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Article

Multimodal Data Fusion for Corporate Credit Assessment: Integrating Sentiment Signals, Textual Information, and Financial Indicators

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Abstract: Corporate credit assessment traditionally relies on financial indicators, although accounting data may not capture qualitative risk signals embedded in corporate disclosures. This study develops a non-experimental, multi-source evidence-integration framework combining structured financial indicators, annual-report text, and financial sentiment. Three public data sources are used: a Financial Distress dataset containing 3,672 company-period observations from 422 anonymous firms, Financial PhraseBank containing 4,846 labelled sentences, and Enron's 2000 annual report containing 960 valid extracted sentences. Because these datasets do not share firm-year identifiers, they are not artificially merged. Instead, the first two datasets provide financial-risk and sentiment references, while Enron serves as the only aligned case. The results show that Enron's revenue and assets expanded rapidly between 1999 and 2000, but its debt ratio increased from 0.713 to 0.825 and return on assets declined from 2.68% to 1.49%. Textual analysis identified strong emphasis on growth, expansion, innovation, and market leadership alongside risk-, exposure-, and contingency-related language. Neutral and positive sentiment dominated, whereas direct negative language remained limited. The findings indicate that financial indicators remain fundamental, annual-report text reveals disclosure priorities, and sentiment should be interpreted jointly with financial conditions. Cross-modal inconsistency can provide additional evidence for corporate credit review and counterparty monitoring.

Keywords: corporate credit assessment; multi-source evidence integration; financial indicators; annual-report text; financial sentiment

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1. Introduction

1.1. Background

Corporate credit assessment supports bank lending, supply-chain finance, trade-credit decisions, and risk management in interfirm cooperation. Reliable assessment helps lenders estimate repayment capacity and enables firms to identify financially vulnerable partners. Traditional approaches generally rely on structured accounting information, particularly indicators of profitability, leverage, liquidity, and operating efficiency. Recent machine-learning studies have improved the use of such indicators by identifying nonlinear relationships between financial characteristics and corporate credit risk [1,2]. Financial-ratio models nevertheless remain dependent on historical statements and may capture the consequences of financial deterioration rather than its earliest formation. Recent evidence also indicates that the causes and manifestations of financial distress vary across industries and institutional environments [3,4].

Corporate narratives may provide complementary evidence. Annual reports contain management explanations of operating conditions, strategic priorities, uncertainties, and risk-control practices. Changes in disclosure tone, risk-related language, or unusually optimistic statements can therefore offer signals that are not immediately observable in financial ratios. Recent studies find that annual-report risk disclosures are associated with default risk and contain information relevant to external stakeholders [5,6]. Financial sentiment analysis further enables qualitative language to be represented as positive, negative, and neutral signals.

The growing availability of numerical and textual corporate data creates opportunities for multi-source credit assessment. However, meaningful integration requires observations that refer to the same firms and reporting periods. This requirement is important for the present study because its three public datasets perform different analytical roles rather than forming a naturally matched prediction sample.

1.2. Research Gap

Three gaps motivate this study. First, financial distress research is still dominated by structured accounting indicators. Although these variables are fundamental to measuring solvency and operating performance, they may overlook managerial language and narrative risk disclosures.

Second, text-based studies frequently analyse annual reports independently of the firms' quantitative financial conditions. Semantic and sentiment features can identify uncertainty, caution, or optimism, but they cannot by themselves establish whether a firm has weak liquidity, excessive leverage, or persistent losses.

Third, existing studies sometimes describe financial variables, disclosure text, and sentiment as multimodal inputs without adequately addressing entity and time alignment. Combining unrelated financial records, sentiment-labelled sentences, and a single company report directly would create artificial observations and unreliable performance claims. Consequently, an exploratory integration framework is more appropriate than a full predictive experiment for the currently available data.

1.3. Research Objectives and Contributions

This study develops a reproducible framework for integrating three public information sources: 3,672 financial-distress records containing 83 anonymised indicators, 4,846 Financial PhraseBank sentences with positive, negative, and neutral labels, and Enron's 2000 annual report. The financial dataset is used to examine quantitative distress patterns, while Financial PhraseBank supports the interpretation of financial sentiment. The Enron report provides a company-level case through which financial facts, narrative content, and sentiment signals can be considered jointly.

