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Audit Risk Evaluation of the Medical CRO Industry: A Method Combining Entropy Weight-TOPSIS and Grey Relational Degree

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Abstract: Under the modern risk-oriented audit, a reasonable evaluation of material misstatement risk is crucial for certified public accountants to determine the level of materiality and implement further substantive procedures. This paper proposes a material misstatement risk assessment model based on the combined use of entropy weight-TOPSIS and grey relational analysis methods and evaluates the material misstatement risk in China's Medical CRO Industry by quantitative means. Taking the medical CRO industry as an example, this paper selects some case companies in the industry for horizontal comparison, and at the same time conducts a multi-year data comparison on the enterprise with the highest audit risk among them. The results show that Bio-Sincerity Pharmaceutical is an enterprise with relatively high audit risk in the Medical CRO Industry in recent years, and the calculation results of the model are basically consistent with the actual analysis. To effectively prevent financial risks and audit risks, financial personnel should participate in business management, analysis and budgeting, and auditors should also focus on audit segments such as dynamic cash flow, debt structure, and business contracts and debt management in combination with the characteristics of the Medical CRO Industry, so as to effectively reduce the risk of audit misstatements.

Keywords: Entropy Weight-TOPSIS Method; Grey Relational Analysis Method; Material Misstatement Risk; Financial Risks of Company

1. Introduction

1.1. Analysis of the CRO Industry Status

In the industrial chain structure, the CRO industry is an important component of the pharmaceutical and life sciences field, mainly providing clinical research outsourcing services for pharmaceutical companies, biotechnology companies, medical device manufacturers, and academic institutions. These services cover various stages from early drug discovery to late-stage clinical trials. By outsourcing these complex and time-consuming tasks, clients can effectively reduce R&D costs, shorten product launch time, and improve success rates. With the advancement of medical technology and the expansion of the pharmaceutical market, a number of excellent enterprises have emerged in China's CRO market, such as Wuxi AppTec, Joinn Laboratories, and Tiger Med. The continuous deepening of national medical reform and the increase in R&D investment have driven the annual growth of the number of applications for drug clinical trials. In the future, with the increasing demand for innovative drugs and generic drugs, the CRO market will further expand. The specific development situation of China's CRO industry is as follows:

(1) Market Scale and Growth: China's CRO industry has achieved rapid growth in recent years, with the market scale expanding continuously. In 2023, the scale of China's CRO market reached 101.4 billion yuan, with a compound annual growth rate of 19.35% from 2019 to 2023. In the future, China's CRO industry will continue to maintain a rapid growth momentum.

(2) Market Structure and Concentration: China's CRO market is dominated by clinical trial CROs, accounting for more than half of the market. However, the industry concentration is relatively low, with the market share of major CRO companies accounting for only 31.86%, far below the global average. International CROs such as Wuxi AppTec account for 35.22% of the market share, while local CROs account for only 64.78%, indicating that the agglomeration degree and enterprise scale of China's CRO industry need to be improved.

(3) Enterprise Scale and Comprehensive Capabilities: Chinese CRO enterprises are generally small in scale, with comprehensive CRO companies accounting for only 3%. Most enterprises focus on pre-clinical and clinical stages. This limits the overall competitiveness and service quality of the industry, and it is necessary to promote the expansion of enterprise scale and the improvement of comprehensive capabilities through policy support and market-driven forces.

(4) Cost Advantages and International Cooperation: China's CRO industry has obvious cost advantages, attracting international pharmaceutical companies to outsource R&D services to China. With the rise of global drug development costs and the complexity of clinical trial requirements, cooperation between domestic and foreign pharmaceutical companies and CROs has deepened, forming strategic partnerships, which provides new opportunities for the development of China's CRO industry.

To sum up, although China's CRO industry has developed rapidly and its market scale has been expanding, there are still problems such as small scale and low industrial clustering degree. The industry concentration and enterprises' comprehensive capabilities still need to be improved.

1.2. Entropy Weight-TOPSIS Method and Grey Relational Analysis Method

The main evaluation methods for material misstatement risk are the fuzzy evaluation method and the analytic hierarchy process (AHP). The former realizes the quantitative evaluation of audit risk, but there is a certain subjectivity in the expert scoring link; the latter can complete the audit risk evaluation with fewer indicator data, but it is difficult to calculate a large number of statistical indicator data, and the determination of weight boundaries is vague. In order to improve the scientificity and rationality of the evaluation method, this paper proposes a method combining entropy weight-TOPSIS and grey relational analysis to evaluate the material misstatement risk in audits. The "entropy" in the entropy weight method is mainly used to measure the uncertainty of information. In the evaluation of material misstatement risk, the information entropy of each indicator is used to reflect its degree of variation. The smaller the information entropy, the greater the difference from the standard value, the more information it provides, and the greater the weight; otherwise, the smaller the weight. The TOPSIS method selects the optimal by calculating the geometric straight-line approximation distance between each sample and the positive and negative ideal solutions, but it cannot reflect its changing pattern. The grey relational analysis method evaluates the degree of correlation with the ideal solution by measuring the similarity of the development trends of each indicator. Combining the TOPSIS method with the grey relational analysis method can consider both the proximity and correlation with the ideal solution, making the evaluation more objective and reasonable.

