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Text Meets Finance:
The Power of NLP in Corporate Bankruptcy Prediction

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Résumé

Cette recherche examine le potentiel synergique entre le Traitement du Langage Naturel (TLN) et les modèles financiers traditionnels dans la prédiction de la faillite des entreprises, se concentrant spécifiquement sur le Score Z d'Altman. Dans un monde en production continue et exponentielle de données non structurées, cette étude met en évidence les contributions significatives, bien que nuancées, que l'analyse textuelle peut apporter à ces modèles traditionnels. En intégrant des caractéristiques textuelles extraites des rapports financiers — en particulier, les scores de sentiment et de lisibilité — notre modèle de régression logistique a montré une amélioration notable de la précision prédictive, passant de 59,8% à 69,1%. Parmi les caractéristiques textuelles, l'analyse de sentiment a surpassé les mesures de lisibilité. La recherche a utilisé un large éventail de mesures de performance pour mesurer rigoureusement ces améliorations. Nos résultats soulignent l'importance d'une approche minutieuse pour intégrer des données non structurées dans les modèles financiers.

Mots-clés

Traitement du langage naturel, Prédiction de faillite d'entreprise, Score-Z d'Altman, Analyse textuelle, Analyse de sentiment, Analyse de lisibilité, Liste de mots Loughran-McDonald, LLMs, Transformers, Données non structurées.

Méthodes de recherche

Analyse de Rapports Financiers, Prétraitement des Données, Analyse de Sentiment Textuel, Métriques de Lisibilité (FKGL, FRE, GFI, ARI, CLI, SMOG), Modèle d'apprentissage automatique pour la faillite corporative, Traitement du Langage Naturel (TAL), Modèles Transformateurs (RoBERTa, FinBERT), Lexiques de Sentiment (Loughran-McDonald), Adaptation de Données Spécifiques au Domaine

Abstract

This research investigates the synergistic potential between Natural Language Processing (NLP) and traditional financial models in predicting corporate bankruptcy, specifically focusing on Altman's Z-score. In a world with exponentially increasing unstructured data, this study explore how textual analysis can augment traditional models relying solely on numerical ratios. By incorporating textual features extracted from financial reports —specifically, sentiment and readability scores —our logistic regression model demonstrated an improvement in predictive accuracy of 10%. Among textual features, sentiment analysis outperformed readability metrics. The research employed a comprehensive array of performance metrics to rigorously measure these enhancements. Our findings point toward the importance of a nuanced approach in integrating unstructured data into financial models, underscoring the necessity for a targeted choice of both features and modeling techniques.

Keywords

Natural Language Processing, Corporate Bankruptcy Prediction, Altman's Z-score, Textual Analysis, Sentiment Analysis, Readability Analysis, Loughran-McDonald Word List, Large Language Models, Transformer Models, Unstructured Data.

Research Methods

Financial Report Analysis, Natural Language Processing (NLP), Data Processing, Textual Sentiment Analysis, Sentiment Lexicons (Loughran-McDonald), Readability Metrics (FKGL, FRE, GFI, ARI, CLI, SMOG), Machine Learning in Bankruptcy Modeling, Transformer Models (RoBERTa, FinBERT), Domain-Specific Data Adaptation.

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Liste des abréviations

NLP Natural Language Processing - *Traitement du langage naturel*

BERT Bidirectional Encoder Representations from Transformers - *Représentations de Transformers Encodées Bidirectionnelles*

GPT-4 Generative Pretrained Transformer 4 - *Transformateur Pré-entraîné Génératif 4*

ANN Artificial Neural Networks - *Réseaux de neurones artificiels*

SVM-Lin Linear Support Vector Machines - *Machines à Vecteurs de Support Linéaires*

LLM Large Language Model - *Grand Modèle de Langage*

RNN Recurrent Neural Network - *Réseau de neurones récurrents*

MLM Masked Language Modeling - *Modélisation de Langage Masquée*

NSP Next Sentence Prediction - *Prédiction de la Prochaine Phrase*

SVM Support Vector Machine - *Machine à Vecteurs de Support*

LM Loughran and McDonald - *Loughran et McDonald*

BART Bidirectional and Auto-Regressive Transformers - *Transformateurs Bidirectionnels et Auto-Régressifs*

SEC U.S. Securities and Exchange Commission - *Commission des valeurs mobilières et des échanges des États-Unis*

EDGAR Electronic Data Gathering, Analysis, and Retrieval - *Collecte, Analyse et Récupération de Données Électroniques*

ROC Receiver Operating Characteristic - *Caractéristique de Fonctionnement du Récepteur*

AUC Area Under the Curve - *Aire Sous la Courbe*

WRDS Wharton Research Data Services - *Services de Données de Recherche de Wharton*

MD&A Management Discussion and Analysis - *Discussion et Analyse de la Gestion*

FKGL Flesch-Kincaid Grade Level - *Grade Flesch-Kincaid*

FRE Flesch Reading Ease - *Facilité de Lecture Flesch*

GFI Gunning Fog Index - *Indice de Brouillard de Gunning*

CLI Coleman-Liau Index - *Indice de Coleman-Liau*

SMOG Simple Measure of Gobbledygook - *Mesure Simple de Charabia*

RNNs Recurrent Neural Networks - *Réseaux de Neurones Récurrents*

LSTMs Long Short-Term Memory Networks - *Réseaux de Mémoire à Long Terme Court*

ARI Automated Readability Index - *Indice de Lisibilité Automatisé*

Sentiment_LM Sentiment score based on the Loughran-McDonald dictionary - *Score de sentiment basé sur le dictionnaire Loughran-McDonald*

sentiment_f Finbert's sentiment score - *Score de sentiment de Finbert*

sentiment_r Roberta's other sentiment score - *Autre score de sentiment de Roberta*

bankrupt Binary variable indicating whether the company went bankrupt (1) or not (0) - *Variable binaire indiquant si l'entreprise a fait faillite (1) ou non (0)*

WC/TA Working Capital/Total Assets - *Capital de travail/Actifs totaux*

RE/TA Retained Earnings/Total Assets - *Bénéfices non distribués/Actifs totaux*

EBIT/TA Earnings Before Interest and Taxes/Total Assets - *Bénéfices avant intérêts et impôts/Actifs totaux*

MV/BV Market Value of Equity/Book Value of Total Liabilities - *Valeur marchande des capitaux propres/Valeur comptable des dettes totales*

S/TA Sales/Total Assets - *Ventes/Actifs totaux*

notCovid Binary variable indicating whether the data was collected before (1) or during (0) the COVID-19 pandemic - *Variable binaire indiquant si les données ont été collectées avant (1) ou pendant (0) la pandémie de COVID-19*

Avant-propos

In the realm where numbers weave a tale,
Bankruptcy looms, a specter pale.
Yet from silicon depths, a glimmer hails,
Artificial Intelligence sets the sail.

Laion.AI

"Now I'm a scientific expert ; that means I know nothing about absolutely everything."

Arthur C. Clarke, 2001 : A Space Odyssey (1968)

Remerciements

C’est avec cet ouvrage corrigé et bientot imprimé, que j’aimerais de tout coeur exprimer ma profonde gratitude a ma famille, amis et collègues de travail pour leur confiance et soutien le long de cette belle aventure. Merci aussi à l’équipe de la cafétéria pour son café toujours bien chaud pour les étudiants du monde avec lesquels j’ai eu le plaisir d’intéragir. L’environnement riche et chaleureux, malgré la frénésie des temps de pandémie, fut toujours un doux échapatoire pour cultiver des idées valant la peine d’etre partagées. J’aimerais conclure avec une citation d’un auteur cher a mes yeux durant mon temps a Montréal et aujourd’hui ;

"À Oran comme ailleurs, faute de temps et de réflexion, on est bien obligé de s’aimer sans le savoir." - La Peste, Albert Camus

Introduction

Corporate bankruptcy prediction has long stood as a cornerstone in the field of corporate bankruptcy. The pressing need to accurately predict a company's financial downfall stems not merely from an academic interest but an uncertain future after an economic slowdown during the covid-19 crisis and the on-going wars affecting the global economy in a short period of time. The repercussions of accurately predicting bankruptcy are far-reaching, affecting not only investors and creditors but also causing ripple effects across job markets, communities, and the economy at large. Historically, the endeavor to predict bankruptcy was largely dominated by statistical models that analyzed financial metrics such as liquidity, profitability, and solvency (E. I. ALTMAN 1968). These traditional models, while pioneering, are not without their shortcomings. Due to their inherent nature, Altman model focus on specific set of quantitative ratios that are well studied in the field. They often turn a blind eye to crucial non-financial factors like management efficacy, market sentiments, and industry trends, which can serve as early signs to predict a company's financial health or lack thereof. This sort of information is usually disclosed in text as opposed to quantitative ratios that are avalaible in the accounting sheets and financial variables readily available without further analysis.

Thanks to recent advances in machine learning, and more specifically natural language processing (NLP), presents a transformative opportunity to overcome these limitations. NLP technologies, enhanced by the public release of large language models like BERT (DEVLIN et al. 2018) and GPT (OUYANG et al. 2022), have the capabilities to mine valuable insights from unstructured text data. This form of data, often disregarded in traditional financial analyses, can range from financial reports and news articles to social media commentary. By integrating these supplementary data points into bankruptcy prediction models we're able to augment the features as quantitative values from our textual analysis of these reports.

The aim of this research is to delve into the potential use of integrating NLP and textual analytics into bankruptcy prediction models to leverage large amounts unstructured sources of data. The question at the core of this exploration is not just whether textual data can improve predictive accuracy, but how. To answer this, a meticulous literature review will serve as our starting point, identifying the state-of-the-art techniques and methodologies in both bankruptcy prediction and textual analytics within the financial domain. Subsequent to this, we will collect a dataset encompassing both financial and non-financial metrics, with a keen focus on unstructured text from financial disclosures, particularly 10-K annual reports.

In practice, this research involves the empirical application of NLP techniques, specifically sentiment and readability analysis, on our sample of data. These methods will serve to extract actionable insights, which will then be integrated into traditional bankruptcy prediction models. To measure the impact of this integration, we will employ different metrics aiming to provide a nuanced understanding of how each instance of the model behave. The research will contrast the performance of these augmented models against their traditional counterparts. This comparative analysis will shed light on the incremental value added by textual analytics, helping us identify which popular textual analysis techniques and data sources works best under our experiments. In light of these findings, we will discuss the broader implications for the field of corporate bankruptcy prediction, outlining both the strengths and limitations of employing NLP and textual analysis.

This research is a small contribution to the evolving landscape of NLP in corporate bankruptcy prediction since the rising popularity of LLMs. The landscape is evolving quickly, this work should be considered part of the early discussions of the use of LLMs in the financial sphere. For the moment LLMs are public but quite opaque, so are financial disclosures. Achieving perfect automation of analysis doesnt seem realistic knowing large corporations possess the ressources to fight back automated techniques.

Chapitre 1

Literary Review

The prediction of corporate bankruptcy is a critical issue that has garnered significant attention in the fields of finance and economy. Various approaches, ranging from statistical and machine learning to theoretical modeling techniques, have been employed to forecast the likelihood of a firm's financial distress. However, the incorporation of unstructured data, such as textual information, holds the potential to enhance the accuracy of these predictions. Recently, Natural Language Processing (NLP) techniques and textual analysis have emerged as promising methods for extracting valuable insights from unstructured data sources (BUBECK et al. 2023), leading to a surge of interest in their possible applications.

1.1 History of Corporate Bankruptcy Modelling

The realm of corporate bankruptcy prediction stands as a critical cornerstone in the interdisciplinary landscape of finance and accounting, emerging prominently in the academic literature around the 1960s. Initially confined to elementary metrics, this field has evolved dramatically, accommodating advancements in statistics, data science, and machine learning, thereby extending the boundaries of predictive accuracy and reliability.

1.1.1 Beaver and Altman Eras

The genesis of corporate bankruptcy prediction can be attributed to the seminal work of Beaver (BEAVER 1966), who was among the first to create a mathematical model to predict bankruptcies. Known as the Beaver Model, this framework relied upon a small set of financial ratios, namely the current ratio, debt-to-equity ratio, and net income to total assets ratio, employed individually to forecast the likelihood of a company facing bankruptcy. Beaver's contributions stand as a foundational layer in this research domain, despite subsequent criticism focused on its somewhat simplistic assumptions and the narrow scope of financial ratios considered.

Following in the wake of Beaver's work, Altman introduced a more nuanced and effective model known as the Altman Z-score (E. I. ALTMAN 1968). This model employed multiple discriminant analysis to amalgamate various financial ratios, including but not limited to working capital to total assets and earnings before interest and taxes to total assets. Altman's model rapidly gained acceptance in credit risk assessment due to its high accuracy rate of 95% in initial tests, and has undergone numerous revisions to remain pertinent across various industries and global settings.

1.1.2 Ohlson's O-Score and Shumway's Hazard Models

A subsequent significant development was Ohlson's introduction of the O-score model (OHLSON 1980). This model diverged from Altman's by incorporating a distinct set of financial ratios and applying logistic regression, a more versatile statistical tool, instead of multiple discriminant analysis. The O-score's methodology offered a continuous probability measure of financial distress, providing alternative insights into credit risk.

Advancing the field in bankruptcy prediction, Shumway introduced hazard models (SHUMWAY 1999), also known as survival or duration models. These models serve to gauge the instantaneous probability of bankruptcy at any point in time, based on a range of financial ratios and other relevant variables. This nuanced approach is particularly valuable for analyzing firms with longer operational timelines and offers a contrast to Altman's and Ohlson's more static methodologies.

1.1.3 Machine Learning Approaches

Recent literature indicates a substantial shift towards machine learning models for bankruptcy prediction (BARBOZA, KIMURA et E. ALTMAN 2017 ; NANNI et LUMINI 2009). For instance, Barboza et al. analyzed the efficacy of machine learning techniques such as support vector machines and ensemble methods like bagging and boosting. They concluded that these modern techniques outperformed traditional discriminant analysis and logistic regression methods by an average of 10%, underscoring the need for ongoing innovation in this research area.

1.1.4 Theoretical Contributions

Although the main thrust of the current research is on the application of Natural Language Processing and machine learning, understanding the historical contributions of theoretical models (BAUER et AGARWAL 2014 ; AZIZ et DAR 2006 ; SCOTT 1981) offers a contextual backdrop. These models, such as Contingent Claims Models and Gambler's Ruin Theory, offer more theoretical perspectives on bankruptcy risk but suffer from issues of complexity and applicability in real-world scenarios.

In summary, corporate bankruptcy prediction has undergone transformative evolution, transitioning from rudimentary financial ratios-based models to complex machine learning frameworks. This journey has navigated through the limitations and potentialities of various statistical tools and methodologies. As the field matures, it is anticipated that the emergence of new predictive models and techniques will continue to enhance both the accuracy and utility of bankruptcy prediction models.

1.2 Natural Language Processing and Textual Analysis

Most modern language computational models try to encapsulate the statistical dependencies of natural language. Formally, the joint probability distribution of a sequence of words can be estimated as follows (words as $w_1, w_2, \dots$)

$$P(w_1, w_2, \dots, w_n) = \prod_{i=1}^{n} P(w_i | w_1, w_2, \dots, w_{i-1}) \tag{1.1}$$

The optimization goal in training these models is to maximize the log-likelihood of the observed dataset, which is mathematically formulated as :

$$\mathscr{L}(\theta) = \sum_{i=1}^{n} \log P(w_i | w_1, w_2, \dots, w_{i-1}; \theta) \tag{1.2}$$

where θ denotes the model parameters.

Traditional language models often grapple with the "curse of dimensionality," a phenomenon wherein computational requirements surge exponentially as the sequence length swells. In nuanced areas like corporate bankruptcy prediction, texts are not only dense but are riddled with interconnected relationships that necessitate broader contextual understanding. For instance, the interpretation of a single financial statement could be swayed by diverse elements : market fluctuations, historical records, and even geopolitical events. The imperative to fathom these intricate interdependencies catapults the computational demands beyond the prowess of classic language models.

Against this background, transformer models have shown significant promise. Their cardinal advantage lies in their aptitude to disperse computational burdens more judiciously, courtesy of their inherent parallelism—an attribute that marries seamlessly with the capabilities of Graphics Processing Units (GPUs). Unlike the sequential processing of traditional models like Recurrent Neural Networks (RNNs), transformers are equipped to concurrently process diverse segments of a text sequence. This simultaneous computation empowers them to navigate exceptionally extensive word sequences without succumbing to crippling computational intricacies.

Yet, it isn't just about computational architecture. The bedrock of transformer models is their nuanced training methodology. Through prolonged, self-supervised pre-training on gargantuan datasets, these models evolve to parameterize attention mechanisms skilled at evaluating the relevance of disparate text segments. This refined attention ability permits transformers to distill the essence from vast textual expanses, highlighting key elements essential for various tasks, whether sentiment analysis or bankruptcy prediction. The attention mechanism, honed through rigorous pre-training, equips transformer models to discern intricate linguistic relationships, a feat traditional models often falter at.

Despite their foundational objective of predicting subsequent tokens in sequences remaining invariant, transformers accentuate this rudimentary competency by maximizing computational efficiency and by immersing in extensive pre-training, thereby grasping linguistic complexities that conventional models often stumble upon.

1.2.1 Pre-training Strategies in Transformer Models

Given these distinct features that differentiate transformer models from their predecessors, the significance of their pre-training becomes clear. These protocols harness the transformer architecture's dexterity in managing intense computational tasks and its acumen in decoding protracted dependencies, making it an exemplar for general as well as specialized language modelling.

Masked Language Modeling (MLM)

MLM is a self-supervised task where certain tokens in the input sequence are masked, and the model aims to predict them. The loss function for MLM can be represented as :

$$\mathscr{L}_{\text{MLM}}(\theta) = -\sum_{t \in \text{Tokens}} \log P(w_t | w_{\text{context},t}; \theta) \tag{1.3}$$

The mechanics of MLM bring to the fore its ability to capture bidirectional context, a feat that enhances the richness of the word representations it generates. Unlike its predecessors such as discrete lexicon-based models or Recurrent Neural Networks (RNNs),

Algorithm 1 Masked Language Modeling Pre-training

```
Initialize model parameters θ
for each batch in training data do
    Mask tokens in input sequence
    Forward propagate to compute predicted probabilities
    Compute ℒ_MLM
    Backpropagate and update θ
end for
```

MLM models are adept at considering both preceding and succeeding contextual information. This bidirectional context capture enhances the model's semantic and syntactic understanding, making its word representations more robust and versatile for a wide range of downstream tasks.

The quantification of the model's performance in predicting masked tokens is typically encapsulated by the cross-entropy loss function. This function serves as a gauge to assess the deviation between the predicted probability distribution across the vocabulary and the true identities of the masked tokens. In simpler terms, cross-entropy loss measures how well the model's predictions align with the actual words that were masked. The goal is to minimize this loss value, which is indicative of improving the model's predictions and, consequently, the quality of the contextualized word representations it produces.

Once the model has been pre-trained through MLM and the cross-entropy loss is minimized, it is then primed for fine-tuning on specific downstream applications. In this phase, the masked tokens that were used during pre-training are reverted back to their original form. Fine-tuning adjusts the model's parameters to optimize its performance for specialized tasks, ranging from text classification to sentiment analysis and beyond, under the paradigm of supervised learning.

Next Sentence Prediction (NSP)

Next Sentence Prediction (NSP) serves as a keystone in understanding the interplay between adjacent sentences, thereby capturing the larger narrative structure of a text. Mathematically, the NSP loss function is defined as :

$$\mathscr{L}_{\text{NSP}}(\theta) = -\sum_{(A,B)\in\text{Pairs}} \log P(\text{IsNextSentence}|A,B;\theta) \tag{1.4}$$

TABLE 1.1 – Illustrative Examples of Positive and Negative Sentence Pairs in NSP

Pair Type	Sentence A	Sentence B
Positive	The cat sat on the mat.	It looked content.
Negative	The cat sat on the mat.	Apples are delicious.

Within the NSP framework, the model is tasked with assessing the likelihood of a second sentence logically ensuing from the first within the context of the original text. This construct imparts a learning incentive for the model to grasp broader contextual coherence, semantics, and syntactic relationships, which prove invaluable for a plethora of applications such as text summarization, question answering, and natural language inference.

During the pre-training phase, the model encounters both positive and negative sentence pairs : the former comprised of contiguous sentences from genuine text, and the latter featuring an arbitrarily sampled, unrelated second sentence. The optimization process involves minimizing the binary cross-entropy loss between the model's probabilistic prediction of sentence succession and the ground truth label.

As we delve into the application of Language Learning Models (LLMs), notably those that are transformer-based, in the realm of accounting and finance, we find an increasingly sophisticated landscape. Textual analysis has surfaced as a potent asset for deriving actionable insights into financial markets and corporate disclosures.

(LOUGHRAN et MCDONALD 2016) have cataloged the primary methods of textual analysis as dictionary-based approaches, which rely on manually curated sets of pertinent terms, and machine learning techniques, which automate the discovery of relevant language patterns. The application of these methods extends beyond traditional financial statements to unconventional data sources, such as news articles and social media platforms.

An extensive review by (CHAKRABORTY et BHATTACHARJEE 2020) chronicles the evolution of automated textual analysis, delineating three distinct epochs : manual coding, dictionary-based methods, and machine learning algorithms. However, these methods bring their own set of constraints. For example, pre-constructed dictionaries may inadvertently introduce bias, while machine learning techniques could be prone to overfitting, demanding sizable datasets for robust analysis.

