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Evaluation of Environmental Information Disclosure of Listed Companies in China's Heavy Pollution Industries: A Text Mining-Based Methodology

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Abstract: Environmental information disclosure (EID) of listed companies is a significant and essential reference for assessing their environmental protection commitment. However, the content and form of EID are complex, and previous assessment studies involved manual scoring mainly by the experts in this field. It is subjective and has low timeliness. Therefore, this paper proposes an automatic evaluation framework of EID quality based on text mining (TM), including the EID index system's construction, automatic scoring of environmental information disclosure quality, and EID index calculation. Furthermore, based on the EID of 801 listed companies in China's heavy pollution industry from 2013 to 2017, case studies are conducted. The case study results show that the overall quality of the EID of listed companies in China's heavily polluting industries is low, and there is a gap differentiation between the 16 industries. Compared with the subjective manual scoring method, TM evaluation can evaluate the quality of EID more effectively and accurately. It has great potential and can become an essential tool for the sustainable development of society and listed companies.

Keywords: text mining; data science; quality of environmental information disclosure; listed companies; sustainability

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1. Introduction

Sustainable development is a balance between economic growth, environmental issues, and social conditions [1]. Mainly promoted by enterprises and the local government [2]. With the rapid development of the global economy, environmental information disclosure (EID) has aroused widespread concern and promoted the environment's sustainable development [3].

According to the industry-driven growth model, the continuous energy consumption of manufacturing and infrastructure investment negatively impacts the environment [4]. Environmental information disclosure (EID) is an efficient method for promoting the standardization of corporate ecological behavior and a fundamental approach for all social sectors to understand and evaluate corporate environmental behavior [5]. To our knowledge, EID is the third environmental regulatory mode, excluding command and control and market-based environmental regulation [6]. The role of EID in environmental protection has received increased attention across several disciplines in recent years [7]. Therefore, corporate EID quality significantly affects government policymaking and public behavior [8].

Additionally, the quality of corporate EID can affect enterprises' performance in the capital market and their value by changing their social image [9]. EID from enterprises is an efficient and vital method of informing the public. It can allow more people to understand the environmental behavior and sustainable development of enterprises [10]. By reviewing the environmental information from enterprises, the governmental environmental protection departments can better understand the overall situation of their environmental

performance and assess their environmental contribution [11]. Evaluating the quality of environmental information disclosure can also allow the public and investors to determine which enterprises should be invested [12].

There are many methods for evaluating the quality of EID. Previous studies explored content analysis, expert opinion [13], qualitative disclosure [14], and quantitative disclosure methods [15]. The index proposed by Clarkson et al., has been used as an evaluation benchmark in assessing the quality of corporate EID [16]. However, the recent increase in the number of listed companies has increased the amount of information they have disclosed, leading to an upsurge in the EID evaluating workload [17]. The rationality and reliability of traditional analysis methods are continuously challenged due to their working time and cost. Therefore, it is difficult for the results to objectively reflect the quality of corporate EID and disclosure motivation [18]. Evaluating the quality of EID from a listed company is objectively and efficiently challenging [19].

With the rapid development of artificial intelligence, text information mining has successfully been applied in text analysis, improving the measurement accuracy of existing indicators and measuring the disclosure of text content more accurately and comprehensively [20]. To our best knowledge, few previous studies have used text mining (TM) to obtain relevant enterprise EID quality assessment and comprehensive evaluation information based on reports from listed companies. This study proposes an automatic EID quality evaluation framework based on the TM technique, and a flow chart of the analysis procedure is provided in Figure 1.

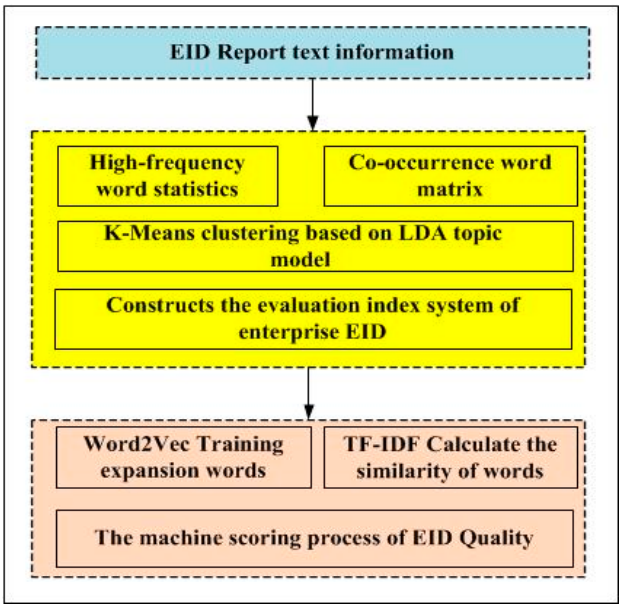


Figure 1. Flow chart of the analysis procedure.

The proposed framework involves constructing an EID index system, automatically scoring the quality of EID, calculating the EID index. We collected EID Report text information from 801 listed companies in China's heavily polluting industries from 2013 to 2017. We are using the K-means clustering based on the LDA topic model to mine helpful text information to enrich the EID quality evaluation method.

This paper's remainder is structured as follows: Section 2 provides an overview of related research. Section 3 constructs the evaluation index system for the enterprise EID. The quality scoring of the EID, based on the TM technique, is conducted. In Section 4, we present an empirical case study of 801 listed companies in heavily polluting industries, whose environmental data were taken from, among others, the Shanghai and Shenzhen stock markets from 2013 to 2017. Finally, Section 5 presents the research conclusions and proposes future work.

2. Literature Review

Sustainability is emerging as an important issue for firms in recent years. EID from listed companies is an essential reference for assessing their environmental protection commitment. Content analysis is the most common methodology used in EID index system studies to analyze economic, social, and environmental details. In 1982, Wiseman et al., added financial indicators of the environmental accounting content to the EDI index system. Many scholars have accepted this index since its development used the economic quantitative information method to develop the EID index system as a supplement to the previous procedure [21]. As global environmental issues have attracted more attention, Al-Tuwaijri et al., introduced environmental regulatory factors to the EID index system [22,23]. According to the literature, scholars have shifted focus on environmental improvement. In this stage, the EID index was mainly divided into qualitative and quantitative. Villiers and Staden added qualitative content to the index [24], and Cho and Patten divided the EID indicators into financial and non-financial indicators for analysis [25].

With the promulgation of the "Sustainable Development Report" (GRI), the quality and quantity of corporate EID must be comprehensively measured. Thus, the EID index system has become more comprehensive and has been adopted by scholars. Halme and Huse used an index of 0–1 to assign the corporate EID status. Neu et al., and Patten used words, sentences, and EID length to calculate the index and quantitative index scoring [26,27]. Aerts assigned different weights and scores to other information items based on their quality in the Corporate Environmental Disclosure Report [28]. Hasseldine combined the quality and quantity index scores to study corporate EID and environmental reputation [29]. Beck et al. proposed measuring the environmental disclosure index consisting of coverage, quality, and quantity [30]. Rupley et al. used a more complex index scoring approach to evaluate the relationship between corporate governance, media, and EID [31].

However, the existing absence of a regulatory framework for the EID's substance has culminated in a largely subjective disclosure, and the standard has been inconsistent. At present, there is no formal documentation on the quality assessment of EID, and there is no standard on the establishment and selection of evaluation indicators and methods. The EID was used as a variable to analyze its influence factors to find a way to enhance EID quality [32]. However, their liability of EID output significantly affects the outcomes of the studies mentioned above. Reinforce oversight and improve the efficiency of EIDs or provide a research base for further research. It is essential to develop a framework of science and realistic evaluations.

However, as Grey and Milne suggested, there is no superior research approach, method, or technique [33]. The most common technique using analyze economic, social, and environmental information is content analysis within business studies. Neuman stated that content analysis is "a technique for gathering and analyzing the content of the text. The content refers to words, meanings, pictures, symbols, ideas, themes or any message that can be communicated" [34]. Content is coded into various categories or concepts depending on selected criteria, and coding can be performed manually or using computer-aided technologies.

Therefore, TM has been widely used in the field of information analysis. Text mining is a computer-assisted technique equipped with the capability to extract information and trends from large amounts of textual data. Feldman and Sanger are giving an overview of the main issues discussed in the reports [35]. It is based on data mining techniques, machine learning, and natural language processing applied to the text. It strongly relies on computer programs and algorithms; thus, it is supposed to overcome the problems associated with content analysis's reliability [36].

Recently, TM has also been used to analyze trends and patterns in sustainability reports [37] and determine which aspects are the most public in company reports [38].

