0.072	3.10
		Negative emotion index	0.417	17.96
		Neutral emotion index	0.035	1.51
		Information frequency	0.125	5.38

The assessment indicators show that the higher-ranking indicators based on weight value are: profitability 18.96%, negative sentiment 17.96%, positive sentiment 15.11%, solvency 13.61%, Development capacity 13.10%, and operating capacity 11.27%. At the same time, 5.38% is distributed explicitly to data frequency in the evaluation system. The results portray that big data indicator significantly impact the corporate financial risk assessment, especially negative and positive sentiments. Based on this, the assumption that the introduction of big data public opinion indicators helps enterprises conduct a financial risk assessment is valid.

4. Financial risk assessment of Capital Spinning Mills Ltd.

4.1 Fuzzy comprehensive evaluation of an enterprise

For further evaluation, suppose the intensity of the firm's financial risk is *F*. The evaluation is further divided into five levels, namely: v_1 means very high, v_2 high, v_3 normal, v_4 low, and v_5 representing very low. The evaluation set V = {v_1, v_2, v_3, v_4, v_5} = {I, II, III, IV, V}. Start with the second-level indicators and determine *rij* to the evaluation level. The fuzzy relationship matrix of the evaluation intensity set corresponding to financial indicators (F_1), big data indicators (BD_1), after expert investigation and probability calculation, we can get:

$$F_1 = \begin{bmatrix} 0.4 & 0.6 & 0 & 0 & 0 \\ 0.3 & 0.2 & 0.4 & 0.1 & 0 \\ 0.2 & 0.5 & 0.1 & 0.1 & 0.1 \\ 0.3 & 0.3 & 0.2 & 0.2 & 0 \end{bmatrix}$$

$$BD_1 = \begin{bmatrix} 0.4 & 0.3 & 0.3 & 0 & 0 \\ 0.2 & 0.2 & 0.4 & 0.2 & 0 \\ 0.1 & 0.2 & 0.4 & 0.3 & 0 \\ 0.1 & 0.2 & 0.3 & 0.3 & 0.1 \\ 0.1 & 0.5 & 0.2 & 0.2 & 0 \end{bmatrix}$$

In the Composite operation, take F (∧, ∨) and normalize it to get:

$$N_1 = W_1^T * F_1$$

$$N_1 = (0.309, 0.382, 0.165, 0.101, 0.024)$$

Normalized to:

$$N_1 = (0.316, 0.389, 0.168, 0.103, 0.024)$$

The maximum- membership method, otherwise known as the height method, is adopted to evaluate the financial indicators. The outcomes reveal that the company's financial risk intensity is at level II, and the financial risk is relatively high.

$$N_2 = W_2^T * BD_1$$

$$N_2 = (0.212, 0.313, 0.309, 0.235, 0.042)$$

Normalized to:

$$N_2 = (0.191, 0.281, 0.278, 0.212, 0.038)$$

The principle of subordination method is used to examine the company's financial risk intensity level for big data indicators and find it at level III. This means financial risk is fair. For the comprehensive evaluation, we used:

$$N = W^T * [N_1, N_2]$$

In normalized form:

$$= (0.262, 0.343, 0.215, 0.149, 0.030)$$

According to the principle of the maximum degree of membership, the result of a comprehensive evaluation of the company shows that the financial risk is fair, and the financial risk intensity is at level III.

4.2 Comparative analysis

First, the comprehensive evaluation results based on financial indicators are: to compare the advantages of both assessment models, it is necessary to further calculate the above fuzzy comprehensive evaluation results. Therefore, set the grade assignment matrix F = (5, 4, 3, 2, 1). The larger the F value, the higher the financial risk of the enterprise.

$$C_1 = N_1 * F^T$$

$$= (0.316, 0.389, 0.168, 0.103, 0.024) * (5, 4, 3, 2, 1)^T$$

$$= 3.87$$

After integrating the big data public opinion indicators, the fuzzy comprehensive evaluation score of the overall financial risk of Capital Spinning Mills Ltd. Company is obtained, as:

$$C_2 = N_2 * F^T$$

$$= (0.191, 0.281, 0.278, 0.212, 0.038) * (5, 4, 3, 2, 1)^T$$

$$= 3.38$$

According to the result of the fuzzy comprehensive evaluation score, the result value of the evaluation using only traditional financial indicators is 3.87, closer to 4. Therefore, it can be judged as a higher risk. The evaluation result value of the model integrating big data public opinion indicators is 3.38, which is closer to three, so it can be arbitrated as a fair risk. Combining Capital Spinning Mills Ltd.'s actual operating conditions and expert evaluation results, its operating conditions are good. Its solvency is slightly insufficient, and its financial risk is slightly higher than usual. This is due to the pandemic situation; productivity, sales, and exports are lower than usual.

In sum, the financial risk model incorporating big data public opinion indicators can be effective. Based on the original evaluation model, amendments make the assessment results more accurate and provides a practical reference for enterprises in financial risk management.