A study by (MAI et al. 2019) underlines the merits of leveraging deep learning models in conjunction with traditional accounting variables to achieve heightened prediction accuracy in bankruptcy forecasting. Despite the promising prospects, challenges such as data sparsity, latent biases, and model interpretability remain to be fully addressed as it is often the cases with neural networks.

(CAO et al. 2020) spotlight the transformative influence of AI on corporate financial disclosure practices. Key findings from their study reveal that firms, particularly those expecting higher machine downloads, have strategically amended their language post-2011, as evidenced in Table 1.1.

Continued advancements in NLP, coupled with interdisciplinary collaborations, are expected to contribute to the formulation of increasingly robust predictive models for corporate bankruptcy. Despite existing challenges, the integrated application of NLP techniques, deep learning models, and traditional financial metrics offers a multidimensional lens for understanding the financial health of firms. This empowers stakeholders, including investors, regulators, and researchers, to make well-informed decisions, thereby driving innovations in corporate finance research and the evolution of bankruptcy prediction models.

1.2.2 The Role of Sentiment Analysis in Finance

Sentiment analysis has become a hot topic for researchers and business folks alike. It's a simple yet powerful idea : we can scan texts like news articles, reports, or social media posts to figure out what people think about a company. By doing this, we get a new

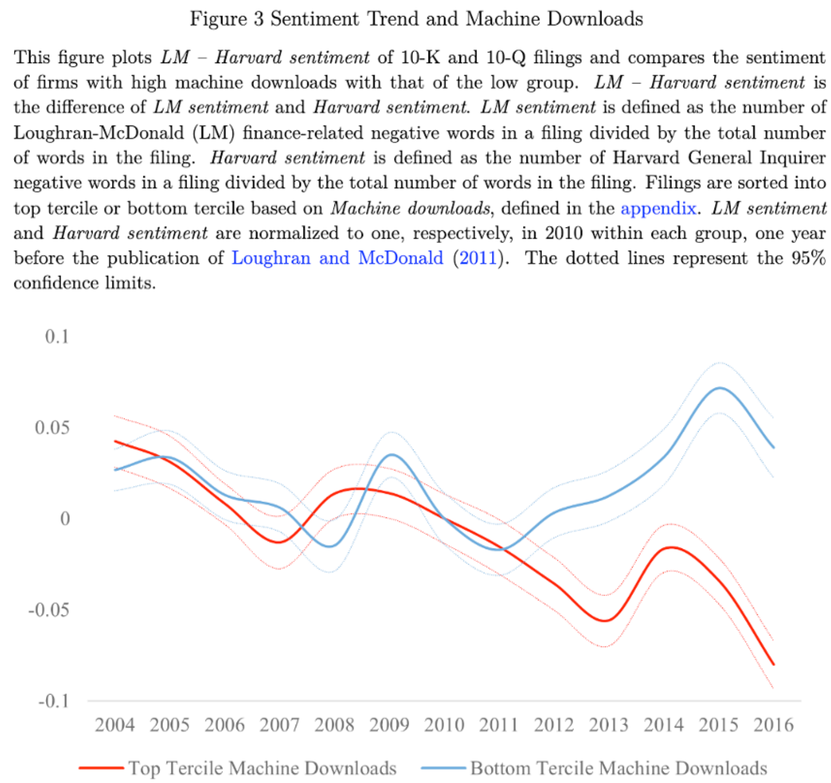


FIGURE 1.1 – Temporal Variations in Sentiment Based on Harvard and LM Lexicons
Source : *(*CAO *et al. 2020)*

layer of information to help us predict a company's financial health, including whether it might go bankrupt.

Most practitioners go one of two ways when trying to figure out the sentiment in text : either they use a dictionary approach or they get help from machine learning. In the dictionary approach, we have a list of words and their 'emotional score.' If a report says a company is "thriving," for example, that word might have a positive score. We tally these up to see if the overall tone of the text is positive, negative, or neutral. The Loughran and McDonald dictionary (LOUGHRAN et MCDONALD 2015) is a popular choice because it was made just for financial texts. But the downside here is that this method can miss out on the subtleties and changes in how we use words over time.

On the other side, we have machine learning. This involves feeding a computer model tons of example texts that have already been labeled as positive, negative, or neutral. The computer learns from these and gets pretty good at labeling new texts on its own. Techniques like Support Vector Machines (SVM) and neural networks like RNNs are common choices here (ARACI 2019).

In financial research, some specific dictionaries or word lists are used a lot. Besides the Loughran and McDonald list (LOUGHRAN et MCDONALD 2015), researchers also use Henry's list (HENRY 2008) and the Harvard General Inquirer (STONE et HUNT 1963). Each has its own strengths and weaknesses, but what matters is picking the right tool for the job. For instance, some studies found that the tone in financial news articles can actually give us hints about future stock market trends (TETLOCK 2007).

In the grand scheme of things, it looks like machine learning methods are pulling ahead. Studies have shown that they can better grasp the nuances of language, and they're better at predicting things like stock returns based on company reports (FRANKEL, JENNINGS et J. A. LEE 2021). Plus, new tech like BART from Facebook shows that machine learning keeps getting better and better (MISHEV et al. 2020).

Finally, we shouldn't ignore new types of data, like what people are saying on social media or in online forums. This might give us insights we can't get from traditional reports or news articles. So, there's still a lot to explore in this field, and it's a pretty exciting time to dig deeper into how sentiment analysis can help us understand companies better.

1.2.3 Readability metrics

In the sphere of corporate finance, predicting bankruptcy has often leaned heavily on traditional numerical indicators. However, Natural Language Processing (NLP) has been opening new avenues for analysis. One noteworthy but less-heralded contribution in this regard is the use of readability metrics. Rooted in linguistics and applied across disciplines ranging from education to healthcare, readability metrics have found a home in corporate finance as tools for scrutinizing financial disclosures such as annual reports, earnings releases, and regulatory filings.

Readability metrics can be considered a measure of the user-friendliness of a text, quantifying how readily a reader can digest and understand its content. This is no trivial matter. Investors, analysts, and regulators rely heavily on textual documents to form assessments of a company's financial health and future prospects. Hence, the accessibility of these documents has implications for market efficiency, corporate governance, and even the stability of the financial system as a whole.

The literature boasts a variety of readability metrics, including but not limited to the Flesch-Kincaid Grade Level, Gunning Fog Index, and the SMOG (Simple Measure of Gobbledygook) Index. These formulas typically amalgamate variables like word length, sentence length, and syllable count into a singular readability score . While the metrics offer a quantitative lens to evaluate textual complexity, they can also track changes in a document's readability over time, serving as a longitudinal indicator of corporate transparency or obfuscation.

Some groundbreaking studies have dived into the implications of readability in financial settings. A pioneering piece of scholarship in this area was Loughran and McDonald's "Measuring Readability in Financial Disclosures" (LOUGHRAN et MCDONALD 2014). By examining a sizable dataset of 10-K filings spanning from 1994 to 2011, they brought to light the vital role that readability plays in financial markets. They used a gamut of established metrics such as the Automated Readability Index (ARI), Coleman-Liau Index, and others, unearthing a positive correlation between readability and perceptions of good corporate governance.

In a subsequent study, Kim et al. extended the conversation to link readability with stock price crash risks (KIM, WANG et ZHANG 2019). Using logistic regression models, the authors revealed that companies with less readable 10-K reports, particularly those with high information asymmetry, were more susceptible to stock price crashes. This suggests that readability doesn't merely affect the legibility of a text but extends its tentacles into market stability and investor risk.

Moreover, there is emerging evidence that poor readability has legal ramifications. For instance, Abhishek et al. discovered that companies with less-readable financial disclosures were more likely to be hit with securities fraud litigation (GANGULY et al. 2019). This points to another layer of complexity : the potential legal consequences of how a firm communicates its financial status.

However, it's also clear that readability metrics are not without limitations. Loughran and McDonald noted the need for more nuanced tools that could better capture the intricacies of financial jargon and the communication of value-relevant information (LOUGHRAN et MCDONALD 2014). Hence, there's a beckoning horizon for researchers to develop more refined or specialized readability measures tailored to the finance domain.

Readability metrics provide an important perspective through which we can view financial disclosures. They hold promise not only as predictive variables for various financial outcomes but also as indicators of market transparency and efficiency. Yet they should not operate in a vacuum. For the most robust insights, they should be used in tandem with other financial metrics and NLP techniques. As the field moves forward, future inquiries may explore innovative methodologies for parsing financial language or even alternative mediums of communication. The overarching aim remains constant : to foster a financial market landscape that is as transparent, reliable, and efficient as possible, serving the diverse needs of investors, analysts, and regulatory bodies alike.

In summary, the existing body of literature provides compelling insights into the complex landscape of corporate bankruptcy prediction. From traditional financial metrics to the emerging use of Natural Language Processing techniques like sentiment analysis and readability metrics, the field is continuously evolving. These analytical tools have shown promise in various contexts, highlighting their potential for enriching our understanding and predictive abilities. However, as we've seen, these approaches come with their own set of challenges and limitations, including algorithmic sensitivity and the need for more nuanced measures.

Having reviewed this extensive body of literature, we now turn our attention to the methodology of our own study. Our aim is to integrate these diverse approaches, drawing on both traditional financial metrics and textual analysis techniques, to construct a more robust and versatile model for predicting corporate bankruptcy. In the next section, we will outline the specific methods and data sets we employ to contribute to this evolving discourse.

Chapitre 2

Methodology

The primary objective of this research is to evaluate whether the incorporation of unstructured textual data extracted from 10-K filings, through sentiment and readability analyses, can enhance the predictive accuracy of bankruptcy prediction models in comparison to the well-established Altman's Z-score as a baseline. This section offers a comprehensive overview of the research design, data collection and preprocessing, the application of Altman's Z-score, the selection and implementation of machine learning models, and the methodology for conducting textual analysis, including sentiment and readability assessments. Additionally, we will outline the process of integrating the newly

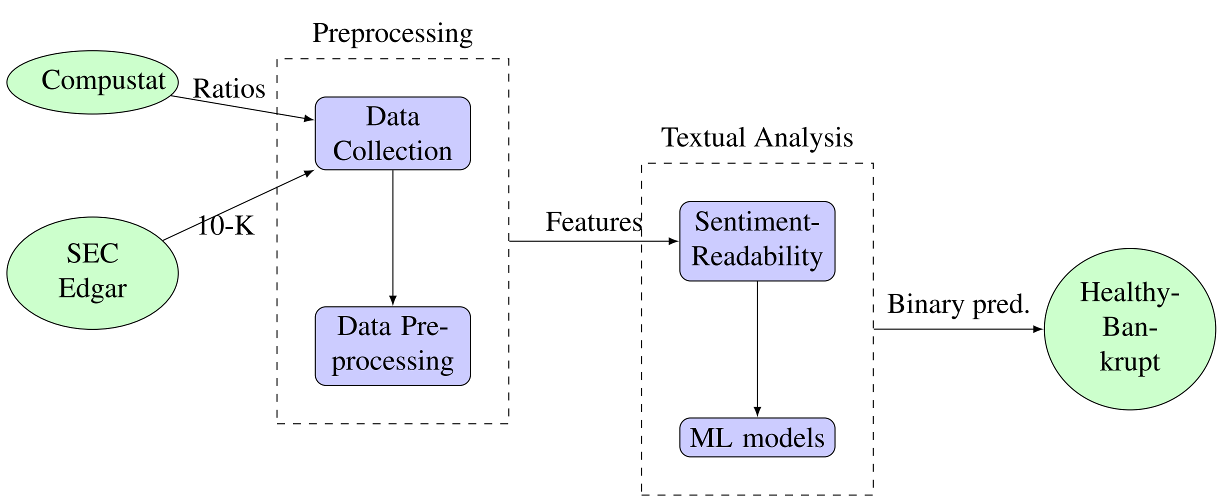


FIGURE 2.1 – Data flow diagram of the project's pipeline.

derived predictors into the machine learning models and evaluating their performance using a range of evaluation metrics. By presenting a clear and concise account of our methodology, we aim to facilitate a thorough understanding of our research approach and the rationale behind each step. This transparency will enable readers to appreciate the robustness and validity of our findings, and potentially replicate or extend the study in future research endeavors. The research design for this study follows a quantitative approach, employing a combination of financial ratios, machine learning models, and textual analyses to predict corporate bankruptcy. The main research question guiding this study is : Can the integration of sentiment and readability analyses of unstructured textual data from 10-K filings improve the predictive accuracy of bankruptcy prediction models in comparison to Altman's Z-score as a baseline ? To address this research question, we employ a stepwise methodology, starting with data collection and preprocessing, followed by the calculation of Altman's Z-score, the implementation of machine learning models, and the integration of textual analysis features. By comparing the performance of models with and without the inclusion of textual data, we aim to assess the potential value of such features in enhancing bankruptcy prediction accuracy. The dataset for this study consists of financial data and 10-K filings from public companies in the United States. Financial data is obtained from sources such as Compustat wrds2023, while the textual data is sourced from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database sec2023 maintained by the U.S. Securities and Exchange Commission (SEC). The data collection process involves gathering historical financial information, including financial ratios and accounting data, as well as the corresponding 10-K filings for each firm in the sample. Altman's Z-score serves as the baseline for comparing the predictive performance of our models. This well-established bankruptcy prediction model combines five financial ratios to produce a score that indicates a firm's likelihood of bankruptcy. Various machine learning models are considered for this study, such as logistic regression, support vector machines, decision trees and random forests. We implement them using financial data and then incorporate the sentiment and readability analyses results to assess the impact of these textual features on prediction accuracy. The textual analysis involves two main components : sentiment analysis and readability assessment. Sentiment analysis aims to quantify the overall sentiment or tone of the 10-K filings, while readability assessment seeks to measure the understandability of the documents. Once the sentiment and readability scores are obtained, we integrate these new features into the selected machine learning models. This step allows us to compare the performance of the models with and without the inclusion of textual data, thereby evaluating the potential contribution of sentiment and readability analyses to the predictive accuracy of bankruptcy prediction models. To assess the performance of the machine learning models, we employ a range of evaluation metrics, such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. These metrics provide a comprehensive understanding of the models' performance, considering both their ability to correctly predict bankruptcies and their potential for generating false alarms.

2.1 Data Collection and Preprocessing

2.1.1 Quantitative data

In our methodology, we adopt a multi-faceted approach to corporate bankruptcy prediction by integrating both financial and accounting quantitative predictors with textual qualitative predictors. This comprehensive model aims to encapsulate diverse aspects of a company's financial health, potentially enhancing the model's predictive performance and generating more accurate results. A crucial component of our methodology is the Z-score, which was introduced by Edward Altman in 1968 altman1968 as a widely acknowledged statistical measure for predicting the likelihood of bankruptcy for firms. Altman's Z-score model combines several financial ratios through multiple discriminant analysis (MDA), initially developed using a sample of publicly traded manufacturing firms. The original formula comprises five financial ratios, each weighted by coefficients derived from MDA :

1. Working capital / Total assets : $\frac{\text{WC}}{\text{TA}}$
2. Retained earnings / Total assets : $\frac{\text{RE}}{\text{TA}}$

3. Earnings before interest and taxes / Total assets : $\frac{\text{EBIT}}{\text{TA}}$

4. Market value of equity / Total liabilities : $\frac{\text{MVE}}{\text{TL}}$

5. Sales / Total assets : $\frac{\text{S}}{\text{TA}}$

By examining these financial and accounting metrics, we can derive valuable insights into a company's financial stability, performance, and overall health. Altman's Z-score is particularly relevant as a baseline in our study due to its well-established and widely-accepted application in bankruptcy prediction. Its extensive history and success across various industries make it an appropriate benchmark against which to compare the performance of other machine learning models in predicting corporate bankruptcy. By establishing Altman's Z-score as a reference point, we can objectively evaluate the effectiveness of alternative models and determine if they present any improvements in predictive accuracy or offer additional advantages over the traditional Z-score method. [1]

To collect the necessary data for our study, we utilize Compustat and the Wharton Research Data Services (WRDS) databases. Compustat, a product of S&P Global Market Intelligence, is a comprehensive database that provides extensive financial and accounting information on publicly traded companies. Launched in 1962, Compustat now covers over 20,000 active and inactive companies in North America and more than 40,000 companies worldwide, offering data on their income statements, balance sheets, cash flow statements, and more. WRDS, on the other hand, is a widely-used data platform that offers researchers access to financial, accounting, and economic data from various sources, including Compustat. Established in 1993 by the Wharton School of the University of Pennsylvania, WRDS has become a leading data research platform that supports over 50,000 users from over 400 academic and research institutions around the globe. These databases enable us to collect the quantitative financial and accounting predictors required for our analysis,

1. For simplicity purposes in our study, we used the 'DLDTE' (date of deletion from the Compustat database) as a proxy for the bankruptcy date. While this approach may not be technically accurate in capturing the exact date of bankruptcy, obtaining the precise bankruptcy date would have required access to additional databases and resources, which may not be easily accessible or feasible for our research. Using the 'DLDTE' as a proxy allows us to maintain a manageable scope for our study while still providing a reasonable approximation of the bankruptcy event.

ensuring a comprehensive and reliable data source for our study on corporate bankruptcy prediction.

Dataset statistics

Number of variables	16
Number of observations	351
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%

Variable types

Numeric	14
Categorical	2

FIGURE 2.2 – Statistical summary of the sample used in our experiments

2.1.2 Qualitative data

The second subsection of the methodology section delves into the collection and pre-processing of qualitative financial data, with a primary focus on 10-K reports filed with the SEC's EDGAR system. EDGAR, the Electronic Data Gathering, Analysis, and Retrieval system, is an online platform maintained by the U.S. Securities and Exchange Commission (SEC) that provides access to a wide array of corporate filings, including annual 10-K reports. We retrieved the qualitative financial data using the SEC API, which streamlines the process of extracting pertinent information from the EDGAR system. The initial step involved gathering the URLs of 10-K reports for all firms within the observation window. To maintain consistency with the quantitative dataset, the observation window for qualitative financial data also spans from 1996 to 2022. 10-K reports are comprehensive annual financial reports filed by publicly traded companies in the United States. These reports are mandated by the U.S. Securities and Exchange Commission (SEC) to offer a detailed overview of a company's financial performance, operations, and management. 10-K reports encompass financial statements, such as the balance sheet, income statement, and statement of cash flows, alongside extensive narrative disclosures on the company's business, financial condition, and risks. Each 10-K report is associated with either the 'periodOfReport', if available, or the date the report was filed 'filedAt'. Due to inconsistencies in fiscal year scheduling among firms, we made certain assumptions about the filing date. If a report was filed between January and June, we assumed it pertained to the previous year. Conversely, if a report was filed between July and December, we assumed it was relevant to the current year. To merge the quantitative and qualitative datasets, we utilized the 'CIK' (Central Index Key) and the year as keys. This ensured that the financial data and the associated 10-K reports were accurately matched. Once the URLs and their corresponding key attributes (i.e. year, CIK) were obtained, we extracted specific sections of the 10-K reports using the Extractor API from the SEC API library. Two sections were extracted from each report : Management Discussion and Analysis (MD&A) and Risk Factors. Samples for both sections are available in the Appendix (See section 3.4.2). Both the MD&A and Risk Factors sections offer valuable qualitative information that can supplement quantitative financial data when assessing a company's financial health and predicting bankruptcy risk. Textual analysis of these sections can uncover crucial insights into management's perspective, the company's competitive position, and potential risks that might impact its future performance. Lastly, we conducted data cleaning on the retrieved sections. Each section was converted into a string by removing newline characters and HTML entities. This preprocessing step ensured that the qualitative financial data was in a suitable format for subsequent textual analysis and integration into our machine learning models.