Yang and Lee proposed a TM method based on organization mapping to extract image semantics from an environmental text [39]. Modapothala and Issac used Bayesian

estimation to assess the relationships between ecological and social performance indicators and listed companies [40]. Huang et al., used TM to analyze financial disclosure in analysts' earnings forecasts [41]. Riffe et al., investigated the negative externalities of corporate emergencies' widespread media coverage using text analysis [42]. Bonzanini and Marco used Python to capture data from new blogs to analyze public environmental services [43]. Lee et al. studied spatial environmental information environmental trends using quantitative analysis and TM techniques [44], and Maeda et al. used TM to determine which managerial regulations could serve as incentives to motivate enterprises to consider the environment [45]. Irina et al., used text analysis to quantitatively analyze research trends in the environmental field [46]. Park and Kremer studied the classification of ecological sustainability indicators based on a TM approach [47]. Rabiei used TM to elucidate knowledge gaps and priorities in Iranian environmental science [48], while Villeneuve et al. explored indoor environmental quality based on Airbnb customer reviews using TM [49]. Wang et al. assessed the environmental performance in tourist areas and used TM of online news to explore the influencing factors [50].

Although text mining technology is widely used, the current EID index system and research perspective are limited to artificial subjective judgment. Machine learning-related content is rarely used, and there is a lack of research that has used text similarity, text clustering, and semantic text analysis to evaluate EID. Therefore, it is difficult for the study results on corporate EID to fully reflect quality and disclosure motivation. Although some researchers have used TM techniques for environmental information quality assessment, there is much room for refinement. Therefore, in this study, we attempted to construct a comprehensive EID evaluation system based on TM techniques and employed machine scoring to improve the listed companies' EID quality.

3. Methodology

The methodology for this study involved three stages. The first stage consisted of the automatic EID quality evaluation framework, including constructing the EID index system. The second stage consisted of the putout indicator weight and automated scoring of EID quality. Finally, the calculation of the EID index is conducted; the framework is presented in Figure 2.

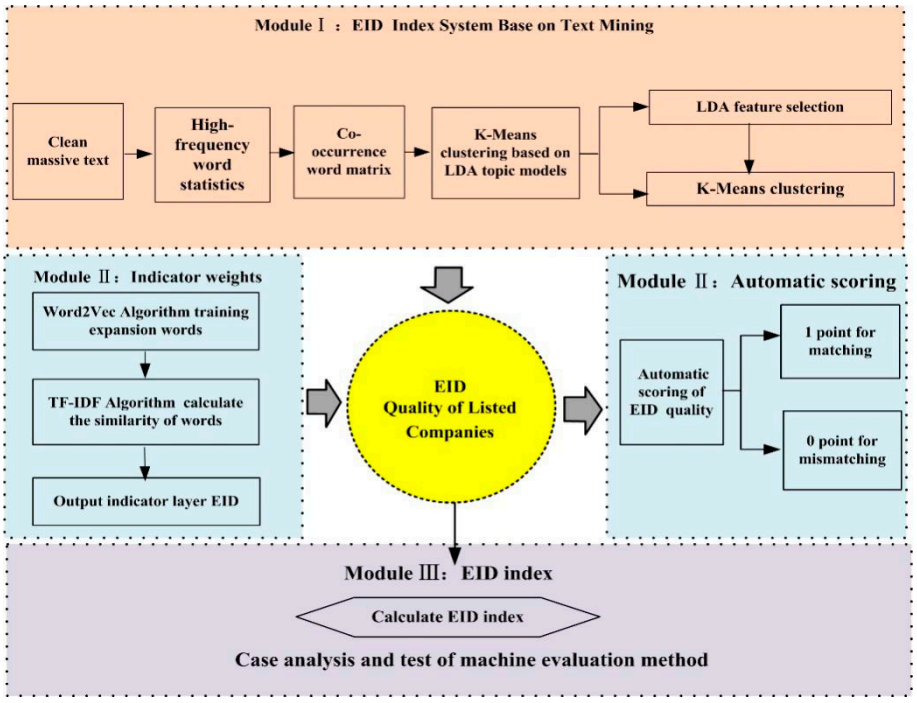


Figure 2. Automatic EID quality evaluation framework.

3.1. Chinese Text Mining Preprocessing Primary Steps

3.1.1. Data Collection

Before text mining, we need to obtain the text data of listed companies' environmental information disclosure in the heavy pollution industry. The Chinese text data acquisition method uses crawler code to crawl the environmental information disclosure text data.

3.1.2. Handling Chinese Encoding Issues

Python does not support Unicode processing. We need to follow Python's principle for Chinese text preprocessing to use utf-8 to store data and use Chinese encoding such as GBK.

3.1.3. Chinese Word Separation

There are many commonly used Chinese word splitting software. This study uses JIEBA word splitting. For example, "pip install Jieba" based on Python can be completed.

3.1.4. Introduction of Stop Words

There are many invalid words in Chinese text, and some punctuation marks that we do not want to introduce in Chinese text analysis need to be removed; therefore, these words are deactivated.

3.2. EID Quality System Construction

The purpose of assessing EID quality is to determine the listed companies' reliability, comprehensiveness, and legal and regulatory compliance. This study used the K-means clustering based on the LDA topic model algorithm to construct the EID index system for mining objective evaluation information through EID topic clustering analysis.

A flowchart of the construction of the EID index system is presented in Figure 3.

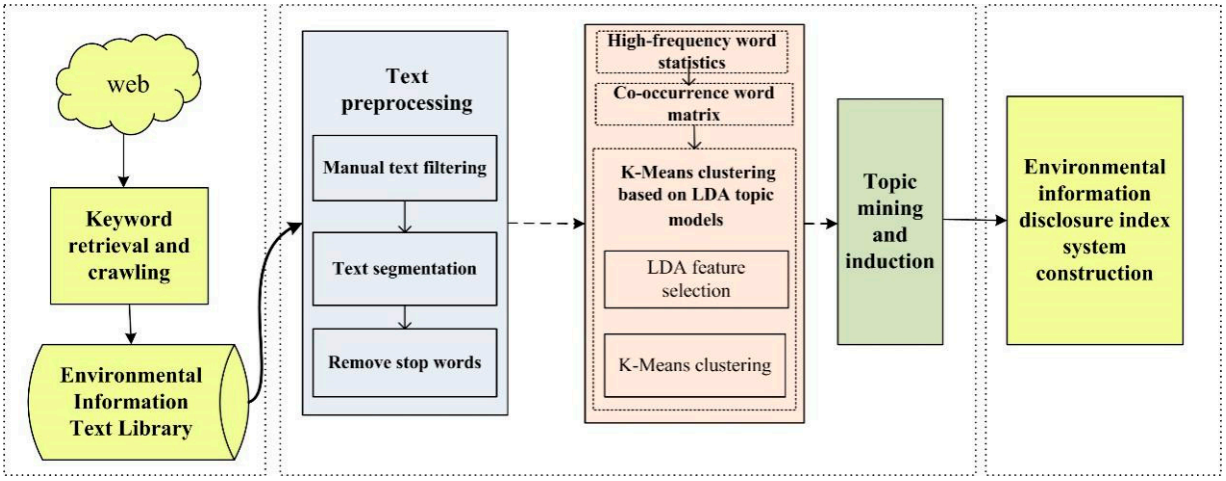


Figure 3. Construction of the EID index system.

We accessed the EID text data through crawling and keyword searching. Following the text preprocessing stage, text preprocessing methods, including manual screening, text segmentation, and removing "stop word," were used. The co-occurrence word matrix was then obtained based on the high-frequency words. Finally, we used the K-means clustering based on the LDA topic model algorithm to cluster the EID topics based on the co-occurrence word matrix and processing steps.

Prihatini et al. used K-means clustering through LDA based on this similarity matrix and finally found good clustering results for this method [51]. Alhawarat et al., clustered the Arabic collection by combining the LDA topic model and K-means clustering [52]. The results confirmed that this method could significantly improve the quality of clustering.

Bui et al., found that combining the LDA topic model and K-means clustering worked well for clustering [53]. In summary, there have been numerous studies showing that K-means clustering based on LDA topic models is better than traditional K-means clustering methods. Therefore, this paper uses the K-means clustering method based on the LDA topic model to improve the text mining of samples and obtain a more accurate topic hierarchical classification.

The LDA topic model is used to obtain a complete analysis of text collections and achieves better text mining results; the more significant the amount of text collection is, the larger the topics. LDA-based topic evolution analysis involves evaluating the model's generalization ability to measure the model's predictive power for unobserved data. We use the accepted metric of perplexity to measure the generalization ability of the model. Therefore, the smaller the perplexity is, the better the model generalization ability. Therefore, when the number of topics varies, the perplexity of the model also varies. The optimal number of topics can be determined by calculating the model's perplexity with different topics. The formula is shown in Equation (1) as follows:

$$\text{perplexity}(D) = \exp\left\{ \frac{-\sum_{d=1}^{D} \log_2 p(w_d)}{\sum_{d=1}^{D} N_d} \right\} \quad (1)$$

where N_d denotes the number of feature words of the D, and $p(w_d)$ is the probability of generating a document, which is calculated in Equation (2) as follows:

$$p(w_d) = \sum_{i \in k} p(z_i|d) p(w|z_i) \quad (2)$$

where $P(z_i \mid d)$ denotes the i topic's probability in the d text, and $P(w \mid z_i)$ denotes the probability of distributing the word of the distribution probability of the sink w.

3.3. EID Index Layer Weight Calculation

The EID index calculation was based on the EID index system and consisted of keyword expansion and word similarity calculation. We first used the EID system (essential seed word list) and EID corpus to obtain an extended word table based on the Word2Vec model. The text similarity of symbolic words was then calculated using the term frequency-inverse document frequency. The TF–IDF weight method is the most widely used weight calculation method in text processing [54]. TF–IDF model and the computed text similarity gave the weight of each EID index layer.