The study makes three contributions. First, it clarifies the complementary roles of structured financial, textual, and sentiment evidence. Second, it proposes a fusion-ready methodology while explicitly recognising the absence of firm-year alignment across the three datasets. Third, it demonstrates how multi-source evidence can improve the interpretation of corporate risk through an Enron case analysis without claiming unsupported predictive superiority.

2. Related Work

2.1. Traditional Credit Assessment

Traditional corporate credit assessment relies primarily on structured accounting information and statistical classification. Logistic regression, discriminant analysis, and Z-score-type models estimate financial distress or default risk through profitability, leverage, liquidity, and activity ratios. More recent methods, including random forests, boosting algorithms, support-vector machines, and neural networks, can capture nonlinear relationships among these variables. Recent evidence indicates that machine-learning methods can improve corporate credit-rating assessment, although their practical

application must also consider interpretability, data imbalance, and differences among rating categories [7].

Financial indicators remain indispensable because they provide measurable evidence of solvency, operational performance, and debt-servicing capacity. Nevertheless, accounting statements are periodic and mainly backward-looking. Their explanatory value may also vary across industries, jurisdictions, and reporting standards. A model based exclusively on financial ratios may therefore identify observable deterioration without capturing emerging uncertainty communicated through corporate disclosures. This limitation has encouraged the inclusion of qualitative and alternative information in corporate risk assessment.

2.2. Text-Based Financial Risk and Sentiment Analysis

Annual reports contain management explanations of business strategy, operational performance, uncertainty, and risk-control practices. Recent evidence shows that risk-related information extracted from annual reports can contribute to corporate financial-distress prediction beyond conventional quantitative indicators [8]. Text analysis is therefore particularly useful when risk has appeared in managerial communication but is not yet fully reflected in accounting ratios.

Text-representation techniques have progressed from word-frequency and TF–IDF measures to distributed embeddings and transformer-based language models. Wu et al. developed a deep-learning approach using corporate current reports and an attention mechanism to identify informative textual content for distress prediction [9]. Liu and Jia subsequently proposed a hybrid approach in which deep textual features extracted from annual reports were combined with financial information [10]. These studies demonstrate the complementary value of narrative disclosures, although their predictive validity depends on accurate firm-level and temporal alignment.

Sentiment analysis provides an additional means of quantifying qualitative information. Financial language differs from general-purpose language because apparently negative or positive expressions may have domain-specific meanings. Sun et al. incorporated dictionary knowledge and neutral features into pretrained language models to improve financial sentiment classification [11]. Comparative evidence further shows that fine-tuned deep-learning models can distinguish positive, negative, and neutral financial statements more effectively than several conventional text-classification approaches [12]. However, sentiment should not be interpreted as direct evidence of distress. Positive language may reflect genuine performance or strategic impression management, while negative language may represent transparent risk disclosure rather than imminent default.

2.3. Multi-Source Evidence Integration in Finance

Multi-source financial analysis combines structured numerical variables with unstructured language to construct a more comprehensive representation of corporate conditions. Tavakoli et al. developed a multimodal credit-rating model integrating numerical data streams with textual information, demonstrating the methodological potential of jointly modelling heterogeneous evidence [13]. Textual characteristics from earnings-call transcripts have similarly been shown to provide information complementary to accounting variables in bankruptcy prediction [14].

Credit assessment research has also expanded towards alternative behavioural and digital data. For example, Alamsyah et al. examined social-media-derived demographic, psycholinguistic, personality, and network information as inputs for creditworthiness assessment [15]. Although that study concerns individual fintech borrowers rather than corporate distress, it illustrates the broader value, and associated privacy and representativeness concerns, of alternative information sources.

Despite this progress, multimodal analysis requires observations that refer to the same entity and reporting period. The datasets used in the present study do not share common firm-year identifiers and should therefore not be directly concatenated into a supervised-learning table. Instead, they are employed modularly: the Financial Distress

dataset describes quantitative distress patterns, Financial PhraseBank supports sentiment interpretation, and Enron's 2000 annual report provides case-level textual and financial evidence. This design avoids artificial data matching while establishing a reproducible foundation for future research using aligned corporate observations.