Parametrization is an important aspect of the methodology as it shapes the dataset to align with the research objectives and offers flexibility for conducting various experiments. The process allows for the adjustment of the observation window, exclusion of specific industries, selection of forecasting lag. Moreover, parametrization plays an essential role in ensuring the creation of a balanced bankruptcy database, maintaining consistency between pairings, and removing outliers from the dataset. Upon merging the quantitative and qualitative datasets, it is possible to adjust the observation window to focus on a specific time period. However, to maintain the largest sample size for our experiments, the observation window will remain between the years 1996 and 2022. The flexibility to exclude specific industries from the sample is provided, such as Finance, Construction, Manufacturing, Retail Trade, and Public Administration. Exclusion of certain industries,

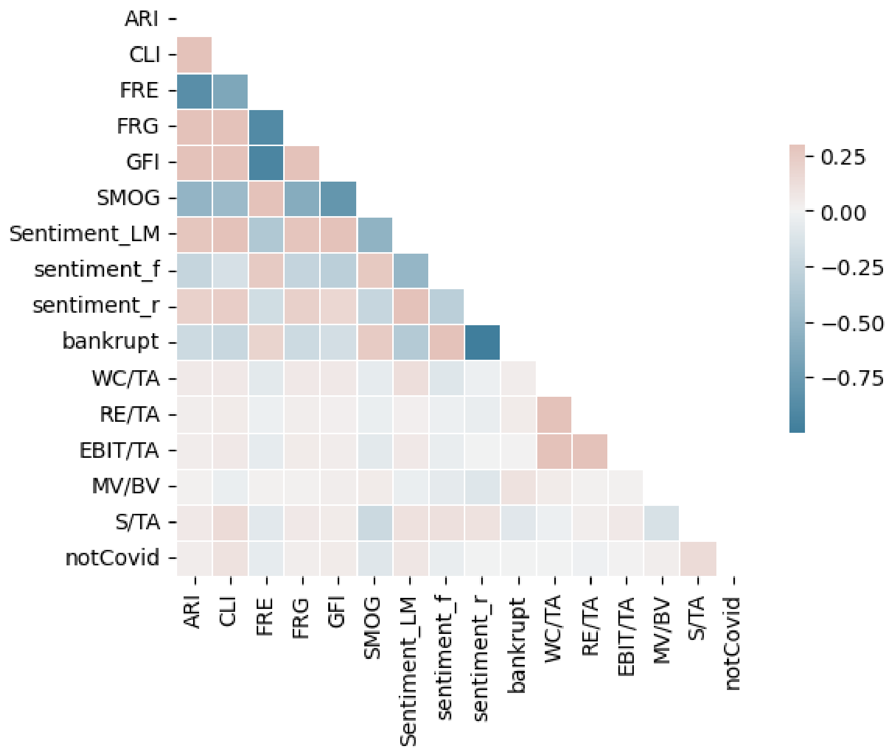


FIGURE 2.3 – Correlation matrix of the features in the study.

particularly the Finance industry, is often implemented in the literature due to the discrepancies observed between these sectors and others. The unique characteristics of financial firms and the distinct regulatory framework governing their operations can impact the effectiveness and relevance of traditional bankruptcy prediction models when applied to these firms. The choice of forecasting lag in corporate bankruptcy prediction is a critical aspect of model design, as it determines the time horizon over which a model seeks to predict the likelihood of bankruptcy. In this study, the chosen forecasting lag of two years is based on the sample size (i.e. larger dataset size for a forecasting of 2 years compared to 1). Selecting a shorter forecasting lag, such as one or two years, has several advantages in the context of corporate bankruptcy prediction, as it enables the models to capture the most relevant and recent financial information. "In this study, the two-year forecasting lag for predicting corporate bankruptcy is chosen for its balance and practicality. This timeframe is long enough to provide a clear picture of a company's financial health by

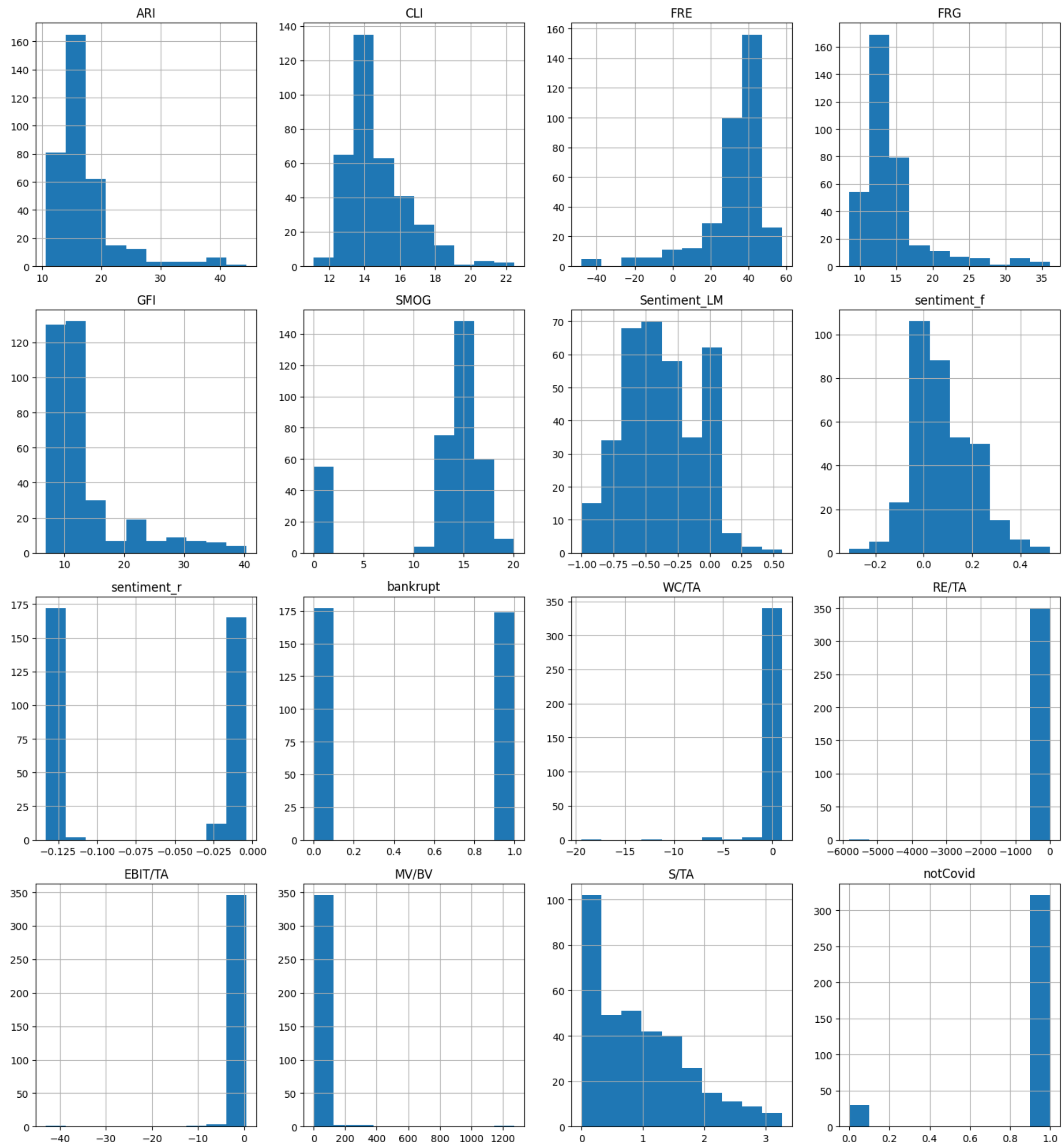


FIGURE 2.4 – Plot of the distributions of the features

including recent and relevant financial data. It's also short enough to remain relevant to current market conditions, avoiding the use of outdated information that may no longer reflect a company's current situation.

A two-year period also matches well with the typical business planning cycles of many companies, making it a practical choice for both businesses and investors. This timeframe allows for effective risk assessment, as it aligns with the short to medium-term decision-making processes commonly used in business and finance. Data wise it also strikes a good balance between having enough data for accurate predictions and not having so much data that it becomes difficult to manage or less accurate due to long-term uncertainties and data quality.

To handle missing values, we drop rows containing missing values. Dropping rows with missing values is the simplest approach to handling incomplete financial data, as it completely removes any observations that have missing values for one or more financial variables. With the dataset parametrized, a balanced bankruptcy database is created by matching each bankrupt firm with a healthy firm. To ensure consistency between pairings each pair shares the same industry at the same year of observation. For the sake of our experiments, the SIC level is usually fixed at 2-digit codes. These divisions provide a broad classification of industries, such as Manufacturing, Mining, and Construction, among others. Corporate bankruptcy prediction typically presents an imbalanced classification problem, as the number of bankrupt companies is considerably smaller than the number of non-bankrupt companies. To address this issue, it is essential to ensure that both classes are well-represented in the test set, which can be achieved through stratified sampling. This subsection focuses on the role of stratified sampling and sample selection in the context of corporate bankruptcy prediction, drawing on Zmijewski's influential work, "Methodological Issues Related to the Estimation of Financial Distress Prediction Models" Zmijewski. Stratified sampling is a method that maintains the proportion of the classes in both the training and testing sets, ensuring a better representation of the minority class (bankrupt companies) in the test set. This technique is crucial in improving the overall performance and generalizability of the models by preserving the class distribution found in the population. In imbalanced classification problems, such as corporate bankruptcy prediction, the application of stratified sampling can help mitigate the risk of overfitting and reduce the bias towards the majority class. In his seminal 1984 article, Zmijewski illuminated the critical aspects of sample selection and model evaluation, which have since become vital considerations for researchers in the field of bankruptcy prediction. Zmijewski argued that the choice of an appropriate sample plays a pivotal role in the development and estimation of financial distress prediction models. He underscored the importance of addressing the issue of sample representativeness, as the accuracy and generalizability of prediction models hinge on the extent to which the chosen sample reflects the target population. According to Zmijewski, the selection of financially distressed firms should be based on a well-defined set of criteria, and researchers should strive to achieve a balanced representation of both bankrupt and non-bankrupt firms. This balanced representation is crucial for enhancing the predictive accuracy and generalizability of the models. Moreover, Zmijewski emphasized the importance of carefully evaluating the performance of the models, considering not only the accuracy but also the robustness and interpretability of the models to ensure their practical applicability. In line with Zmijewski's recommendations, our study employs stratified sampling to address the imbalanced classification problem inherent in corporate bankruptcy prediction. By maintaining the proportion of bankrupt and non-bankrupt firms in both the training and testing sets, we seek to ensure that our models accurately represent the minority class and achieve better generalization performance. Lastly, outliers are removed from each variable of the dataset by measuring the distribution of each column and removing the upper and lower quantiles, as defined by the percentage between 0.1 and 5%. This final step helps to ensure a robust and reliable dataset for use in the experiments and analysis, allowing for the effective assessment of various bankruptcy prediction models in the context of the chosen research objectives.

Textual Analysis

10-K reports filed by publicly traded companies in the United States serve as comprehensive annual financial reports, mandated by the U.S. Securities and Exchange Commission (SEC). These reports furnish an in-depth overview of a company's financial performance, operations, and management, encompassing financial statements such as the balance sheet, income statement, and statement of cash flows, along with extensive narrative disclosures detailing the company's business, financial condition, and risks.

Two crucial sections within the 10-K report are the Management Discussion and Analysis (MD&A) and the Risk Factors sections. The MD&A section provides a detailed narrative, authored by the company's management, delving into the company's financial performance, business strategies, and future prospects. This section generally covers aspects such as :

— Overview of the company's business and operations

— Analysis of the company's financial performance, including explanations for fluctuations in revenues, expenses, and profits

— Discussion of the company's liquidity, capital resources, and cash flows

— Identification and assessment of critical accounting policies and estimates

— Evaluation of the company's exposure to market risks, such as interest rate or currency fluctuations

The MD&A section offers insights into management's perspective on the company's operations and financial health, addressing the firm's financial results, operational performance, industry trends, and future outlook. By analyzing the sentiment and readability of the MD&A section, we can assess management's communication of the firm's performance and future prospects, potentially providing insights into the company's underlying financial stability. A negative sentiment or decreased readability in the MD&A section could indicate that management is struggling to convey a positive outlook or that the firm faces complex challenges, which may contribute to an increased likelihood of bankruptcy. Machine learning techniques can help detect subtle changes in sentiment or readability patterns that may not be easily discernible to human analysts, thus potentially improving the accuracy of bankruptcy prediction models.

In addition to the MD&A section, we sought to explore an alternative data source within the 10-K reports for the purpose of corporate bankruptcy prediction. The Risk Factors section emerged as a strong candidate for analysis in this context. The Risk Factors section, another vital part of the 10-K report, enumerates the potential risks and uncertainties that could materially impact the company's financial condition, operations, and future performance. These risks may include, but are not limited to :

— Market and industry risks, such as competition, economic conditions, or regulatory changes

— Operational risks, such as disruptions in the supply chain, product recalls, or cybersecurity incidents

— Financial risks, such as access to capital, interest rate fluctuations, or foreign currency exposure

— Legal and regulatory risks, including potential litigation, intellectual property disputes, or changes in tax laws

— Strategic risks, such as the ability to execute growth strategies, maintain key partnerships, or manage acquisitions and divestitures

The Risk Factors section presents a comprehensive overview of the firm's risk exposures and the strategies employed to mitigate and manage these risks. By analyzing the sentiment and readability of the Risk Factors section using machine learning techniques, we can gain insights into the company's risk exposure and management strategies' effectiveness. A higher level of negative sentiment or lower readability in the Risk Factors section could indicate that the company is grappling with significant threats and vulnerabilities, or that the firm's risk management strategies are not clearly articulated, potentially increasing the risk of bankruptcy. Through the examination of the sentiment and readability of these two critical sections in the 10-K reports using machine learning techniques, our methodology aims to derive valuable information that can enhance the predictive power of our corporate bankruptcy prediction models. (See Appendix)

2.2 Readability metrics

In this segment of our methodology, we employ a wide range of readability metrics to evaluate the complexity of companies' financial disclosures, Readability metrics are formulas that can be applied on any text to evaluate how easy it is to read and understand a text. While these metrics are useful for getting a general sense of a text's complexity, they don't capture the intricacies of natural language. They focus mainly on simple aspects of the text and don't fully consider the meaning, context, or reader's background knowledge. The readability influenced by the text organization layout, font size is not considered either. In various areas like education, healthcare, and business, readability metrics help in choosing texts that are suitable for the intended audience. For instance, in financial reports, these metrics can indicate whether the language used is too complex, which might affect how well stakeholders understand the company's financial situation. These metrics serve as instruments for objectively quantifying the ease or difficulty of comprehending textual financial information. Let's delve deeper into each of these metrics :

Flesch-Kincaid Grade Level (FKGL)

The FKGL metric estimates the U.S. school grade level needed to comprehend a text. It leverages the average sentence length and syllabic structure of words as proxies for complexity. It does not consider the semantics of words or the complexity of sentence structures beyond their length and syllables. The equation is as follows :

$$FKGL = 0.39\left(\frac{Total\ Words}{Total\ Sentences}\right) + 11.8\left(\frac{Total\ Syllables}{Total\ Words}\right) - 15.59 \tag{2.1}$$

— Total Words : Number of words in the text.

— Total Sentences : Number of sentences in the text.

— Total Syllables : Number of syllables in the text.

Higher FKGL scores could potentially imply that a company's financial data is obscured by linguistic intricacy, thereby raising red flags about its financial health.

Flesch Reading Ease (FRE)

The FRE, another widely used metric, generates a score based on the average sentence length and the average syllabic count per word. It may misjudge texts with longer, yet straightforward sentences. The formula is :

$$FRE = 206.835 - 1.015\left(\frac{Total\ Words}{Total\ Sentences}\right) - 84.6\left(\frac{Total\ Syllables}{Total\ Words}\right) \tag{2.2}$$

Here, lower scores indicate increased textual complexity, which might correlate with higher bankruptcy risks as investors or stakeholders grapple to understand the company's status.

Gunning Fog Index (GFI)

GFI estimates the number of years of formal education needed to understand a text. It considers both average sentence length and the proportion of words with more than two syllables. The equation is :

$$GFI = 0.4\left(\left(\frac{Total\ Words}{Total\ Sentences}\right) + 100\left(\frac{Complex\ Words}{Total\ Words}\right)\right) \tag{2.3}$$

Complex Words : Words with three or more syllables.

Higher scores on the GFI might suggest a greater likelihood of bankruptcy due to the perceived complexity of a company's financial narrative.

Automated Readability Index (ARI)

ARI computes an approximate U.S. grade level required to understand a text using the average number of characters per word and average sentence length :

$$ARI = 4.71\left(\frac{Total\ Characters}{Total\ Words}\right) + 0.5\left(\frac{Total\ Words}{Total\ Sentences}\right) - 21.43 \tag{2.4}$$

Total Characters : Number of characters in the text.

A higher ARI score could be a cause for concern if the intricate language clouds stakeholders' understanding, possibly leading to an increased bankruptcy risk.

Coleman-Liau Index (CLI)

CLI provides another perspective, estimating the U.S. grade level required for text comprehension based on average character count and sentence length :

$$CLI = 0.0588\left(100\left(\frac{Total\ Characters}{Total\ Words}\right)\right) - 0.296\left(100\left(\frac{Total\ Sentences}{Total\ Words}\right)\right) - 15.8 \tag{2.5}$$

Here again, higher scores may signal an elevated risk of bankruptcy, particularly if this complexity interferes with stakeholders' ability to fully grasp the financial situation.

SMOG (Simple Measure of Gobbledygook)

SMOG evaluates text complexity based on the frequency of complex words (those with three or more syllables) :

$$SMOG = 1.043\sqrt{30\left(\frac{Complex\ Words}{Total\ Sentences}\right)} + 3.1291 \tag{2.6}$$

Complex words : those with three or more syllables.

A higher SMOG score might suggest that a greater likelihood of bankruptcy is looming if the verbose language prevents clear comprehension of the company's financial health. SMOG evaluates text complexity based on the frequency of complex words (those with three or more syllables).

By meticulously applying these readability metrics to the financial disclosures in our dataset, we seek to uncover the potential relationship between textual complexity and the probability of corporate bankruptcy. Our work offers a fresh angle on evaluating corporate bankruptcy risk, incorporating linguistic complexity as an informative variable. In doing so, we hope to contribute a novel yet rigorously examined layer of understanding to this critically important subject matter.

2.3 Sentiment Analysis : Unveiling Financial Narratives

2.3.1 Dictionary-based Sentiment Analysis

One of the core avenues of exploration in this study revolves around sentiment analysis of financial texts, particularly within the prism of corporate bankruptcy prediction. Here, we venture into dictionary or lexicon-based sentiment analysis, a technique that remains a cornerstone in the domain of textual sentiment quantification. The crux of this method lies in identifying and quantifying words imbued with positive or negative sentiments, which are listed in what are often termed as sentiment dictionaries or lexicons.

Selecting a suitable sentiment dictionary is not merely an ancillary step but a pivotal decision that fundamentally shapes the fidelity of our sentiment capture. In contrast to general-purpose dictionaries, we chose to employ the Loughran and McDonald (LM) lexicon, an influential sentiment lexicon specifically calibrated for financial discourse. This lexicon has undergone rigorous validation and is particularly adept at capturing the industry-specific jargon and nuances that are often opaque to more general dictionaries.

Implementation-wise, we developed a Python function named `loughran mcdonald sentiment(text)`, constituting the operational backbone of our sentiment analysis. In essence, this function conducts a series of steps, starting from tokenizing the text input into individual words. It then converts these tokens into uppercase forms, ensuring case insensitivity and alignment with the LM lexicon, which is formatted in uppercase. The function subsequently traverses through the text, tallying the frequency of words that resonate with the LM lexicon's lists of positive and negative terms. The final act of this function is to calculate a weighted sentiment score, essentially a normalized ratio of the frequency of positive and negative words. This calculated score serves as a gauge of the overall sentiment tilt in the text, scaled to remain independent of text length.

2.3.2 Transformer-based Sentiment Analysis

Pivoting from dictionary-based approaches, we expanded our analytical horizon to incorporate transformer-based sentiment analysis models, notably RoBERTa and FinBERT. These models have catalyzed a paradigm shift in the field of Natural Language Processing (NLP), eclipsing earlier models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) in both performance and capabilities.

Key features that elevate transformer models include :

Parallelization : Through the self-attention mechanism, transformers natively support parallel processing of input sequences. This makes them synergistically compatible with Graphics Processing Units (GPUs), which are designed for parallel computation. While originally crafted for graphic rendering tasks, GPUs have found a second calling in machine learning due to their proficiency in matrix operations—something quintessential for transformers.

Long-range Dependencies : The self-attention mechanism imbues transformers with a proclivity to manage long-range dependencies in textual data effectively. The capability to relate each word to every other word in a given sequence makes transformers remarkably adept at capturing both local and global contextual relationships.

Pre-training and Fine-tuning : Transformers often employ a two-stage learning process involving pre-training on large-scale data and fine-tuning on specific tasks. This architecture facilitates the capture of generic language features initially, followed by domain-specific refinements, leading to remarkably effective models for a wide range of NLP applications.

Scalability : One can scale transformers by expanding the number of layers or attention heads, making them incredibly adaptable. This scalability has led to the advent of gargantuan models like GPT-3 and BERT that can generate and understand text in an almost human-like manner.

Rich Contextual Representations : Transformers produce embeddings that encapsulate a broad spectrum of syntactic and semantic details, resulting from their ability to assess the entire input sequence in one go. This depth in contextual understanding is particularly invaluable when deciphering the intricate fabric of financial narratives.

Specifically, in our study, we employ RoBERTa and FinBERT models to delve into the sentiment of financial texts. These models are trained on vast, diversified corpuses, making them linguistically astute and capable of deciphering complex text structures. RoBERTa builds on the architecture of BERT but incorporates strategic improvements such as dynamic masking and larger batch sizes. These tweaks have furnished it with exemplary capabilities across various NLP benchmarks. Conversely, FinBERT is a specialized child of the BERT architecture, fine-tuned to resonate with the nuances and lexicons specific to financial literature.

2.3.3 Aligning LLMs : Domain Adaptation

A noteworthy aspect in the context of FinBERT is the concept of domain adaptation. In essence, domain adaptation aspires to transfer knowledge gained from a source domain, often with abundant data, to a target domain that may be data-scarce or different in distribution. Two critical techniques are commonly employed : Feature space alignment, which works to align features that are similar across both domains, and self-supervised learning, a strategy that employs unlabeled data in the target domain to optimize the model further. FinBERT offers an archetypal example of a model that leverages domain adaptation, acquiring general linguistic features from the vast data available during pre-training and then fine-tuning these features to adapt to financial texts.