3.3.1. Keyword Expansion

We obtained the critical seed word list for keyword expansion based on the EID evaluation index system. We combined it with the EID corpus to obtain a hybrid corpus. We then used the Word2Vec model to train extended words and obtained a comprehensive wordlist based on the hybrid corpus. The Word2Vec model was prepared as follows:

First, we converted the training data into the format of the Word2Vec model. In our work, we first input large-scale text corpus to Word2Vec to produce word vectors. Using the structure of the Word2Vec, we can train and expand more exclusive vocabulary in the field of environmental information.

Second, the skip-gram algorithm expanded crucial seed words based on the complete corpus' environmental information. Through feeding the text corpus into one learning model, Word2Vec finally generates the word vectors. Word2Vec is not a single algorithm, but it includes two learning models—the continuous bag of words (CBOW) and skip-gram [55]. The skip-gram model's training objective is to find word representations helpful in predicting the surrounding words in a sentence or a document. Skip-gram indicates the context given the word [56]. The vectors of all expanded words were obtained as the

output after completing the training. Finally, the first 15 expanded words in each index layer and closest key seed word vector were selected according to the EID index system to form an expanded vocabulary.

3.3.2. Extended Word Similarity Calculation Based on the TF–IDF Model

The TF–IDF model is a keyword extraction method based on the word bag algorithm, widely used in TM to evaluate the word's importance to the text (Figure 4).

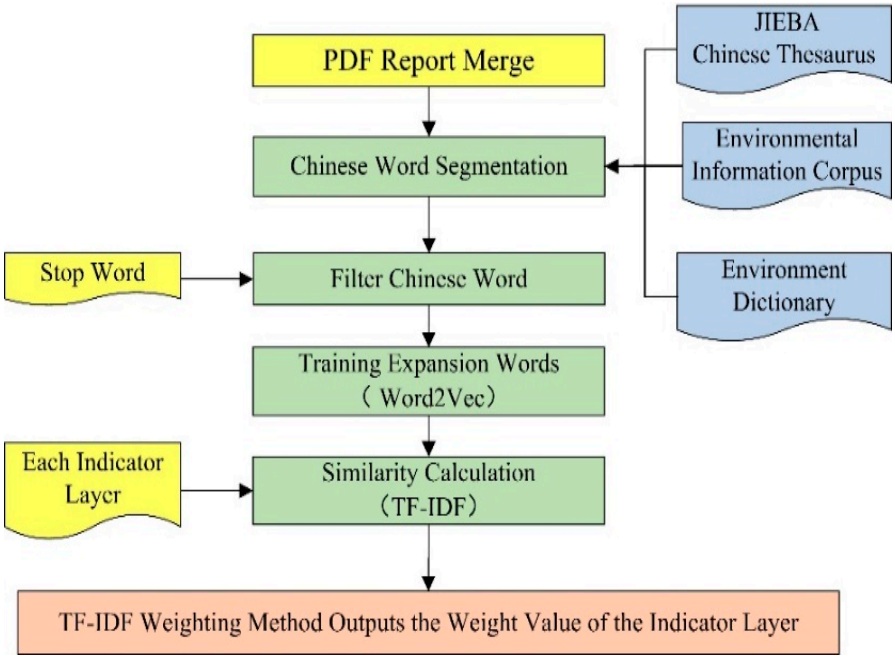


Figure 4. Extended word similarity calculation.

TF–IDF is used to choose an optimum indexing vocabulary for a collection of documents. Typical evaluation results are shown demonstrating the usefulness of the model [57]. The TF–IDF model is a keyword extraction method based on the word bag algorithm. It is widely used in TM to evaluate its importance to the text [58]. This study used the TF–IDF model to extract keywords from the studied text [59]. The similarity of expansion words was then calculated according to the TF–IDF model and the weight of each index layer was obtained [60].

3.4. Automatic Scoring of EID Quality

In this study, Python was used to read the text. The companies EID index system evaluation criteria were loaded into the operating system. Therefore, the model was read, and the corresponding string input in the system was obtained. Platform plurality was also used to train the word vectors and obtain an expanded corpus of EID. We used Python packages in the text mining process, e.g., Wordcount, Jieba, and Gensim collections, to clean and filter these reports, extract content related to environmental information, and form sample files after multiple rounds of compounding. Further, we performed text preprocessing, word segmentation, word frequency statistics operations on the sample files and used Gensim of the word2vec model to train word vectors.

Interactive technology was used to observe the expansion of the keyword language.

There have been various previous works on keyword extraction, primarily on different text domains. The TF–IDF-based selection has been widely used. It is computationally efficient and performs reasonably well [61]. Keyword extraction has also been treated as a supervised learning problem. A classifier is used to classify candidate words into positive

or negative instances using a set of features [62]. The Word2Vec model was used to improve the corpus' ability regarding semantics and semantic recognition for context.

Finally, the core process of the EID quality scoring system was discussed. It searched for keywords or keyword combinations in the company's environmental information disclosure report. Additionally, calculated the window in variety with the weight value of the EID index system and then evaluated and scored the EID quality of the listed companies during the scoring process, as shown in Figure 5.

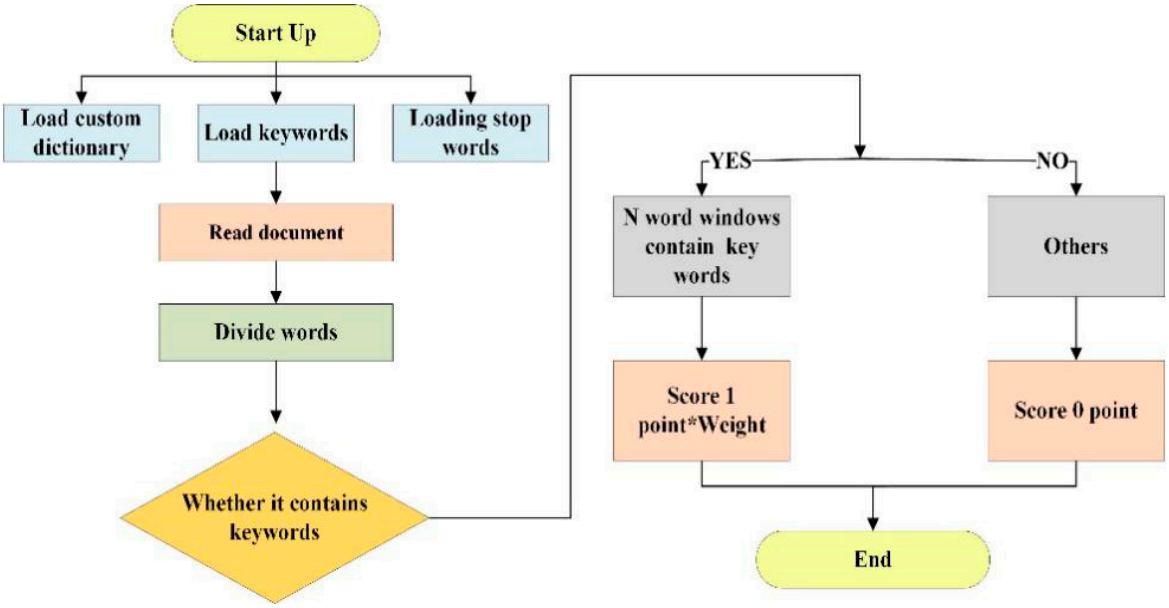


Figure 5. Automatic scoring of the EID quality.

The EID quality index was calculated based on the variable setting method and EID index system. The parameter values were binary and set to 0 or 1 [63]. We supposed a keyword with a corresponding meaning appeared in the vocabulary window of the text of EID. Specifically, if there were content consistent with the sub variable in the text for environmental information, this sub variable parameter would be "1"; otherwise, it would be "0." An EID scoring was constructed, as shown in Equations (3)–(6).

Firstly, we put the main variables and sub-variables into the EID index system table.

Secondly, we tabulated the sub-variable sub-variable from the same main variable through text mining and Equations (3) and (4).

$$X \sim N[0,1] \tag{3}$$

$$X = \{XR : [0 \sim 1]\} \tag{4}$$

Thirdly, calculating the EDI score of the environmental information disclosure quality to be evaluated by Equations (5) and (6), equal to the sum of all main variables.

$$X_i \left[\sum_{j=1}^{n} \frac{X_{ij}}{T(X_{ij})} \right] \ (i = 1,2,3,4,5 \ldots m) \tag{5}$$

$$\begin{aligned} EID = [X_1(\sum_{j=1}^{7} \tfrac{x_{1j}}{7}) + X_2(\sum_{j=1}^{1} x_{2j}) + X_3(\sum_{j=1}^{5} \tfrac{x_{3j}}{5}) + \\ X_4(\sum_{j=1}^{2} \tfrac{x_{4j}}{2}) + X_5(\sum_{j=1}^{3} \tfrac{x_{5j}}{3}) + X_6(\sum_{j=1}^{1} \tfrac{x_{6j}}{1}) + \\ X_7(\sum_{j=1}^{1} x_{7j}) + X_8(\sum_{j=1}^{1} x_{8j}) + X_9(\sum_{j=1}^{3} \tfrac{x_{9j}}{3})] \end{aligned} \tag{6}$$

The EID quality was calculated based on the variable setting method and the EID index system, where "i" is the main variable, i = 1,2,3,· · · ,m; and j is the sub variable, j = 1, 2,· · · ,n. The number of sub-variables in each main variable is unlimited.