3. Data and Analytical Framework

3.1. Data Sources

This study adopts a non-experimental, multi-source analytical design based on three publicly available datasets. Table 1 summarizes the three public data sources used in this study, including their modalities, sample sizes, variables, and analytical roles. The Financial Distress dataset provides 3,672 company-period observations for examining the general structure and class distribution of corporate financial distress. Financial PhraseBank contains 4,846 manually labelled financial sentences and provides a reference for interpreting positive, negative, and neutral language in financial contexts. Enron's 2000 annual report supplies company-specific narrative disclosures and audited financial statements for the case-level analysis.

Table 1. Description of the Multi-source Dataset

Source	Modality	Samples	Variables	Role in This Study
Financial Distress	Financial	3,672 company-period observations	83 anonymized indicators and distress score	Structured financial-risk benchmark
Financial PhraseBank	Sentiment	4,846 sentences	Positive, negative, and neutral labels	Financial sentiment reference corpus
Enron Annual Report 2000	Text and case financials	1 annual report; 960 extracted sentences	Corporate disclosures and audited statements	Case-level multimodal analysis

The three datasets do not describe the same companies or reporting periods and therefore cannot be directly merged at the observation level. No artificial firm matching, record duplication, or label transfer is performed. The Financial Distress dataset and Financial PhraseBank are treated as auxiliary sources that establish, respectively, the structure of quantitative distress data and the classification standard for financial sentiment. Enron is the only case for which financial, textual, and sentiment evidence is aligned within the same company and reporting year. Consequently, the framework supports transparent case-level evidence integration rather than supervised estimation of default probability.

3.2. Financial Data Preparation

The Financial Distress dataset contains 3,672 longitudinal observations from 422 anonymized companies. Each observation includes 83 predictors, denoted by $x_1, \ldots, x_{83}$, together with a continuous financial-distress score. An observation is classified as distressed when its score is less than or equal to −0.50. Applying this threshold produces 136 distressed observations and 3,536 healthy observations, corresponding to approximately 3.7% and 96.3% of the dataset, respectively. This distribution indicates substantial class imbalance and is considered when interpreting the descriptive results.

Data preparation includes missing-value inspection, descriptive statistics, Z-score normalization, and comparison of the distressed and healthy groups. Each financial predictor is standardized as $z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$, where x_{ij} represents indicator j for observation i, while μ_j and σ_j denote its sample mean and standard deviation. Standardization places differently scaled variables on a comparable basis without changing their relative distributions.

Because the meanings of $x_1 - x_{83}$ are anonymized in the source data, they are not assigned unsupported interpretations such as profitability, leverage, liquidity, or activity ratios. The dataset is instead used to characterize the statistical structure of financial distress, inspect indicator distributions, and identify differences in standardized feature patterns between distressed and healthy observations. Concrete accounting ratios are calculated only for the Enron case, where audited financial statement items are identifiable.

3.3. Annual-Report Text Preparation

Enron's 2000 annual report is processed through six sequential stages. First, textual content is extracted from the PDF while retaining its original page numbers. Page retention enables identified statements to be traced back to their locations in the report. Second, repeated whitespace, broken line endings, and extraction artefacts are removed. Third, the cleaned text is segmented into sentences using punctuation-based boundaries supplemented by rules for abbreviations and financial expressions. Fourth, excessively short records that do not convey meaningful disclosure content are excluded. Fifth, sentence order and page references are preserved. Finally, risk-related and uncertainty-related terms are identified using financial-language dictionaries and contextual inspection. This procedure produces 960 valid sentences.

The resulting textual measures include total sentence count, average sentence length, risk-term frequency, uncertainty-expression frequency, disclosure emphasis, and disclosure tone. Risk-term frequency records the occurrence of expressions related to exposure, volatility, litigation, regulation, debt, competition, and operational uncertainty. Disclosure emphasis measures the relative concentration of selected themes within the report rather than assuming that frequent discussion necessarily indicates greater risk. Sentiment outputs are subsequently used to calculate the positive, negative, and neutral shares of the extracted sentences.