To sum up, our exploration into sentiment analysis unfolds through two distinct paradigms : dictionary-based and transformer-based models. Each offers unique merits and limitations. Dictionary-based approaches offer straightforward interpretations and lower computational costs but may lack the nuance and depth to capture intricate textual relationships. On the other hand, transformer-based models, particularly RoBERTa and FinBERT, offer high performance and can understand intricate linguistic structures but come with increased computational costs and require specialized expertise for fine-tuning.

2.3.4 Comparing Sentiment Analysis Using FinBERT, RoBERTa, and Loughran MacDonald Sentiment Word List

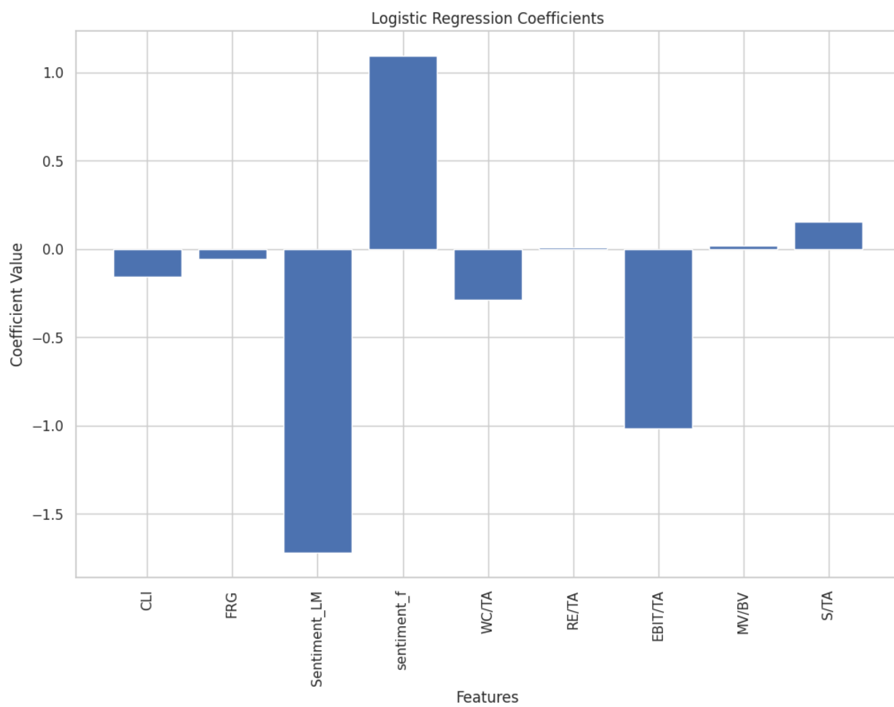
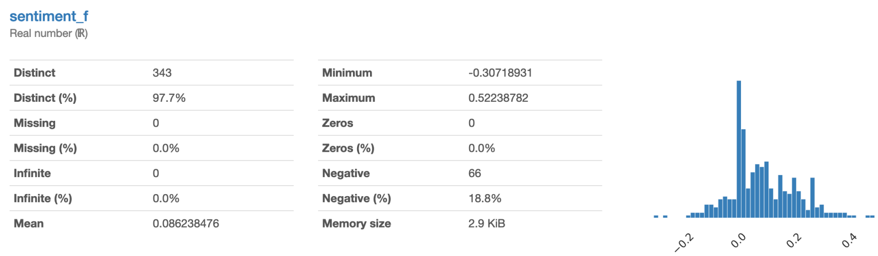


FIGURE 2.5 – Coefficient of regression for Altman + Sentiment + Readability set of features.

Our research delved into the intricate world of sentiment analysis models to investigate how different machine learning architectures interpret financial text. Specifically, we examined three unique models—FinBERT, RoBERTa, and the Loughran MacDonald Sentiment Word List—each bringing its own set of strengths and weaknesses to the table (see Figure 2.5). While all are incredibly sophisticated tools for text analysis, it's crucial to remember that no model is perfect; they each have their own quirks and idiosyncrasies that reflect the complexities inherent in machine learning, particularly in sentiment analysis.

Take FinBERT, a model specifically engineered for financial sentiment analysis, as an example (see Figure 2.6). It exhibited an intriguing behavior when it identified a text chunk detailing an increase in revenues across various segments within a fiscal year as



sentiment_f
Real number (ℝ)

Distinct	343	Minimum	-0.30718931
Distinct (%)	97.7%	Maximum	0.52238782
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	66
Infinite (%)	0.0%	Negative (%)	18.8%
Mean	0.086238476	Memory size	2.9 KiB

FIGURE 2.6 – Sentiment scores derived using FinBERT.

the most negative chunk. Traditionally, one would expect an increase in revenues to be a positive indicator, but FinBERT assigned it a negative score of -0.941.

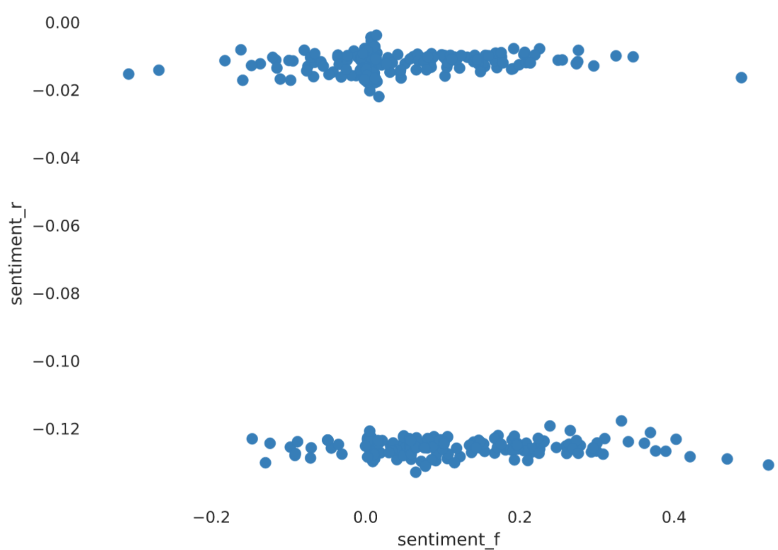


FIGURE 2.7 – Interaction between FinBERT and RoBERTa sentiment scores.

RoBERTa, on the other hand, is a robustly optimized derivative of the BERT model and showed a somewhat more intuitive grasp of financial sentiment (see Figures 2.7 and 2.8). It identified text discussing losses from operations and weighted average shares as the most negative chunk, which aligns more closely with human interpretation.

Lastly, the Loughran MacDonald Sentiment Word List offered yet another angle (see Figures 2.9 and 2.10). It echoed the most negative and positive chunks identified by FinBERT but with more extreme sentiment scores of -1.0 and 1.0, respectively. These scores

sentiment_r
Real number (ℝ)

Distinct	344	Minimum	-0.1329329
Distinct (%)	98.0%	Maximum	-0.0038666427
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	351
Infinite (%)	0.0%	Negative (%)	100.0%
Mean	-0.068264904	Memory size	2.9 KiB

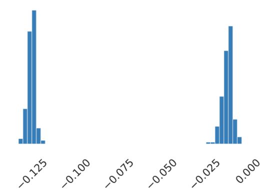


FIGURE 2.8 – Sentiment scores derived using RoBERTa.

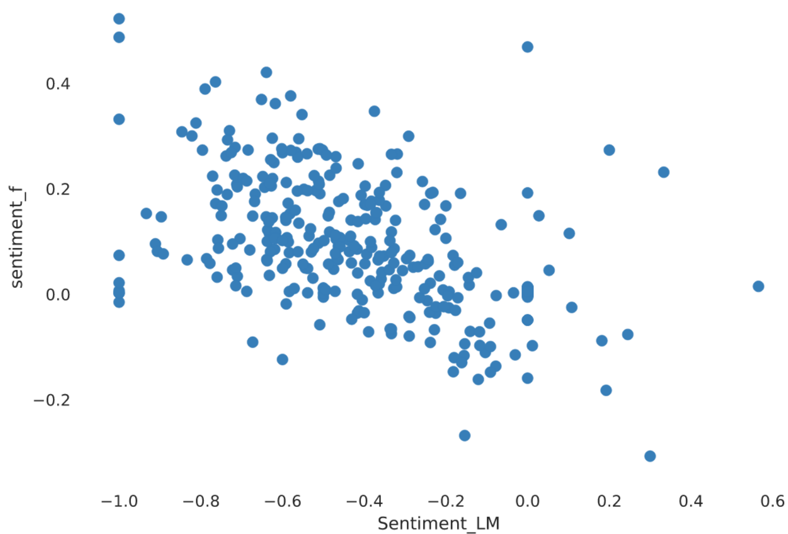


FIGURE 2.9 – Interaction between Loughran MacDonald Sentiment Word List and FinBERT sentiment scores.

indicate a high level of confidence in its sentiment classification, which may be due to the presence of more overtly positive or negative language in these chunks.

This variance in sentiment scores across models underscores the imperative of careful model selection. It's crucial to match the model's capabilities with the text's nature and the analysis's objectives. Despite their computational prowess, these models do not "understand" text as a human does ; they identify patterns in the data they were trained on and apply them to new data. Thus, their efficacy is strongly influenced by the quality and context of their training data.

The discrepancies in these models' sentiment scores underscore the importance of mo-

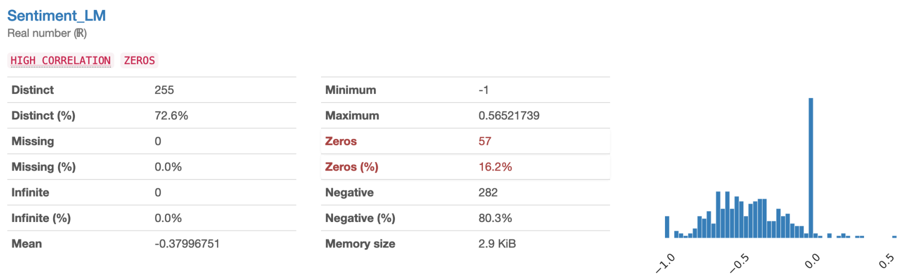


FIGURE 2.10 – Sentiment scores derived using Loughran MacDonald Sentiment Word List.

del selection for sentiment analysis. It's crucial to align the choice of the model with the nature of the text and the specific objectives of the analysis. The models, while powerful tools capable of analyzing large amounts of text, don't "understand" the text in the way humans do. They detect patterns in their training data and apply these patterns to new data. Hence, their performance heavily relies on the quality and context of the training data.

LM Method

Most negative chunk :

[..] Operating loss (17) (1) (14) Net loss (19)% (6)% (27)% COMPARISON OF TWELVE MONTHS ENDED DECEMBER 31, 2005 AND 2004 Consolidated revenues decreased 12% for the year ended December 31, 2005 compared to the prior year. Ophthalmic segment revenues decreased 24%, or $7,153,000, primarily due to reduced sales of diagnostic and anesthetic products. Injectable segment revenues increased 11%, or $1,378,000 for the year, reflecting the increased volumes of anesthesia [..]

Sentiment scores :

- FinBERT : 0.966
- RoBERTa : -0.084
- LM : -1.0

Most positive chunk :

"Item 7. Managements Discussion and Analysis of Financial Condition and Results of Operations RESULTS OF OPERATIONS We added key management personnel, including a new vice president of global quality and a vice president of manufacturing in 2005 and a new chief financial officer in 2004. Management has reduced our cost structure, improved our processes and systems and implemented new controls over capital and operational spending. Management believes these activities will improve our results of operations [..]"

Sentiment scores :

— FinBERT : -0.923

— RoBERTa : -0.081

— LM : 1.0

FinBERT Method

Most negative chunk :

"[..] increased 11.5% for the year ended December 31, 2004 compared to the prior year. Ophthalmic segment revenues increased 14.4%, or $3,756,000, due to increased sales volume for our existing diagnostic ophthalmic products. Injectable segment revenues increased 1.5%, or $186,000 for the year, reflecting the higher volumes of Lidocaine Jelly, partially offset by lower sales of our antidote kits. Our Contract services revenues increased by 17.5%, or $1,275,000, due to increased shipments of Baxter and Pfizer [..]"

Sentiment scores :

— FinBERT : -0.941

— RoBERTa : -0.071

— LM : 0

Most positive chunk :

"[..] Operating loss (17) (1) (14) Net loss (19)% (6)% (27)% COMPARISON OF TWELVE MONTHS ENDED DECEMBER 31, 2005 AND 2004 Consolidated revenues decreased 12% for the year ended December 31, 2005 compared to the prior year. Ophthalmic segment revenues decreased 24%, or $7,153,000, primarily due to reduced sales of diagnostic and anesthetic products. Injectable segment revenues increased 11%, or $1,378,000 for the year, reflecting the increased volumes of anesthesia [..]"

Sentiment scores :

— FinBERT : 0.966

— RoBERTa : -0.084

— LM : -1.0

RoBERTa Method

Most negative chunk :

"[..] manufacturing variances at our Decatur manufacturing facility. Selling, general and administrative (SGA) expenses increased 23%, to $16,405,000 for 2005 from $13,300,000 for 2004, due to the 2005 management bonuses ($1,479,000), reduced bad debt recoveries in 2005 ($777,000) and increased FDA fees ($557,000). Amortization and write-down of intangibles decreased by $1,901,000 due to an impairment charge of $2,037,000 in 2004 related to product license intangible assets for Biolon, Erythromycin, Cromolyn [..]"

Sentiment scores :

— FinBERT : 0.953

— RoBERTa : -0.092

— LM : -1.0

Most positive chunk :

"[..] covenant computations for the periods ended December 31, 2005 and March 31, 2006. The revisions adjusted the defined EBITDA for certain RD expenses and the interest coverage formula to exclude interest paid on the NeoPharm promissory note retirement and thereby resolved a default on the debt covenants of the Credit facility at December 31, 2005. In addition it provided consent for the private placement of common stock in March of 2006 and waived certain potential defaults arising therefrom. [..]"

Sentiment scores :

— FinBERT : -0.005

— RoBERTa : -0.055

— LM : 0

In addition to the aforementioned considerations, it's pivotal to address the current lack of transparency in the operation of large language models (LLMs). Unlike traditional analytical techniques, where methodologies and data sources are often explicitly defined, LLMs present a challenge in terms of opacity. This issue is twofold :

Firstly, the sheer scale and complexity of these models, often encompassing billions of parameters, render them somewhat 'black boxes.' Understanding the specific reasoning behind a model's output is challenging, as the internal workings are not as interpretable as simpler models. This complexity can obscure the path from input to output, making it difficult for users to discern how the model arrived at a particular conclusion.

Secondly, the proprietary nature of many LLMs exacerbates this lack of transparency. Details regarding the training process, the exact nature of the training data, and the specific algorithms used are often closely guarded secrets of the companies that develop these models. This commercial confidentiality leads to a situation where users and researchers can observe the outputs of these models but have limited insight into the underlying mechanics that drive these results.

This opacity contrasts sharply with traditional techniques, where the process from data input to analytical output is generally more transparent and understandable. The black-box nature of LLMs poses significant challenges, particularly when these models are applied in critical domains where understanding the rationale behind decisions is as important as the decisions themselves. Consequently, while LLMs offer unparalleled capabilities in processing and interpreting vast amounts of data, their lack of transparency remains a notable limitation that needs addressing, especially in contexts requiring clear audit trails and explainability.

In summary, our exploration into the sentiment analysis capabilities of FinBERT, RoBERTa, and the Loughran MacDonald Sentiment Word List reveals that each model brings a unique perspective to the table. The idiosyncrasies observed in sentiment scores across these models emphasize the importance of judicious model selection tailored to the specific needs of a project. Understanding these nuances can guide researchers and analysts in choosing the most appropriate tool for their work, ever mindful that these models, however advanced, do not possess the nuanced understanding of human language and its intricacies.

2.4 Predictive models

Having established Altman's Z-score as a baseline for corporate bankruptcy prediction, it is essential to explore various machine learning models that have gained prominence in the field due to their distinct strengths and capabilities. Each model provides unique opportunities for understanding and predicting bankruptcy, which makes them valuable for both researchers and practitioners. In this section, we will delve into the methodologies of different machine learning models, including Logistic Regression, Random Forest, Support Vector Machines and discuss their application in the context of corporate bankruptcy prediction. By comparing their advantages and limitations, we aim to provide a comprehensive understanding of these models, allowing the reader to make informed decisions when selecting the most suitable approach for their specific needs. Logistic Regression, a widely used statistical technique, has been applied in numerous studies for corporate bankruptcy prediction. Within this context, Logistic Regression estimates the probability of a firm going bankrupt based on a linear combination of various financial and non-financial features. One advantage of Logistic Regression is its interpretability, as the coefficients of the model can be easily explained in terms of the odds ratio, providing valuable insights into the drivers of corporate bankruptcy. However, the linear nature of Logistic Regression imposes limitations on its ability to capture more complex, non-linear relationships between features and bankruptcy outcomes. We implement the model with an L2 penalty to prevent overfitting and a standard regularization strength (C=1.0). The 'lbfgs' solver is chosen for its ability to handle small datasets efficiently, and the maximum number of iterations is set to 2000 to ensure convergence.

Multilayer Perceptron (MLP) is a class of feedforward artificial neural network that has demonstrated remarkable results in a variety of machine learning tasks, including the prediction of corporate bankruptcy. An MLP consists of at least three layers of nodes : an input layer, a hidden layer, and an output layer. Each node, also known as a neuron, in one layer connects to every neuron in the next layer, making MLP a fully connected network. We employed the MLPClassifier from the sklearn.neural_network module. This classifier uses backpropagation for training and supports multiple activation functions and solvers for weight optimization. The MLPClassifier was instantiated with the following hyperparameters : a single hidden layer with 16 neurons, the activation function set to 'relu', the solver set to 'adam', the regularization term (alpha) set to 0.0001, the learning rate policy set to 'constant', the initial learning rate set to 0.001, and the maximum number of iterations for the solver to converge set to 200. The selection of these hyperparameters was not arbitrary but the result of a rigorous hyperparameter through a grid search optimization process. This process involves testing various combinations of hyperparameters to determine the set that yields the best performance on the validation set.

Hyperparameters explored

Hyperparameter	**Values Explored**
Hidden Layers	1, 2, 3
Neurons per Layer	16, 32, 64, 128
Activation Function	ReLU, Sigmoid, Tanh
Solver	Adam, SGD, Adamax
Regularization Term (Alpha)	0.0001, 0.001, 0.01
Learning Rate	0.001, 0.01, 0.1
Learning Rate Policy	Constant, Adaptive
Maximum Iterations	100, 200, 300

TABLE 2.1 – Grid Search of Hyperparameters for the MLP

In the context of our study, we used methods such as grid search and cross-validation to systematically explore the hyperparameter space and select the optimal parameters for our MLP model. MLPs are prone to overfitting, especially when the network has too many layers or neurons. This is because the model might start to learn the noise in the training data, leading to poor generalization to unseen data. Furthermore, MLPs require a large amount of data to perform well, and training are more computationally expensive and time-consuming than other models.

A Random Forest model combines multiple Decision Trees, each trained on a random subset of the data with replacement (bagging) and a random subset of the features. This ensemble approach reduces overfitting and improves the generalization performance of the model. Nevertheless, the increased complexity of Random Forests compared to single Decision Trees makes them less interpretable, which may limit their usefulness for stakeholders seeking a clear understanding of the bankruptcy prediction process. We set the number of trees (n_estimators) to 100 and apply similar hyperparameters as the Decision Tree algorithm, but with a larger max_depth of 5, allowing for more complex decision boundaries.

SVM has been employed in various corporate bankruptcy prediction studies for its ability to find the optimal decision boundary between bankrupt and non-bankrupt firms, especially when dealing with high-dimensional feature spaces. The core idea behind SVM is to maximize the margin between the two classes, which can be achieved by solving a convex optimization problem. The kernel trick allows SVM to model complex, non-linear relationships between financial features and bankruptcy status by implicitly mapping the data into a higher-dimensional space. SVM can be particularly effective when the dataset has a clear margin of separation, but its performance may be sensitive to the choice of kernel function and hyperparameters. Additionally, SVM models can be harder to interpret compared to other methods, such as Logistic Regression and Decision Trees, which may limit their applicability in situations where interpretability is crucial. We employ a standard regularization strength (C=1.0) and a Radial Basis Function (RBF) kernel to model nonlinear decision boundaries. The gamma parameter, controlling the shape of the kernel function, is set to 0.1 to prevent overfitting.

Each of the mentioned machine learning models offers unique advantages and limitations in the context of corporate bankruptcy prediction. Logistic Regression provides a simple, interpretable model that captures linear relationships between features and bankruptcy outcomes. Random Forests offer more flexibility in modeling non-linear relationships and handling high-dimensional feature spaces, but may trade off interpretability for performance. SVM excels in handling high-dimensional data and finding the optimal decision boundary, but its performance is sensitive to hyperparameter tuning and kernel selection, and it offers limited interpretability. A table describing all hyper-parameters is available in the Appendix (See section **??**).

2.5 Evaluation

The evaluation of predictive machine learning models is often far more nuanced than merely calculating the accuracy rate. Given the intricacy of bankruptcy prediction in corporate settings—a subject often characterized by class imbalance and the absence of a one-size-fits-all solution—it is imperative to use a multifaceted approach for performance assessment.

The first metric under our scanner is accuracy. Accuracy represents the ratio of correct predictions (both positive and negative) to the total number of observations. It is mathematically denoted as :

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN stand for the number of true positives, true negatives, false positives, and false negatives, respectively.