1.3. Literature Review

When international scholars apply the entropy weight method in their research, they mainly focus on aspects such as the characterization of risk indicators and the determination of indicator weights. Some scholars have constructed financial risk early warning models by applying the theory of entropy, and believe that among various early warning methods, the entropy method can more comprehensively and accurately judge the degree of corporate financial risks[1]. Other scholars have used the entropy weight method to screen out key indicators that have a significant impact on financial crises and proposed effective methods to solve financial crises[2].

Meanwhile, the shortcomings of this method have also attracted the attention of relevant scholars. Some scholars pointed out that attention should be paid to the scientificity of determining the weights of attribute indicators in the traditional TOPSIS method and improved the TOPSIS method[3]. Some scholars use the Analytic Hierarchy Process (AHP) to determine the weights in the TOPSIS method, while others use the entropy weight method[4]. With the continuous advancement of research, some scholars have also adopted the combined method of grey relational analysis and entropy weight-TOPSIS to determine financial risks[5].

With the continuous advancement of technology, the entropy - weight TOPSIS method has been introduced into the field of financial risk analysis and has been continuously developing within this domain. Some researcher use Entropy-Based topsis approach to research the performance appraisal of iron and steel enterprises listed on BIST[6]. And it also used to measure the financial risk on the Internet insurance industry[7]

2. Scope of the Research

2.1. Dataset and Method of the Research

In 2004, the International Auditing and Assurance Standards Board (IAASB) incorporated the basic principles of risk-oriented auditing into International Standards on Auditing (ISAs), which accelerated the prevalence and implementation of modern risk-oriented auditing worldwide. Currently, the mainstream audit risk model is ISA 200, i.e., audit risk = material misstatement risk × detection risk. However, this model has certain subjectivity due to the professional judgment of auditors. To more objectively compare the levels of material misstatement risks among different companies in the same industry, this paper adopts the combination of entropy weight-TOPSIS method and grey relational analysis method proposed by Zhang et al.(2022) to conduct the assessment of material misstatement risk. The specific system evaluation indicators are shown in Table 1.

Table 1. Fiscal rates utilized in the exploratory

Indicators	Financial Ratios	TOPSIS Ideal Solution Target	Code
Solvency	Current ratio	Min	A1
	Quick ratio	Min	A2
	Cash flow ratio	Min	A3
	Debt-to-Asset ratio	Max	A4
	Cash ratio	Min	A5
	Long-term debt ratio	Min	A6
Operating	Accounts receivable turnover	Min	B1
	Inventory turnover	Min	B2
	Total asset turnover	Min	B3
Profitability	Net profit rate of total assets	Min	C1
	Operating profit rate	Min	C2
	Operating net profit rate	Min	C3
	Selling period expense rate	Max	C4
Development	Total asset growth rate	Min	D1
	Net profit growth rate	Min	D2
	Operating revenue growth rate	Min	D3
	Selling expense growth rate	Max	D4

In the study, we calculated the performance scores of these enterprises using some financial ratios calculated based on the enterprises' balance sheets and income statements, and these data were obtained normally from the companies' official websites. Specifically, the Debt-to-Asset Ratio is defined as a positive indicator (Max type) because a higher value of this indicator means greater debt-servicing pressure for the enterprise and weaker stability of its financial structure. This increases the number of misstatement risk points requiring attention during the audit, leading to a corresponding rise in audit risk, resulting in a positive correlation between the two. In contrast, the Current Ratio is defined as a negative indicator

(Min type) because a higher value of this indicator indicates stronger short-term debt-servicing capacity of the enterprise and lower liquidity risk, which reduces the pressure of risk assessment related to short-term financial health during the audit, and audit risk decreases accordingly, showing a negative correlation between the two.