Therefore, the value of the EID score reflects different levels of environmental information disclosure quality consistency. To give the same weight to all sub-variables, it is necessary to use a binary system. The binary system (0,1) helps to maintain a balance among all variables [64]. We supposed a keyword with a corresponding meaning appeared in the vocabulary window of the EID text and verified that the content is consistent with the sub variable in the text.

4. Case Study

4.1. Sample and Data Source

The study focuses on listed firms in heavy pollution industries in China. The government requires mandatory disclosure of environmental information in China's heavy pollution industries. The study included 801 valid samples from 846 heavy polluting companies in China. The environmental information disclosure text data come from Shanghai Stock Exchange (http://www.sse.com.cn/, accessed on 8 March 2019) and Shenzhen Stock Exchange (http://www.szse.cn/, accessed on 14 June 2019) Juchao Consulting Network (http://www.cninfo.com.cn/new/index, accessed on 18 August 2019), Business Consulting Network (http://www.sytao.com/, accessed on 8 March 2019), RIX (http://www.rkraings.cn/, accessed on 4 November 2019), WIND (https://www.wind.com.cn/, accessed on 4 November 2019), and CSMR (http://www.gtarsc.com, accessed on 4 November 2019). According to the environmental industry classification management list (circular letter 2008 No. 373) issued by China in 2008, the 16 types of heavily polluting industry codes were determined. A-share-listed heavy pollution industry companies from 2013 to 2017 were selected as research subjects. This study text information focused on the environmental information section, including the listed companies' annual, social responsibility, sustainable development, and environmental protection reports. It contained 4005 annual reports, 1954 corporate social responsibility reports, 282 environmental protection reports, and 204 sustainable reports—a total of 6445 documents.

4.2. EID Index System Construction

4.2.1. Keyword Extraction

In this study, Python and Jieba third-party databases were used for word segmentation and frequency statistics and building a corpus in EID. First, the sample report dataset was cleaned, screened, related to the environmental information content, and extracted as the sample file. It is complete information from the environmental perspective.

Text segmentation, stop word deletion, and word frequency statistics were then conducted on the sample files, and 18,691 high-frequency words in the field of environmental information were obtained. According to the literature [65], the collected glossary was sent to five experts in relevant fields, who judged and scored whether the environmental information was appropriate. After three rounds of screening, the exclusive vocabularies for the area of environmental information were obtained. Finally, using the words were sorted from large to trim based on their frequency, and the top 60 keywords were selected, as shown in Table 1.

Table 1. High-frequency vocabulary statistics table.

High-Frequency Words	Frequency		High-Frequency Words	Frequency		High-Frequency Words	Frequency	
Environment	511,106	0.011119	Construction	66,305	0.001442	Industry	24,778	0.000539
Protection	510,009	0.011095	Service	61,809	0.001345	Energy	24,396	0.000531
Cost-effective	497,984	0.010834	Invention	60,013	0.001306	Funds	21,412	0.000466
Investment	487,238	0.010600	Science	59,544	0.001295	Improvement	21,116	0.000459
Project	452,814	0.009851	Investment	58,548	0.001274	Operation	17,829	0.000388
Cost	188,522	0.004101	Economy	55,960	0.001217	Reduction	15,730	0.000342
Pollution	163,831	0.003564	Responsibility	55,275	0.001203	Safeguard	15,727	0.000342
Development	137,724	0.002996	Chemistry	54,805	0.001192	Manufacture	13,961	0.000304
Management	136,666	0.002973	Society	53,020	0.001153	Power	10,338	0.000225
Production	134,863	0.002934	Accomplishment	51,753	0.001126	Patent	10,091	0.000220
Reduction								
2/5000	109,370	0.002379	Execution	50,266	0.001094	Equipment	8431	0.000183
reduce								
Matters	109,237	0.002376	System	50,070	0.001089	Retrofit	8393	0.000183
Emission	103,176	0.002245	Conservation	46,919	0.001021	Engineering	7993	0.000174
Technology	102,848	0.002237	Safety	46,166	0.001004	Operation	7199	0.000157
Production	98,763	0.002149	Governance	42,869	0.000933	Green	7146	0.000155
Information	98,715	0.002148	Development	28,605	0.000622	Decrease	7067	0.000154
Policy	97,351	0.002118	Enhancement	28,379	0.000617	Operations	6382	0.000139
Research	70,553	0.001535	Resources	26,634	0.000579	Cycle	6273	0.000136
Implement	66,873	0.001455	Quality	26,131	0.000568	Waste	5437	0.000118
Fulfillment	66,438	0.001445	Organization	26,045	0.000567	Surroundings	5321	0.000116

4.2.2. Co-occurrence Word Matrix Construction

From the high-frequency words identified above, co-occurrence analysis was conducted to form a co-occurrence word matrix. Only the first 10 high-frequency words are presented in Table 2. The lower-ranked words appear less frequently.

Table 2. Matrix of co-occurrence words.

	Environment	Protection	Cost-Effective	Investment	Project	Cost	Pollution	Development	Management	Production
Environment	0	–	–	–	–	–	–	–	–	–
Protection	338	0	–	–	–	–	–	–	–	–
Cost-effective	39	146	0	–	–	–	–	–	–	–
Investment	84	826	3812	0	–	–	–	–	–	–
Project	4	55	2	14	0	–	–	–	–	–
Cost	72	16	19	8	21	0	–	–	–	–
Pollution	72	27	8	28	6	31	0	–	–	–
Development	2	11	5	1	2	0	4	0	–	–
Management	6	4	3	2	1	5	71	0	0	–
Production	2	3	7	4	0	17	2	1	13	0

4.2.3. Topic Clustering Based on K-Means Clustering Based on LDA Topic Model

According to the keyword co-occurrence matrix, the keywords were divided into different categories. Whether the high-frequency keyword threshold is reasonable or not will significantly impact the co-word analysis results. This article adopts Pareto's law selection method to set the point. In Table 3. Based on the 60 high-frequency words, a threshold value of 20 was established, and the keywords in the co-word matrix were clustered using the K-means clustering based on the LDA topic model algorithm; the threshold was correctly defined.

We calculated the model's perplexity under each number of topics and plotted the line graph in Figure 6. There is a clear inflection point in the confusion curve from the graph when the number of topics is nine. Additionally, the curve flattens out, indicating that increasing the number of topics again does not significantly reduce the confusion. Therefore, the optimal number of topics is determined to be nine.

Table 3. The set threshold method.

Number	Threshold Definition Meth	High-Frequency Threshold	Number of High-Frequency Words Extracted
1	Pareto's law selection method [66]	10	30
2	Donohue method [67]	50	3
3	Drake Price method [68]	8	34
4	g-index method [69]	10	26

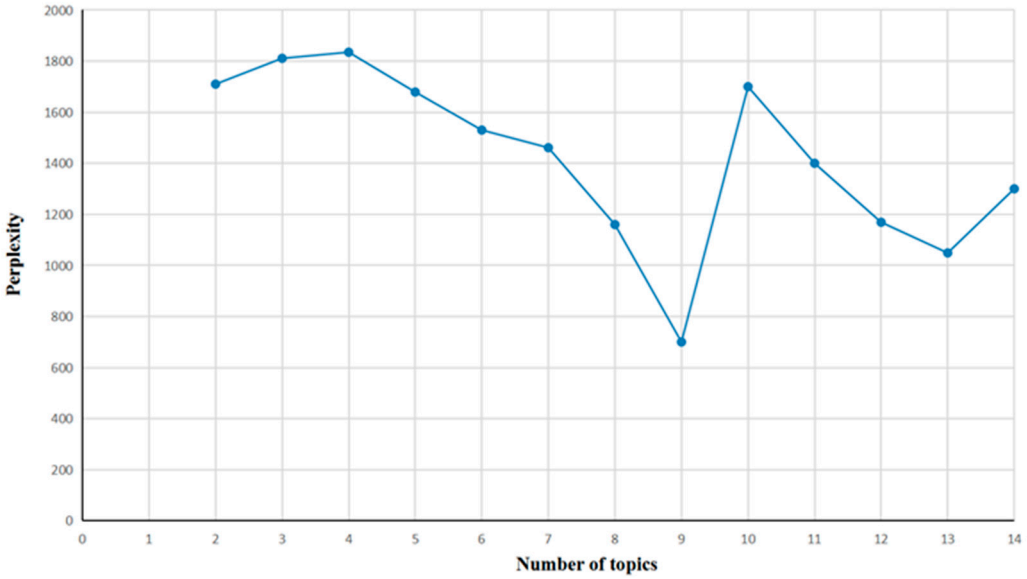


Figure 6. The choice of K-means clustering is based on the LDA topic model.

