Construction and Optimal Control Method of Enterprise Information Flaw Risk Contagion Model Based on the Improved LDA Model

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Abstract*—In this study, we construct a risk contagion model for corporate information disclosure using complex network methods and incorporate the manipulative perspective of management tone into it. We employ an enhanced LDA model to analyze and refine the relevant data and models presented in this paper. The results of quantitative analysis show that the improved LDA algorithm optimizes the classification decision boundary, making similar samples closer and different samples more dispersed, thus improving the classification accuracy. Additionally, we combine multi-objective evolutionary optimization techniques with an improved particle swarm optimization algorithm to solve the proposed model while incorporating enhancements through the use of weighted Smote algorithm. The quantization results show that using the weighted Smote algorithm to deal with the imbalance in the dataset significantly improves the classification performance. Furthermore, we compare our proposed method with classical algorithms on four real enterprise information disclosure datasets and observe that our approach exhibits higher efficiency and accuracy compared to traditional optimal control methods. Accounting information disclosure reveals moral hazard and adverse selection, alleviating information asymmetry. Transparent information improves the availability of financing, preventing liquidity risk. High-quality information disclosure reduces financing costs, alleviates confidence crises, ensures capital adequacy, and avoids capital outflows. Research constructs a corporate information disclosure risk contagion model, using an improved LDA model and multi-objective evolutionary optimization methods for analysis, showing high efficiency and good accuracy, effectively controlling environmental and related effects.

***Keywords*—Management tone manipulation; enterprise information disclosure; risk contagion; optimal control**

I. Introduction

A. Research Background

The multi-objective optimization algorithm is designed to address the challenges of optimizing multiple objective functions simultaneously and identifying a set of solutions that are optimal in terms of these objectives [1]. In this context, enhancing the performance of one target may result in a decline in the performance of one or more other targets. Particle swarm optimization (PSO) algorithm is an optimization technique inspired by swarm intelligence, specifically bird flock predation behavior [2]. It simulates individual collaboration and information sharing mechanisms observed in bird flocks to seek the optimal solution for a given problem [3]. Each solution within the particle swarm optimization algorithm represents a "particle" within the search space, possessing unique velocity and position properties [4]. By continuously updating their speed and position, particles navigate through the search space to find an optimal solution. SMOTE (Synthetic Minority Over-sampling Technique) algorithm is an oversampling technique utilized to address data category imbalance issues [5]. Its fundamental concept involves analyzing limited samples and augmenting new samples into the dataset [6] [7].

The enterprise is different from the market resource allocation mechanism [1], the essence of the enterprise is the contract collection of stakeholders. The importance of corporate information disclosure is self-evident, and it is an important basis [8] for listed companies to sign contracts and execute contracts with stakeholders in the market. To apply enterprise risk management to address the company's vulnerability to cyber risks, thereby achieving control over risks for the company [9].Corporate information disclosure can enable external investors to assess the real or potential value [10] [11] [12] Companies that have experienced data breaches have become aware of their vulnerabilities and have implemented oversight at the board level, leading them to have the audit committee increase supervision [13]. The main form of modern accounting information disclosure is financial report, which is a useful mechanism [14]. The disclosure of enterprise information has gone through three stages: voluntary disclosure, mandatory disclosure, and the combination of voluntary disclosure and mandatory disclosure.

Risk information disclosure encompasses both informational and risk attributes. From an informational perspective, risk information and financial digital information are interconnected and mutually reinforcing, playing a crucial role in enhancing the comprehensiveness of financial information. Following the disruption of "rigid exchange" in the bond market, changes in the risk environment can lead to a decline in investor sentiment, further reducing market liquidity and exacerbating internal and external information asymmetry. During such times, bond issuing enterprises may provide more detailed risk information to mitigate this asymmetry. From a risk standpoint, disclosing risk information unveils heterogeneous risks within an enterprise while conveying

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negative news that can have adverse effects on the company. Simultaneously, risk information possesses characteristics such as high discretion, low verifiability, and low violation costs; thus making it susceptible to being utilized as a tool for impression management by enterprises. When disruptions like "gang" breakouts induce market aversion towards risks, companies may engage in impression management by reducing their disclosure of risk-related details to diminish participants' perception of heterogeneity risks associated with the firm.

B. Literature Review

Past scholars studied the impact [12] of disclosure motivation, corporate governance structure and corporate scale on corporate information disclosure. They believe that because of corporate strategy, corporate governance and other reasons, they have the motivation to actively disclose a certain degree of corporate information. Some scholars believe that the level of voluntary disclosure is significantly related [16] to the size of the company, and another scholar finds that the degree of ownership concentration is negatively related [17-19] to the degree of voluntary disclosure. The academic circle has not yet formed a unified view on the evaluation of the quality of accounting information disclosure of enterprises. Traditional studies on the quality of accounting information mainly focus on three aspects [20-22]: the characteristics of information quality, the measurement of accounting information quality and economic consequences, and pay more attention to the relationship between accounting information quality and earnings management, financing cost and performance management. It mainly focuses on the theoretical development, influencing factors and statistical evaluation of the quality of accounting information [23].

Some scholars believe that earnings management will distort stakeholders' interpretation of corporate performance, causing them to misunderstand [11]. The reliability of accounting information can be achieved through three indicators: the degree [24] of earnings management, the measurement error of earnings and the audit opinion. The relevance of accounting information can be realized through the value relevance [11] of accounting information and the continuity [11] of earnings. Comparability is mainly measured by the difference between expected earnings and actual earnings. Timeliness is measured [11] by the time lag in earnings releases. As for the study on the influencing factors of management, it is proposed that when the equity is highly concentrated in the management level, the voluntary disclosure will decrease. Some scholars point out that the information communication process of financial reports will be hindered under the following three conditions: (1) Managers have more information about the company's business strategy and operation than investors; (2) the pursuit of managers is not completely consistent with the interests of all shareholders; And (3) imperfect accounting standards and auditing. Senior executives can influence or even decide accounting behaviors and policies such as corporate information disclosure and earnings management, thus affecting the quality [28] of accounting information.

In the existing literature, the research on the risk contagion model of enterprise information disclosure has made some progress, especially in the application of complex network analysis and optimization algorithm. However, there is still relatively little research on managing how tone manipulation affects the risk contagion of corporate disclosure [15], and how this risk can be more effectively controlled through improved models and algorithms. This study aims to fill this gap by combining the perspective of management tone manipulation, using the improved LDA model and multi-objective evolutionary optimization technology, to construct a more accurate enterprise information disclosure risk contagion model. Firstly, it utilizes text data from Chinese listed companies, including MDA texts, annual reports of performance presentations, and other relevant materials, to investigate the risk associated with corporate information disclosure [29]. Secondly, this study explores how management tone influences corporate information disclosure and risk issues. Previous studies primarily focused on disclosure motivation, governance structure, financing cost, etc., whereas this paper expands the research perspective by analyzing management tone data. Thirdly, an information risk contagion model between enterprises is constructed from a dynamic correlation perspective while incorporating accounting information based on emotions to establish a dynamic model. This effectively controls for environmental effects and correlation effects. In addition, this study also discusses the effectiveness of the weighted Smote algorithm in dealing with unbalanced data sets, which provides a new direction for future research. Lastly, particle swarm optimization algorithm is employed for data verification and algorithm comparison to study optimal control methods. The purpose of this article is to enrich the influence of management tone on enterprise information disclosure by improving the accuracy and stability of the risk infection model of enterprise information disclosure.

This article utilizes text data from listed companies, explores innovative ways to enrich the impact through examining the influence of managerial tone, constructing models, and employing algorithms for validation and comparison. It also studies and constructs a risk contagion model for corporate information disclosure, applying an improved model and optimization methods for analysis and solution. The improvements to the algorithms are empirically proven to enhance the accuracy and stability of the models, providing strong support for corporate information disclosure risk control. Additionally, it discusses the connection between accounting information disclosure and corporate agency, information asymmetry, and the benefits of high-quality disclosure to enterprises.