While accuracy is an elementary and popular choice, it doesn't always provide a complete picture, particularly when the dataset is imbalanced. For instance, in bankruptcy prediction, companies not going bankrupt far outnumber those that do, thus potentially skewing the accuracy metric. Therefore, we also use other metrics to probe deeper into the models' performance.

One such metric is Precision. Precision helps us understand the model's capacity to make true positive predictions while avoiding false positives—those instances when the model wrongly predicts bankruptcy. Mathematically,

$$P = \frac{TP}{TP + FP}$$

Another complementary metric is Recall or Sensitivity, which looks at how well the model picks out the bankrupt cases from the total actual bankrupt cases. This measure is crucial when the cost of a false negative—missing a bankruptcy—is high.

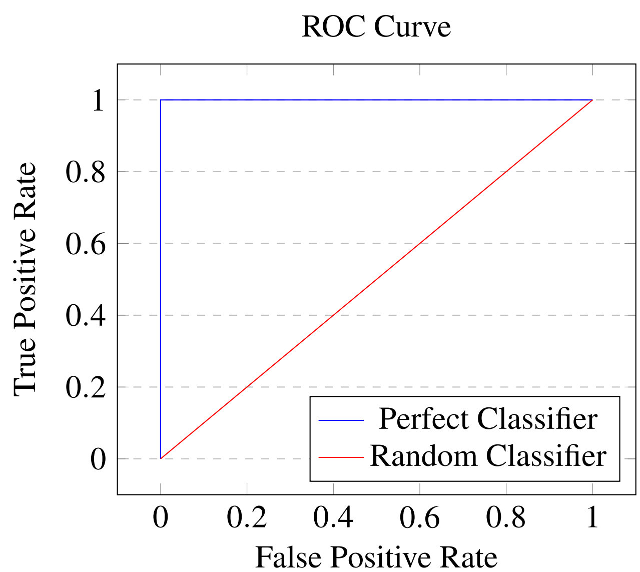
$$R = \frac{TP}{TP + FN}$$

The F1 Score harmonizes Precision and Recall, serving as a balanced mean of both metrics. It is particularly useful for datasets where class imbalance is an issue, as it takes into account both false positives and false negatives.

$$F1 = \frac{2PR}{P+R}$$

An integral part of our evaluation toolkit is the AUC-ROC curve. The Receiver Operating Characteristic (ROC) curve is a graphical plot that captures the true positive rate (also called Sensitivity) against the false positive rate at varying thresholds. The Area Under this Curve (AUC) provides a single scalar value that summarizes the model's ability to discriminate between the classes effectively.

To facilitate an intuitive grasp of our findings, we also employ visual aids, including the plotting of ROC curves. The curve allows us to compare multiple models or configurations visually and decide which one strikes the best balance between sensitivity and specificity.



Lastly, we employ a Confusion Matrix as a more straightforward way to understand model performance. A Confusion Matrix displays the raw counts of each class (true positive, true negative, false positive, false negative), providing an immediate snapshot of what the model gets right and where it errs.

By applying these diverse metrics and visualization tools, we seek to present a comprehensive, nuanced evaluation of machine learning models for corporate bankruptcy prediction. This approach equips researchers and practitioners to make well-informed decisions, considering not just accuracy, but a host of other critical performance metrics and visual indicators.

In essence, our methodology is a blend of traditional financial metrics and advanced textual analysis, targeted at offering a more accurate and holistic view of corporate bankruptcy risk. We start with gathering financial metrics and textual data from corporate reports. Rather than only leaning on numbers, we delve into the textual narratives to add another layer of insight.

We've adopted two textual features : readability and sentiment. Readability metrics aren't just academic exercises; they help us understand if the financial data is presented in a way that's easy to grasp, shedding light on its potential impact. Sentiment analysis is even more intricate, combining dictionary-based approaches for linguistic accuracy with machine learning techniques for computational depth. We also ensured that these methods are fine-tuned to the language of finance, validating them through comparison with established NLP models like FinBERT and RoBERTa.

Chapitre 3

Experimental Results and Interpretation

Bankruptcy prediction has traditionally relied on quantitative financial metrics, typically extracted from income statements, balance sheets, and cash flow statements. The Altman's Z-score model is a prime example of this methodology. Relying solely on structured financial metrics may not capture the entirety of relevant information. This study aims to fill this gap by integrating Natural Language Processing (NLP) techniques into bankruptcy prediction models. This study integrates NLP techniques into bankruptcy prediction models for a more comprehensive assessment.

3.1 Altman's Z-Score : The Traditional Pillar of Bankruptcy Prediction

The Altman's Z-score model operates under certain assumptions that have their own set of limitations. Firstly, it assumes that publicly disclosed financial ratios are accurate representations of a company's financial health. This assumption, while generally valid, can be problematic if companies manipulate their financial statements. Secondly, the model presupposes a constant relationship between financial ratios and bankruptcy risk over time, an assumption that may not hold true in rapidly changing economic conditions. The model is also susceptible to temporal bias, as financial ratios can fluctuate due to market volatility or managerial decisions. Additionally, the model's one-size-fits-all approach does not account for industry-specific financial norms and overlooks real-time market dynamics such as share price fluctuations and geopolitical events, which can have immediate impacts on a company's solvency.

3.2 Textual Analysis Metrics : Readability and Sentiment

3.2.1 Readability Metrics

Readability metrics quantify the complexity of textual data in financial reports. Financial disclosures need to balance detailed, technical information with clarity and accessibility. Metrics like the Automated Readability Index (ARI) and Flesch Reading Ease (FRE) gauge how easily a text can be understood. ARI calculates readability based on the number of characters per word and the number of words per sentence. This approach can be advantageous in financial disclosures where the complexity is often not just in the vocabulary (i.e., word length or syllables) but in the length and structure of sentences. Long, convoluted sentences can make financial information more challenging to understand. FRE assesses readability based on the average sentence length and the number of syllables per word. This is relevant in financial disclosures where complex financial terms (often polysyllabic) are common. A higher syllable count per word can indicate more specialized language, which could be a barrier to understanding for the general public. These metrics are predicated on the idea that simpler language may indicate a financially stable company, while complex language could be a red flag. However, this assumption can be misleading in industries that naturally use complex jargon, such as biotechnology. Companies might deliberately use simple language to mask financial issues, or they may be forced to use complex language due to regulatory requirements.

3.2.2 Sentiment Analysis

Sentiment analysis employs NLP techniques to gauge the emotional tone of textual data. Using lexicon-based methods and machine learning models like FinBERT, we can identify positive, neutral, and negative sentiments within financial texts. However, this approach is not without its pitfalls. Companies often craft narratives to shape public perception, which can distort the genuine sentiment. Moreover, machine learning models can inherit biases from their training data, and they may also struggle with interpreting complex or nuanced expressions of sentiment.

In this study, we integrate traditional financial ratios from the Altman's Z-score model with textual features derived from readability and sentiment metrics. We employ multiple regression models to assess the impact of these combined features on bankruptcy prediction. Statistical tests like chi-square and t-tests are used to rigorously evaluate the predictive power of this augmented model. We operate under the assumption that the inclusion of textual data will complement, rather than dilute, the predictive power of traditional financial metrics.

3.3 Empirical Results about the Role of Textual Analysis

To provide a quantitative assessment of our methodology, we present the following table that summarizes the test performance metrics across different combinations of features and machine learning models.

Our empirical findings reveal that the integration of NLP techniques—specifically, readability and sentiment analysis—can significantly enhance the predictive accuracy of traditional bankruptcy models like the Altman's Z-score. For instance, the predictive accuracy of a Logistic Regression model soared from 59.8% to 69.1% upon the inclusion of textual features. The impact of these textual features varies across different machine learning algorithms. For example, while Multilayer Perceptron (MLP) showed an increase in accuracy with readability metrics, the addition of sentiment analysis had a negative

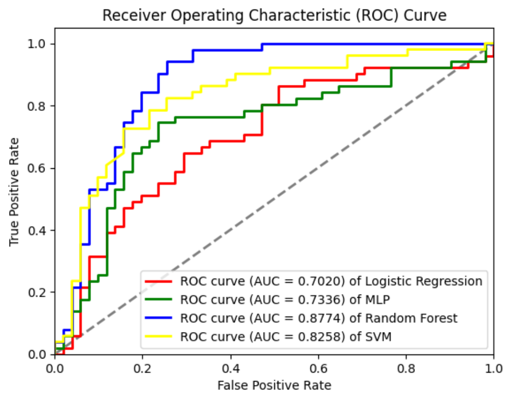
TABLE 3.1 – Test performance metrics for 5 set of features.

(a) Abbreviations represent various models : Altman's bankruptcy prediction (Alt.) combined with either Logistic Regression (Log. Reg.), Multilayer Perceptron (MLP), Random Forest (R. Forest), or Support Vector Machine (SVM). Additional combinations use readability metrics (Read.) or financial sentiment scores (Fin. Sent.).

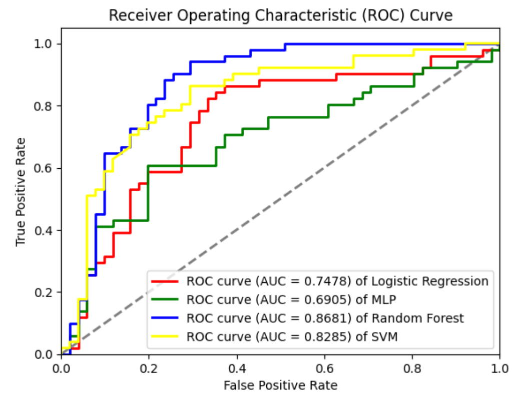
Model	**Acc.**	**Prec.**	**Recall**	**F1**	**AUC**	**In-sample AUC**
Logistic Regression						
Alt.	0.598	0.727	0.314	0.438	0.702	0.8071
Alt.+Read.	0.624	0.600	0.647	0.623	0.691	0.7384
Alt.+LM Sent.	0.677	0.683	0.647	0.664	0.743	0.7941
Alt.+Fin. Sent.	0.657	0.718	0.529	0.610	0.757	0.8215
Alt.+Read.+Sent.	0.691	0.683	0.686	0.684	0.746	0.8039
Multilayer Perceptron (MLP)						
Alt.	0.566	0.643	0.235	0.344	0.660	0.7751
Alt.+Read.	0.757	0.778	0.726	0.751	0.792	0.8254
Alt.+LM Sent.	0.614	0.579	0.667	0.620	0.632	0.7198
Alt.+Fin. Sent.	0.598	0.875	0.255	0.395	0.729	0.7855
Alt.+Read.+Sent.	0.743	0.721	0.765	0.742	0.802	0.8390
Random Forest						
Alt.	0.873	0.829	0.922	0.873	0.944	0.9719
Alt.+Read.	0.853	0.829	0.873	0.850	0.925	0.9731
Alt.+LM Sent.	0.853	0.797	0.922	0.855	0.938	0.9712
Alt.+Fin. Sent.	0.858	0.824	0.892	0.857	0.944	0.9780
Alt.+Read.+Sent.	0.843	0.789	0.902	0.842	0.931	0.9790
Support Vector Machine (SVM)						
Alt.	0.838	0.797	0.882	0.838	0.915	0.9208
Alt.+Read.	0.824	0.773	0.882	0.824	0.906	0.9221
Alt.+LM Sent.	0.838	0.797	0.882	0.838	0.915	0.9208
Alt.+Fin. Sent.	0.838	0.797	0.882	0.838	0.915	0.9244
Alt.+Read.+Sent.	0.854	0.826	0.882	0.853	0.931	0.9462

impact. In the case of Random Forest, which already had a high baseline accuracy, the addition of textual features led to negligible improvements. However, Support Vector Machine (SVM) displayed robust performance, achieving an 85.4% accuracy level when all metrics were considered.

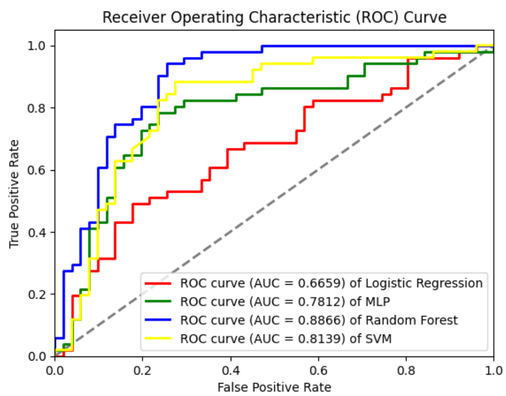
To visually represent the Receiver Operating Characteristic (ROC) curves for various models, we provide the following figure : Figure 3.1.



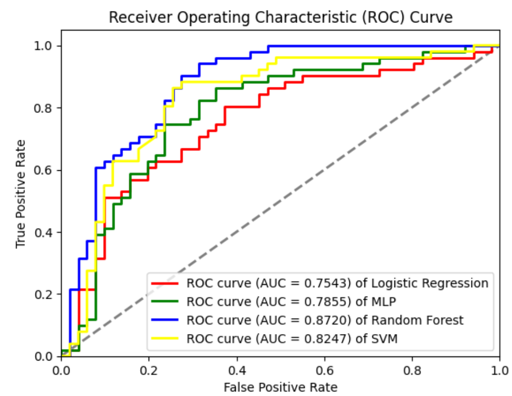
(a) Baseline ROC



(b) FinBERT ROC



(c) Readability ROC



(d) Readability + Sentiment ROC

FIGURE 3.1 – ROC curves for various models.

Our findings also indicate that the introduction of textual features significantly improves the model's sensitivity, or its ability to correctly identify actual bankruptcy cases. However, this comes at the cost of a slight decrease in precision and specificity, suggesting a trade-off that businesses would need to consider when adopting these enhanced models.

To illustrate the model's performance in classifying companies, we present the following confusion matrices :

1. **Sensitivity (or Recall)** :
   — Baseline :

$$\frac{TP}{TP+FN} = \frac{16}{16+35} = 31.37\% \tag{3.1}$$

— Textual Features :

$$\frac{34}{34+17} = 66.67\% \tag{3.2}$$

2. **Precision** :

— Baseline :

$$\frac{TP}{TP+FP} = \frac{16}{16+6} = 72.73\% \tag{3.3}$$

— Textual Features :

$$\frac{34}{34+14} = 70.83\% \tag{3.4}$$

3. **Specificity** :

— Baseline :

$$\frac{TN}{TN+FP} = \frac{45}{45+6} = 88.24\% \tag{3.5}$$

— Textual Features :

$$\frac{37}{37+14} = 72.55\% \tag{3.6}$$

3.4 Making Sense of the Nuances of Textual Analysis

Our study further explores the isolated effects of readability and sentiment metrics. Readability scores were particularly influential in Logistic Regression and MLP models, suggesting that the complexity of a firm's financial reports could be an underexplored indicator of financial stability. Sentiment analysis, implemented via lexicons and machine learning models, offered a new perspective on corporate financial reports. While sentiment analysis had a significant impact on Logistic Regression, its influence was less pronounced in MLP models.

3.4.1 Measuring the Impact of Textual Features

Building on our initial findings, which highlighted the value of incorporating Natural Language Processing (NLP) techniques into traditional bankruptcy prediction models, we delve deeper into the nuanced contributions of each feature. Our ablation studies aim to

TABLE 3.2 – Differences in performance metrics between two feature sets : Altman (baseline) and Altman + Sentiment + Readability. Positive values indicate that the Altman + Sentiment + Readability set outperformed the baseline, while negative values indicate the opposite.

Model	Acc. Diff	Prec. Diff	Rec. Diff	F1 Diff	AUC Diff
Logistic Regression	0.0980	-0.0189	0.3529	0.2485	0.0523
MLP	0.1373	0.0391	0.3922	0.3067	0.0519
Random Forest	-0.0392	-0.0247	-0.0588	-0.0395	-0.0054
SVM	0.0294	0.0127	0.0588	0.0331	-0.0012

dissect the individual impact of readability and sentiment metrics across different predictive models, specifically Multi-layer Perceptron (MLP) and Logistic Regression.

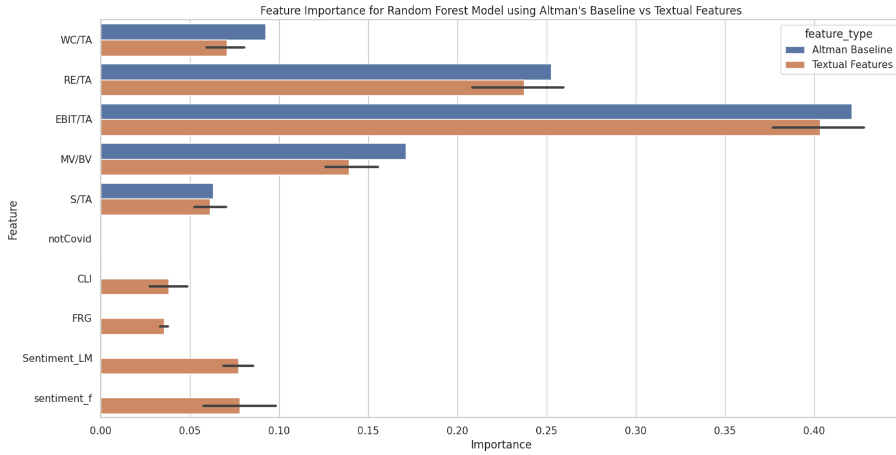
We start by examining the Altman's Z-score, a well-established model for bankruptcy prediction that traditionally relies on five financial ratios. These ratios—Working Capital to Total Assets (WC/TA), Retained Earnings to Total Assets (RE/TA), Earnings Before Interest and Taxes to Total Assets (EBIT/TA), Market Value of Equity to Book Value of Debt (MV/BV), and Sales to Total Assets (S/TA)—are correlated to varying degrees. High correlations among WC/TA, RE/TA, and EBIT/TA suggest that these features share predictive value, making them less individually informative. On the other hand, MV/BV and S/TA show low correlation with other features, potentially adding unique predictive value.

To provide a visual representation of these correlations, we present the following correlation matrices :

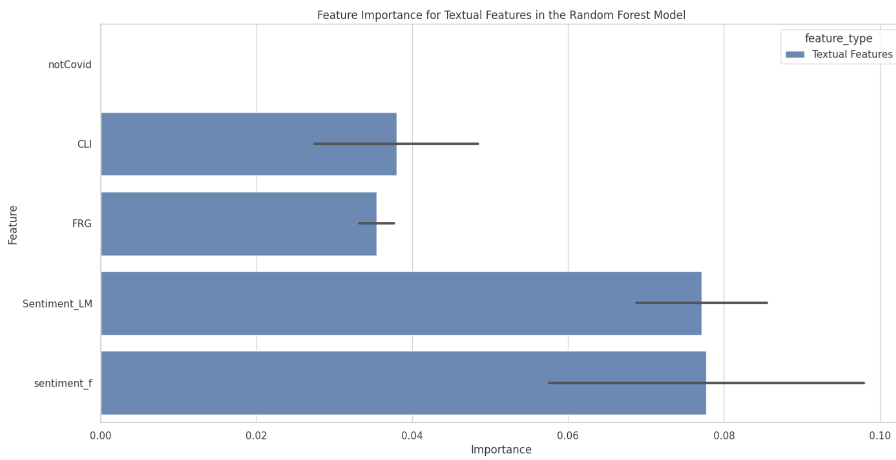
When we incorporate readability and sentiment metrics into the Altman's Z-score, the correlation matrix becomes more intricate. Notably, these new textual features show moderate to low correlation with the traditional Altman features, suggesting they add orthogonal, or non-redundant, information to the model. For instance, sentiment scores based on the Loughran-McDonald lexicon (‘Sentiment_LM‘) and FinBERT (‘sentiment_f‘) are not highly correlated with each other, indicating that they capture different facets of corporate sentiment in financial reports.

To provide a more visual perspective, we use box plots to compare the distribution

Feature importance of textual feature



(a) Comparing readability vs sentiment



(b) Textual Feature Importance (Readability vs. Sentiment)

FIGURE 3.2 – Analysis of feature importance using Gini score in Random Forest.

of features between bankrupt and non-bankrupt firms. These plots offer insights into the discriminative power of each feature, revealing that traditional financial ratios like WC/TA and RE/TA exhibit stark differences between the two classes. Textual features, although less discriminative, still show some degree of separation, reinforcing the idea that they bring complementary information to the model.