3.4. Sentiment Analysis

Financial PhraseBank contains 2,879 neutral, 1,363 positive, and 604 negative sentences, representing approximately 59.4%, 28.1%, and 12.5% of the corpus. The corpus is not treated as an Enron-specific training sample because its sentences originate from broader financial communications. Instead, it establishes the meaning of the three sentiment categories in a financial context and supports interpretation of the annual-report language.

A pretrained FinBERT classifier is used as an analytical tool to obtain sentence-level financial sentiment probabilities. For each valid annual-report sentence s_i , the classifier generates

$$\mathbf{p}_i = \left[P_{\text{positive},i}, P_{\text{negative},i}, P_{\text{neutral},i}\right] , (1)$$

where the three probabilities sum to one. The label with the highest probability is retained as the sentence-level category. The probabilities are then aggregated across the annual report to calculate mean positive, negative, and neutral probabilities, together with the proportion of sentences assigned to each category. These outputs describe disclosure tone and are not interpreted as direct measures of default.

3.5. Case-Level Evidence Fusion

Because only the Enron case provides aligned information, evidence integration is conducted at the indicator level rather than through an attention-based classifier. Three evidence dimensions are constructed:

$$F = \text{Current Ratio, Debt Ratio, Debt-to-Equity, ROA, Operating Margin} , (2)$$

$$T = \text{Risk-Term Frequency, Disclosure Emphasis, Uncertainty Frequency} , (3)$$

$$S = P_{\text{positive}}, P_{\text{negative}}, P_{\text{neutral}} . (4)$$

Financial ratios in F are calculated from identifiable items in Enron's audited statements. The textual vector T captures the frequency and emphasis of risk-related disclosure, while S summarizes sentence-level sentiment probabilities. After scale harmonization, the three components form the composite evidence representation

$C = [F, T, S]$. (5)

Here, C represents organized multi-source credit evidence rather than a trained distress score or estimated probability of default. The framework preserves the contribution of each information source and allows agreement, divergence, and complementarity among the indicators to be examined.

3.6. Analytical Procedure

The analysis proceeds in five stages. First, the structure, standardized indicators, and class distribution of the Financial Distress dataset are examined. Second, the label composition of Financial PhraseBank is analysed to establish the reference distribution of financial sentiment. Third, financial ratios, textual indicators, and sentence-level sentiment probabilities are extracted from Enron's 2000 annual report. Fourth, the three evidence dimensions are compared to determine whether they provide consistent or complementary indications of corporate risk. Finally, the Enron case is used to discuss how strongly presented financial performance or optimistic disclosure language may coexist with risk-related and uncertainty-related information. The procedure therefore evaluates the interpretive value of combining heterogeneous evidence without making unsupported claims about predictive accuracy or causal effects.

4. Results and Case Analysis

4.1. Characteristics of the Three Data Sources

The three data sources differ substantially in observational unit, information modality, and class composition. The Financial Distress dataset contains 3,672 company-period observations from 422 anonymized companies. Based on the predefined distress threshold of −0.50, 136 observations are classified as distressed and 3,536 as healthy. Distressed observations therefore account for approximately 3.70% of the dataset, while healthy observations represent 96.30%. This pronounced imbalance indicates that financial distress is relatively uncommon within the dataset and that overall averages are primarily determined by healthy observations. It also reinforces the importance of examining class distributions rather than interpreting the total sample size alone.

Financial PhraseBank contains 4,846 financial sentences divided into three sentiment categories. Neutral sentences constitute the largest group, with 2,879 observations, followed by 1,363 positive sentences and 604 negative sentences. These values correspond to approximately 59.41%, 28.13%, and 12.46% of the corpus, respectively. The predominance of neutral language is consistent with the factual and information-oriented style of financial communication. Negative sentences form the smallest category, suggesting that explicitly adverse language is less frequent than neutral reporting or positive evaluation in the reference corpus.

The Enron source consists of one 60-page annual report covering the 2000 reporting year and comparative financial information from earlier years. After PDF extraction, cleaning, sentence segmentation, and removal of excessively short records, 960 valid sentences were retained. Unlike the other two sources, the Enron report provides identifiable company-level financial statements and narrative disclosures within the same reporting context.