Ratio analysis refers to a methodology that employs mathematical formulas to calculate ratios derived from account items in financial statements, such as the balance sheet and income statement. Given the distinct dynamics and operating principles across industries and companies, the analytical approaches and applicable ratios may vary significantly. This method reveals fundamental financial insights, yet the interpretation of results depends critically on the insight, expertise, and experience of corporate managers, individual investors, and professional investors. Consequently, beyond applying formulas to financial statements and formulating new strategies, interpreting these ratios can contribute more proactively to organizational or individual decision-making. Crucially, businesses must maintain a strategic balance between liquidity and profitability during operations.

The indicators selected in this paper include the following aspects:

Solvency Indicators：Some scholars believe that the solvency of an enterprise is directly related to financial risk[8]. In this paper, we choose some ratios to measure the solvency of company: Current ratio: It is formulated as Current Assets / Current Liabilities, reflecting a company's short-term solvency by measuring the ability to cover short-term debts with short-term assets; Quick ratio: It is calculated as (Current Assets - Inventory) / Current Liabilities, excluding inventory to better assess immediate short-term liquidity; Cash flow ratio: It is Operating Cash Flow / Current Liabilities, indicating the ability to repay short-term debts with cash generated from operations; Debt-to-asset ratio: It is Total Liabilities / Total Assets, showing the proportion of assets financed by debt; Cash ratio: It is calculated as (Cash + Cash Equivalents) / Current Liabilities, representing the most liquid assets available to cover short-term obligations; Long-term debt ratio: It is Long-term Liabilities / Total Assets, reflecting the proportion of long-term debt in total assets;

Operating Indicators: Accounts receivable turnover: It is calculated as Operating Revenue / Average Accounts Receivable, measuring how efficiently a company collects its receivables; Inventory turnover: It is Cost of Goods Sold / Average Inventory, indicating the efficiency of inventory management; Total asset turnover: It is formulated as Operating Revenue / Average Total Assets, reflecting how effectively a company uses its assets to generate revenue;

Profitability Indicators：Some research find that profitability is the most important factor affecting company financial risk[9]. Therefore we use some indictors to measure the profitability of company: Net profit rate of total assets: It is Net Profit / Average Total Assets, showing the profitability relative to total assets; Operating profit rate: It is Operating Profit / Operating Revenue, measuring profitability from core operations; Operating net profit rate: It is Net Operating Profit / Operating Revenue, indicating the net profit margin from operations; Selling period expense rate: It is (Selling Expenses + Administrative Expenses + Financial Expenses) / Operating Revenue, reflecting the proportion of period expenses in revenue;

Development Indicators: Some scholars established COX proportional risk model empirical study that development ability can play an important role in early warning of financial risk[10]. In this paper, we choose some indictors to measure the development of company: Total asset growth rate: It is (Current Total Assets - Previous Total Assets) / Previous Total Assets, showing the growth of total assets; Net profit growth rate: It is (Current Net Profit - Previous Net Profit) / Previous Net Profit, indicating the growth in net profit; Operating revenue growth rate: It is (Current Operating Revenue - Previous Operating Revenue) / Previous Operating Revenue, reflecting the growth in operating revenue; Selling expense growth rate: It is (Current Selling Expenses - Previous Selling Expenses) / Previous Selling Expenses, measuring the growth in selling expenses.

This paper selects three listed companies in the same industry as Bio-Sincerity Pharmaceutical, namely R&G, Tiger Med, and Medprin Regenerative, as well as High Hink, a company on the New Third Board's Growth Enterprise Layer, for the assessment and analysis of material misstatement risk. R&G focuses on the clinical CRO field, with a high overlap in its clinical business module with that of Bio-Sincerity. Tiger Med, as the leading domestic clinical CRO, has a business model and risk characteristics that serve as industry benchmarks, providing a basis for large-scale comparison. High Hink directly competes with Bio-Sincerity in the clinical trial segment. As a non-listed company, it has been questioned by the China Securities Regulatory Commission three times in the past year, representing a high-risk case among growing CRO enterprises. Medprin Regenerative, as an innovative enterprise in the medical device field, has a close business connection with the CRO industry. Through its risk characteristics, potential material misstatement risks of Bio-Sincerity Pharmaceutical in policy response and compliant operation can be evaluated.

Based on the above analysis, this paper selects the above-mentioned well-known and representative enterprises in the CRO industry, and examines their corporate performance during 2024. The relevant companies are listed in Table 2.

Table 2. Company operating in CRO

	Company Code	Company Name
1	301333.SZ	R&G
2	300347.SZ	Tiger Med
3	873896.BJ	High Hink
4	301096.SZ	Bio-Sincerity
5	301033.SZ	Medprin Regenerative

In this study, the performance scores of these enterprises were calculated using financial ratios derived from their balance sheets and income statements. The balance sheets and income statements of the companies were obtained from their official websites.