The document-potential-topic model output by the LDA topic model is used as samples, and the category is set to nine. In turn, K-means clustering is performed, and the effect of clustering K-means based on the LDA topic model is shown in Figure 6. As shown in Figure 7, the samples are better divided into nine categories, and each category has a clear demarcation line.

Table 4 shows the text topic clustering results based on the K-means clustering based on the LDA topic model algorithm. Cluster1 contained keywords such as policies, regulations, and departments; therefore, it could be summarized as "corporate governance structure"; Cluster2 included consumption and energy; thus, this category was classified as "energy consumption environmental liability information"; Cluster3 contained wastewater and discharge, and was classified as "environmental pollution discharge information"; Cluster4 had waste, and was classified as "waste disposal"; Cluster5 included R&D and environmental protection, and was classified as "environmental governance expenditure"; Cluster6 included ecological protection and fines, and was classified as "environmental penalty expenses"; Cluster7 contained sewage discharge and greening as keywords, and was classified as "environmental greening and sewage discharge expenditure information"; Cluster8 included tax and relief, and was classified as "environmental tax relief"; finally, Cluster9 included awards and revenue as keywords, and the category was summarized as "income from environmental incentives."

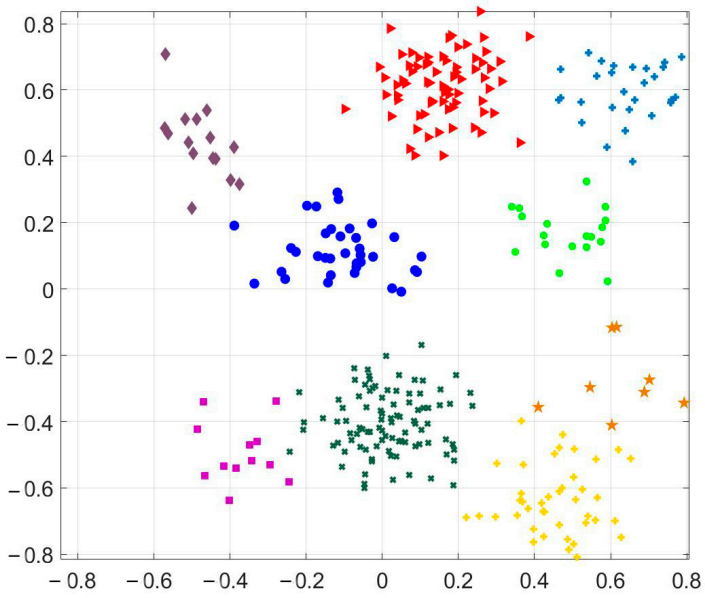


Figure 7. Clustering results graph.

Table 4. K-means clustering based on LDA topic model clustering results.

Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9
Policy	Consume	Wastewater	Waste materials	Research	Environmental	Sewage	Tax	Reward
System	Energy	Emission	Waste product	Protection	Fine	Greening	Exemption	Income
Department	Loss	Trash	Castoff	Expenditure	Expenditure	Service	Financial	Benefit
Management	Consumption	Poisonous	Recycle	Energy saving	Cost	Governance	Subsidy	Utilization
Aims	Expenditure	Noise	Dispose	Surroundings	Pay	Clean	Discount	Exploitation
Measures	–	Dust	–	Engineering	Punishment	–	Return	Operations
Systematism	–	–	–	Governance	–	–	–	–
Standard	–	–	–	Equipment	–	–	–	–
Accident	–	–	–	Detect	–	–	–	–
Education	–	–	–	–	–	–	–	–
Construction	–	–	–	–	–	–	–	–
Production	–	–	–	–	–	–	–	–

Table 5 presents the K-means clustering based on the LDA topic model-based EID index system. According to the clustering results, a similar EID index system hierarchy was constructed from the EID index system with 9 subject-level structures and 24 index levels. The companies' environmental disclosure index was measured based on this system, which could be used to assess whether the enterprise EID quality was consistent with regulatory agencies' requirements.

Table 5. EID System for heavily polluting industries.

Thematic Layer	Index Layer	Connotation
Corporate Governance Structure (X_1)	Environmental protection concept (X_{11}) Environmental management organization (X_{12}) Environmental goals (X_{13}) ISO14001 standard (X_{14}) Environmental accident (X_{15}) Environmental education and training (X_{16}) Implement the "Three Simultaneous System" (X_{17})	It mainly refers to the EID management mechanism principles and components. The relevant information reflects the importance of environmental protection by listed companies and their intention to release environmental information. Includes information regarding environmental standards used by listed companies, preparations for environmental management systems, and managers' attitudes towards ecological management
Environmental Responsibility (X_2)	Total resource consumption (X_{21})	Shows the specific energy consumption of the company. The company's total energy consumption can directly reflect its actual performance in energy conservation. Relevant information can be used to assess the managers' expectations for environmental protection contributions

Table 5. *Cont.*

Thematic Layer	Index Layer	Connotation
Environmental Pollution Discharge (X_3)	Wastewater disposal (X_{31}) Stable waste discharge (X_{32}) Toxic emissions (X_{33}) Noise emission (X_{34}) Dust emissions (X_{35})	Describes the company's specific quantities of waste gas, wastewater, industrial waste, emission noise, and dust. Related information refers to the impacts of the company's production and operation activities on the natural environment. Relevant information can be used to evaluate the achievements of listed companies in treating environmental pollution.
Waste Disposal (X_4)	Waste disposal (X_{41}) Waste recycling (X_{42})	Shows the disposal of waste products and waste by listed companies.
Environmental Governance Expenditure (X_5)	Environmental research expenditure (X_{51}) Environmental protection expenditure (X_{52}) Environmental equipment expenditure (X_{53})	Records the company's expenditure on environmental management research and development. Reflect the company's work in environmental protection for some time, including environmental research expenditures, environmental protection governance expenditures, and environmental equipment expenditures. It can prompt companies to take more significant measures in environmental management.
Environmental Fine Expenditure (X_6)	Environmental acceptable payment (X_{61})	Companies' fines for environmental protection
Environmental Protection Expenditure (X_7)	Pollution discharge fee, greening fee, environmental protection fee (X_{71})	Shows the company's pollution discharge, greening, and environmental protection fees.
Environmental Protection Tax Relief (X_8)	Tax deduction (X_{81})	Explains the environmental protection tax reduction and exemption of listed companies.
Environmental Rewards (X_9)	Environmental rewards (X_{91}) Environmental income (X_{92}) Waste utilization income (X_{93})	Explains the companies' incentive income for environmental protection.

4.3. EID Index Layer Weight Calculation

Based on the Word2Vec model, we used the skip-gram algorithm to train extended words and obtain a comprehensive word list. The text-similarity of the broad terms was calculated by the TF–IDF model for the EID index system, as shown in Table 6.

Table 6. The EID index layer weight value.

Thematic Layer	Index Layer	Index Layer Weight Value
Corporate Governance Structure (X_1)	Environmental protection concept (X_{11})	0.4415
	Environmental management organization (X_{12})	0.4899
	Environmental goals (X_{13})	0.5394
	ISO14001 standard (X_{14})	0.4600
	Environmental accident (X_{15})	0.5487
	Environmental education and training (X_{16})	0.3706
	Implement the "Three Simultaneous System" (X_{17})	0.5476
Environmental Responsibility (X_2)	Total resource consumption (X_{21})	0.6859
Environmental Pollution Discharge (X_3)	Wastewater disposal (X_{31})	0.6851
	Stable waste discharge (X_{32})	0.2859
	Toxic emissions (X_{33})	0.4415
	Noise emission (X_{34})	0.4899
	Dust emissions (X_{35})	0.4600
Waste Disposal (X_4)	Waste disposal (X_{41})	0.3706
	Waste recycling (X_{42})	0.4899
Environmental Governance Expenditure (X_5)	Environmental research expenditure (X_{51})	0.5476
	Environmental protection expenditure (X_{52})	0.4394
	Environmental equipment expenditure (X_{53})	0.5394
Environmental Fine Expenditure (X_6)	Environmental acceptable payment (X_{61})	0.5476
Environmental Protection Expenditure (X_7)	Pollution discharge fee, greening fee, environmental protection fee (X_{71})	0.4415
Environmental Protection Tax Relief (X_8)	Tax deduction (X_{81})	0.4899
Environmental Rewards (X_9)	Environmental rewards (X_{91})	0.3859
	Environmental income (X_{92})	0.4899
	Waste utilization income (X_{93})	0.4600

4.4. Automatic Scoring of EID Quality

Python was used to read the samples' enterprise environmental information content, and machine scoring was conducted according to the experimental process. The massive pollution industry's EID index listed its distribution across industries, as shown in Table 7 and Figure 8.

Table 7. EID quality score for China's heavily polluting industries in 2013–2017.