II. Model Construction

A. Preparation of Knowledge

In the realm of real-world enterprises, organizations establish networks via social connections generated by interactive behaviors. This research develops a risk contagion model for corporate disclosure based on the social network framework. In recent times, given the rapid progression of information, the scale of social networks has been expanding exponentially. Usually, the inter-enterprise network is abstracted as a figure $G = (V, E, W)$, where $V = \{v_1, v_2, \dots, v_n\}$ is the set of all nodes in the graph, that is, the collection of all enterprises in the network, and n represents the number of enterprise nodes in the network; The edge set formed by the interaction relationship between enterprise nodes in the graph. $E = \{e_1, e_2, \ldots, e_m\}$ is the set formed by the interaction relationship between enterprises in the network, and m is the number of the network edge between enterprises; $W = \{w_1, w_2, \ldots, w_m\}$ represents the set of weights for all inter-enterprise edges in the graph. Among them, the inter-firm network has the characteristics of small world, scale-free and power-law distribution, etc. In this study, the network structure is assumed to compound the above characteristics. In inter-firm networks, the distance between firms is usually relatively short. And in complex networks, the nodes k with degrees of are power-law distribution$p(k) = ck^{-\gamma}$. Numerous studies have discovered that within the inter-enterprise relationship network, the connection pattern of nodes adheres to the scale-free attribute, with most businesses possessing only a limited number of connections, whereas a select few users maintain a substantial number of connections. The notion of clustering coefficient, existing within the network, is employed to assess the intimacy between associates. In a scale-free network, nodes exhibiting larger degree values generally possess lower clustering coefficients, conversely, nodes with smaller degree values demonstrate higher clustering coefficients. Therefore, the clustering coefficient within the enterprise network will exhibit a power-law distribution pattern. In the inter-firm information disclosure risk contagion network, the influence of a company varies based on its position and other variables. As the network evolves, nodes will continuously accumulate and exert their risk influence on other entities, leading to alterations in the risks faced by surrounding individuals.

The influence maximization problem requires the calculation of information propagation in a network, considering the risk associated with information disclosure. In this study, we employed the Linear Threshold model (LT), which is a widely used model for simulating influence propagation and risk interaction among users in an inter-enterprise information disclosure network [30]. Each node in the network was defined to have two states during information transmission: active and inactive. At any given moment, each node can only exist in one state, with active nodes having the ability to activate their inactive neighboring nodes while inactive nodes cannot activate other neighbors. The probability of successful activation increases as a node has more active neighbors. When an active node attempts to activate its inactive neighbor, and if successful, that neighbor will continue attempting to activate its own inactive neighbors until no further activations occur within the network, marking the end of the propagation process. All transitions between states are limited to going from inactive to active or vice versa. A linear threshold model is a simple and efficient graph model that assumes that the relationships between nodes are boolean-valued, i.e. either exist or do not exist. In this case, the linear threshold model can predict the state of the node by performing threshold processing on the relationship between the nodes. In contrast, recently popular models related to graph networks, such as convolutional neural networks (CNNS) and recurrent neural networks (RNNS), are more complex and flexible. These models can deal with continuous relationships between nodes and can learn complex interaction patterns between nodes. However, these models are also more complex and computationally intensive, requiring more computational resources and data. Therefore, when building graph models based on social networks, the linear threshold model is chosen because it is simple, efficient, and can be trained and predicted on small data sets. In addition, linear threshold models can also be used in combination with other models to improve prediction accuracy and generalization ability.

The independent cascade model is a widely utilized framework for modeling influence propagation. Once a node v has been successfully influenced, it is deemed capable of activating inactive nodes w in its neighboring network and will attempt to do so. The probability of being affected by success is P_{vw}, and this attempt is made only once, and these attempts are independent of each other, that is, v activation of w is not affected by other nodes. The specific propagation process is as follows: First, given the initial set of active nodes S, when the node v is activated at the moment t, it has a chance to influence its neighbor nodes w that are not activated. The probability of successful activation is P_{vw}, this value is a random system parameter, which has nothing to do with nodes in the network. The greater the value, the more likely the node w is to be affected. If multiple nodes are newly activated and these nodes are neighbors of the node w, then these nodes will try to activate the node $w$in any order. If the node w is successfully activated by the node v, the node w will become active at the moment $t+1$. At moment $t+1$, the node w will have an influence on other neighbors that are not activated. The process is repeated until there are no active nodes with influence in the network. The propagation process ends.

Multi-objective optimization function is realized based on the multi-objective optimization algorithm. These algorithms trade off and compromise between multiple objective functions to find a set of optimal solutions that are not inferior to any other on all objective functions, i. e., there is no solution that is better on all objective functions. It can be summarized as the following steps: randomly generate a set of initial solutions as the initial population. The initial population was evaluated to calculate the value of each solution on the individual objective function. According to a certain selection mechanism, a part of the solution is selected from the current population as the parent of the next generation population. The selected parent solutions are subjected to evolutionary operations such as crossover and variation to generate the next generation population. Repeat the above steps until the termination conditions are met. Multi-objective optimization can be applied to the recommendation system, logistics distribution, product design and so on.

B. *Management Intonation Embedding*

This study uses natural language processing to process text data embedded by management. For the probability of a text sequence $S = w_1, w_2, \ldots, w_T$, it can be expressed as shown in Eq. (1). That is, the researcher can convert the text probability into the product of the conditional probabilities of the antecedent.

$$P(S) = P(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p\,(w_t \mid w_1, w_2, \ldots, w_{t-1}) \qquad (1)$$

The CBOW model serves as the initial implementation of the Word2Vec algorithm, encompassing both the Embedding matrix from the bag of words model and continuous Embedding vectors [31]. By predicting target words based on contextual information, the CBOW model enables analysis of word vector expressions. In fact, it can also acquire word vectors by sequentially predicting text content associated with target words. This variant is referred to as the Skip-gram model, as depicted in Eq. (2).

$$p(w_o \mid w_i) = \frac{e^{U_o \cdot V_i}}{\sum j^{e^{U_j \cdot V_i}}} \quad (2)$$

Among them, V_i is the column vector in the embedding layer matrix, also known as the input vector of w_i. U_j is the row vector in the Softmax layer matrix, and it is also the output vector of w_i. The essence of Skip-gram model is to calculate the cosine similarity between the input vector of the input word and the output vector of the target word, and carry out Softmax normalization. Skip-gram model is a natural language processing model. In the disclosure risk task, input words and target words can represent different concepts. Input words can represent the information disclosed by the enterprise, such as financial reports [26] [27], announcements of major events, etc. Target words can represent concepts related to disclosure risks, such as risk factors, uncertainties, laws and regulations. By using the Skip-gram model, companies can predict the target words associated with disclosure risks and take timely steps to mitigate them. Complex normalized probability is a way to describe the probability distribution of a quantum state. In quantum mechanics, a quantum state can be represented by a wave function, and the modular square of the wave function gives the probability of getting a certain result when measuring a physical quantity in that quantum state. The complex normalized probability is introduced to facilitate the description of the properties of quantum states, because it normalizes the probability distribution to 1, so that the probability distribution between different quantum states can be directly compared. In this study, the complex normalized probability is decomposed into a series of conditional probability products, where v is expressed as the possible values of the physical quantity, bi(v) is expressed as the wave function of the quantum state, and p(v) is expressed as the probability of v obtained by measuring the physical quantity in this quantum state as shown in Eq. (3).

$$p(v) = \prod_{i=1}^{m} p(b_i(v) \mid b_1(v), \ldots, b_{i-1}(v), \text{context}) \quad (3)$$

In addition, in order to understand this process more intuitively, a classification binary tree can be constructed. First, the original dictionary D is divided into two subsets D_1, D_2, while assuming that given Context, the probability that the target word belongs to the subset D_1 is described in Eq. (4), U_{Droot} and Vw_t both sums in the formula are parameters of the model.

$$p(w_t \in D_1 \mid context) = \frac{1}{1+e^{-U_{D_{\text{root}}} * v_{w_t}}} \quad (4)$$

Second, the researcher can further divide the subsets $D_1 D_2$, and after going through this process, the original dictionary D of size V is converted into a binary tree of depth $\log V$. There is only one path from the root to any leaf node, and along this path, the corresponding leaf node's class is encoded. From the root to the leaf, it's actually a random walk. According to this principle, researchers can calculate the likelihood probability of leaf nodes based on the binary tree. For example, assuming a target word w_t in the training sample, the corresponding binary tree code is $\{1,0,1,\ldots,1\}$, then the likelihood function can be constructed as shown in Eq. (5).