2.2. Research Methods

Material misstatement risks are often accompanied by abnormal fluctuations in financial report indicators. Therefore, several secondary indicators are selected from each primary indicator of the four major capabilities of enterprise financial management to complete the construction of the risk evaluation indicator system. For example, the higher the debt-to-asset ratio, the greater the possibility of the enterprise being insolvent; if the selling period expense rate and selling expense growth rate do not match the operating revenue growth rate, material misstatement risks may arise, and it is necessary to increase substantive procedures for selling expenses.

2.3. Combination of Entropy Weight-TOPSIS and Grey Relational Analysis

For the material misstatement risk evaluation indicator system of listed companies, a comprehensive evaluation model based on the combination of the entropy weight-TOPSIS method and the grey relational analysis method is established. Firstly, the entropy weight method is used to determine the weights of each material misstatement risk evaluation indicator, and the TOPSIS method is applied to calculate the positive and negative ideal solutions of each sample. A preliminary evaluation of the samples is conducted based on the relative proximity of each indicator to the ideal solution. Then, the grey relational analysis method is employed to calculate the correlation degree between each sample and the positive and negative ideal solutions. By combining the two, a more accurate proximity to the ideal solution is calculated to achieve the final decision-making evaluation. The specific steps are shown in Table 3.

Table 3. Steps of Combination of Entropy Weight-TOPSIS and Grey Relational

ENTROPY and TOPSIS Method	
Creating the Decision Matrix (A)	
Step1	$A=\begin{bmatrix} X_{11} & \cdots & X_{m1} \\ \vdots & X_{ij} & \vdots \\ X_{1n} & \cdots & X_{mn} \end{bmatrix}$
Creating the Standard Decision Matrix (R)	
Step2	$Y_{ij}=\dfrac{X_{ij}-\min\left(X_{1j},\cdots,X_{mj}\right)}{\max\left(X_{1j},\cdots,X_{mj}\right)-\min\left(X_{1j},\cdots,X_{mj}\right)}$ (Max type) $Y_{ij}=\dfrac{\max\left(X_{1j},\cdots,X_{ij}\right)-X_{ij}}{\max\left(X_{1j},\cdots,X_{mj}\right)-\min\left(X_{1j},\cdots,X_{mj}\right)}$ (Min type) $R=\begin{bmatrix} Y_{11} & \cdots & Y_{m1} \\ \vdots & Y_{ij} & \vdots \\ Y_{1n} & \cdots & Y_{mn} \end{bmatrix}$
Calculate the Weights of Evaluation Objects	
Step3	$P_{ij}=\dfrac{Y_{ij}}{\sum_{j=1}^{n} Y_{ij}} \quad (i=1,2,\cdots,m;\ j=1,2,\cdots,n)$
Calculate the ENTROPY value of index	
Step4	$e_i=-\dfrac{1}{\ln n}\sum_{j=1}^{n} P_{ij}\ln P_{ij} \quad (i=1,2,\cdots,m;\ j=1,2,\cdots,n)$