Industry Code	Heavily Polluting Industry	Samples	EID Quality Scores					
			2013	2014	2015	2016	2017	Average
B06	Coal mining and washing	23	10.97	10.93	11.00	11.34	11.72	11.20
B07	Oil and gas extraction	3	11.16	10.52	11.35	11.29	12.59	11.38
B08	Ferrous metal mining and dressing	5	7.86	8.88	9.51	10.16	10.51	9.38
B09	Non-ferrous metal mining and dressing	18	11.28	10.75	11.26	11.27	11.75	11.26
C17	Textile	31	7.11	7.48	8.00	9.21	9.49	8.26
C19	Manufacturing of leather, fur, feathers	12	9.20	9.80	9.52	9.89	10.19	9.72
C22	Paper and paper products	22	8.03	8.30	8.70	10.29	10.92	9.25
C25	Petroleum processing, coking and nuclear fuel	10	11.49	10.67	10.73	11.49	11.53	11.18
C26	Chemical raw materials and chemical products	198	10.32	10.65	10.76	11.15	11.42	10.86
C27	Pharmaceutical Manufacturing	191	6.75	7.20	7.95	8.90	10.86	8.33
C28	Chemical fibre manufacturing	15	10.05	10.23	10.33	11.22	11.37	10.64
C30	Non-metallic mineral products	73	10.21	10.84	10.45	10.75	11.03	10.66
C31	Ferrous metal smelting and rolling processing	25	11.07	11.49	11.56	11.80	12.13	11.61
C32	Non-ferrous metal smelting and rolling	58	10.60	10.85	10.73	11.01	11.29	10.89
C33	Metal products	54	6.03	9.67	9.75	10.30	10.62	10.19
D44	Electricity and thermal power production	63	10.16	10.36	10.59	10.86	10.94	10.58
	Total	801	–	–	–	–	–	–

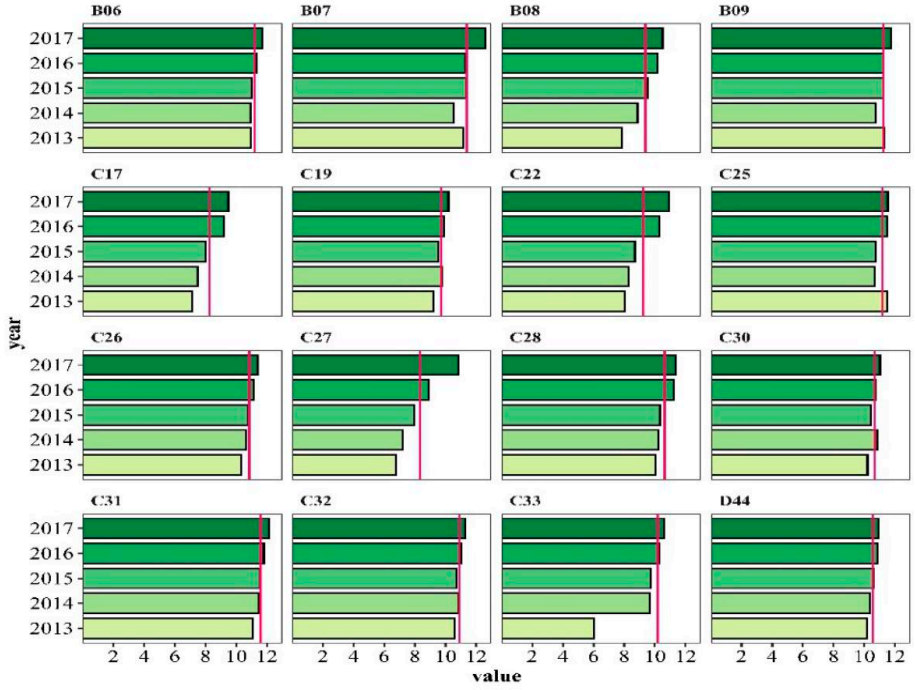


Figure 8. Distribution map of the EID quality score for China's heavily polluting industries in 2013–2017.

4.5. Constructing the EID-Surface

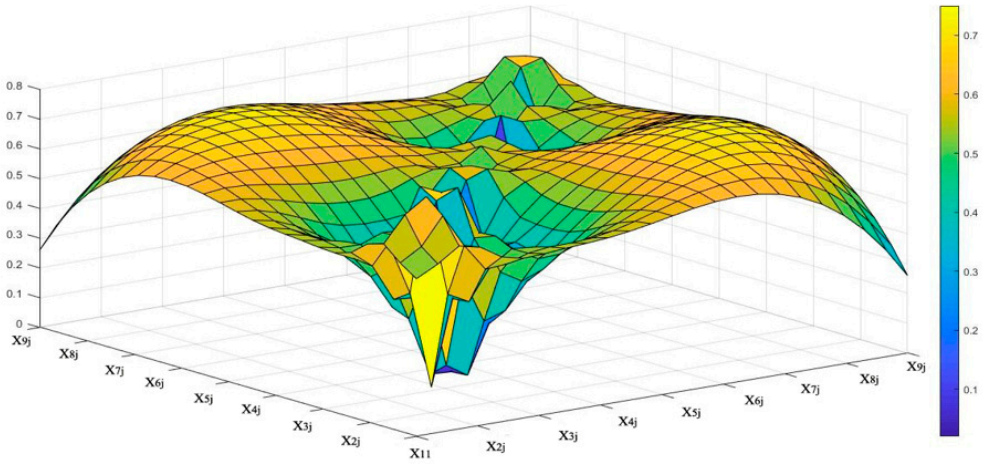
The purpose of constructing the EID-Surface is to represent all results in the EID–Matrix graphically. The EID-Surface vertical axes show the strengths and weaknesses

within EID scores (in Appendix A, Table A1) on a multidimensional coordinate space. Horizontal axes in the EID-Surface representative involve 24 sub-variables distributed in 9 main variables. The construction of the EID-Surface is based on the EID–Matrix results. The EID–Matrix is a three-by-three matrix containing the individual results of all 9 main variables and 24 sub-variables.

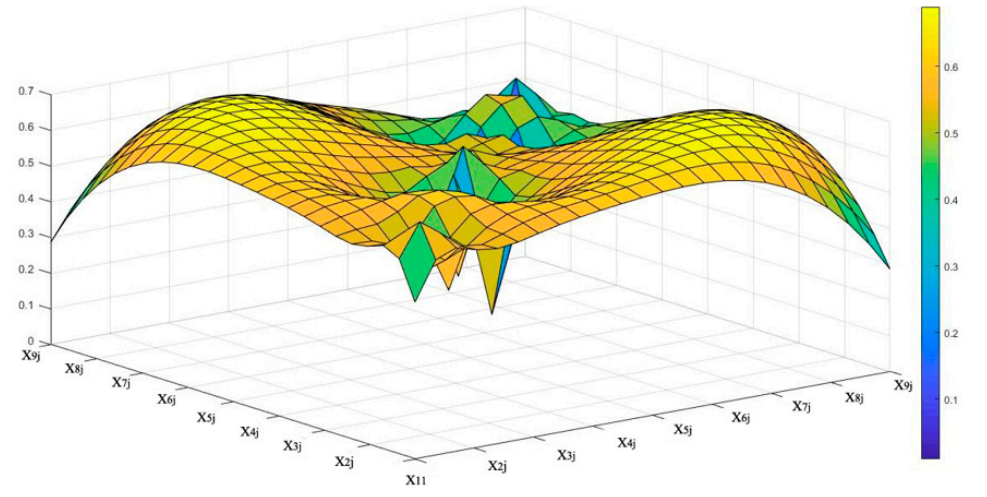
EID exponent's visual processing exponent by EID surface form shows the result of parallelism intuitively through matrix transformation of nine main variables designed in this paper. Considering the matrix's symmetry and the EID surface's balance, form a matrix of order three by three. The area of the EID area is calculated by using Equation (7).

$$\text{EID-Surface} = \begin{pmatrix} X_{1j} & X_{2j} & X_{3j} \\ X_{4j} & X_{5j} & X_{6j} \\ X_{7j} & X_{8j} & X_{9j} \end{pmatrix} \quad (7)$$

This study only presents the EID surface charts for the industries with the top and bottom two EID scores. From the surface graph, it is more intuitive to see the scores on each indicator layer of industry (in Appendix A, Table A1). Figure 9a,b represents C31, the ferrous metal smelting, and rolling processing industry EID-Surface, and B07 oil and gas extraction industry EID-Surface. These two industries have the highest scores. Figure 10a,b represents C17 textile industry EID-Surface and C27 pharmaceutical manufacturing industry EID-Surface. These two industries have the lowest scores.



(**a**)



(**b**)

Figure 9. (**a**) C31 ferrous metal smelting and rolling processing industry EID-Surface and (**b**) B07 oil and gas extraction industry EID-Surface.