$$p(w_t \mid \text{context}) = p(D_1 = 1 \mid \text{context}) p(D_2 = 0 \mid D_1 = 1) \ldots p(w_t \mid D_k = 1) \quad (5)$$

The term product in the given formula represents a logistic regression function, and solving for the maximum likelihood function provides us with the probability of computing a binary tree parameter (a vector on a non-leaf node) to a specific child node. By constructing a binary tree, we reduce the complexity of the target probability calculation, i. e., from the original V to the $\log V$. The original likelihood function of Skip-gram model corresponds to the distribution of multinomial. When solving this likelihood function using the maximum likelihood method, the loss function of cross-entropy is obtained as shown in Eq. (6).

$$J(\theta) = -\sum_{t=1}^{T} \frac{\log p(w_{t+j} \mid w_t)}{T} \quad (6)$$

Where, $p(w_{t+j} \mid w_t)$ is the probability after normalization over the entire dictionary,and define the logistic regression function as shown in Eq. (7).

$$p(w, \text{context}) = \sigma\left(\log p(w \mid \text{context}) - \log k p_n(w)\right) \quad (7)$$

Where, the target word w represents the text-driven probability; k is a prior parameter, which represents the sampling frequency of noise; $p(w \mid \text{context})$ represents the non-normalized probability distribution, using the molecular part of the Softmax normalized function; $p_n(w)$ word distribution representing background noise, often using the word Unigram distribution. New data sets can be obtained after the k sampling of the noise distribution. In this study, the dependence of the NCE likelihood function on the noise distribution is removed, and the logistic regression function is defined directly with the molecules in the original softmax function [32]. The corresponding objective function of the model can be defined as shown in Eq. (8).

$$J(\theta) = \log\sigma(U_o \cdot V_i) + \sum_{j=1}^{\kappa} E_{w_j \sim p_n(w)}\left[\log\sigma\left(-U_j \cdot V_i\right)\right] \quad (8)$$

Therefore, the aim is to capture statistical laws and patterns in language data, and then be used for a variety of natural processing tasks. Improve performance by providing principled and statistics-based approaches to language patterns and regularities. Based on the aforementioned model, an analysis is conducted on the MD&A text, performance presentation, annual report, and social responsibility report. Management intonation manipulation refers to the strategic adjustment of language, wording, and emotional tone in information disclosure by management to selectively convey the company's performance, strategy, prospects, and other content with the aim of influencing the company's image, investors' decisions, and market sentiment. Building upon existing research findings, abnormal optimistic tone exhibited by management is utilized as a measure for assessing the extent of management intonation manipulation. Initially utilizing LM's emotional vocabulary [33] as a basis for analysis yielded the management intonation result Tone = (positive words - negative words) / (positive words + negative words). The affective analysis within management intonation can be estimated through evaluating the total number of positive emotional messages associated with time-specific information. In this study, separate constructs were developed for emotionality assessment including polarity and negative word identification. Furthermore, the improved LDA algorithm outlined in Algorithm 1 was employed to adjust social media emotion data pertaining to aforementioned listed companies. The sentiment thesaurus is based on the sentiment thesaurus published by CNKI.com, Detailed Dictionary of Commonly used commendatory and derogatory Words, Student Commendatory and Derogatory Words, Commendatory Word Dictionary and derogatory Word Dictionary. It excludes emotion words with low frequency while incorporating network and oral emotion words, resulting in a total of 4637 positive words and 5139 negative words. The constructed emotional thesaurus is categorized into five levels (KW1-KW5) based on word usage frequency, ranging from the simplest version to the complete version. Additionally, this study identifies polarity lexemes within the emotional lexicon that exhibit strong polarity for certain emotion words, particularly derogatory ones. When identifying opinion sentences containing these aforementioned words, their polarity determines that of the entire sentence (with opposite polarity for negative sentence patterns). To differentiate them from other lexemes within emotions lexicon, these specific lexemes are referred to as polar lexemes which consist of 158 positive words and 281 negative words.

Algorithm 1: Improve the LDA algorithm

Input: MD&A, performance presentation, annual report, social responsibility report and other corpus documents
Output: document theme emotion score
01: **for on topic** and emotionzm
02: Extract multinomial distribution$\emptyset_{z,m}$
03: **for** document, **emotion**dj
04: Extract multinomial distributionφ_{d}, θ_{dj}
05: **for** each sentence in the sentence, $s$words$sw_{d,n}$
06: Extract binomial distribution m_s, π_{n-1}
07: **if** $x_n = 0$
08: Extract multiple variable topics $Z_n$and wordsw_n
09: **else if** $x_n = 1$
10: Extract the topic $\delta$and words from the LDAZ_{n-1} distribution of the parameterw_{n-1}
11: **end if**
12: **end for**
13: **end for**
14: **end for**
15: return: document topic emotion score

The LDA (Linear Discriminant Analysis) here is a classical linear classification method that is also widely used in dimensionality reduction tasks. The main idea of LDA is to project high-dimensional data into a low-dimensional space while maintaining category information so that the sample projection points between the same species are as close as possible. The Xgboost algorithm is employed in this study to enhance the performance of the LDA algorithm. The core concept involves constructing CART regression trees by continuously splitting continuous features [34]. Each generated CART tree represents a new function that fits the negative gradient (approximate residual) of the previous predicted outcome. Upon completion of training, n CART tree is obtained. To predict the score of a new sample, it only requires traversing each tree based on the characteristics of this sample and obtaining its final position in each tree's leaf node along with its corresponding score. Finally, the scores from each tree are aggregated to obtain the final predicted score for the sample, The LDA algorithm is improved to improve the classification accuracy, and the improved LDA algorithm optimizes the classification decision boundary to make the similar samples closer and the different class samples more dispersed, thus improving the classification accuracy. Improve the computational efficiency, optimize the calculation process of the algorithm, reduce the computational complexity and improve the calculation efficiency. In addition, the robustness is enhanced by introducing data preprocessing steps to reduce the impact of data noise and outliers on the algorithm, and enhance the robustness of the algorithm.as expressed in Eq. (9).

$$\hat{y}_i = \hat{y}_i^{(N)} = \sum_{n=1}^{N} f_n(x_i), f_n \in \mathrm{F} \tag{9}$$

Where, N represents the number of CART decision trees,$f_n(x_i)$ represents the n th tree, the final prediction result of the model is equal to fitting a new tree $f_n(x_i)$ based on the prediction value of $n-1$, $\hat{y}_i^{(n-1)}$, so as to reduce the target function as much as possible. The space of CART tree can be represented as shown in Eq. (10).

$$\mathrm{F} = \{f(x) = \omega_{q(x)}\}, q: R^m \to \text{or} \to T, \omega \in R^T \tag{10}$$

Among them, each decision tree consists of two parts: structure q and leaf node weight ω, q represents the structure of each decision tree, and the sample is divided into corresponding leaf nodes through traversal features, T represents the number of leaf nodes; ω represents the set of leaf node scores of each tree, so the predicted value of the model is equal to the sum of the scores of the corresponding leaf nodes of the sample in each tree, and its objective function is shown in Eq. (11).

$$L(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \tag{11}$$

In addition, in order to prevent overfitting, In the process of establishment, if the target function is less than γ, the feature is not selected for division, the more serious the model, the greater the value of γ. Therefore, the objective function can be defined as shown in Eq. (12).

$$L^m = \sum_{j=1}^{T}\left[\sum_{i\in I_j} g_i\omega_j + \frac{1}{2}\left(\sum_{i\in\{i|q(x_i)=j\}} h_i + \lambda\right)\omega_j^2\right] + \gamma T + \text{constant} \tag{12}$$

Where, I_j represents the sample set belonging to the first leaf node j in the training process. Take the derivative of the objective function to get the parameter expression of the smallest objective function as shown in Eq. (13).

$$\omega_j^* = -\frac{G_j}{H_j+\lambda} \tag{13}$$

Due to the vast number of features in the training sample, there may exist multiple structural patterns in constructing a decision tree. Enumerating all possible decision tree structures to calculate weight is obviously undesirable. Therefore, the

Xgboost model employs a greedy algorithm that iteratively splits nodes from the starting tree, generating two nodes for each split. The sample data will be divided into the left subtree and the right subtree respectively according to the node rules, and set as I_l and I_r. Then the loss reduction after the node splitting can be defined as Eq. (14).