Calculating Criteria Weights	
Step5	$w_i=\frac{1\text{-}e_{ij}}{\sum_{i=1}^{m}\left(1\text{-}e_{ij}\right)}$ (i=1,2,⋯,m; j=1,2,⋯,n)
Creating the Same-trend Transformation Decision Matrix ($R_x^{'}$)	
Step6	$R_x^{'}=\begin{bmatrix} X_{11}^{'} & \cdots & X_{m1}^{'} \\ \vdots & X_{ij}^{'} & \vdots \\ X_{1n}^{'} & \cdots & X_{mn}^{'} \end{bmatrix}$
Creating Normalized Decision Matrix ($R_x^{''}$)	
Step7	$X_{ij}^{''}=X_{ij}^{'}/\sqrt{\sum_{j=1}^{n}X_{ij}^{'2}}$ $R_x^{''}=\begin{bmatrix} X_{11}^{''} & \cdots & X_{m1}^{''} \\ \vdots & X_{ij}^{'} & \vdots \\ X_{1n}^{''} & \cdots & X_{mn}^{''} \end{bmatrix}$
Creating the Weighted Standard Decision Matrix($V=\left[v_{ij}\right]$)	
Step8	$V=\begin{bmatrix} v_{11} & \cdots & v_{m1} \\ \vdots & v_{ij} & \vdots \\ v_{1n} & \cdots & v_{mn} \end{bmatrix}$
Creating Ideal (V^+) and Negative Ideal (V^-) Solutions	
Step9	$V^+=\left\{\left(\max_{1\leq j\leq n} v_{ij}\right)\mid j\in J,\left(\min_{1\leq j\leq n} v_{ij}\right)\mid j\in J^{'}\right\}=\{v_1^+,\cdots,v_j^+,\cdots,v_m^+\}$ $V^-=\left\{\left(\min_{1\leq j\leq n} v_{ij}\right)\mid j\in J,\left(\max_{1\leq j\leq n} v_{ij}\right)\mid j\in J^{'}\right\}=\{v_1^-,\cdots,v_j^-,\cdots,v_m^-\}$ J means Ideal and $J^{'}$ means negative Ideal
Calculating Separation Measures	
Step10	$d_j^+=\sqrt{\sum_{i=1}^{m}\left(v_{ij}\text{-}v_j^+\right)^2}$ $d_j^-=\sqrt{\sum_{i=1}^{m}\left(v_{ij}\text{-}v_j^-\right)^2}$
Calculating Grey Relational Coefficients with Positive and Negative Ideal Solutions	
Step11	$r_{ij}^+=\frac{\min_i \min_j \left\|v_i^+\text{-}v_{ij}\right\| +\rho \max_i \max_j \left\|v_i^+\text{-}v_{ij}\right\|}{\left\|v_i^+\text{-}v_{ij}\right\|+\rho \max_i \max_j \left\|v_i^+\text{-}v_{ij}\right\|}$ $r_{ij}^-=\frac{\min_i \min_j \left\|v_i^-\text{-}v_{ij}\right\| +\rho \max_i \max_j \left\|v_i^-\text{-}v_{ij}\right\|}{\left\|v_i^-\text{-}v_{ij}\right\|+\rho \max_i \max_j \left\|v_i^-\text{-}v_{ij}\right\|}$
Determine the Grey Relational Degrees	
Step12	$r_j^+=\frac{1}{n}\sum_{i=1}^{n} r_{ij}^+$, j=1,2,…,m

	$r_j^- = \frac{1}{n}\sum_{i=1}^{n} r_{ij}^-, \quad j=1,2,\ldots,m$
Dimensionless Processing	
Step13	$D_j^+ = \frac{d_j^+}{\max_j d_j^+}, \quad D_i^- = \frac{d_j^-}{\max_j d_j^-}$ $R_j^+ = \frac{r_j^+}{\max_j r_j^+}, \quad R_j^- = \frac{r_j^-}{\max_j r_j^-}$
Fusing Grey Relational Degree and Euclidean Distance	
Step14	$S_j^+ = \alpha D_j^- + \beta R_j^+, \quad j=1,2,\ldots,m$ $S_j^- = \alpha D_j^+ + \beta R_j^-, \quad j=1,2,\ldots,m$
Calculating Relative Closeness to the Ideal Solution	
Step15	$C_j = \frac{S_j^-}{S_j^+ + S_j^-} \quad (j=1,2,\cdots,n)$

Table 3 presents the Steps of Combination of Entropy Weight-TOPSIS and Grey Relational Analysis. Ultimately, we obtain the relative closeness (C_j) for each object under evaluation. Based on the magnitude of C_j, the N objects are ranked in descending order. A larger C_j, indicates that the object is farther from the negative ideal solution and closer to the positive ideal solution, thus receiving a better evaluation; conversely, a smaller C_j implies a worse evaluation.

3. Analysis of Research Data and Findings

3.1. Calculating Relative Closeness in CRO Industry

Based on the previous analysis and data collection, the original data of each case company in 2024 are shown in Table 4. The weights of the Solvency, Operating, Profitability, and Development evaluation indicators were calculated according to Steps 1-5, and the result is ω = (0.3174, 0.1137, 0.2778, 0.2910).

Table 4. the Raw Data of Each Company

Indicators	R&G	Tiger Med	High Hink	Bio-Sincerity	Medprin Regenerative
A1	4.88	1.72	2.00	2.01	6.58
A2	4.74	1.71	2.00	1.78	5.86
A3	35.46	29.96	0.20	-25.46	245.14
A4	21.41	16.07	45.64	30.68	12.46
A5	244.84	56.13	129.27	55.76	235.76
A6	0.04	0.36	0.74	0.48	0.20
B1	6.91	5.04	9.48	2.86	13.18
B2	8.04	157.57	9.61	2.85	1.90
B3	0.34	0.23	0.96	0.22	0.35
C1	6.43	1.54	12.51	-1.43	9.94