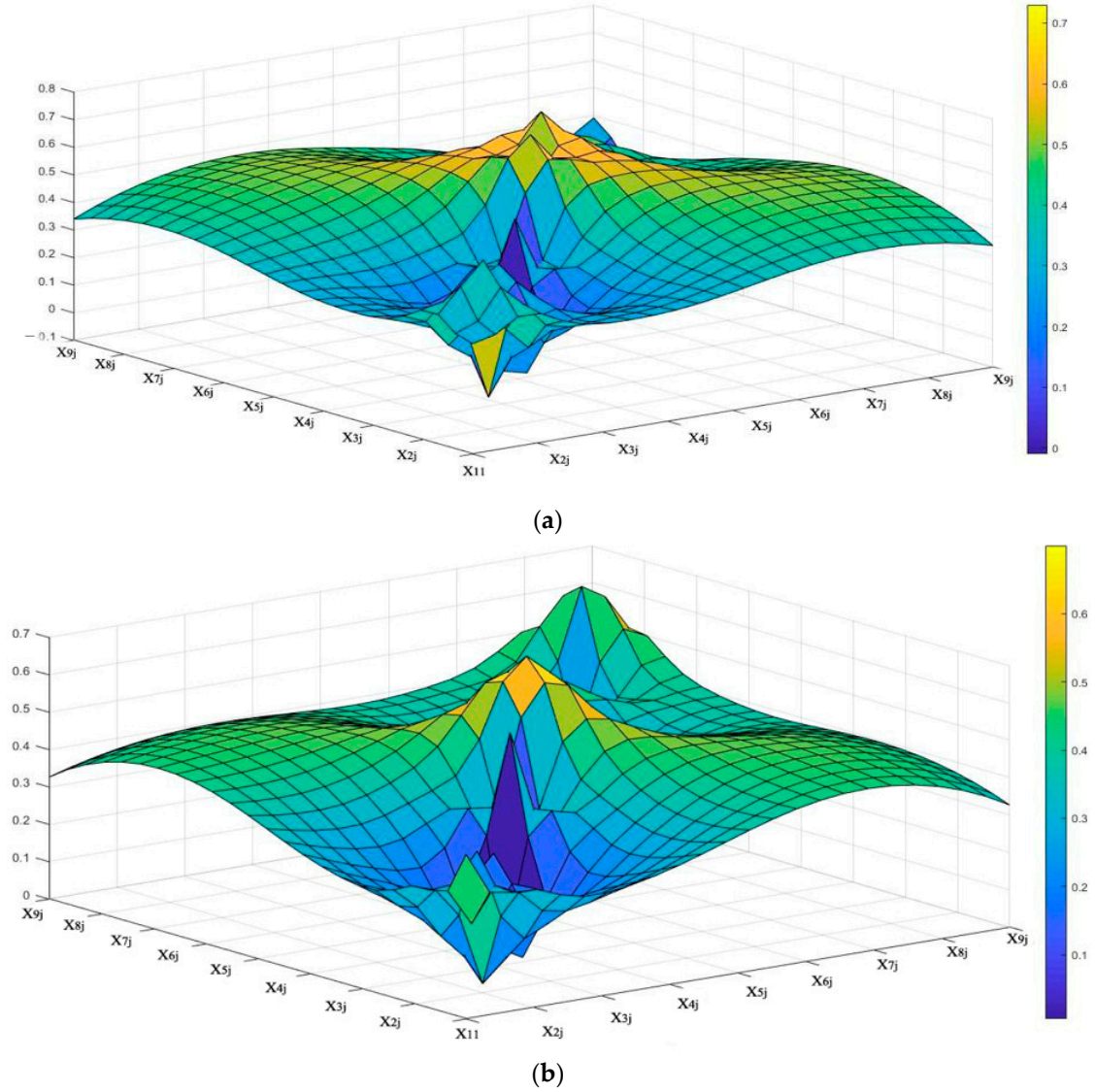


Figure 10. (**a**) C17 textile industry EID-Surface and (**b**) C27 pharmaceutical manufacturing industry EID-Surface.

It can be seen that the environmental disclosure information of the ferrous metal smelting and rolling processing and oil and gas extraction industry was very comprehensive and detailed, and the relevant environmental information was disclosed in the annual and social responsibility reports. The textile, pharmaceutical, paper, leather, fur, feather industries accounted for the low EID quality score for their most proportion.

Under the nine leading indicators, 98% of companies disclosed the corporate governance structure of "environmental policies, guidelines, and concepts," which is the highest disclosure rate. The construction, investment, and operation costs of environmental protection facilities and the "three wastes" treatment approach were second only to the indicators, which all exceeded 80%. The disclosure rate of environmental responsibility information indicators, such as "emissions and emission reductions" and "emission reduction targets," was below 30%. Generally, the sample enterprises' disclosure of environmental information needs to be improved since many vital indicators have not been sufficiently disclosed.

4.6. The Calculation of the EID Index

To compare the degree of environmental information disclosure of 16 in heavy pollution industries better, we calculated the maximum possible score for each sample company's environmental information disclosure as 24, evaluated by Equation (8) (corporate governance structure scored 7, environmental responsibility scored 1, environmental pollution discharge scored 5, waste disposal scored 2, environmental governance expenditure scored 3, acceptable environmental expenditure scored 1, environmental protection expenditure scored 1, environmental protection tax relief scored 1, environmental rewards scored 3). EID quality evaluation indices for China's heavily polluting industries in 2013–2017 are listed in Table 8.

$$\text{EID-Index} = \text{EID}/24 \times 100\% \quad (8)$$

Table 8. The descriptive statistics of EID quality evaluation indices.

Industry	Observations	Environmental Information Disclosure Quality Evaluation Index (%)								
		2013	2014	2015	2016	2017	Min	Max	AVG	SD
B06	23	45.7083	45.5417	45.8333	47.2500	48.8333	45.5416	48.8333	46.6333	1.5098
B07	3	46.5000	43.8333	47.2917	47.0417	52.4583	43.8333	52.4583	47.4250	3.5677
B08	5	32.7500	37.0000	39.6250	42.3333	43.7917	32.7500	43.7916	39.1000	3.0040
B09	18	47.0000	44.7917	46.9167	46.9583	48.9583	44.7916	48.9583	46.9250	1.7015
C17	31	29.6250	31.1667	33.3333	38.3750	39.5417	29.6250	39.5416	34.4083	4.0012
C19	12	38.3333	40.8333	39.6667	41.2083	42.4583	38.3333	42.4583	40.5000	1.1502
C22	22	33.4583	34.5833	36.2500	42.8750	45.5000	33.4583	45.5000	38.5333	5.2205
C25	10	47.8750	44.4583	44.7083	47.8750	48.0417	44.4583	48.0416	46.5916	1.9524
C26	198	43.0000	44.3750	44.8333	46.4583	47.5833	43.0000	47.5833	45.2500	1.4808
C27	191	28.1250	30.0000	33.1250	37.0833	45.2500	28.1250	45.2500	34.7167	6.5947
C28	15	41.8750	42.6250	43.0417	46.7500	47.3750	41.8750	47.3750	44.3333	2.4609
C30	73	42.5417	45.1667	43.5417	44.7917	45.9583	42.5416	45.9583	44.4000	1.0071
C31	25	46.1250	47.8750	48.1667	49.1667	50.5417	46.1250	50.5416	48.3750	1.2040
C32	58	44.1667	45.2083	44.7083	45.8750	47.0417	44.1666	47.0416	45.4000	1.0092
C33	54	25.1250	40.2917	40.6250	42.9167	44.2500	25.1250	44.2500	38.6416	1.8895
D44	63	42.3333	43.1667	44.1250	45.2500	45.5833	42.3333	45.5833	44.0916	1.1031

As shown in Table 8, the listed companies' average EID quality evaluation index in China's heavily polluting industries indicated that the overall EID quality of the listed companies is insufficient. There were also differences in the EID quality evaluation index between the 16 heavily polluting industries. Listed companies in the non-ferrous metal smelting industry, oil and gas extraction industry reported the highest quality corporate environmental information, which was significantly higher than that of other industries. As the focus of environmental protection, these enterprises are facing significant pressure from the government and public. Therefore, they tend to focus on improving the EID quality.

Additionally, most of these enterprises have a large production scale, environmental solid management capabilities, and excellent EID aids in strengthening their market competitiveness. Some listed companies in less-polluting industries, such as pharmaceutical manufacturing, exhibited poor EID performance. Additionally, most listed companies in high-polluting industries are gradually improving the quality of their environmental information. The EID index is related to the enterprises' commitments, capacity building, business performance, and external environmental regulation changes.

The disclosure score ratio of the "corporate governance structure" indicator was highest. This information was disclosed the most. The ratio of "environmental responsibility information" was lowest, significantly lower than those of the other indicators. The listed companies in China's heavily polluting industries were more active and comprehensive in disclosing their environmental protection requirements, environmental protection concepts, and additional relevant information. They tended to respond proactively to China's rising enthusiasm toward environmental protection in recent years, formulate environmental

protection policies, and have been committed to establishing the company's environmental protection image. Listed companies in China's heavily polluting industries rarely disclose their environmental requirements due to a lack of environmental constraints. It should be noted that the "environmental pollution emissions" indicator score was very high because listed companies in China's heavily polluting industries have actively responded to the latest EID policy requirements announced by the China Securities Regulatory Commission and promoted various "three wastes." The pollutant discharge data have also been actively disclosed.

4.7. Testing the Evaluation

Researchers have recently conducted manual surveys and evaluations of the EID of listed companies in China. In 2016 and 2017, 172 listed Shanghai Stock Exchange companies were selected by the Environmental and Economic Research Center of Fudan University. The quality and quality of their EID and public disclosure information was analyzed from the 2015 and 2016 annual, corporate social responsibility, sustainable development, and environmental reports, and the index scores were ranked. Thus, this report was authoritative in the industry.