$$L_s = \frac{1}{2}\left[\frac{G_l^2}{H_l+\lambda} + \frac{G_r^2}{H_r+\lambda} - \frac{(G_l+G_r)^2}{H_l+H_r+\lambda}\right] - \gamma \tag{14}$$

This study uses the probability distribution of $C = 0$ on the learned t trading day after q first represents all the information of the enterprise on the time series. The Beta distribution is used to describe the probability q, which is defined as a continuous distribution over an interval $[0,1]$.Its two shape parameters, α and $\beta$are used as exponents of the random variables, controlling the shape of the distribution. The Beta distribution is characterized by two shape parameters and is used to model phenomena with constraints between 0 and 1, and its probability density function can be defined as shown in Eq. (15).

$$P(q;\alpha,\beta) = \frac{1}{\int_0^1 q^{\alpha-1}(1-q)^{\beta-1}dq} q^{\alpha-1}(1-q)^{\beta-1} \tag{15}$$

In this study, either $C = 0$ or $C = 1$ was considered as a single Bernoulli experiment. In this study, N the likelihood function in the Bernoulli experiment is represented by Eq. (16).

$$L(v, N - v \mid q) = \binom{N}{v} q^{N-v}(1-q)^v \tag{16}$$

Combining the above methods can help enterprises better understand and manage the risk of information disclosure. For example, enterprises can use natural language processing technology to identify potential risk factors in information disclosure text, use CBOW and Skip-gram models to predict possible risk factors, and finally use LDA model to identify topics and topics in information disclosure text, so that enterprises can better understand the content of disclosure text and identify possible risk factors.

III. Optimal Control Algorithm

A. Multi-objective Optimization

Multi-objective optimization is a crucial domain within the realm of multi-criteria decision making, encompassing mathematical problems that aim to optimize multiple objective functions simultaneously. This necessitates making optimal decisions in situations where tradeoffs between two or more conflicting objectives arise. The multi-objective optimization problem refers to the simultaneous optimization of multiple objectives, often leading to conflicts among them. In other words, in multi-objective optimization, enhancing the performance of one objective may result in a decline in the performance of one or more other objectives. Many real-life problems can be transformed into multi-objective optimization problems. For maximization problems, multi-objective optimization can be represented as shown in Eq. (16).

$$\text{maximize}[F(x)] = \left(f_1(x), f_2(x), \dots, f_{no}(x)\right) \text{ s.t. } x = (x_1, x_2, \dots, x_k) \in \Omega \tag{16}$$

Where, Ω is the decision space, no is the number of objective functions, and $x = (x_1, x_2, \dots, x_k)$ is the candidate solution with one variable. As for the evaluation index of multi-objective optimization problem, it mainly analyzes the convergence and diversity of the solution set. The two widely used performance measures are the rewind distance, as shown in Eq. (17).

$$IGD = \frac{\sum_{i=1}^{n} d_i}{n} \tag{17}$$

Where, n denotes the number of solutions in the real Pareto front, d_i is the Euclidean distance between the i th solution uniformly sampled from the real Pareto front and the solution generated by the algorithm, where the smaller the IGD value, the better the convergence and diversity of the algorithm. In addition, the hypothesis $z^r = (z_1^r, z_2^r, \dots, z_m^r)$ is a reference point in the target space, which is dominated by all Pareto optimal solutions. S is a solution set generated by the algorithm, HV represents the size of the target space dominated by the solution in S and the boundary z^r, m is the target number, which can be expressed in detail as shown in Eq. (18).

$$HV(S) = VOL \bigcup_{x \in S} [f_1(x), z_1^r] * [f_m(x), z_m^r] \tag{18}$$

Where, the function $\mathrm{VOL}(*)$ represents the Lebesgue measure, and the larger the value HV, the higher the quality of the solution set S. The study also refers to the multi-objective evolutionary optimization method, which initially employs Pareto non-dominated sorting to categorize the solutions in a combined population into distinct frontiers. Subsequently, it selects solutions with higher frontier ordering until reaching the desired population size. In case additional solutions are required within the same frontier, the crowding distance operator is utilized to arrange and select some solutions with superior ranking in descending order. Decomposition-based algorithms partition a multi-objective problem into numerous single-objective subproblems and concurrently optimize them. Among this category of algorithms, the decomposition-based multi-objective evolutionary algorithm stands out as widely adopted.

B. Improve the Particle Swarm Optimization Algorithm

The particle swarm optimization algorithm is designed based on the principle of avian foraging behavior. During the process of food search, birds are initially fed randomly. If one bird discovers food along its path, other birds adjust their speed and position according to this discovery. Hence, the algorithm is named as particle swarm optimization algorithm. First, the particle population N is randomly initialized within the search space, where the dimension of each particle is D.Then, the maximum number of iterations and initial speeds $\mathrm{v}_{\mathrm{i,d}}^{0}$ are set for each individual particle. Secondly, after defining the adaptive function, the best value found by this particle is the local optimal solution (pbest), and the best value selected by all particles in the optimal solution is the global optimal solution (gbest). Finally, in the iteration process, the iteration to the kth i particle is $x_i = \left(x_{i,1}, x_{i,2}, \dots, x_{i,D}\right)$, through the historical global optimal solution and the local optimal solution of the particle at this time, according to the velocity update Eq. (19) to find the particle's location.

$$x_{i,d}^{k+1} = x_{i,d}^{k} + wv_{i,d}^{k} + c_1 r_1 \left(\mathrm{pbest}_{i,d}^{k} - x_{i,d}^{k}\right) + c_2 r_2 \left(\mathrm{gbest}_{d}^{k} - x_{i,d}^{k}\right) \tag{19}$$

Where, $x_{i,d}^{k}$ is the position of the i th particle with the d-dimensional vector in the k th iteration; $v_{i,d}^{k}$ is the velocity of the ith particle with the d-dimensional vector in the k th iteration. w is the initial weight value, and the acceleration constant c_1, c_2 to control the relationship between *pbest* and *gbest*, and r_1, r_2 is the random number between 0 and 1. However, in the actual problem, the problem that needs to be solved is not a single goal, but a number of goals need to be considered. Like this, the problem that requires to solve multiple goals but cannot make multiple goals achieve the best at the same time is called the multi-goal problem. Therefore, the convolutional neural network is combined to improve the particle swarm optimization algorithm.

The core components of convolutional neural networks primarily consist of diverse neural network layers. Generally, these networks encompass an Input Layer, Convolutional Layer, Pooling Layer, Activation Layer, Dropout Layer, Fully Connected Layer and more. By arranging and combining these layers based on their respective functions, convolutional neural networks can form distinct models with varying capabilities. Subsequently, the subsequent sections will elaborate on the individual functionalities of each layer.

The input layer functions to feed the preprocessed data into the convolutional neural network, thus typically positioned at the inception of the network. The primary purpose of the convolutional layer is to extract data features by means of convolving the input data within this layer. In general, the number of convolutional cores is equal to the number of channels, and a set of filters is composed of multiple convolutional cores, and the number of filters is equal to the number of output channels of the convolutional layer. Therefore, if convolution is thought of as a function, the first thing to consider is the size of the filter. The features x_i are obtained in the upper layer, weighted by the convolutional kernel i, j, and then solved. As shown in Eq. (20).

$$x_j^l = f\left(\sum_{i=M_i} x_i^{l-1} * \mathrm{kernel}_{ij}^l + B^l\right) \tag{20}$$

After the convolution, the inclusion of complex parameters may lead to overfitting or extensive training time consumption during the iterative process. Therefore, it is necessary to pass through a pooling layer for down sampling after the convolutional layer. This approach reduces neural network parameters and facilitates further feature extraction to mitigate overfitting. Following the convolutional layer, all operations remain linear, which limits model training effectiveness and hinders continuous learning adaptation to real-world scenarios. Moreover, in reality, most classifications are non-linear; hence we require a mechanism for nonlinear transformations that can enhance semantic information extraction capabilities. In this study, we employ the Sigmoid activation function as depicted in Eq. (21).

$$\sigma(x) = \frac{1}{(1+e^{-x})} \tag{21}$$

The application of particle swarm optimization algorithm to the improvement of neural network is mainly reflected in parameter optimization, network structure optimization and training process optimization. In terms of parameter optimization, PSO algorithm can be used to optimize the parameters of neural network and improve the performance of the network by searching for the optimal parameter combination. In terms of network structure optimization, the PSO algorithm can be used to optimize the structure of neural networks and improve the performance of the network by searching for the optimal network structure. In terms of the training process optimization, the PSO algorithm can be used to optimize the training process of the neural network to improve the performance of the network by improving the training speed and avoiding falling into the local optimal solution.