C2	21.24	10.06	15.13	-4.29	32.94
C3	19.06	6.78	13.02	-6.60	28.32
C4	0.11	0.15	0.17	0.12	0.40
D1	12.65	-3.40	14.57	1.42	1.56
D2	-12.94	-79.17	28.27	-119.46	92.90
D3	3.14	-10.58	22.95	-21.18	20.61
D4	-7.14	10.83	6.00	55.01	-7.36

Through steps 6-9, the indicator matrix was standardized and the positive and negative ideal solutions were calculated, yielding:

Z+= (0.5546，0.7187，0.5943，0.8744，0.5121)
Z- = (0.6660，0.5260，0.6732，0.4520，0.8223)

The Euclidean distances between each sample and the positive and negative ideal solutions were calculated in Step 10, resulting in:

D+= (0.8099，0.5126，0.7675，0.3804，1.0000)
D- = (0.5295，0.8482，0.6762，1.0000，0.4538)

The grey relational degrees between each sample and the positive and negative ideal solutions were calculated in Steps 11 and 12, obtaining:

R+= (0.6343，0.8219，0.6797，1.0000，0.5857)
R- = (0.8100，0.6396，0.8187，0.5497，1.0000)

With $\alpha = \beta = 0.5$, the relative closeness was calculated through Steps 13 - 15, the results are giving in Table 5:

Table 5. the Relative Closeness of Each Company

Company Name	Relative Closeness	Rank
Bio-Sincerity	0.6826	1
Tiger Med	0.5918	2
High Hink	0.4609	3
R&G	0.4181	4
Medprin Regenerative	0.3420	5

3.2. Further analysis

3.2.1. financial risks of Bio-Sincerity

To intuitively illustrate whether the final evaluation results of the material misstatement risk evaluation model based on entropy weight-TOPSIS and grey relational analysis are reasonable, this paper conducts an analysis and verifies the model's accuracy based on the data from 2021-2024 annual reports disclosed by Bio-Sincerity and the industry average.

Bio-Sincerity's accounts receivable turnover in 2024 decreased by 50.86% compared with 2023, a decline far exceeding the 14.78% average drop of comparable companies and the industry. It ranked 27th among 30 listed companies in the research and experimental development sector. This significant change in the indicator means that Bio-Sincerity's payment collection speed has slowed down, with customers occupying more of the company's working capital, leading to capital difficulties for Bio-Sincerity.

In fact, Bio-Sincerity saw a negative cash flow ratio in 2024, indicating that the company could not generate sufficient cash flow from operating activities to repay its short-term debts. Its net cash flow from operating activities dropped by 316.53% year-on-year, while the industry average decline was 9.57%. Bio-Sincerity faces a serious risk of capital chain rupture; if the liquidity pressure cannot be alleviated, there will be significant uncertainty regarding the company's going concern ability.

Bio-Sincerity's operating revenue in 2024 decreased by 21.18% year-on-year, far exceeding the industry average of -2.73%. However, its selling expense growth rate surged by 138.36%, while the selling expenses of listed companies across the industry showed an overall downward trend. Selling expense growth should have driven revenue recovery, but Bio-Sincerity's revenue decline contradicts the surge in selling expenses, clearly indicating that the investment did not translate into effective output.

The abnormalities in the above indicators mean that Bio-Sincerity has material misstatement risks in the recognition and valuation of revenue recognition and accounts receivable. Moreover, indicators such as selling expense growth rate, cash flow ratio, and operating revenue growth rate account for a large weight in the material misstatement risk evaluation model based on entropy weight-TOPSIS and grey relational analysis, resulting in a high material misstatement risk for Bio-Sincerity.

In summary, the results of evaluating material misstatement risks of pharmaceutical companies using entropy weight-TOPSIS and grey relational analysis are relatively reliable and have high practical value.

3.2.2. audit risks of Bio-Sincerity

By applying the material misstatement risk evaluation model based on entropy weight-TOPSIS and grey relational analysis, combined with Bio-Sincerity's financial data over the years, we have reason to suspect that Bio-Sincerity has material misstatement risks, mainly manifested in the following aspects:

3.2.2.1. Risks related to the occurrence and accuracy of revenue

Bio-Sincerity's operating revenue in 2024 decreased by 21.18% year-on-year, far exceeding the industry average of -2.73%. Moreover, according to the earnings forecast revision announcement released by the company on April 17, 2025, the company originally expected a profit of 45 million to 65 million yuan, but revised it to an expected loss of 31.5 million to 53.5 million yuan, mainly affected by R&D projects. Due to R&D projects showing signs of contract termination, the company needs to reverse 40 million yuan of revenue. The company mainly recognizes revenue from R&D projects using the percentage-of-completion method. However, R&D projects have long cycles and highly subjective progress judgments. Under the pressure of declining revenue, there may be cases of recognizing revenue in advance—i.e., overestimating the completion percentage to inflate revenue when the project has not reached the scheduled progress.