The evaluation results were further compared based on machine evaluation and artificial subjective evaluation to verify the results' reliability. The automatic scoring approach was used to reassess the enterprise EID scores for the same sample of 172 listed companies in 2015 and 2016. Given the difference between the respective index system's construction and the score, the scores cannot be directly compared.

Therefore, rank and nonparametric tests were conducted to compare the same sample of companies' rankings [70]. The rank-sum test is only used to reach particular values in a given parameter distribution.

Sort the scoring results according to the company's stock code to obtain two sets of random sequences and use the correlation coefficient between the two sets of sequences to measure the consistency of the two scoring methods. The correlation coefficient is,

$$\gamma = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (9)$$

where X_i, x_i, y_i is manual and machine scoring, and $\overline{x}$, $\overline{y}$ Are the sample mean. The new method of evaluating the quality of EID based on machine scoring provided reliable results of the quality of corporate EID. The corresponding results of the rank and rank test are shown in Table 9.

Table 9. Results of the rank tests.

Text	2015	2016
z-Statistics	−0.205	−0.012
p-value	0.837	0.921

For a significance of 0.01, the respective values corresponding to the annual P-statistics were always more significant than the critical importance of 0.05.

Therefore, there was no significant difference between the two approaches' evaluation results, and the new method of EID quality evaluation based on machine scoring is accurate. Additionally, the original form can save more time and achieve better accuracy than the traditional subjective evaluation method.

5. Conclusions

In conclusion, key findings suggest that it helps investigate firms' strategic sustainability intentions based on the critical issues identified in their EID quality. This paper aims to propose a new method to evaluate the subjectivity and objectivity of environmental

information disclosure based on text mining tools, enrich the research content, and open up more text data sources. The research content and information sources of text big data in environmental management can be further refined and enriched.

First, the TM method was used to improve the current EID index system. The EID index system's content was adjusted dynamically, and complete corpora and scoring systems of the EID quality were also constructed. The EID quality scoring system could generate indices at all levels and corresponding indicator-layer weights under various classification dimensions according to different scoring standards required. The accuracy of the index scoring standard was significantly improved through the proposed method. This analysis no longer requires simple manual counting and judging or the simplified mathematical conversion method. The EID index scoring value extraction was convenient and quick, and the accuracy was significantly improved.

Second, calculating the comprehensive evaluation index of enterprise EID was enriched based on the K-means clustering based on the LDA topic model algorithm and Word2Vec model. The more comprehensive exploration and application of the EID index calculation via the proposed method than the current artificial subjective index calculation model ensures comprehensive, objective, and valuable information disclosure and overcomes the limitations of the previous synthetic personal calculation method. The combination of multiangle measurements based on TM could more accurately and objectively reflect the content and extent of environmental information disclosed in enterprise reports. The resulting EID index was more representative and convincing. The proposed method could comprehensively represent an enterprise's EID status.

Third, machine scoring resolves the inefficiency and limitation of human subjective judgment regarding corporate EID quality. According to the machine scoring results, China's listed companies in heavily polluting industries exhibited moderate EID performance. Although most companies are striving to improve, only some high energy-consuming industries achieved a relatively high EID score. The environmental protection requirements of listed companies in China's heavily polluting industries are rarely disclosed, and the Chinese government lacks sufficient constraints regarding corporate environmental liability requirements.

Our work's main limitation is mining the quantity and quality of company environment information disclosure from text content. Future research should try to apply more advanced text mining instruments closer to LSA, LDA, and other implicit topic models. Human language leads to more similar results to those obtained from the content analysis.

This study offers several possibilities for further work. Machine learning technology can be improved to better mine and assess EID performance and explore the internal and external mechanisms. Additionally, the environmental information disclosure corpus can be further improved and be better applied to evaluation methods. This study only conducted empirical research based on heavy pollution industry-related enterprises. Therefore, to analyze the accuracy and reliability of the way, we should further expand the practical research samples' scope. Finally, the quality of enterprises' environmental information disclosure will significantly affect the government's formulation of relevant policies and public behavior. Therefore, it is also necessary to study EID quality measurement's economic impacts on enterprises and policy choices.

In 2020, the Securities and Futures Commission of China revised the Guidelines on Investor Relations Management for Listed Companies, including communication on "information on environmental protection, social responsibility, and corporate governance of companies." Our team will continue to follow the development of this ESG practice in China. ESG related research will also become the future research direction of our team.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The average score for each indicator level of China's 16 heavily polluting industries.

Thematic Layer	Index Layer	China's 16 Heavily Polluting Industries															
		B06	**B07**	**B80**	**B09**	**C17**	**C19**	**C22**	**C25**	**C26**	**C27**	**C28**	**C30**	**C31**	**C32**	**C33**	**D44**
(X1)	(X11)	0.39	0.44	0.44	0.49	0.44	0.44	0.36	0.44	0.43	0.30	0.52	0.44	0.53	0.40	0.38	0.45
	(X12)	0.48	0.64	0.12	0.34	0.23	0.46	0.40	0.41	0.46	0.35	0.49	0.23	0.61	0.43	0.24	0.24
	(X13)	0.55	0.54	0.67	0.64	0.40	0.64	0.50	0.62	0.62	0.54	0.75	0.46	0.75	0.54	0.36	0.54
	(X14)	0.46	0.46	0.01	0.12	0.02	0.12	0.03	0.46	0.46	0.01	0.04	0.06	0.08	0.06	0.46	0.46
	(X15)	0.56	0.61	0.24	0.40	0.16	0.16	0.01	0.48	0.41	0.30	0.43	0.33	0.68	0.38	0.18	0.40
	(X16)	0.66	0.63	0.50	0.60	0.32	0.60	0.32	0.59	0.54	0.43	0.59	0.36	0.68	0.48	0.48	0.43
	(X17)	0.58	0.58	0.01	0.12	0.04	0.01	0.67	0.55	0.07	0.01	0.10	0.67	0.07	0.14	0.67	0.14
(X2)	(X21)	0.49	0.30	0.01	0.68	0.01	0.17	0.01	0.69	0.51	0.01	0.01	0.56	0.02	0.69	0.58	0.68
(X3)	(X31)	0.58	0.60	0.68	0.60	0.57	0.59	0.50	0.61	0.55	0.50	0.55	0.52	0.58	0.62	0.55	0.57
	(X32)	0.32	0.29	0.38	0.20	0.13	0.04	0.10	0.24	0.15	0.11	0.11	0.18	0.24	0.18	0.19	0.11
	(X33)	0.57	0.63	0.52	0.55	0.56	0.57	0.55	0.56	0.54	0.53	0.52	0.57	0.58	0.57	0.54	0.54
	(X34)	0.40	0.49	0.59	0.52	0.70	0.49	0.54	0.59	0.57	0.71	0.72	0.66	0.60	0.62	0.68	0.53
	(X35)	0.60	0.57	0.48	0.52	0.57	0.48	0.55	0.48	0.50	0.52	0.56	0.51	0.51	0.53	0.53	0.53
(X4)	(X41)	0.37	0.51	0.71	0.44	0.18	0.60	0.51	0.66	0.72	0.73	0.69	0.68	0.61	0.76	0.70	0.62
	(X42)	0.34	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.55	0.55	0.54	0.54	0.54	0.55	0.54	0.55
(X5)	(X51)	0.57	0.53	0.53	0.53	0.39	0.48	0.53	0.56	0.51	0.39	0.53	0.53	0.59	0.54	0.45	0.56
	(X52)	0.13	0.01	0.01	0.24	0.01	0.04	0.02	0.06	0.01	0.01	0.01	0.24	0.10	0.03	0.03	0.08
	(X53)	0.52	0.42	0.32	0.48	0.36	0.29	0.59	0.50	0.50	0.43	0.47	0.48	0.60	0.49	0.45	0.49
(X6)	(X61)	0.38	0.55	0.28	0.34	0.46	0.46	0.53	0.47	0.40	0.49	0.46	0.49	0.51	0.48	0.50	0.31
(X7)	(X71)	0.46	0.55	0.44	0.42	0.37	0.25	0.44	0.63	0.50	0.44	0.40	0.43	0.66	0.50	0.30	0.48
(X8)	(X81)	0.19	0.15	0.22	0.57	0.26	0.57	0.26	0.26	0.24	0.30	0.50	0.26	0.37	0.20	0.27	0.20
(X9)	(X91)	0.64	0.55	0.77	0.69	0.64	0.70	0.60	0.01	0.61	0.01	0.61	0.58	0.65	0.65	0.54	0.65
	(X92)	0.43	0.41	0.41	0.73	0.54	0.73	0.41	0.23	0.55	0.27	0.56	0.50	0.66	0.40	0.36	0.48
	(X93)	0.53	0.38	0.50	0.50	0.36	0.29	0.28	0.54	0.46	0.39	0.48	0.38	0.39	0.65	0.21	0.54
		11.20	11.38	9.38	11.26	8.26	9.72	9.25	11.18	10.86	8.33	10.64	10.66	11.61	10.89	10.19	10.58

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