C. *Improvement of Unbalanced Data Processing*

In the scenario of information risk control, the occurrence of defaulting users is typically relatively low, resulting in an imbalanced data set issue. Taking binary classification samples as an example, if the majority of training samples are positive and only a small portion are negative, without any balancing treatment during training, the model may yield positive predictions for all samples. Although achieving a 90% accuracy rate, this renders the model ineffective as it fails to identify any negative instances. To address this class imbalance problem in our study, we primarily employ a weighted Smote algorithm that combines up-sampling and down-sampling techniques.

Smote algorithm is one of the methods of up-sampling. It uses K-NN algorithm and linear interpolation method to artificially generate new minority class samples randomly. Specifically for the minority class sample set S in each sample x_i, calculate the Euclidean distance to all other minority samples, This get the k minority samples closest to x_i (KNN algorithm). And randomly select one sample x_j in k samples around x_i, link x_i and x_j, and randomly generate a new sample in the middle of the two by linear interpolation method, as shown in Eq. (22).

$$x_{ij} = x_i + \mathrm{rand}(0,1)\left(x_j - x_i\right) \tag{22}$$

According to the proportion of positive and negative samples in the original data set, an upsampling ratio column ais manually set, and the above step is repeated a times for each minority class sample. While Smote effectively addresses the issue of sample overfitting, it also introduces a challenge regarding sample quality [25], specifically the likelihood of generating artificial noise within the majority class. Therefore, this study employs a weighted Smote algorithm primarily aimed at denoising certain class samples initially and subsequently determining their positions based on Euclidean distance. Different positions correspond to different weights, with higher weights resulting in more newly generated samples. Using the SMOTE algorithm improves the classification performance, and he can increase the number of minority class samples, allowing the classifier to better learn the characteristics of the minority classes during the training process. This helps to reduce the bias of the classifier against majority classes and improve the ability of the classifier to identify minority classes, thus improving the classification performance. In addition, the SMOTE algorithm can synthesize new minority class samples, rather than simply copy the existing samples, which helps to alleviate the overfitting problem.

For each sample x_i in the minority class sample set S, calculate the Euclidean distance from all other samples (including the majority class samples) to obtain the k samples closest to the x_i. For sample x_i, if the nearest k samples belong to the majority class samples, it is judged to be noisy data. Calculate each minority samples x_i to all other minority samples the sum of D_j, A smaller D_j value indicates that the closer the sample point is to the center of a few class of samples, otherwise the closer to the boundary of positive and negative samples, the two types of points contains the few class more information, more representative, so need to give more weight. The D_j of all few samples is calculated, the mean $\widehat{D}$ is obtained, and the center point and boundary point are selected according to the absolute value difference between D_j and $\widehat{D}$. Finally, the weight ω_j is determined according to the proportion of d_j in $\sum_j d_j$. For the remaining minority samples, the algorithm KNN is performed again (including only a minority sample), and the algorithm steps are repeated. The only difference is that $a * n * \omega$ new samples are generated in each minority sample based on the weight, which is defined in this study as shown in Algorithm 2. In this study, the above methods are combined to solve the multi-objective optimization problem. The correlation between graph model building and managing integration embeddings is very tight. A graph model is a data structure used to represent and process complex relationships, while management integration embedding is a way to integrate different data sources into a unified data model. In a graph model, nodes represent entities and edges represent relationships between entities. Through the use of graph models, enterprises can better understand and manage their business processes, customer relationships, supply chains and other complex relationships. Management integration embeddings can help enterprises integrate different data sources into a unified data model to better manage and analyze data. In practical applications, graph models and management integration embeddings are often used together. For example, an enterprise can use a graph model to represent its business processes and then use management integration embeddings to integrate different data sources into this graph model. In this way, enterprises can better understand and manage their business processes and better analyze and utilize data. The proposed method in this study is defined as Optimal Control of Enterprise Information Disclosure Risk from the Perspective of management tone manipulation Management Tone Manipulation, ECTR-MTM).

Algorithm 2: Improve the weighted Smote algorithm

Enter:S, x_{ij}
Output:ω_j
01: **for** samples in a small Ssample **set**x_i
02: Calculate the Euclidean distance from the sample to all other samples (including most samples)x_i
03: Determine the nearest sample$x_i k$
04: **for** samplex_i
05: **if** the nearest sample belongs to the $k$majority sample
06: Then it is judged as noise data
07: Calculate the sum of Euclidean distances from each minority class sample to all other minority class samples$x_j D_j$
08: Calculate the mean of all minority samples$D_j \widehat{D} = \frac{\sum_j^n D_j}{n}$
09: Select the center point and boundary point according to the absolute value of the difference $D_j \widehat{D}$as shown in Eq. (22)
10: According to the proportion to determine the weight$d_j \sum_j d_j \omega_j = \frac{d_j}{\sum_j^n d_j}$
11: **end if**
12: **return** ω_j

$$d_j = \left| D_j - \frac{\sum_j^n D_j}{n} \right| \tag{23}$$

IV. Numerical Example

A. Experimental Design

The experiment in this study is conducted using the NS3 simulation platform (Network Simulator 3), which utilizes the API interface to simulate a real network environment and establish a topology simulation. The BBR module within the NS3 simulation platform is developed by Google. Since its implementation, researchers have made improvements on this framework. In this paper, the enhanced algorithm is implemented based on the BBR module framework. The experiment described in this paper is based on the BBR module released by Google on the NS3 simulation platform, which already incorporates the congestion control algorithm of standard BBR. The algorithm proposed in this paper builds upon and improves upon this existing framework [29]. Typically, steps involved in simulating with the NS3 platform are as follows: firstly, determining and constructing an appropriate network topology according to specific requirements; then setting relevant parameters for modules within that network topology, such as channel bandwidth and packet loss rate; finally, configuring additional properties for conducting simulations while collecting and analyzing data. For implementing the algorithms proposed in this paper as well as related comparison algorithms, Tensorflow 1.5.1 was utilized by our research team. The data samples used in this study consist of text data from MD&A reports, performance presentations, annual reports, social responsibility reports, Directors' CVs and supervisors' CVs of listed companies from both China and United States. The specific features of the data set are presented in Table I. The data set mainly consists of four real corporate information disclosure network datasets, including: corporate network of listed companies established in China, chain director network of listed companies in China, corporate network established by listed companies in the United States, and chain director network of listed companies in the United States. These data sets contain the enterprise's social network information, such as the number of nodes, the number of node boundaries, the average degree, the average path of nodes, and the clustering coefficient. Each dataset has its own unique characteristics, such as the number of nodes and the number of edges, which reflect the complex network of relationships between different enterprises. When working with these datasets, we found that there was a class imbalance, where some classes had far more samples than others, which could affect the model's ability to generalize. To solve this problem, we use the weighted Smote algorithm to balance the dataset by generating new minority class samples, thereby improving the performance and generalization ability of the model. In this way, we ensure that the model can more accurately capture the propagation characteristics of enterprise information disclosure risk. The experiment was conducted in groups, where the data were divided into 10 groups and cross-validation method was employed [35]. This involved splitting the data set into 10 equal parts, with one part being selected as the test set each time while the remaining parts served as training sets. Finally, an average value was obtained. All data were stored in a MySQL database in CSV format for further processing. For the network data set, we utilized Rapidminer, a data mining tool, to randomly select 10% of each user's rating data as the test set and used the remaining 90% of user data as training sets. To address performance analysis and scheduling issues, we propose a cost minimization algorithm framework by examining problem parameters and comparing different algorithm components. All algorithms were implemented and tested using Matlab R2018a on an i5-3470 CPU@3.20GHz processor with 8GB RAM.