Meanwhile, the explanation for the change in operating revenue mentions that the generic drug business is affected by policies such as centralized procurement and the Marketing Authorization Holder (MAH) system. Under such industry policy impacts, some customers may reduce orders or delay cooperation. To cover up the actual situation of declining revenue, the company may engage in fraudulent behaviors, leading to misstatements in the "occurrence" assertion of revenue. In addition, the operating revenue growth rate, which has a high weight in the model, has abnormal changes, further increasing the material misstatement risk related to revenue assertions.

3.2.2.2. Material misstatement risk in the occurrence assertion of selling expenses

In 2024, Bio-Sincerity's selling expense growth rate reached 55.01%, while operating revenue decreased by 21.18% year-on-year. The growth in selling expenses did not drive revenue recovery, which is contrary to normal business logic, and this growth rate far exceeded the industry level. Promotional fees accounted for approximately 72% of selling expenses, but there was a lack of proof of specific service results. Furthermore, according to its 2024 annual report, its sales and profit models are mainly "entrusted"-based, which is inconsistent with the explanation in the annual report that "the increase is mainly due to the company's increased sales promotion during the reporting period."

With declining revenue and profit losses, the company risks inflating selling expenses to transfer funds, which are then returned to the company in other forms to cover up the real operational difficulties. This further exacerbates the material misstatement risk in the occurrence assertion of selling expenses.

3.2.2.3. Material misstatement risk in the occurrence assertion of accounts receivable

Bio-Sincerity's accounts receivable turnover in 2024 was 2.86 times, significantly lower than the industry average of 7.11 times, with accounts receivable balance reaching 412 million yuan. Among them, the proportion of receivables with a tenure of more than 1 year rose to 35%, while the bad debt provision ratio was 12.35%, lower than the industry average of 15%.

The accounts receivable turnover, which has a high weight in operational capability indicators, has a long cycle, highlighting the material misstatement risk in the valuation and allocation assertions of accounts receivable. Due to the extended recovery cycle of accounts receivable, the recoverability of some payments has decreased, and there may be insufficient provision for bad debts on overdue accounts receivable, with the aim of maintaining asset book values by underestimating impairment losses.

Meanwhile, the company has a high customer concentration, with the top five customers contributing 31.08% of revenue. If core customers encounter financial problems, the recovery risk of accounts receivable will further increase. Finally, as the company's performance is under pressure, the extended recovery cycle of accounts receivable may be related to related-party transactions. The company may inflate revenue through related parties, resulting in long-term outstanding accounts, leading to misstatements in the "existence" assertion of accounts receivable.

Its audit risks are summarized in Table 6.

Table 6. Circumstances Events and Risks

N	Circumstances and Events	Material Misstatement Risks	Assertions
1	Revenue Recognition and Measurement Risk	Understated Revenue or Overstated Costs	Operating Revenue (Completeness,)、Operating Costs (Occurrence)
2	Accounts Receivable	Overstated R&D Expenses	Accounts Receivable (Valuation and Allocation, Existence)
3	Mismatch between Selling Expenses and Operating Revenue	Overstated Selling Expenses	Selling Expenses (Occurrence)

4. Suggestions and Conclusions

4.1. Suggestions

The combined use of the entropy weight-TOPSIS method and grey relational analysis helps information users understand the financial risks of enterprises in the industry across different periods, identify significant audit risk factors, and support information users in making investment and financing decisions. From the results of this paper, indicators reflecting an enterprise's operational capabilities, such as revenue and sales expenses, are the most critical factors and also the most powerful tools for grasping financial and audit risks. Therefore, to effectively prevent the risk of audit misstatements, in audit work, auditors can conduct a preliminary review of various sectors of the audited entity using quantitative indicators to clarify the focus of audit work; at the same time, financial personnel need to integrate finance with business and deeply participate in the actual operation of the company, including the following specific aspects:

(1) Participate in business management. Financial personnel should deeply integrate into the core business processes of medical CRO enterprises, especially the full-cycle management of clinical trial projects. At the project initiation stage, it is necessary to evaluate the financial feasibility of the project in combination with industry compliance requirements and financial standards, including the matching between cost structures (such as subject fees and testing equipment investment) and expected returns. During project execution, real-time monitoring of the correlation between business progress and financial data should be conducted, such as tracking deviations between actual project costs and budgets, coordinating resource allocation to avoid waste or shortage of funds, and paying attention to the impact of partners' credit risks on the recovery of business payments, so as to ensure the synergy and

unification of business management and financial control.