The box plots in Figure 3.4 reveal that readability metrics, while informative, have limited discriminatory power. Sentiment metrics, particularly those derived from the Loughran-McDonald lexicon, exhibited more significant differences between bankrupt and non-

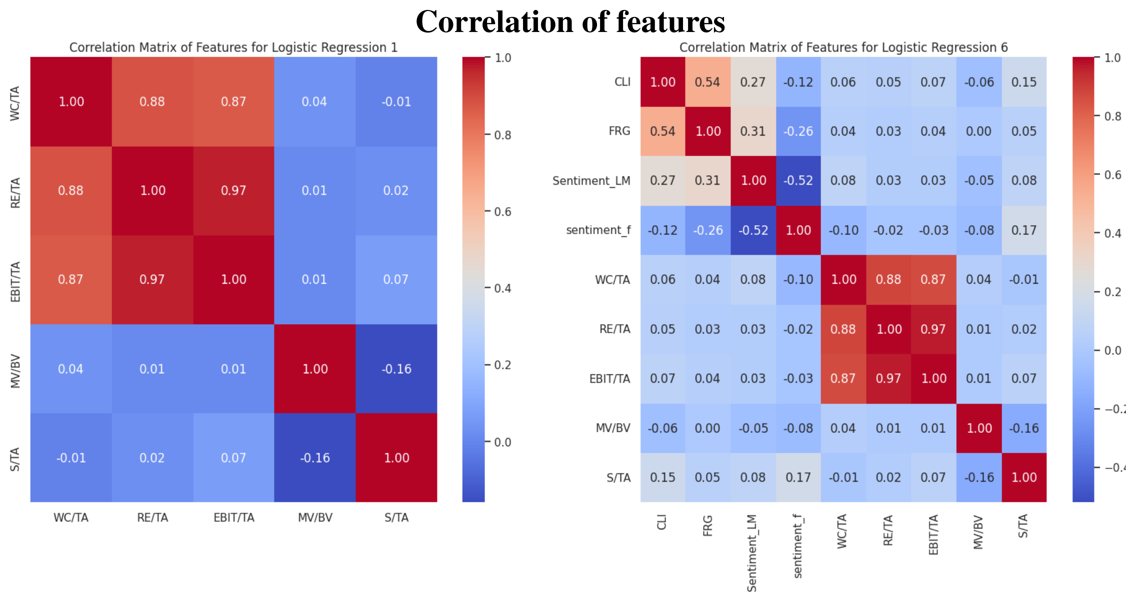


FIGURE 3.3 – Baseline (Altman) vs. Sentiment and readability augmented

bankrupt companies. This observation aligns with our earlier findings and adds another layer of confirmation to the utility of sentiment metrics in bankruptcy prediction models.

Our analysis reveals that readability metrics have limited power to distinguish between bankrupt and healthy companies. This corroborates our earlier observations from the correlation matrices. In contrast, sentiment metrics offer a more compelling dimension. Specifically, the Loughran-McDonald sentiment score (‘Sentiment_LM‘) is more negative for bankrupt companies, suggesting that these reports often carry a somber tone. On the other hand, FinBERT sentiment scores (‘sentiment_f‘) are higher for bankrupt companies, possibly indicating a false sense of optimism in these reports.

Our ablation studies underscore the nuanced role each feature plays in bankruptcy prediction. While traditional financial metrics remain robust indicators, the incorporation of textual features adds a new layer of interpretability and predictive power. Readability metrics, although useful, offer limited discriminatory ability. Sentiment metrics, on the other hand, provide a compelling dimension that correlates well with a company’s financial stability—or lack thereof.

As we navigate the complex landscape of bankruptcy prediction, our research was guided by three main questions. These questions shaped our study and provided a fra-

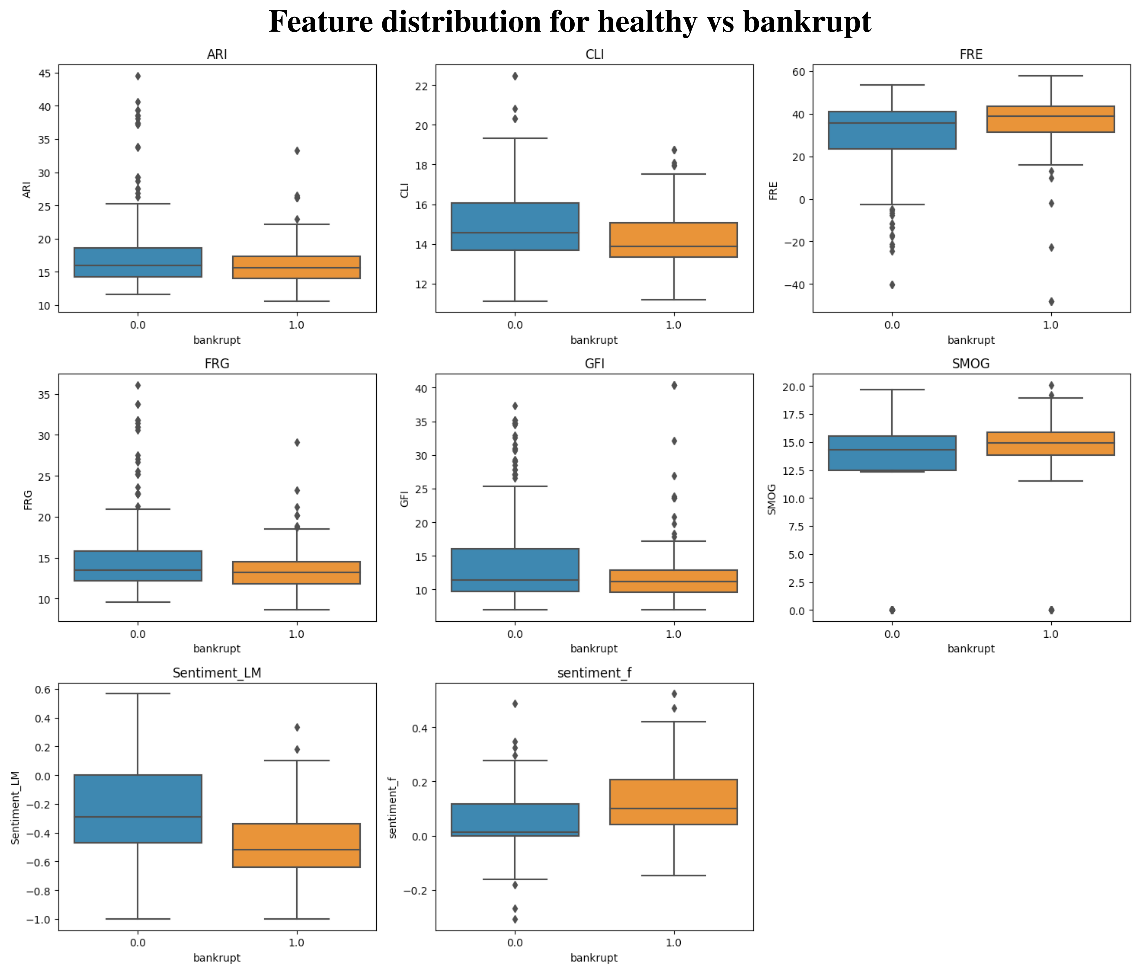


FIGURE 3.4 – Box plot comparing feature distributions between bankrupt and non-bankrupt firms.

mework to evaluate the impact of integrating textual features with classical bankruptcy models like Altman's Z-score.

The central question that motivated our research was whether textual features extracted through Natural Language Processing (NLP) techniques could add value to existing corporate bankruptcy prediction models. Our empirical findings offer a compelling response to this question. As shown in Table 3.1a, the predictive accuracy of Logistic Regression models, for instance, experienced a marked improvement from 59.8% to 69.1% with the inclusion of textual features.

Our second research question sought to explore under what conditions these textual features manifest their added value. One crucial insight we derived is that the effectiveness of these textual features is not uniform across various machine learning algorithms. This phenomenon is depicted vividly in Figure 3.5, where the confusion matrices for Logistic Regression and Random Forest models indicate distinct patterns of True Positives, True Negatives, False Positives, and False Negatives.

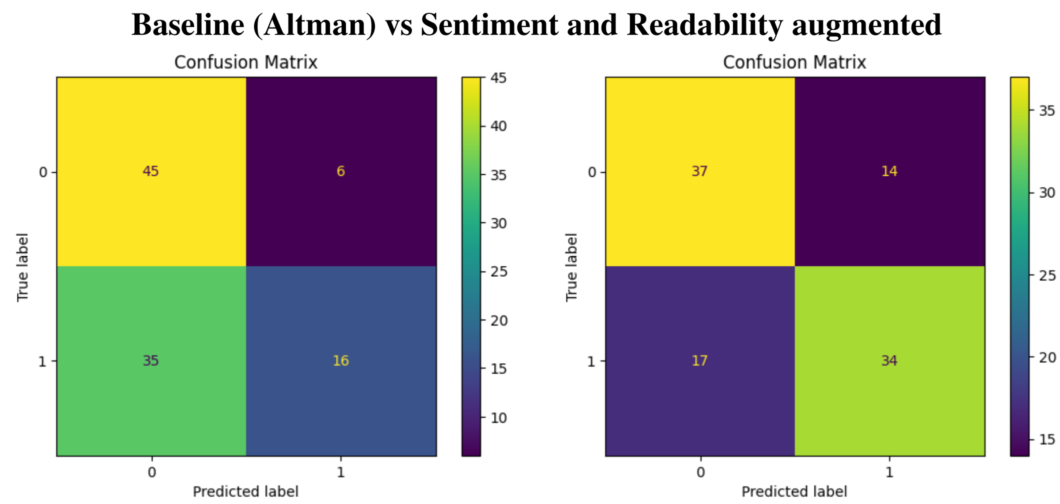


FIGURE 3.5 – Comparing the confusion matrices of baseline vs best performing model

For example, while the inclusion of sentiment features had a strong positive effect on the performance of Logistic Regression models, this was not the case for Multilayer Perceptron (MLP) models. Thus, the choice of algorithm can significantly influence the effectiveness of textual features, implying that a one-size-fits-all approach may not be appropriate.

Now, how do we measure the impact of these textual features ? The third research question is inherently linked to this query. We employed a range of performance metrics such as accuracy, precision, recall, and F1 score to quantify this impact. This rigorous measurement helped us confirm that sentiment analysis, for example, exhibited superior predictive power compared to readability analysis, a point substantiated by the feature importance graphs shown in Figure 3.6.

To delve deeper into the trade-offs involved, we examined the differences in performance metrics between two feature sets : the baseline Altman set and the augmented

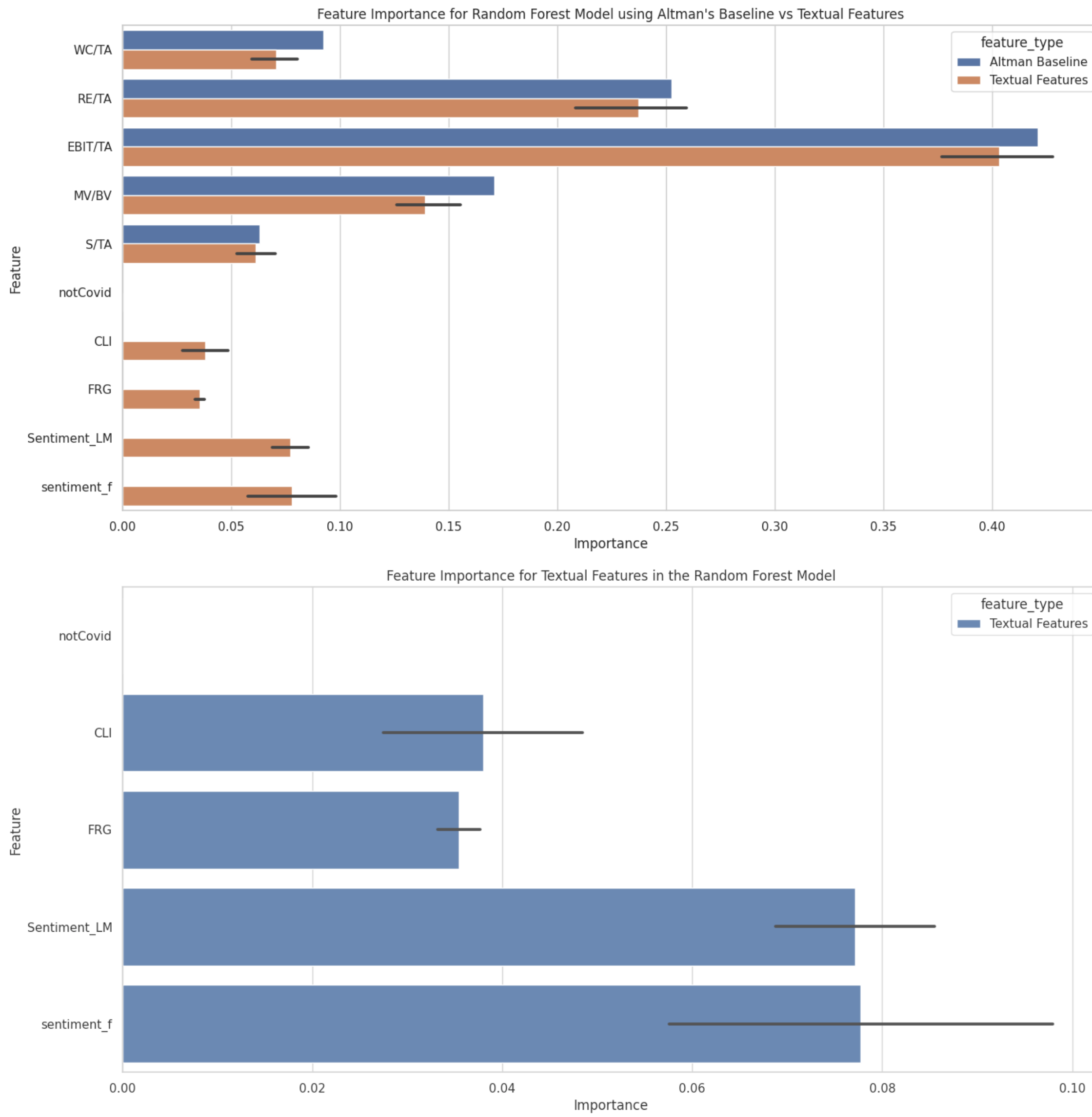


FIGURE 3.6 – Analysis of feature importance using Gini score in Random Forest.

Altman + Sentiment + Readability set. Positive values indicate that the augmented set outperformed the baseline, while negative values suggest the opposite. This nuanced look reinforces the need for a balanced approach when incorporating textual features, as gains in one metric may be offset by losses in another.

3.4.2 Concluding Notes

Based on our research, we draw the following conclusions. The empirical evidence suggests a practical need for integrating financial metrics with textual data. Through meticulous analysis and empirical validation, we've demonstrated that Natural Language Processing (NLP) techniques can significantly augment traditional bankruptcy prediction models. Figures 3.4 and 3.3 further solidify this claim by showing how textual features add unique, non-redundant information to the models.

Our study, however, is not without limitations. The effectiveness of these textual features varies across algorithms, necessitating a tailored approach for each predictive model. Additionally, the incorporation of textual features like sentiment and readability, while powerful, must be nuanced and context-aware.

Conclusion

To conclude this work, corporate bankruptcy will remain a popular field of research as long as the economy exists. Specially when the economy is uncertain, people will want to predict it. So, accurately predicting the financial resilience of a company is of importance for investors, institutions and corporations alike. Trends to improve the state of the art in the field will come and go but we tried, in this research, to apply traditional methods and contrast them with more recent state-of-the-art techniques to see how they compared using Altman's model as baseline. Altman's Z-score has been a staple in predictive bankruptcy modelling, offering a standardized metric that allow practitioners to evaluate a corporation's fiscal health and risk of bankruptcy overtime and into the future. We tried to augment this score by leveraging textual features that were derived from 10-K reports using popular textual analysis techniques for the problem of prediction bankruptcy. We used LLMs to perform some of the sentiment analysis, these models were made public through this proprietary platform HuggingFace for free. Our experiments revealed an interesting synergy between text and numbers (i.e. if one is able to align correctly their sources of quantitative and qualitative information). The results were mixed and under our first expectations when we stated the research questions. The market seems to give more importance to sentiment (how others will react) than readability. Sentiment analysis is trendy and a lot of new methodologies are proposer everyday while readability metrics follow simpler formulas that fail to capture useful insights when used alone. We also noted in our work, the difference in sentiment between Roberta and FinBert was quite surprising. We noticed that not all languages (e.g. Managerial discourse is different than everyday's discussions) and LLMs (e.g. RoBERTa vs FinBERT) are created equal as evidenced by the radically different outputs from one transformer to another. Such variability underlines the importance of ongoing research and careful application of these tools before using them in the real world, especially in the financial world where consequences often ripple down to those who really need innovation and change in their day-to-day lives. At the time when we started this paper, LLMs and ChatGPT were taking the world by storm, the hype was overwhelming and less controversial than it is today, one year later. However, it is important to note that these large neural networks are well known for their opacity ('Black boxes') and although publicly available the methodologies to collect and process the quasi-infinite amount of unstructured data used by these models is not transparent to say the least. For now, they lack of substance when it comes to theory and mathematical demonstrations making the work of researcher using such system less usefull to the scientific community. Still, LLMs seem to work well as evidenced by the real world applications according to their website. But this asymmetry between the real world, research institutions and tech corporations creates a unique environment where people are incentivized to use tools they don't fully understand potentially to profit private interests. It is also important to note the ongoing market and political dynamics between large corporation and the financial world is not static. Companies and researchers/practitioners quickly adapts to the new tools. They have the talents and financial resources to have an edge. From a game theory perspective, players are adapting quickly to these new tools, with companies consciously modifying how they redact their financial reports, like 10-K filings, to align with automated scoring systems as evidences by the changes of readability and sentiment over-time. Only time will tell if the hype behind LLMs was deserved, nonetheless we answered our main research questions and open some more for those interested in pursuing this kind of exploration.

Testing our research questions we found that incorporating textual data from financial reports can enhance the predictive accuracy of the Altman's Z-score. We managed to exceed the baseline by 10% under the logistic regression model. Among the types of textual features, sentiment analysis showed the most promises in terms of predictive power outperforming readability metrics in our experiments. Also, the perspectives of applying retrieval-augmented generation in tasks like question-answering or fact verification within financial reports can be of interest for practitioners and researchers alike in the future. This paper also explored the difference in performance when integrating textual features into different modeling techniques. For instance, Multi-layer Perceptron (MLP) models showed unstable and mixed improvement while other models demonstrated more significant gains in performance. Again, neural networks are more unstable than traditional statistical models both during training and inference. Choosing the right algorithm to match the specific features is of importance and requires an in-depth understanding of the mathematical intricacies of each model and how it relates to our data distribution of the sample used. Qualitative analysis will always be more subjective and nuanced than quantitative analysis due to the deterministic nature of numbers as opposed to words, images, odors, (...) . Researchers and practitioners should carefully understand the tools and methods they're using to avoid falling into the automation paradox fallacy. The paradox of automation says that the more efficient the automated system become, the more crucial the human contribution of the operators. Humans are less involved, but their involvement becomes more critical. There's an urgent need to better understand the tools we're using and define dynamically what human-machine interactions mean in the context these tools are used. But these question are beyond our scope. For now, we've answered our research questions and introduced possible venues of research for interested. NLP holds some valuable insights for the field of bankruptcy prediction and should be further explored in more rigorous ablation studies. This research underscores the importance of a combined approach that integrates both structured and unstructured data, in a more transparent way, to improve our understanding of financial resilience and the limitations the tools we use in the process.

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Appendix

Training performance metrics

(a) Altman's bankruptcy prediction (Alt.) combined with Logistic Regression (Log. Reg.), Multilayer Perceptron (MLP), Random Forest (R. Forest), or Support Vector Machine (SVM). Additional combinations use readability metrics (Read.) or finBert's sentiment scores (Fin. Sent.).

Model	**Acc.**	**Prec.**	**Recall**	**F1**	**ROC AUC**
Alt. - Log. Reg.	0.6867	0.8571	0.4390	0.5806	0.8071
Alt. - MLP	0.6265	0.8000	0.3252	0.4624	0.7751
Alt. - R. Forest	0.9036	0.8779	0.9350	0.9055	0.9719
Alt. - SVM	0.8474	0.8195	0.8862	0.8516	0.9208
Alt.+Read. - Log. Reg.	0.6506	0.6429	0.6585	0.6506	0.7384
Alt.+Read. - MLP	0.7912	0.8257	0.7317	0.7759	0.8254
Alt.+Read. - R. Forest	0.8956	0.8540	0.9512	0.9000	0.9731
Alt.+Read. - SVM	0.8594	0.8284	0.9024	0.8638	0.9221
Alt.+LM Sent. - Log. Reg.	0.7390	0.7377	0.7317	0.7347	0.7941
Alt.+LM Sent. - MLP	0.6827	0.6618	0.7317	0.6950	0.7198
Alt.+LM Sent. - R. Forest	0.8795	0.8540	0.9512	0.9055	0.9712
Alt.+LM Sent. - SVM	0.8474	0.8195	0.8862	0.8516	0.9208
Alt.+Fin. Sent. - Log. Reg.	0.7149	0.7826	0.5854	0.6700	0.8215
Alt.+Fin. Sent. - MLP	0.6546	0.8936	0.3415	0.4941	0.7855
Alt.+Fin. Sent. - R. Forest	0.9036	0.8667	0.9512	0.9070	0.9780
Alt.+Fin. Sent. - SVM	0.8635	0.8296	0.9106	0.8682	0.9244
Alt.+Read.+Sent. - Log. Reg.	0.7470	0.7308	0.7724	0.7510	0.8039
Alt.+Read.+Sent. - MLP	0.7751	0.7638	0.7886	0.7760	0.8390
Alt.+Read.+Sent. - R. Forest	0.8795	0.8298	0.9512	0.8864	0.9790
Alt.+Read.+Sent. - SVM	0.8755	0.8382	0.9268	0.8803	0.9462

Hyperparameters values for the experiments

Parameter	Logistic Regression	Random Forest	Support Vector Machine	Multilaye
penalty	l2	-	-	-
C	1.0	-	1.0	-
solver	lbfgs	-	-	adam
max_iter	2000	-	-	200
n_estimators	-	100	-	-
criterion	-	gini	-	-
max_depth	-	5	-	-
min_samples_split	-	10	-	-
min_samples_leaf	-	5	-	-
max_features	-	sqrt	-	-
kernel	-	-	rbf	-
gamma	-	-	0.1	-
hidden_layer_sizes	-	-	-	16
activation	-	-	-	relu
alpha	-	-	-	0.0001
learning_rate	-	-	-	constant
learning_rate_init	-	-	-	0.001

	re	ebit	sale	at	lt	wcap	MVE	dldte
count	122155	125502	127507	127629	125925	104256	121877	5634
mean	1515	614	4244	16715	14086	348	6117	2012
std	10386	3226	17854	120439	113486	2512	30707	6
min	-143336	-80053	-15009	0	0	-43133	0	1992
25%	-55	-2	15	45	14	0	53	2008
50%	3	17	218	497	257	25	339	2012
75%	321	201	1675	3388	2177	193	2155	2016
max	534421	130622	569962	4305288	4245011	123889	2324390	2023

Descriptive statistics of the global quantitative dataset

Model Performance and Coefficients

Model	Signif. Features	Coeff.	P-val.	Acc.	Preci.	Recall	F1 Score	Contribution %
Baseline (Altman's Z-score)	WC/TA, RE/TA, EBIT/TA	0.6253, -0.0180, -0.6961	0.0003, 0.1214, 0.0012	0.69	0.784	0.519	0.625	*Baseline*
Baseline with FRG	FRG, WC/TA, RE/TA, EBIT/TA	-0.0341, 0.3655, 0.0033, -0.5531	0.0109, 0.1045, 0.0343, 0.0252	0.57	0.565	0.578	0.571	FRG : 6.54%
Baseline with LM Sentiment	Sentiment_LM, WC/TA, RE/TA, EBIT/TA	-0.8214, 0.2336, 0.0023, -0.3347	0.0128, 0.2075, 0.1308, 0.1044	0.73	0.744	0.711	0.727	Sent_LM : 8.4%
Baseline with FinBERT Sentiment	sentiment_f, WC/TA, RE/TA, EBIT/TA	3.6325, 0.1189, 0.0018, -0.2020	0.0003, 0.5066, 0.2479, 0.2573	0.72	0.81	0.577	0.67	sentiment_f : 8.9%

CO2 Emission Related to Experiments

Experiments were conducted using Google Cloud Platform in region europe-west1, which has a carbon efficiency of 0.27 kgCO_2eq/kWh. A cumulative of 100 hours of computation was performed on hardware of type A100 PCIe 40/80GB (TDP of 250W).