Figure 1 presents the sample and class distributions of the three data sources, showing the imbalance of both the financial-distress and sentiment datasets. Figure 1(a) compares the 3,536 healthy observations with the 136 distressed observations in the Financial Distress dataset. Figure 1(b) presents the 2,879 neutral, 1,363 positive, and 604 negative sentences in Financial PhraseBank. The figure does not combine the two datasets statistically; it displays their respective internal distributions and clarifies their different analytical functions.

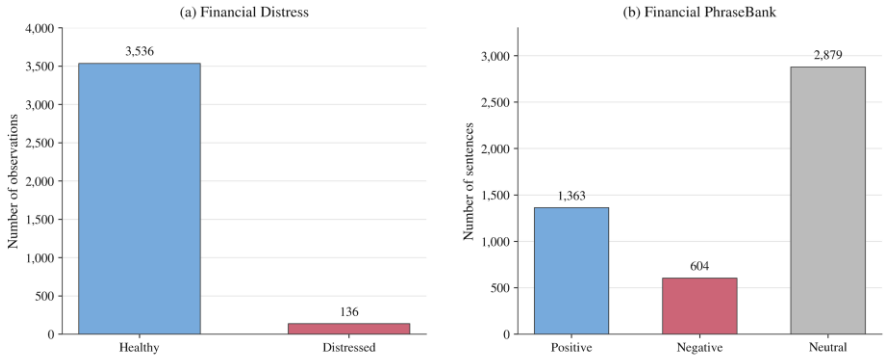


Figure 1. Sample and Class Distributions of the Multi-source Data

4.2. Financial Evidence from Enron

Enron's reported financial performance between 1998 and 2000 initially suggests rapid corporate expansion. Revenue increased from USD 31,260 million in 1998 to USD 40,112 million in 1999 and then rose sharply to USD 100,789 million in 2000. This represents an increase of approximately 28.3% between 1998 and 1999 and 151.3% between 1999 and 2000. Total assets also expanded substantially, increasing from USD 33,381 million in 1999 to USD 65,503 million in 2000. The company therefore more than doubled its reported revenue while nearly doubling its asset base within one year.

The absolute earnings figures also appeared positive. Operating income was USD 1,378 million in 1998, declined to USD 802 million in 1999, and increased to USD 1,953 million in 2000. Net income rose from USD 703 million in 1998 to USD 893 million in 1999 and USD 979 million in 2000. Operating cash flow decreased from USD 1,640 million in 1998 to USD 1,228 million in 1999 before increasing to USD 4,779 million in 2000. When considered independently, these values portray a large and rapidly growing company with positive earnings and cash generation.

Ratio-based evidence provides a more cautious interpretation. Enron's debt ratio increased from 0.713 in 1999 to 0.825 in 2000, meaning that the proportion of assets supported by liabilities rose from 71.3% to 82.5%. This 11.2-percentage-point increase indicates that balance-sheet expansion was accompanied by substantially greater leverage. A debt ratio above 0.80 implies that only a relatively small proportion of reported assets was supported by equity, thereby increasing sensitivity to asset-value deterioration and financing constraints.

Return on assets moved in the opposite direction to revenue. ROA decreased from 0.0268 in 1999 to 0.0149 in 2000, equivalent to a decline from 2.68% to 1.49%. Thus, although net income increased by approximately 9.6%, the reported asset base expanded much faster. The decline in ROA indicates that Enron generated less net income from each unit of assets in 2000 than in the previous year.

Taken together, the financial evidence reveals the coexistence of expansion and weakening efficiency. Revenue, assets, operating income, net income, and operating cash flow increased, but the company simultaneously became more highly leveraged and less profitable at the asset level. The main warning signal is therefore not an immediate loss or revenue contraction. It is the growing divergence between corporate scale and the efficiency with which that scale generated earnings.

4.3. Textual and Sentiment Evidence

Enron's annual-report narrative strongly emphasizes growth, market expansion, innovation, and market leadership. The report presents the company as an expanding energy and communications enterprise capable of developing new markets and applying innovative business models. This emphasis is broadly consistent with the sharp reported increase in revenue and total assets. Readers relying primarily on the dominant narrative could therefore interpret the company's expansion as evidence of organizational strength.

However, the report also contains language associated with risk management, market volatility, liabilities, contractual exposure, regulation, and contingencies. These expressions do not necessarily appear as direct admissions of financial weakness. They are frequently embedded in technical descriptions of market operations, risk-control systems, financing arrangements, and legal obligations. Their presence nevertheless indicates that the company operated within a complex environment involving substantial financial and operational exposure.