(2) Participate in business analysis. Financial personnel need to combine the business characteristics of the medical CRO industry, such as "long project cycles and revenue recognition relying on completion progress", to conduct in-depth correlation analysis between financial indicators and business data. For example, identify high-value-added business segments by analyzing the revenue composition and cost proportion of different types of clinical trial projects (e.g., Phase I to Phase IV); analyze the correlation between the growth of sales expenses and business expansion to evaluate the effectiveness of expense input; and track the impact path of business fluctuations on core financial indicators such as revenue and profit, so as to provide support for business decisions from a financial perspective.

(3) Participate in business budgeting. Financial personnel should establish a dynamic budgeting system based on the business plans of medical CRO enterprises. At the budget formulation stage, it is necessary to refine the matching logic between cost budgets and revenue budgets according to the characteristics of project cycles. During budget execution, a linked tracking mechanism between business progress and budget implementation should be established; for example, when a project is delayed, adjust relevant cost budgets in a timely manner to prevent budgets from being disconnected from actual business. By comparing the differences between budgeted and actual data and analyzing the causes, it can provide a basis for optimizing resource allocation and adjusting business plans, and improve the support effectiveness of budgets for business development.

4.2. Conclusions

This paper introduces the combined application of the entropy weight-TOPSIS method and grey relational analysis from two aspects: the application of the methods and their purposes. Through the empirical test of the model, it can be known that in 2024, among the selected case companies in the medical CRO industry, Bio-Sincerity Pharmaceutical faces the highest audit risk. Based on the analysis of Bio-Sincerity Pharmaceutical's financial data, it is found that its significant misstatement risks mainly focus on the risks of occurrence and accuracy of revenue, as well as the significant misstatement risks in the recognition of sales expenses and accounts receivable.

It is found in the evaluation of audit risks in the CRO industry and Bio-Sincerity Pharmaceutical that solvency indicators account for the largest average weight and are also the most noteworthy type of financial indicators in this industry. This is closely related to the business characteristics of the CRO industry. Firstly, the core businesses of CRO enterprises are characterized by long project cycles and large upfront capital investment. There is a significant time lag from project initiation to final payment collection, which requires long-term occupation of a large amount of working capital to cover costs such as subject fees, researchers' salaries, laboratory equipment purchases, and compliance certification expenses. Secondly, the CRO industry is a capital-intensive field. To expand business scale and enhance technological competitiveness, enterprises often obtain funds through debt financing methods such as bank loans and bond issuances, resulting in generally high asset-liability ratios. However, the uncertainty of pharmaceutical R&D (such as clinical trial failures and project delays) may exacerbate cash flow fluctuations. If solvency is insufficient, it is prone to trigger the risk of short-term capital chain rupture, directly affecting project continuity and contract performance capabilities. In addition, when selecting CRO partners, downstream pharmaceutical companies usually take solvency as the core indicator to evaluate the stability of their continuous operation. Weak solvency may lead to the loss of cooperation opportunities, further weakening enterprises' profitability and industry competitiveness. Therefore, solvency not only reflects an enterprise's ability to cope with short-term debt pressure but also relates to its business sustainability and industry reputation, thus becoming a financial indicator that needs priority attention in the audit risk evaluation of the CRO industry.

Therefore, enterprises in the CRO industry need to manage their own debt-servicing funds well to more effectively cope with the debt pressure and capital risks brought by the industry characteristics, provide stable capital support for business expansion and technological upgrading, and then consolidate their sustainable operation advantages in the industry competition.

From an audit perspective, the effectiveness of debt-servicing fund management in the CRO industry is crucial to audit risk assessment. Auditors need to focus on three key aspects: first, for the dynamic cash flow forecasting model, verify the rationality of the matching degree between project cycles, payment rhythms in the parameters and historical data, validate the reliability of prediction results under extreme scenarios, and be alert to the situation where parameters are artificially adjusted to whitewash solvency; second, for the debt structure, conduct in-depth checks on the matching between the use of long-term and short-term debts and project cycles, pay attention to the comprehensiveness of scenarios in debt-servicing stress tests and the application of results, so as to avoid enterprises covering up hidden dangers in the capital chain; third, for the linkage between business contracts and debt-servicing management, sample-check the performance of payment clauses, focus on the compliance of accounting treatments for default compensation, and guard against the risk of material misstatement in overstating solvency. These procedures can reveal financial fraud or information distortion, provide a basis for evaluating the sustainable operation ability of enterprises, and also confirm the core position of solvency indicators in the audit risk evaluation of this industry.

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