5. Conclusion

This article puts forward the theory of the impact of big data on corporate financial risk assessment, integrates big data public opinion indicators into the traditional corporate financial risk assessment index system, and conducts empirical analysis. The results show that big data indicators, especially negative sentiment, and positive indexes, positively affect corporate financial risk assessment. Therefore, the financial risk assessment based on big data indicators shows better performance. In addition, the risk assessment model built with big data public opinion indicators can effectively correct the shortcomings of the original assessment model and improve the accuracy of risk assessment results.

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Appendix A

First, we compute the fuzzy and non-fuzzy comparison matrix. Then we calculate the consistency rate of the matrix. Tables A, B, and B1 are linked with financial indicators, while C, D, and E are summarizing the results of big data indicators.

Table A

Matrix with defuzzified values for financial Indicators

	Non-fuzzy matrix				Normalized matrix				Weighted Sum	Ratio
	F1	F2	F3	F4	F1	F2	F3	F4		
F1	1	1.510	1.353	0.966	0.291	0.333	0.318	0.238	1.188	4.029
F2	0.662	1	1.024	0.954	0.193	0.221	0.241	0.235	0.895	4.026
F3	0.739	0.976	1	1.137	0.215	0.215	0.235	0.280	0.952	4.025
F4	1.036	1.048	0.880	1	0.301	0.231	0.207	0.246	0.993	4.029
λ		4.027			CI	0.009		CR	0.011	

Table B

The lower (L) and upper (U) bound values of the comparison matrix

	F1		F2		F3		F4	
	L	U	L	U	L	U	L	U
F1	1	1	1.230	1.868	1.065	1.763	0.768	1.244
F2	0.535	0.813	1	1	0.767	1.316	0.761	1.193
F3	0.567	0.939	0.760	1.303	1	1	0.926	1.433
F4	0.804	1.302	0.838	1.315	0.698	1.079	1	1

Table B1

Empirical outcome of lower (L) and upper (U) bound matrix

	Non-fuzzy matrix				Normalized matrix				Weighted Sum	Ratio
	A	B	C	D	A	B	C	D		
A	1	1.516	1.370	0.978	0.293	0.332	0.323	0.239	1.196	4.029
B	0.660	1	1.005	0.953	0.193	0.219	0.237	0.233	0.889	4.026
C	0.730	0.995	1	1.152	0.214	0.218	0.236	0.282	0.956	4.025
D	1.023	1.050	0.868	1	0.300	0.230	0.205	0.245	0.986	4.028
λ		4.027			CI	0.009		CR	0.0343	

Note: $CI = (\lambda_{max} - n)/(n-1)$ and $CR = CI/RI$

$M_{crisp} = (4m + l + u) / 6$

Where RI is the random index

Table C

Matrix with de-fuzzified values for Big data Indicators

	Non-fuzzy matrix					Normalized matrix					Weighted Sum	Ratio
	A	B	C	D	E	A	B	C	D	E		
D_1	1	1.357	0.998	2.376	1.201	0.250	0.217	0.280	0.318	0.198	1.28	5.08
D_2	0.737	1	0.595	1.000	0.813	0.185	0.160	0.167	0.134	0.134	0.79	5.05
D_3	1.002	1.680	1	2.168	1.968	0.251	0.268	0.281	0.290	0.325	1.43	5.07
D_4	0.421	1.000	0.461	1	1.070	0.105	0.160	0.129	0.134	0.177	0.71	5.06
D_5	0.833	1.230	0.508	0.935	1	0.209	0.196	0.143	0.125	0.165	0.85	5.04
	λ	5.0596		CI >	0.0149		CR >>	0.0139				

Table D

The lower (L) and upper (U) bound values of the comparison matrix of big data

	D_1		D_2		D_3		D_4		D_5	
	L	U	L	U	L	U	L	U	L	U
D_1	1	1	1.111	1.639	0.821	1.216	1.843	2.826	0.882	1.603
D_2	0.610	0.900	1	1	0.478	0.765	0.786	1.272	0.612	1.096
D_3	0.823	1.218	1.308	2.093	1	1	1.740	2.627	1.535	2.471
D_4	0.354	0.543	0.786	1.272	0.381	0.575	1	1	0.866	1.303
D_5	0.624	1.134	0.913	1.633	0.405	0.652	0.767	1.155	1	1

Table E

Empirical outcome of lower (L) and upper (U) bound matrix

	Non-fuzzy matrix					Normalized matrix					Weighted Sum	Ratio
	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5		
D_1	1.00	1.35	1.00	2.28	1.19	0.25	0.22	0.28	0.31	0.20	1.27	5.07
D_2	0.74	1.00	0.60	1.00	0.82	0.18	0.16	0.17	0.14	0.14	0.79	5.05
D_3	1.00	1.65	1.00	2.14	1.95	0.25	0.27	0.28	0.29	0.32	1.42	5.06
D_4	0.44	1.00	0.47	1.00	1.06	0.11	0.16	0.13	0.14	0.18	0.72	5.05
D_5	0.84	1.22	0.51	0.94	1.00	0.21	0.20	0.14	0.13	0.17	0.85	5.04
		λ	5.05	**CI**	0.01	**CR**	0.04					