Total emissions are estimated to be 6.75 kgCO_2eq of which 100 percents were directly offset by the cloud provider.

Estimations were conducted using the MachineLearning Impact calculator presented in lacoste2019quantifying.

	WC/TA	RE/TA	EBIT/TA	MV/BV	S/TA
			X training		
count	257	257	257	257	257
mean	-12.117268	-322.573825	-1.809653	15.211149	1.064260
std	180.904380	3228.102278	20.731958	85.996348	1.385918
min	-2898.375000	-37217.750000	-328.750000	0.001968	0.
25%	0.	-1.493157	-0.165062	0.388838	0.187022
50%	0.154251	-0.156220	-0.004782	1.650768	0.770082
75%	0.411479	0.142933	0.076556	7.222559	1.496813
max	0.995197	1.433024	2.972222	1272.720588	14.133929
			X testing		
count	111	111	111	111	111
mean	-0.197303	-22.554062	-0.302137	17.926001	0.920318
std	3.608765	150.280078	1.092578	61.134571	1.036661
min	-37.	-1535.409091	-9.600000	0.	0.
25%	-0.000073	-2.094452	-0.208915	0.368546	0.110005
50%	0.174785	-0.188754	-0.004009	1.523742	0.468934
75%	0.434395	0.139091	0.074720	6.918117	1.445036
max	0.996449	1.464296	0.490409	374.362500	5.053695

Descriptive statistics of baseline training and testing samples

y training		y testing	
count	257.	count	111
mean	0.501946	mean	0.495495
std	0.500972	std	0.502247
min	0	min	0
25%	0	25%	0
50%	1	50%	0
75%	1	75%	1
max	1	max	1

Descriptive statistics of the baseline's labels for training and testing samples

AKORN INC Management's Discussion and Analysis

Item 7. Managements Discussion and Analysis of Financial Condition and Results of Operations RESULTS OF OPERATIONS We added key management personnel, including a new vice president of global quality in 2005 and a new chief financial officer in

Model performance on a 2-year and 4-year forecasting lag.

Model	Metric	2 Years		4 Years	
		Baseline	LM + FinBERT	Baseline	LM + FinBERT
Logistic Regression	Accuracy	0.690	0.778	0.601	0.646
	Precision	0.784	0.791	0.700	0.635
	Recall	0.519	0.756	0.346	0.673
	F1 Score	0.625	0.773	0.463	0.653
	AUC	0.689	0.778	0.600	0.647
MLP	Accuracy	0.800	0.767	0.638	0.737
	Precision	0.761	0.786	0.704	0.702
	Recall	0.870	0.733	0.469	0.816
	F1 Score	0.812	0.759	0.563	0.755
	AUC	0.800	0.767	0.637	0.738
Random Forest	Accuracy	0.806	0.822	0.767	0.758
	Precision	0.737	0.784	0.742	0.736
	Recall	0.948	0.889	0.815	0.796
	F1 Score	0.830	0.833	0.776	0.765
	AUC	0.807	0.822	0.767	0.758
SVM	Accuracy	0.787	0.833	0.699	0.727
	Precision	0.734	0.826	0.705	0.696
	Recall	0.896	0.844	0.679	0.796
	F1 Score	0.807	0.835	0.692	0.743
	AUC	0.788	0.833	0.699	0.728

	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025**	**0.975]**
WC/TA	-0.2276	0.1861	-1.2229	0.2214	-0.5923	0.1372
RE/TA	0.0070	0.0052	1.3412	0.1798	-0.0032	0.0172
EBIT/TA	-0.6616	0.3310	-1.9988	0.0456	-1.3103	-0.0128
MV/BV	0.0009	0.0029	0.2977	0.7659	-0.0047	0.0064
S/TA	0.0037	0.0865	0.0433	0.9654	-0.1657	0.1732

Logistic regression coefficients for baseline's experiements.

2004. Management has reduced our cost structure, improved our processes and systems and implemented new controls over capital and operational spending. We anticipate sales growth through internal product development efforts, additional contract services opportunities which we are actively pursuing and ongoing progress we are seeing with our strategic partners on new products development. Management believes these activities will improve our results of operations, cash flow from operations and our future pros-

Comparison of FinBERT's analysis on the Risk factors and MD&A sections

	Accuracy	**Precision**	**Recall**	**F1 Score**	**AUC**
Logistic regression(Risk Factors)	0.514	0.523	0.411	0.460	0.514
Random forest (Risk Factors)	0.739	0.737	0.750	0.743	0.739
SVM (Risk Factors)	0.712	0.707	0.732	0.719	0.712
Logistic regression(MD&A)	0.812	0.577	0.675	0.722	0.648
Random forest (MD&A)	0.78	0.866	0.821	0.811	0.911
SVM (MD&A)	0.818	0.8	0.808	0.811	0.851

Additional performance metrics for different models with different sets of predictors

Set of features and model used	Metrics					
	Accuracy	Precision	Recall	F1 Score	AUC	In-sample Accuracy
Baseline with FRG and GFI readability metrics						
Logistic regression	0.567	0.556	0.636	0.593	0.568	0.576
MLP	0.739	0.724	0.764	0.743	0.739	0.817
Random forest	0.784	0.782	0.782	0.782	0.784	0.887
SVM	0.712	0.683	0.782	0.729	0.712	0.864
Baseline with all readability metrics						
Logistic regression	0.656	0.635	0.733	0.680	0.656	0.696
MLP	0.678	0.682	0.667	0.674	0.678	0.719
Random forest	0.789	0.741	0.889	0.808	0.789	0.893
SVM	0.667	0.636	0.778	0.700	0.667	0.941
Baseline with Roberta's sentiment						
Logistic regression	0.532	0.583	0.250	0.350	0.534	0.549
MLP	0.739	0.755	0.714	0.734	0.739	0.872
Random forest	0.766	0.768	0.768	0.768	0.766	0.887
SVM	0.712	0.707	0.732	0.719	0.712	0.837
Baseline with Finbert's sentiment (Risk & MDA sections)						
Logistic regression	0.685	0.706	0.649	0.676	0.685	0.604
MLP	0.699	0.674	0.784	0.725	0.697	0.828
Random forest	0.808	0.767	0.892	0.825	0.807	0.899
SVM	0.726	0.743	0.703	0.722	0.726	0.840
Baseline with FinBERT and RoBERTa sentiments						
Logistic regression	0.658	0.696	0.571	0.627	0.658	0.603
MLP	0.748	0.750	0.750	0.750	0.748	0.875
Random forest	0.757	0.764	0.750	0.757	0.757	0.895
SVM	0.712	0.707	0.732	0.719	0.712	0.821
Baseline with FRG readability, LM & FinBERT sentiments						
Logistic regression	0.722	0.717	0.733	0.725	0.722	0.678
MLP	0.756	0.897	0.578	0.703	0.756	0.707
Random forest	0.822	0.784	0.889	0.833	0.822	0.893
SVM	0.833	0.841	0.822	0.831	0.833	0.867

pects. Our revenues are derived from sales of diagnostic and therapeutic pharmaceuticals by our ophthalmic segment, from sales of diagnostic and therapeutic pharmaceuticals by our hospital drugs and injectables segment, and from contract services revenue. The following table sets forth the percentage relationships that certain items from our Consolidated Statements of Operations bear to revenues for the years ended December 31, 2006, 2005 and 2004. ##TABLE_START Years Ended December 31, 2006 2005 2004 Revenues Ophthalmic 27 % 51 % 59 % Hospital Drugs Injectables 60 31 24 Contract Services 13 18 17 Total revenues 100 100 100 Gross profit Ophthalmic 9 % 18 % 29 % Hospital Drugs Injectables 26 13 6 Contract Services 3 3 1 Total Gross Profit 38 34 36 Selling, general and administrative expenses 26 37 26 Amortization and write-downs of intangibles 2 4 7 Research and development expenses 17 10 4 Operating loss (7) (17) (1) Net loss (8)% (19)% (6)% ##TABLE_END COMPARISON OF TWELVE MONTHS ENDED DECEMBER 31, 2006 AND 2005 Consolidated revenues increased 60%, or $26,766,000 for the year ended December 31, 2006 compared to the prior year. Ophthalmic segment revenues decreased 14%, or $3,131,000, primarily due to reduced sales of diagnostic and anesthetic products. Hospital Drugs and Injectables segment revenues increased 210% or $28,770,000 for the year, reflecting the increased volumes of anesthesia and antidote products. In particular, sales of $25,464,000 of DTPA radiation antidote products to HHS were a primary driver for the sales increase in this category. This large order level for DTPA is not expected to recur, although we do anticipate continued orders for this antidote product. Contract services revenues increased by 14%, or $1,127,000, mainly due to increased order volumes on contract products. The chargeback and rebate expense, a component of net revenues, for the year ended December 31, 2006 increased to $26,295,000 from $24,391,000 in 2005, due to a general increase in the product sales mix of higher chargeback and rebate percentage items along with increased price competition. Note that sales of our DTPA antidote product to HHS were not subject to chargeback or rebate expense. Consolidated gross profit of $26,880,000 was 38% for 2006 as compared to a gross profit of $14,944,000 or 34% for 2005. The gross profit of our ophthalmic segment decreased $2,000,000 or 25% due to a less favorable product mix and increased price competition. Our hospital drugs and injectables segment gross profit increased $12,374,000 or 216% mainly due to sales of DTPA radiation antidote products to HHS as noted above. Our contract services segment gross profit improved $1,562,000 or 138% from the prior year mainly due to an improved sales mix combined with process cost reductions. Selling, general and administrative (SGA) expenses increased 13%, to $18,603,000 for 2006 from $16,405,000 for 2005, mainly due to FAS 123R stock compensation expense of $1,229,000 in 2006, increased FDA fees of $537,000 and consulting fees for Sarbanes-Oxley 404 implementation of $435,000. Research and development (RD) expense increased significantly, by 162% in 2006, to $11,797,000 from $4,510,000 for the year 2005, mainly due to RD expenses related to lyophilization testing and validation, clinical studies costs for our new ophthalmic anesthetic product (Akten) and funding for product development with our strategic partners including costs for development of an oral anti-infective product. We anticipate continued higher spending levels in our RD for new product development activities. Interest expense decreased to $604,000 in 2006 from $2,325,000 in 2005, which represents a 74% decrease. This decrease is primarily due to lower outstanding borrowings in 2006 as we paid off debt and generated interest income in the latter part of 2006. This was partially offset by higher interest rates in 2006. Other income (expense) in 2006 was ($451,000) which was mainly due to an early debt retirement fee of $391,000 to retire high-interest debt in the first quarter of 2006. We recorded a valuation allowance to reduce the deferred income tax assets to the amount that is more likely than not to be realized. Accordingly, the income tax expense (benefit) recorded for 2006 and 2005 represents various minimum federal/state income tax expenses. As a result of the matters described above, net loss for 2006 was $5,963,000 versus a net loss in 2005 of $8,609,000, a $2,646,000 decrease in loss. After consideration of preferred stock dividends and adjustments in 2006 of $843,000 and 2005 of $4,082,000 related to specific accounting for our preferred stock (see Item 8. Financial Statements and Supplementary Data, Note H Preferred Stock), loss per share for 2006, on both a basic and diluted basis, was $0.09 on weighted average shares outstanding of 73,988,000 compared to a basic and diluted loss per share for 2005 of $0.49 on weighted average shares outstanding of 26,095,000. COMPARISON OF TWELVE MONTHS ENDED DECEMBER 31, 2005 AND 2004 Consolidated revenues decreased 12% for the year ended December 31, 2005 compared to the prior year. Ophthalmic segment revenues decreased 24%, or $7,153,000, primarily due to reduced sales of diagnostic and anesthetic products. Injectable segment revenues increased 11% or $1,378,000 for the year, reflecting the increased volumes of anesthesia and antidote products. Contract services revenues decreased by 5%, or $449,000, mainly due to lower volumes of contract research project work. The chargeback and rebate expense, a component of net revenues, for the year ended December 31, 2005 increased to $24,391,000 from $16,915,000 in 2004, due to a general increase in the product sales mix of higher chargeback and rebate percentage items along with increased price competition. Consolidated gross profit of $14,944,000 was 34% for 2005 as compared to a gross profit of $18,202,000 or 36% for 2004. The gross profit of our ophthalmic segment decreased $6,417,000 or 44% due to a less favorable product mix and increased price competition. Our hospital drugs and injectables segment gross profit increased $2,452,000 or 75% due to a sales mix shift toward higher margin antidote products and additional manufacturing volume efficiencies for these products. Our contract services segment gross profit improved $707,000 or 165% from the prior year mainly due to a reduction in unfavorable plant manufacturing variances at our Decatur manufacturing facility. SGA expenses increased 23%, to $16,405,000 for 2005 from $13,300,000 for 2004, due to the 2005 management bonuses ($1,479,000), reduced bad debt recoveries in 2005 ($777,000) and increased FDA fees ($557,000). Amortization and write-down of intangibles decreased by $1,901,000 due to an impairment charge of $2,037,000 in 2004 related to product license intangible assets for Biolon, Erythromycin, Cromolyn Sodium, AKWA Tears and Tears Renewed products. The carrying value of the intangible assets for these products was reduced to zero in 2004. RD expense increased significantly, by 142% in 2005, to $4,510,000 from $1,861,000 for the year ended December 31, 2004, mainly due to RD expenses related to lyophilization validation ($1,073,000) and product development expenses for Akorn-Strides, LLC ($757,000). We anticipate continued growth in our RD spending for new product development activities. Interest expense decreased to $2,325,000 in 2005 from $4,218,000 in 2004, which represents a 45% decrease. This decrease is primarily due to a decrease in Series A Preferred Stock interest expense ($1,064,000) and a decrease in deferred financing for warrants ($874,000). The residual difference is mainly due to lower outstanding borrowings in 2005 as a result of using a portion of our Series B Preferred Stock issuance in August 2004 to pay down bank debt and retire a promissory note held by NeoPharm, Inc. (NeoPharm) in 2005. This was partially offset by higher interest rates in 2005. Other income (expense) in 2005 was $1,212,000 due to gains related to retirement of the promissory note held by NeoPharm. The gain of $1,562,000 in 2004 was mainly the result of settlements of disputes which resulted in a gain on the sale of our investment in Novadaq Technologies, Inc. (Novadaq) and a lower than accrued payout on a prior dispute settlement. See Item 8. Financial Statements and Supplementary Data, Note E Investment in Novadaq Technologies. We recorded a valuation allowance to reduce the deferred income tax assets to the amount that is more likely than not to be realized. Accordingly, the income tax expense (benefit) recorded for 2005 and 2004 represents various minimum federal/state income tax expenses. As a result of the matters described above, net loss for 2005 was $8,609,000 versus a net loss in 2004 of $3,026,000, a $5,583,000 increase in loss. After consideration of preferred stock dividends and adjustments in 2005 of $4,082,000 and 2004 of $34,436,000 related to specific accounting for our preferred stock (see Item 8. Financial Statements and Supplementary Data, Note H Preferred Stock), loss per share for 2005, on both a basic and diluted basis, was $0.49 on weighted average shares outstanding of 26,095,000 compared to a basic and diluted loss per share for 2004 of $1.80 on weighted average shares outstanding of 20,817,000. FINANCIAL CONDITION AND LIQUIDITY Overview As a result of the factors outlined above, we have experienced losses from operations in 2006 and 2005 of $4,905,000 and $7,479,000, respectively and the net losses for these years were $5,963,000 and $ 8,609,000, respectively. As of December 31, 2006, we had cash and cash equivalents of $21,818,000. Our net working capital at December 31, 2006 was $29,401,000 versus a net working capital of $234,000 at December 31, 2005, resulting primarily from the increased cash levels from stock issuances and the decrease in debt as we retired our major debt instruments in the first quarter of 2006 (see discussion below). This reduced current debt by $6,650,000 from the prior year level. During the year ended December 31, 2006, we generated $2,509,000 in cash from operations as the net loss was offset by non-cash expenses of $6,379,000 for the period, a $785,000 change in working capital items and a $1,308,000 increase in the product warranty reserve related to our DTPA antidote product (see Critical Accounting Policies below). During 2005, we used $148,000 in cash from operations as the net loss was offset by $6,957,000 in non-cash expenses and a $2,966,000 reduction in working capital items (mainly attributable to lower receivables with wholesalers) while the non-cash gain on retirement of debt reduced the operating cash flow. Investing activities for 2006 generated a $4,377,000 reduction in cash flow mainly due to capital expenditures for production equipment. Investing activities during 2005 required $1,857,000 in cash and included $1,782,000 of property, plant, and equipment additions to our lyophilization facility and other manufacturing equipment in 2005. Financing activities for 2006 provided $22,895,000 in cash primarily due to the $18,078,000 net proceeds from the March 2006 common stock and warrants offering and an additional $3,543,000 from the September 2006 private placement with Serum. Financing activities for 2005 used $1,314,000 in cash primarily due to the $2,500,000 payment to retire the NeoPharm promissory note offset by $1,556,000 received from the sale of stock and exercise of warrants. On October 7, 2003, a group of investors (the Investors) purchased all of our then outstanding senior bank debt from The Northern Trust Company (Northern Trust), a balance of $37,731,000, at a discount and exchanged such debt with us (the Exchange Transaction) for (i) 257,172 shares of our Series A Preferred Stock, (ii) subordinated promissory notes in the aggregate principal amount of approximately $2,767,000 (the 2003 Subordinated Notes), (iii) warrants to purchase an aggregate of 8,572,400 shares of our common stock with an exercise price of $1.00 per share (Series A Warrants), and (iv) $5,473,862 in cash from the proceeds of the term loan under the Credit Facility described in a following paragraph. The 2003 Subordinated Notes and cash were issued by us to (a) The John N. Kapoor Trust dated 9/20/89 (the Kapoor Trust), the sole trustee and sole beneficiary of which is Dr. John N. Kapoor, our chairman of the board of directors and the holder of a significant stock position in Akorn, (b) Arjun Waney, a holder of a significant stock position in Akorn, and (c) Argent Fund Management Ltd., for which Mr. Waney serves as Chairman and Managing Director and 52% of which is owned by Mr. Waney. We also issued warrants (Note Warrants) to the holders of the 2003 Subordinated Notes to purchase an aggregate of 276,714 shares of common stock with an exercise price of $1.10 per share and paid a portion of the legal fees of the Investors. Simultaneously with the consummation of the Exchange Transaction, we entered into a credit agreement with LaSalle Bank National Association (LaSalle Bank) providing us with two term loans (collectively, the Term Loans) which consisted of a $5,500,000 term loan A, and a $1,500,000 term loan B, totaling $7,000,000, and a revolving line of credit of up to $5,000,000 (the Revolver) to provide for working capital needs (the Credit Facility) secured by substantially all of our assets. Our obligations under the Credit Facility were guaranteed by the Kapoor Trust and Mr. Waney. In exchange for this guaranty, we issued additional warrants (the Guaranty Warrants) to purchase 880,000 and 80,000 shares of common stock to the Kapoor Trust and Mr. Waney, respectively, with an exercise price of $1.10 per share. Such guarantees have since been released by LaSalle Bank. On August 23, 2004, we completed a private placement of 141,000 shares of our Series B Preferred Stock at a price of $100 per share, convertible into common stock at a price of $2.70 per share, with warrants to purchase 1,566,667 additional shares of our common stock exercisable until August 23, 2009, with an exercise price of $3.50 per share (Series B Warrants). The net proceeds to us after payment of investment banker fees and expenses and other transaction costs of approximately $1,056,000 were approximately $13,044,000. A portion of the net proceeds of the private placement of the Series B Preferred Stock paid off the outstanding debt from LaSalle Bank. The remainder of the net proceeds was used for working capital, payment of the NeoPharm promissory note, validation and testing of our new lyophilization facility and general corporate purposes. An additional common stock private placement offering was completed on March 8, 2006 which yielded net proceeds to us of approximately $18,078,000 which was used to reduce debt and fund additional product development activities and build a fund for future product development spending. On March 20, 2006 we retired the 2003 Subordinated Notes for a cash payment of $3,288,000 which included principal and interest. In September 2006, we issued 1,000,000 shares of our common stock in a private placement with Serum at a price of $3.56 per share. The offering price was $3,560,000 and the net proceeds to us, after payment of approximately $17,000 in expenses, were approximately $3,543,000. As of December 31, 2006, we had approximately $ 21,818,000 in cash and approximately $7,369,000 of undrawn availability under the Credit Facility with LaSalle Bank. We believe that our realigned balance sheet, access to our line of credit and capital markets and our cash flows from operations will be sufficient to operate our business for the next twelve months. Facility Expansion We are in the final stages of completing an expansion of our Decatur, Illinois manufacturing facility to add capacity to provide lyophilization manufacturing services, a manufacturing capability we currently do not have. As of December 31, 2006, we had spent approximately $22,433,000 on the lyophilization expansion and anticipate the need to spend approximately $200,000 of additional funds to complete the expansion related to the lyophilization equipment. These additional funds will primarily be used for testing and validation as the major capital equipment items are currently in place. In December 2006, we placed the building and sterile solutions portion of this operation ($17,237,000) in service which augments our existing production capacities. The remaining $5,196,000 of construction in progress, which is specific to lyophilization (freeze-dry) operations, is awaiting final review and a PAI by the FDA for us to place this equipment into commercial production. We anticipate the PAI review in the first half of 2007. In addition, we are working toward the development of an internal ANDA lyophilized product pipeline for these operations. Credit Facility As stated above, and further described in Item 8. Financial Statements and Supplementary Data, Note G Financing Arrangements, we entered into a Credit Facility with LaSalle Bank in 2003. The Credit Facility included the Term Loans, as well as the Revolver secured by substantially all of our assets. The Credit Facility will mature on September 30, 2008. The Term Loans carried interest at prime plus 1.75% and required principal payments of $195,000 per month commencing October 31, 2003, with the payments first to be applied to term loan B. The Revolver bears interest at prime plus 0.50 % (previously prime plus 1.50%). The Term Loans were paid off with the proceeds from our Series B Preferred Stock offering in August 2004 and we had a zero balance on the Revolver at December 31, 2006. Availability under the Revolver is determined by the sum of (i) 80% of eligible accounts receivable, (ii) 50% of raw material, finished goods and component inventory excluding packaging items, not to exceed $5,000,000, and (iii) the difference between 90%