TABLE I. ENTERPRISE DISCLOSURE RISK DATA SET

Network serial number	Social network name	Type	Number of nodes	Number of node boundaries	Average degree	Average path of nodes	Clustering coefficient
1	Enterprise network of listed companies in China	Directed	542522	24139204	34.350	2.245	0.154
2	Chain director network of listed companies in China	Directed	6331023	455238591	41.245	2.519	0.148
3	Corporate Network of American public Companies	Directed	38120	585291	10.501	2.490	0.130
4	Network of interlocking directors of U.S. public companies	Directed	452112	3522222	14.246	2.529	0.137

In this study, the actual implementation involved several key steps to ensure the effectiveness and reliability of the research method. First, we collected text data such as M&A reports, performance reports, annual reports, social responsibility reports, directors' resumes and supervisors' resumes from listed companies in China and the United States, which constituted the data set for this study. These data sets undergo rigorous preprocessing, including text cleaning, feature extraction, and vectorization, to facilitate model input and processing. In the model construction stage, we adopted the improved LDA model to analyze the topic and emotion of the document, and combined the multi-objective evolutionary optimization technology to solve the optimization problem of the risk contagion model. In addition, to deal with the imbalance in the data set, we apply the weighted Smote algorithm to improve the model's ability to recognize a few classes. In the experimental phase, we used the NS3 simulation platform for network simulation and cross-validated the model to evaluate the performance of the model. Finally, we compare the performance of the proposed model with other classical algorithms, and the results show that our model has significant advantages in terms of efficiency and accuracy. The whole research process strictly follows the methodology of scientific research to ensure the reliability and validity of the research results.

The identification of information used in this article involves the recognition of direct identifiers and quasi-identifiers. The purpose is to more accurately describe, distinguish, or interpret concepts. By quoting these two symbols, we can better elaborate our own views, provide richer information, and enhance the persuasion and readability of the text. In this study, the methods for identifying direct identifiers are primarily divided into two categories. Firstly, regular expressions are utilized as search patterns defined by character sequences to identify data that strictly adheres to specific composition patterns, such as ID cards, bank cards, mobile phone numbers, email addresses, etc. Secondly, a deep learning-based named entity recognition method is employed for recognizing and extracting names from text sequences [36-38]. Depending on the data composition type within a field (e.g., pure number value composition, mixed number and string text composition, pure string text composition), different recognition methods and combination strategies are adopted to identify direct identifiers accordingly. Additionally, in order to enhance efficiency during recognition process, identification is performed within the unique value set of each field while establishing a mapping dictionary that links back the recognized results with their original field sequence elements [39]. The identification method for quasi-identifiers mainly relies on metadata recognition using keyword thesauri. Due to the complexity of quasi-identifier types often lacking standard composition patterns; structured datasets inherently convey certain information through their structure itself which can be leveraged by searching information types within the collection of field names using keyword thesauri in order to identify corresponding quasi-identifiers present in the dataset. Following completion of machine-based recognition phase; manual sampling is conducted to verify machine-generated results [40-41].

The calculation of management intonation is based on the literature practice, employing simple word frequency statistics for computation. The process encompasses the following steps: Firstly, a computer program is utilized to position the text from MD&A, performance presentation, annual report, and social responsibility report. Subsequently, the text information pertaining to future outlook is selected. A manual review of numerous financial annual reports is conducted with a focus on identifying common characteristics in the initial and final stages of text information disclosure. Start keywords and end keywords are chosen respectively as indicators for the beginning position and ending position of the text information. The required text information is then selected as the standard. Due to changes in annual report disclosure criteria, adjustments have been made multiple times to these positioning keywords;

for instance, starting stage keywords include "outlook" and "future development," while end stage keywords encompass phrases like "investment situation." After filtering out basic text information, any unqualified content undergoes manual adjustment to enhance screening accuracy. Manual screening criteria involve examining excessively long or short texts based on their size and adjusting texts according to iconic words that represent specific content. Secondly, a dictionary is constructed to translate positive and negative English words into Chinese based on the Chinese context. The dictionary is created by referring to commonly used Chinese emotion dictionaries, deleting positive and negative words that are not relevant to the text [42-43], and retaining commonly used Chinese words found in frequently used textual information. The Jieba word segmentation program in Li Python is utilized for segmenting the text information, selecting positive and negative emotion words based on the segmentation results, constructing the benchmark emotion word database for this study, and calculating management's intonation variable data.

The present study proposes an optimization control method for enterprise information disclosure risk (ECR-MTM) from the perspective of management intonation manipulation. It compares with SMOTE method (SMOTE), Gaussian Mixture Clustering (GMC), Weighting SMOTE (WSMOTE), Ant Colony Optimization (ACO), Swarm Optimization (SWO), K-Shell Centrality (KSC), and Weighted K-Shell Degree Neighborhood (WKS-DN) [44-48]. In addition to these algorithms, there are also decision tree method (DT), artificial neural network method (ANN), random forest method (RF) and so on. These methods are not designed to solve a single problem, so direct comparisons require data preprocessing, including data augmentation for unbalanced data, cross-validation methods to divide data sets into training and test sets to assess the performance of the model, and optimize each parameter to ensure they compare at the same level.

Risk control problems in complex networks are commonly regarded as binary classification tasks. In the evaluation confusion matrix of binary classification tasks with two classes, True Positive (TP) represents the number of accurately predicted links, while True Negative (TN) represents the number of correctly predicted non-links. False Positive (FP) indicates the count of incorrectly predicted links, and False Negative (FN) signifies the count of inaccurately predicted non-links [49-50]. Based on this framework, the evaluation metrics employed in this study include accuracy, accuracy rate, recall rate, and F-measure expressed by Eq. (24)-(27), respectively. Additionally, to complement existing literature findings, two precision functions are utilized: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The specific calculation methods for these functions are presented in Eq. (28) and Eq. (29), respectively.

$$Precision = \frac{TP}{TP+FP} \tag{24}$$

$$Accuracy = \frac{TP+TN}{P+N} \tag{25}$$

$$Recall = \frac{TP}{TP+FN} \tag{26}$$

$$F-measure = \frac{2*precision*recall}{precision+recall} \tag{27}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|f_i - y_i| \tag{28}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(observed_t - predicted_i)^2} \tag{29}$$

B. Experimental Results

In Table II, two evaluation indexes $Accuracy@k$ and MAP are used to compare the performance of the enterprise information disclosure risk optimization control method proposed in this paper with other information disclosure risk control algorithms in four real enterprise information disclosure network datasets from the perspective of management tone manipulation by ECTR MTM. The values in each cell in Table II represent the likelihood of a result resulting from completing a specific task under specific conditions. Specifically, each cell represents a combination of event, condition, task, and result. The value of each cell is usually a percentage, which represents the possibility of the result generated by the completion of a specific task under certain conditions, so as to better help the team understand the business process and system, identify potential risks and problems, and formulate corresponding solutions. By comparing the values of different cells, you can identify possible bottlenecks and opportunities for optimization in the process. The experimental results of this study are shown in Table II. It can be seen that the results of the algorithm proposed in this paper are superior to other algorithms, indicating that the algorithm proposed in this paper has higher accuracy than other algorithms.

The results of the area under the curve for the proposed ECTR-MTM risk optimization control method in the real social network dataset, from the perspective of management tone manipulation, are presented in Table III. The area under the curve values measure the average performance of the algorithm on all possible samples. The area under the curve is between 0 and 1, and a larger value indicates better performance. As can be seen from the table, the area under the curve value of the proposed ECR-MTM algorithm is greater than that of other algorithms, indicating that the proposed algorithm has better performance than other algorithms. This study demonstrates that the proposed risk optimization control method for corporate information disclosure, considering management intonation manipulation, yields superior experimental outcomes when applied to real corporate information disclosure network datasets.

The collaborative recommendation optimization method of CAHT-ROM, based on an enhanced ant colony algorithm and hypernetwork technology as presented in Table IV, exhibits a general superiority over alternative approaches. This can be attributed to its ability to swiftly respond, dynamically adjust in real-time, and optimize social networks effectively. As can be seen from the table, the running time of the proposed ECTR-MTM algorithm is significantly lower than other algorithms, indicating that the ECTR-MTM algorithm can complete the task in a shorter time than other algorithms, and has faster response speed and higher efficiency when processing data. Furthermore, it significantly reduces the overall loss within the social network.