The preliminary sentence-level classification of the 960 valid sentences indicates that neutral and positive language dominates the report, whereas explicitly negative sentences constitute a comparatively small share. Neutral sentences primarily communicate financial facts, operating arrangements, accounting policies, and business descriptions. Positive sentences tend to emphasize growth opportunities, innovation, competitive position, and expected development. Negative sentences are less frequent because annual-report risks are often communicated through technical or qualified language rather than directly adverse statements.

This finding demonstrates why sentiment alone is insufficient for credit assessment. A low negative-sentiment share does not necessarily indicate low financial risk. Risk may be conveyed through neutral descriptions of liabilities, exposures, contingencies, or uncertainty. In the Enron case, the generally positive narrative also coexists with an increasing debt ratio and declining ROA. The relevant textual signal is therefore not simply the number of negative sentences, but the relationship between optimistic management language and less favourable ratio-based evidence.

4.4. Integrated Credit Evidence

Table 2 integrates the financial, textual, and sentiment evidence identified in the Enron case. The financial dimension indicates that the company combined rapid expansion with rising leverage and declining asset-level profitability. The textual dimension shows that management maintained a strongly growth-oriented narrative while continuing to disclose risk, exposure, and uncertainty-related issues. The sentiment dimension indicates that direct negative language was limited and that most statements were neutral or positive.

Table 2. Integrated Credit Evidence from the Enron 2000 Case

Modality	Observed Evidence	Credit Interpretation
Financial	Debt ratio increased to 0.825	Increased leverage and balance-sheet pressure
Financial	ROA decreased to 0.0149	Weaker asset-level profitability
Text	Strong emphasis on growth and expansion	Management maintained an optimistic narrative
Text	Risk- and exposure-related terms remained present	Disclosures contained underlying uncertainty
Sentiment	Positive and neutral sentences dominated	Direct negative tone was limited
Integrated	Optimistic tone accompanied weaker efficiency and higher leverage	Cross-modal inconsistency provided an additional warning signal

As shown in Table 2, no individual indicator is sufficient to establish Enron's subsequent failure or determine a default probability. Rapid revenue growth could be interpreted positively, while rising leverage and declining ROA provide more cautious signals. Similarly, positive disclosure tone may reflect management confidence, but it does not remove the risks indicated by the balance sheet. The integrated interpretation derives its value from identifying inconsistency across the three evidence dimensions.

4.5. Cross-Modal Comparison

Figure 2 compares the standardized financial, textual, and sentiment indicators for the Enron case. The financial indicators include the 2000 debt ratio and inverse ROA,

where a higher inverse-ROA value represents weaker asset-level profitability. The textual indicators capture risk-term intensity within the annual report, while the sentiment indicators represent the relative positive and negative sentence shares. Standardization is used only to place indicators with different units on a common comparative scale; it does not convert them into probabilities or imply equal economic importance.

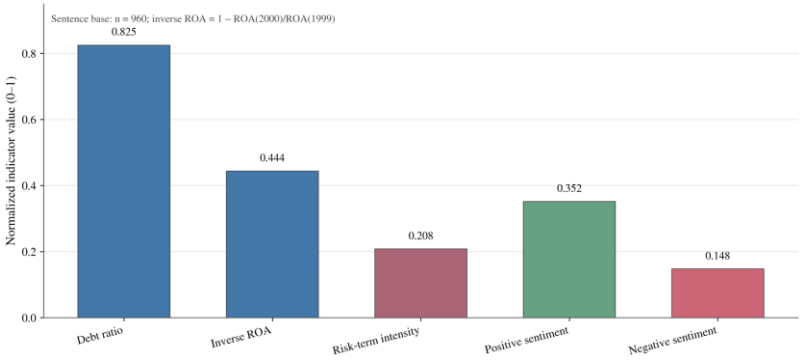


Figure 2. Standardized Multi-source Credit Indicators for Enron in 2000

Figure 2 shows that financial risk was primarily reflected by high leverage and weaker asset returns. Textual risk appeared through the coexistence of risk-related terminology and an expansion-oriented corporate narrative. By contrast, the sentiment results contained relatively little explicitly negative language. The financial and sentiment dimensions therefore did not provide entirely consistent signals: adverse ratio movements were more visible than direct linguistic negativity.