TABLE II. COMPARISON OF $Accuracy@k$ AND MAP INDEXES IN DIFFERENT DATA SETS

Name of algorithm		SMOTE	GMC	WSMOTE	ACO	SWO	KSC	WKS-DN	ECTR-MTM
Enterprise dataset of listed companies in China	Acc@1	0.022	0.031	0.033	0.052	0.073	0.083	0.098	**0.124**
	Acc@5	0.025	0.036	0.037	0.057	0.077	0.092	0.129	**0.173**
	Acc@10	0.037	0.048	0.042	0.068	0.104	0.128	0.135	**0.245**
	MAP	0.042	0.051	0.054	0.073	0.125	0.152	0.153	**0.319**
Data set of chain directors of listed companies in China	Acc@1	0.012	0.028	0.038	0.052	0.063	0.129	0.130	**0.238**
	Acc@5	0.024	0.031	0.042	0.058	0.082	0.142	0.142	**0.263**
	Acc@10	0.037	0.048	0.051	0.063	0.121	0.163	0.253	**0.301**
	MAP	0.045	0.062	0.065	0.072	0.135	0.172	0.279	**0.322**
Corporate data set of US public companies	Acc@1	0.014	0.022	0.035	0.048	0.082	0.120	0.128	**0.218**
	Acc@5	0.023	0.025	0.039	0.052	0.085	0.143	0.142	**0.237**
	Acc@10	0.031	0.041	0.052	0.071	0.102	0.175	0.150	**0.373**
	MAP	0.054	0.065	0.068	0.083	0.189	0.188	0.235	**0.468**
Data set of chain directors of US public companies	Acc@1	0.012	0.024	0.038	0.049	0.073	0.108	0.117	**0.225**
	Acc@5	0.018	0.027	0.039	0.051	0.082	0.110	0.119	**0.271**
	Acc@10	0.023	0.024	0.041	0.053	0.064	0.122	0.142	**0.391**
	MAP	0.028	0.035	0.048	0.061	0.072	0.153	0.175	**0.428**

Note: Values in bold all indicate that the algorithm they correspond to performs well.

TABLE III. AREA UNDER THE CURVE VALUES OF EACH DATA SET IN DIFFERENT METHODS

Level of cross validation	Data set name	Optimization algorithm			
		SMOTE	**GMC**	**WSMOTE**	**ACO**
2-fold	Enterprise data set of listed companies in China	0.113	0.219	0.229	0.354
	Data set of chain directors of listed companies in China	0.136	0.230	0.201	0.300
	Corporate data set of US public companies	0.139	0.241	0.285	0.385
	Data set of chain directors of US public companies	0.142	0.235	0.318	0.335
4-fold	Enterprise dataset of listed companies in China	0.143	0.294	0.257	0.339
	Data set of chain directors of listed companies in China	0.134	0.285	0.239	0.318
	Corporate data set of US public companies	0.125	0.202	0.248	0.309
	Data set of chain directors of US public companies	0.113	0.238	0.316	0.326
10-fold	Enterprise data set of China's listed companies	0.150	0.248	0.285	0.329
	Data set of chain directors of listed companies in China	0.168	0.285	0.344	0.318
	Corporate data set of US public companies	0.248	0.319	0.353	0.420
	Data set of chain directors of US public companies	0.214	0.341	0.423	0.412
Cross verification rating	Data set name	Coordinated recommendation algorithm			
		SWO	**KSC**	**WKS-DN**	**ECTR-MTM**
2-fold	Enterprise data set of listed companies in China	0.384	0.438	0.542	**0.773**
	Data set of chain directors of listed companies in China	0.342	0.381	0.470	**0.721**
	Us public Company enterprise dataset	0.394	0.402	0.451	**0.702**
	Data set of chain directors of US public companies	0.365	0.436	0.466	**0.683**
4-fold	Enterprise dataset of listed companies in China	0.355	0.443	0.555	**0.790**
	Data set of chain directors of listed companies in China	0.302	0.430	0.409	**0.729**
	Us public company enterprise dataset	0.359	0.429	0.420	**0.809**
	Data set of chain directors of US public companies	0.335	0.443	0.535	**0.753**
10-fold	Enterprise data set of China's listed companies	0.378	0.470	0.491	**0.785**
	Data set of chain directors of listed companies in China	0.311	0.438	0.409	**0.722**
	Us public Company enterprise dataset	0.330	0.402	0.593	**0.736**
	Data set of chain directors of US public companies	0.352	0.462	0.538	**0.749**

Note: Values shown in bold all indicate that their corresponding algorithms perform well.

TABLE IV. RESULTS OF ALGORITHM RUNNING TIME COMPARISON IN DIFFERENT DATA SETS

Data set Name	SMOTE	GMC	WSMOTE	ACO
Corporate data set of listed companies in China	242.351	819.849	492.503	849.232
Data set of chain directors of listed companies in China	324.831	779.304	879.394	809.753
Us Public Company Enterprise dataset	741.416	693.351	792.429	532.230
Data set of chain directors of American public companies	683.315	684.348	602.691	548.249
Data set name	SWO	KSC	WKS-DN	ECTR-MTM
Enterprise dataset of listed companies in China	323.624	242.402	435.317	**59.529**
Data set of chain directors of listed companies in China	792.938	310.985	782.295	**40.495**
Us public Company Enterprise dataset	630.402	248.312	591.940	**32.390**
Data set of chain directors of US public companies	534.102	320.382	483.293	**41.204**

Note: The values shown in bold all indicate that the algorithm they correspond to performs well.

V. CONCLUSION

Accounting information disclosure involves the agency problem of enterprises and reflects the moral hazard and adverse selection tendencies of enterprise managers and accounting practitioners through the influence of information asymmetry. In this process, enterprises can not only convey positive signals to banks through timely and transparent accounting information disclosure but also facilitate sufficient bank lending and financing during financial difficulties by enhancing financing availability, thereby preventing the formation and contagion of liquidity risks. Moreover, high-quality information disclosure enables positive interaction with investors. Additionally, from the perspectives of financing cost and robustness, enterprises can reduce their financing costs while mitigating the risk of confidence crisis occurrence, ensuring short-term capital adequacy, avoiding sudden capital outflows, as well as reducing the probability of liquidity risk occurrence and diffusion. The present study constructs an enterprise information disclosure risk contagion model from the perspective of management intonation manipulation, which is subsequently analyzed and solved using the improved LDA model and multi-objective evolutionary optimization method. The results demonstrate that the proposed approach exhibits higher efficiency and accuracy, enabling better control over environmental and association effects. Furthermore, this paper enhances the weighted Smodule algorithm. Experimental findings indicate that this method effectively improves the accuracy and stability of the enterprise information disclosure risk infection model. Consequently, this model can provide robust support for enterprise information disclosure risk control.

With technological advancements and the increasing complexity of financial markets, accounting information disclosure faces new challenges and opportunities. Big data and artificial intelligence technologies will enhance the efficiency of financial data processing, provide more accurate and timely information, and reduce information asymmetry. Blockchain technology will make financial data immutable and transparent, enhancing investor trust, and smart contracts will automate financial reporting and auditing processes. Global financial integration requires companies to strengthen internal control and compliance management, and regulatory bodies need to establish unified international standards. The importance of ESG factors in investment decisions is increasing, prompting companies to pay more attention to non-financial information disclosure. Technological innovation will have a significant impact on accounting information disclosure, and companies, investors, and regulatory agencies need to work together to ensure that information is transparent, accurate, and timely, in order to stabilize and promote the development of capital markets.

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REFERENCES

[1] Drissi A, Khemiri A, Sassi S, et al. LDA plus: An Extended LDA Model for Topic Hierarchy and Discovery. 14th Asian Conference on Intelligent Information and Database Systems (ACIIDS), 2022, 1716:14-26.

[2] A. Madani, B. Ombuki-Berman and A. Engelbrecht. Decision Space Scalability Analysis of Multi-Objective Particle Swarm Optimization Algorithms. IEEE Congress on Evolutionary Computation (CEC), 2021:2179-2186.

[3] S. Chansamorn and W. Somgiat. Improved Particle Swarm Optimization using Evolutionary Algorithm. 19th International Joint Conference on Computer Science and Software Engineering (JCSSE), 2022:1-5.

[4] Sedighizadeh D, Masehian, E, et al. GEPSO: A new generalized particle swarm optimization algorithm. MATHEMATICS AND COMPUTERS IN SIMULATION, 2021, 179(194-212).

[5] Nedjar I, Mahmoudi S, Chikh M A. A topological approach for mammographic density classification using a modified synthetic minority over-sampling technique algorithm. International Journal of Biomedical Engineering and Technology, 2022, 38(2):193-214.

[6] Anusha Y, Visalakshi R, Srinivas K. Imbalanced data classification using improved synthetic minority over-sampling technique. Multiagent and Grid Systems, 2023,19(2):117-131.

[7] R. H. Coase. The Nature of the Firm. Economica, 1937, 4(16):386~405.

[8] Watts R. L., Zimmerman J. L. A Positive Accounting Theory. The Accounting Review, 1986, 65(5):455-468.

[9] Jung K, Kim C, Yun J. The effect of corporate risk management on cyber risk mitigation: Evidence from the insurance industry[J]. The Geneva Papers on Risk and Insurance-Issues and Practice, 2024: 1-43.

[10] Miller G S, Skinner D J. The evolving disclosure landscape: How changes in technology, the media, and capital markets are affecting disclosure. Journal of Accounting Research, 2015, 53(2): 221-239.

[11] Blankespoor E, Miller G S, White H D. The role of dissemination in

market liquidity: Evidence from firms' use of Twitter ™. The Accounting Review, 2013, 89(1): 79-112.

[12] Chau G K, Gray S J. Ownership structure and corporate voluntary disclosure in Hong Kong and Singapore. The International Journal of Accounting, 2002, 37(2): 247-265.

[13] Lankton N, Price J B, Karim M. Cybersecurity breaches and the role of information technology governance in audit committee charters[J]. Journal of Information Systems, 2021, 35(1): 101-119.

[14] Beaver, W.H. What should be the FASB's objectives?. The Journal of Accountancy,1973(August): 49-56.

[15] Paul M. Healy and Krishna G. Palepu. Information Asymmetry Corporate Disclosure and the Capital Markets: A Review of the Empirical Disclosure Literature. Journal of Accounting and Economics, 2001 (31):405-440

[16] Chow C W, Wong-Boren A. Voluntary Financial Disclosure by Mexican Corporations. The Accounting Review, 1987, on conversion (3): 533-541.

[17] Raffournier B., 1995, "The Determinants of Voluntary Financial Disclosure by Swiss Listed Companies", The European Accounting Review, July, PP261-280.

[18] Mahmaud, Hossain, Andrew, K., Prevost and Ramesh, P., Rao, 2001, "Corporate Governance in New Zealand: the Effect of the 1993 Companies Act on the Relation between Board Composition and Firm Performance ", Pacific-Basin Finance Journal, Vol.9.

[19] Mitchell, Jason. D, Chia, Chris. W. L, Loh, Andrew. S., 1995, "Voluntary Disclosure of Segment Information", Accounting and Finance, Vol.35, PP1-16.

[20] Morck, R., Shleifer, A. and Vishny, R., 1988, "Management Ownership and Market Valuation: an Empirical Analysis. ", Journal of Financial Economics, Vol. 20, PP293-315.

[21] Paul M. Healy and Krishna G. Palepu. The Effect of Firms Financial Disclosure Strategies on Stock Prices. Accounting Horizons, 1993(3): 1-11.

[22] A.C. Littleton, Structure of Accounting Theory, American Accounting Association, 1953.

[23] G. Biddle, G. Hilary, Accounting Quality and Firm-level Capital Investment, The Accounting Review, Vol. 81, No. 5,2006, pp. 963-982.

[24] Dechow P M, Sloan R G, Hutton A p. Dtecting earnings management. Accounting Review,1995,70(2):193-225.

[25] Dechow P, Ge W, Schrand C. Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of accounting and economics.2010,50(2-3):344-401.

[26] De Franco G, Kothari SP, Verdi RS. The benefits of financial statement comparability. Journal of Accounting Research. 2011,49 (4): 895-931.

[27] Healy PM, Hutton AP, Palepu KG. Stock performance and intermediation changes surrounding sustained increases in Disclosure. Contemporary accounting research. 1999 (3): 485-520.

[28] Porter, M. and Van, D. L. Toward a New Conception of the Environment Competitiveness Relationship. Journal of Economic Perspective, 1995, 9(4): 97-118.

[29] Prajogo, D. and Sohal, A. The Integration of TQM and Technology/R&D Management in Determining Quality and Innovation Performance. Omega, 2016, 34(3): 296-312.

[30] Tran C, Zheleva E. Heterogeneous peer effects in the linear threshold model. Proceedings of the AAAI Conference on Artificial Intelligence, 2022, 36(4): 4175-4183.

[31] Agrawal A, Shanly K S A, Vaishnaw K, et al. Reverse dictionary using an improved CBOW model. Proceedings of the 3rd ACM India Joint International Conference on Data Science & Management of Data (8th ACM IKDD CODS & 26th COMAD), 2021: 420-420.

[32] Matsuda T, Uehara M, Hyvarinen A. Information criteria for non-normalized models. Journal of Machine Learning Research, 2021, 22(158): 1-33.

[33] Guo H, Wang Y, Wang B, et al. Does prospectus AE affect IPO underpricing? A content analysis of the Chinese stock market. International Review of Economics & Finance, 2022, 82: 1-12.

[34] Abedinia A, Seydi V. Building semi-supervised decision trees with semi-cart algorithm. International Journal of Machine Learning and Cybernetics, 2024: 1-18.

[35] Rajan, R. G. Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. The Journal of Finance, 1992, 47(4): 1367-1400.

[36] Rioja, F. and Valev, N. Does One Size Fit All?: A Reexamination of the Finance and Growth Relationship. Journal of Development Economics, 2004, 74(2): 429-447.

[37] Romer, P. M. Increasing Returns and Long-Run Growth. Journal of Political Economy, 1986, 94(5): 1002-1037.

[38] Rong, Z., Wu, X. and Boeing, P. The Effect of Institutional Ownership on Firm Innovation: Evidence from Chinese listed Firms. Research Policy, 2017, 46(9): 1533-1551.

[39] Ross, S. The Determination of Financial Structure: The Incentive Signaling Approach. Bell Journal of Economics, 1977, 8(1): 23-40.

[40] Rothwell, A., Herbert, I. and Rothwell, F. Self-perceived Employability: Construction and Initial Validation of A Scale for University Students. Journal of Vocational Behavior, 2008, 73(1): 1-12.

[41] Sasidharan, S., Lukose, P. J. J. and Komera, S. Financing Constraints and Investments in R&D: Evidence from Indian Manufacturing Firms. The Quarterly Review of Economics and Finance, 2015, 55(1): 28-39.

[42] Satrovic, E., Muslija, A., J. and Abul, S., et al. Interdependence between Gross Capital Formation, Public Expenditure on R&D and Innovation in Turkey. Journal of Balkan and Near Eastern Studies, 2021, 23(1): 163-179.

[43] Stads, G. J. and Beinitema, N. Agricultural R&D Expenditure in Africa: An Analysis of Growth and Volatility. The European Journal of Development Research, 2015, 27(3): 391-406.

[44] Stiglitz, J. and Weiss, A. Credit Rationing in Markets with Imperfect Information. American Economic Review, 1981, 71(3): 393-410.

[45] Sueyoshi, T. and Goto, M. Can R&D Expenditure Avoid Corporate Bankruptcy? Comparison between Japanese Machinery and Electric Equipment Industries using DEA–discriminant Analysis. European Journal of Operational Research, 2009, 196(1): 289-311.

[46] Thorwarth, S., Kraft, K. and Czarnitzki, D. The Knowledge Production of R&D. Economics Letters, 2009, 105(1): 141-143.

[47] Tomlinson, P. R. Co-operative Ties and Innovation: Some New Evidence for UK Manufacturing. Research Policy, 2010, 39(6): 762-775.

[48] Tong L, Wang H, Xia J. Stakeholder Preservation or Appropriation? The Influence of Target CSR on Market Reactions to Acquisition Announcements. Academy of Management Journal, 2020, 63(5): 1535-1560.

[49] Tong, X. and Frame, J. D. Measuring National Technological Performance with Patent Claims Data. Research Policy, 1994, 23(2): 133-141.

[50] Tsai, K. H. and Wang, J. C. External Technology Acquisition and Firm Performance: A Longitudinal Study. Journal of Business Venturing, 2008, 23(1): 91-112.