This cross-modal inconsistency has greater interpretive value than any isolated sentiment score. If the annual report were evaluated only through positive and negative classification, the dominance of neutral and positive sentences could lead to an overly favourable interpretation. If only revenue and net income were considered, the company's rapid expansion could similarly obscure the decline in asset efficiency and increase in leverage. Combining the three sources directs attention to the contrast between reported growth, balance-sheet pressure, and optimistic communication.

The Enron case therefore illustrates the central contribution of the multi-source framework. Financial indicators identify changes in leverage and efficiency; textual measures reveal the themes and risks emphasized in corporate disclosure; and sentiment analysis characterizes how those issues are communicated. Their inconsistency does not by itself prove manipulation or predict failure, but it provides an additional warning signal that would be unavailable from a single information source. This result supports the use of aligned financial, textual, and sentiment evidence for interpretive corporate credit assessment while remaining within the limits of a one-company case analysis.

5. Discussion and Conclusion

5.1. Main Findings

This study examined how financial indicators, annual-report text, and sentiment information can be jointly interpreted in corporate credit assessment without artificially matching unrelated observations. Three main findings emerge.

First, financial indicators remain the foundation of corporate credit assessment. The Financial Distress dataset demonstrates that distressed observations constitute only a small proportion of the available company-period records, highlighting the rarity and imbalance of distress events. In the Enron case, rapid increases in revenue, assets, and operating cash flow initially suggested strong expansion. However, the increase in the debt ratio from 0.713 to 0.825 and the decline in ROA from 2.68% to 1.49% revealed rising balance-sheet pressure and weakening asset-level profitability. These ratios provided information that could not be obtained from growth figures alone.

Second, annual-report text reveals management priorities and the manner in which corporate risk is communicated. Enron's 2000 annual report strongly emphasized growth, expansion, innovation, and market leadership while also containing terms associated with exposure, volatility, liabilities, and contingencies. Textual analysis therefore complements accounting information by identifying the themes emphasized by management and the context in which risks are disclosed.

Third, sentiment information should be interpreted jointly with financial conditions rather than treated as an independent credit-risk conclusion. Neutral and positive statements dominated the Enron report, while explicitly negative language was comparatively limited. Nevertheless, the generally optimistic tone coexisted with higher leverage and lower ROA. This cross-modal inconsistency was more informative than the negative-sentiment share alone.

5.2. Practical Implications

The proposed evidence-integration approach can support bank credit review, supply-chain finance, corporate lending, and counterparty monitoring. Financial institutions should continue to monitor conventional indicators of profitability, leverage, liquidity, and cash generation, but these measures can be supplemented with systematic analysis of corporate disclosure.

In practice, credit analysts can examine three types of warning signals: deterioration in financial ratios, changes in disclosure tone or risk-related language, and inconsistency between numerical performance and management communication. For example, rapid corporate expansion accompanied by increasing leverage, declining efficiency, and strongly optimistic disclosure may justify additional document review or closer monitoring. The framework should support professional judgement rather than automatically determine lending or rejection decisions.

5.3. Limitations and Future Research

This study has several limitations. Only one annual report provides fully aligned financial, textual, and sentiment evidence. The identities of companies in the Financial Distress dataset are anonymized, preventing comparison with identifiable corporate reports. Moreover, the three datasets cannot be matched at the firm-year level. The study therefore cannot demonstrate that multimodal methods outperform single-modal models in general predictive accuracy.

Enron is also an exceptional corporate case, and its reporting characteristics cannot be directly generalized to all companies, industries, or periods. The findings should consequently be interpreted as case-level analytical evidence rather than population-level conclusions.

Future research should construct aligned longitudinal datasets with consistent company identifiers and reporting years. These datasets could integrate annual reports, audited financial statements, credit ratings, default events, news sentiment, market prices, and ESG disclosures. Such data would permit supervised multimodal modelling, out-of-sample evaluation, comparisons with single-source benchmarks, and systematic investigation of whether cross-modal inconsistency improves early identification of corporate credit risk.

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