of the forced liquidation value of machinery and equipment ($4,092,000) and the sum of $1,750,000 and the outstanding balance under term loan B (the term B loan was retired in August 2004). The Credit Facility contains certain restrictive covenants including but not limited to certain financial covenants such as EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization) to interest expense and Senior Debt to EBITDA ratios. If we are not in compliance with the covenants of the Credit Facility, LaSalle Bank has the right to declare an event of default and all of the outstanding balances owed under the Credit Facility would become immediately due and payable. The Credit Facility also contains subjective covenants providing that we would be in default if, in the judgment of the lenders, there is a material adverse change in our financial condition. We negotiated an amendment to the Credit Facility effective December 31, 2003 that clarified certain covenant computations and waived certain technical violations. Because the Credit Facility also requires us to maintain our deposit accounts with LaSalle, the existence of these subjective covenants, pursuant to EITF Abstract No. 95-22, require that we classify outstanding borrowings under the Revolver as a current liability (zero as of December 31, 2006). On August 13, 2004, we entered into the First Amendment to the Credit Facility (the First Amendment). Among other things, the First Amendment amended certain of our financial covenants and LaSalle Bank agreed to waive certain events of default arising out of our noncompliance with certain of our obligations. Certain financial conditions in the Kapoor Trust guaranty were also amended as a result of the First Amendment. On August 26, 2004, we entered into the Second Amendment to the Credit Facility (the Second Amendment), which released the Kapoor Trust guaranty and eliminated certain event of default provisions that were related to the Kapoor Trust guaranty. In addition, on August 27, 2004, LaSalle Bank cancelled each of the irrevocable standby letters of credit posted by Dr. Kapoor and Mr. Waney. On October 8, 2004, we entered into the Third Amendment to the Credit Facility (the Third Amendment) which waived events of default associated with the warrants issuance to AEG Partners, LLC (see Preferred Stock and Warrants discussion below) and the NeoPharm promissory note default (discussed below). In addition, the Third Amendment amended definitions of the Computation Period and EBITDA to Interest Expense Ratio for covenant calculations. On September 30, 2005, we entered into the Fourth Amendment to Credit Facility, (the Fourth Amendment) which, among other things, extended the term through September 30, 2008 and increased the revolving commitment amount under the Credit Facility from $5,000,000 to $10,000,000. On March 1, 2006, a subsequent Amendment, Waiver and Consent to Credit Agreement was made effective which adjusted the Credit Facility debt covenant computations for the periods ended December 31, 2005 and March 31, 2006. The revisions adjusted the defined EBITDA for certain RD expenses and the interest coverage formula to exclude interest paid on the NeoPharm promissory note retirement and thereby resolved a default on the debt covenants of the Credit facility at December 31, 2005. In addition it provided consent for the private placement of common stock in March of 2006 and waived certain defaults therefrom. On March 5, 2007, another Amendment, Waiver and Consent to Credit Agreement was made effective which adjusted the Credit Facility debt covenant computations for the periods ended December 31, 2006 and beyond. The revisions adjusted the defined EBITDA for certain RD expense levels and waived defaults prior to this revision. Subordinated Debt In 2001, we entered into a $5,000,000 convertible subordinated debt agreement including a $3,000,000 Tranche A note (Tranche A Note) and a $2,000,000 Tranche B note (Tranche B Note) with the Kapoor Trust (collectively, the Convertible Note Agreement). Under the terms of the Convertible Note Agreement, both Tranche A Note and Tranche B Note, which were due December 20, 2006, bore interest at prime plus 3% and were issued with detachable warrants (the Tranche A Warrants and the Tranche B Warrants) to purchase shares of common stock. Interest payments were prohibited under the terms of a subordination arrangement. The convertible feature of the Convertible Note Agreement, as amended, allowed for conversion of the subordinated debt plus interest into our common stock, at a price of $2.28 per share of common stock for Tranche A and $1.80 per share of common stock for Tranche B. The Company negotiated an early settlement of the Tranche A Note and the Tranche B Note in March 2006. The associated principal and accumulated interest of approximately $7,298,000 was retired by conversion into 3,540,281 shares of the Companys common stock on March 31, 2006. A debt retirement fee of approximately $391,000 was paid as an inducement to retire these notes prior to the original maturity date of December 20, 2006. In December 2001, we entered into a $3,250,000 five-year loan (the NeoPharm Note) with NeoPharm to fund the completion our lyophilization facility located in Decatur, Illinois. Dr. Kapoor, our chairman, is also a director of NeoPharm and holds a substantial stock position in NeoPharm, as well as in Akorn. Under the terms of the NeoPharm Note evidencing the loan, interest accrued at the initial rate of 3.6% to be reset quarterly based upon NeoPharms average return on its cash and readily tradable long and short-term securities during the previous calendar quarter. In consideration for the loan, under a separate processing agreement between us and NeoPharm, we agreed to provide NeoPharm with access to at least 15% of the capacity of its lyophilization facility each year upon completion of the lyophilization facility. The NeoPharm Note was subordinate to our senior debt owed to LaSalle Bank but was senior to the subordinated debt owed to the Kapoor Trust. On October 6, 2004, we received a notice from NeoPharm indicating that an event of default had occurred on the NeoPharm Note. The notice stated that an event of default was triggered when the processing agreement between NeoPharm and Akorn, which was contractually obligated to go into effect on or before October 1, 2004, failed to occur. The processing agreement failed to become effective, in part, because of our inability to remove the sanctions imposed by the FDA on our Decatur manufacturing facility. The event of default under the NeoPharm Note also triggered a cross-default provision under the Convertible Note Agreement. The Kapoor Trust waived the cross-default. Because of this default, we recorded the $3,250,000 of debt and $362,000 of accrued interest as current obligations as of December 31, 2004. On May 16, 2005, we paid all principal and interest due under the NeoPharm Note with a one-time cash payment of $2,500,000 and terminated the processing agreement between NeoPharm and us. On May 13, 2005, we entered into a Waiver and Consent to Credit Agreement with LaSalle Bank pursuant to which LaSalle Bank agreed to waive events of default arising out of our noncompliance with our obligations under the Credit Facility resulting from our pay-off of the NeoPharm Note. As part of the Exchange Transaction, we issued the 2003 Subordinated Notes to the Kapoor Trust, Arjun Waney and Argent Fund Management, Ltd. The 2003 Subordinated Notes were to mature on April 7, 2006 and bore interest at prime plus 1.75%. On March 20, 2006 the Company retired the 2003 Subordinated Notes with a cash payment of $3,288,000 which included the original $2,767,000 principal balance plus the accrued interest up to the date of payment. Other Indebtedness In June 1998, we entered into a $3,000,000 mortgage agreement with Standard Mortgage Investors, LLC, of which there were outstanding borrowings of $602,000 and $938,000 at December 31, 2006 and 2005, respectively. The principal balance is payable over 10 years, with the final payment due in June 2008. The mortgage note bears a fixed interest rate of 7.375% and is secured by the real property located in Decatur, Illinois. The fair value of the debt obligations approximated the recorded value as of December 31, 2006. Preferred Stock and Warrants Series A Preferred Stock Prior to its conversion, the Series A Preferred Stock accrued dividends at a rate of 6.0% per annum, which rate was fully cumulative, accrued daily and compounded quarterly. While the dividends could have been paid in cash at our option, such dividends were being deferred and were converted into our common stock. All shares of Series A Preferred Stock had liquidation rights in preference over junior securities, including the common stock, and had certain anti-dilution protections. The Series A Preferred Stock and unpaid dividends were convertible at any time into a number of shares of common stock equal to the quotient obtained by dividing (x) $100 per share plus any accrued but unpaid dividends on that share by (y) $0.75, as such numbers could be adjusted from time to time pursuant to the terms of the Restated Articles of Incorporation. All shares of Series A Preferred Stock were to convert to shares of common stock on the earlier to occur of (i) October 8, 2006 and (ii) the date on which the closing price per share of common stock for at least 20 consecutive trading days immediately preceding such date exceeds $4.00 per share. Until our shareholders approved certain provisions regarding the Series A Preferred Stock (the Stockholders Approval), which occurred in July 2004, the Series A Preferred Stock was also redeemable in October 2011. Holders of Series A Preferred Stock had full voting rights, with each holder entitled to a number of votes equal to the number of shares of common stock into which its shares could be converted. The initial amount recorded for the Series A Preferred Stock, as described in Item 8. Financial Statements and Supplementary Data, Note H Preferred Stock, was $5,174,000 below its stated value. Until the July 8, 2004 Stockholders Approval date we had been accreting this difference over the time period from issuance to the mandatory redemption date in October 2011. Accretion was $267,000 in 2004 and $220,000 in 2003. Pursuant to FASB No. 150 Accounting for Certain Financial Instruments with Characteristics of Both Liabilities and Equity, as amended, the Series A Preferred Stock was originally reflected as a liability because of its mandatory redemption feature. That characterization remained through July 8, 2004 and as such, dividends have been reflected as interest expense in the statement of operations through July 8, 2004. As a result of the Stockholders Approval on July 8, 2004, the carrying value of the Series A Preferred Stock was reclassified into shareholders equity and future dividends are reflected as adjustments to accumulated deficit and are shown in the financial statements as impacting income (loss) available to common stockholders. Additionally, and in accordance with EITF Abstract No. 00-27, we also recorded in July 2004 the value of the conversion option imbedded at issuance in each share of Series A Preferred Stock, subject to limitations described in the EITF. That value, approximately $20,874,000, reduced the carrying value of the Series A Preferred Stock to near zero with the offsetting excess to common stock. The carrying value of the Series A Preferred Stock was then adjusted to its full aggregated stated value, plus unpaid dividends (approximately $26,552,000) with a charge directly to accumulated deficit. That charge did not impact net earnings for the third quarter of 2004, but substantially reduced earnings available to common stockholders and generated a loss per share for that period. Effective as of January 13, 2006, pursuant to the automatic conversion provisions set forth in our Restated Articles of Incorporation, all 241,122 outstanding shares of Series A Preferred Stock immediately and automatically converted into an aggregate of 36,796,755 shares of our common stock, no par value. As set forth in our Restated Articles of Incorporation, all outstanding shares of Series A Preferred Stock immediately and automatically converted into shares of our common stock on the day after the closing price per share of the common stock exceeded $4.00 for 20 consecutive trading days. The closing price per share of the Common Stock as reported on the American Stock Exchange exceeded \$4.00 for 20 consecutive trading days as of the close of the market on January 12, 2006. Consequently, all outstanding shares of Series A Preferred Stock automatically converted into shares of our common stock on January 13, 2006. No shares of Series A Preferred Stock remain outstanding. Akorn received no consideration in connection with the automatic conversion. Series B Preferred Stock On August 23, 2004, we issued an aggregate of 141,000 shares of Series B Preferred Stock at a price of \$100 per share, convertible into common stock at a price of \$2.70 per share, to certain investors, with Series B Warrants to purchase 1,566,667 additional shares of common stock exercisable until August 23, 2009, with an exercise price of \$3.50 per share. The net proceeds to us after payment of investment banker fees and expenses and other transaction costs of approximately \$1,056,000 were approximately \$13,044,000. A portion of the proceeds was used to pay off the Term Loans and reduce the Revolver to zero. That early pay down and resulting elimination of certain personal guarantees of that debt resulted in the write-off of \$245,000 of unamortized deferred financing fees. Remaining proceeds were used for working capital and other general corporate purposes, including validation testing of our lyophilization facility. In accounting for the issuance of the Series B Preferred Stock and Series B Warrants, we recorded additional charges directly to accumulated deficit of \$5,998,000. That charge did not impact net earnings for the third quarter, but substantially reduced earnings available to common stockholders and earnings per share for that period. Prior to its conversion, the Series B Preferred Stock accrued dividends at a rate of 6.0% per annum, which rate was fully cumulative, accrued daily and compounded quarterly. While the dividends could be paid in cash at our option, such dividends were deferred and added to the Series B Preferred Stock balance. Each share of our Series B Preferred Stock, and accrued and unpaid dividends with respect to each such share, was convertible by the holder thereof at any time into a number of shares of our common stock equal to the quotient obtained by dividing (x) \$100 plus any accrued but unpaid dividends on such share by (y) \$2.70, as such numerator and denominator could be adjusted from time to time pursuant to the anti-dilution provisions of our Restated Articles of Incorporation governing the Series B Preferred Stock. We had the option of converting all shares of Series B Preferred Stock into shares of our common stock on any date after August 23, 2005 as to which the closing price per share of the common stock for at least 20 consecutive trading days immediately preceding such date exceeded \$5.00 per share. As required under the terms of the Series B Preferred Stock transaction, we completed the registration with the SEC of the common shares into which the Series B Preferred Stock is convertible in October 2004, among others. Had the registration statement not become effective within 270 days from August 23, 2004, each holder would have had the right to compel us to purchase its shares of Series B Preferred Stock for cash in an amount equal to \$115 per share (the Put Option). As a result of the Put Option, and pursuant to SEC rules and regulations, our Series B Preferred Stock was reflected outside of the shareholders equity section of our consolidated balance sheet until the registration statement became effective. Due to that registration, the holders of the Series B Preferred Stock could no longer put their shares back to us, and accordingly, the Series B Preferred Stock was reclassified into equity in October 2004. Immediately after the private placement of the Series B Preferred Stock, the purchasers of Series B Preferred Stock held approximately 31% of the aggregate voting rights represented by outstanding shares of common stock and Series B Preferred Stock. Immediately after the Series B Preferred Stock private placement and assuming the exercise of all outstanding conversion rights, warrants and options to acquire common stock, the purchasers of Series B Preferred Stock would hold approximately 9% of the common stock, on a fully-diluted basis. Prior to the Series B Preferred Stock private placement, the purchasers of Series B Preferred Stock held approximately 5% of the outstanding voting securities and would have held approximately 18% of the common stock on a fully-diluted basis. All outstanding shares of our Series B Preferred Stock were to immediately and automatically convert into shares of common stock on the day after the closing price per share of the common stock exceeded \$5.00 for 20 consecutive trading days and this occurred as of the close of the market on the American Stock Exchange on December 13, 2006. Consequently, all 66,000 outstanding shares of Series B Preferred Stock immediately and automatically converted into an aggregate of 2,804,800 shares of common stock on December 14, 2006. As of December 31, 2006, no shares of Series B Preferred Stock remain outstanding. Akorn received no consideration in connection with the automatic conversion. Warrants The Series A Warrants issued in connection with the Exchange Transaction for 8,572,400 shares of common stock at an exercise price of $1.00 per share were exercisable at any time prior to expiration on October 7, 2006. The Guaranty Warrants for 960,000 shares of common stock at an exercise price of $1.10 per share were issued in consideration of the debt guaranty as part of the Exchange Transaction. Also, as part of the Exchange Transaction, we issued the Note Warrants for 276,714 shares of common stock at an exercise price of $1.10 per share. In addition, there were Tranche A Warrants and Tranche B Warrants that were outstanding prior to the Exchange Transaction for 1,000,000 and 667,000 shares of common stock with per share exercise prices of $2.85 and $2.25, respectively. As of December 31, 2006, all of the outstanding Series A Warrants, Guaranty Warrants, Note Warrants, Tranche A, and Tranche B Warrants were exercised. The Series B Warrants are exercisable at any time prior to expiration on August 23, 2009. The warrants for 1,566,667 shares of common stock were issued on August 23, 2004 and have an exercise price of $3.50 per share. As of December 31, 2006, 555,555 warrants were exercised. As of December 31, 2006, there were 1,011,112 outstanding Series B Warrants. As further described in Item 8. Financial Statements and Supplemental Data, Note N Commitments and Contingencies, we have issued to AEG Partners, LLC (AEG) warrants (the AEG Warrants) to purchase 1,250,000 shares of our common stock at an exercise price of $0.75 per share . AEG exercised 200,000 of the AEG Warrants during 2006 and 800,000 AEG Warrants remain outstanding as of December 31, 2006. On March 8, 2006 we issued 4,311,669 shares of our common stock in a private placement with various investors at a price of $4.50 per share which included warrants to purchase 1,509,088 additional shares of common stock. The warrants are exercisable for a five year period at an exercise price of $5.40 per share and may be exercised by cash payment of the exercise price or by means of a cashless exercise. The aggregate offering price of the private placement was approximately $19,402,000 and the net proceeds to us, after payment of approximately $1,324,000 of commissions and expenses, was approximately $18,078,000. The net proceeds were allocated based on the relative fair market values of the common stock and warrants with $16,257,000 allocated to the common stock and $1,821,000 allocated to the warrants. CONTRACTUAL OBLIGATIONS (In Thousands) The following table details our future contractual obligations as of December 31, 2006. ##TABLE_START Payment Due by Period More than Description Total Less than 1 year 1-3 years 3-5 years 5 years Current and Long Term-Debt $ 602 $ 394 $ 208 $ $ Operating Leases 10,635 1,125 2,375 2,416 4,719 Interest Payments on Debt 35 31 4 Total : $ 11,272 $ 1,550 $ 2,587 $ 2,416 $ 4,719 ##TABLE_END SELECTED QUARTERLY FINANCIAL DATA (UNAUDITED) In Thousands, Except Per Share Amounts ##TABLE_START Net Income (Loss) Gross Per Share Per Share Revenues Profit Amount Basic Diluted Year Ended December 31, 2006 : 1st Quarter $ 29,730 $ 11,733 $ 3,126 $ 0.05 $ 0.04 2nd Quarter 12,475 4,955 (1,963) (0.03) (0.03) 3rd Quarter 14,490 5,951 (1,067) (0.02) (0.02) 4th Quarter 14,555 4,241 (6,059) (0.07) (0.07) Year Ended December 31, 2005 : 1st Quarter $ 10,181 $ 3,343 $ (2,287) $ (0.13) $ (0.13) 2nd Quarter 12,578 4,852 (67) (0.04) (0.04) 3rd Quarter 10,985 3,668 (2,614) (0.14) (0.14) 4th Quarter 10,740 3,081 (3,641) (0.18) (0.18) ##TABLE_END CRITICAL ACCOUNTING POLICIES Revenue Recognition We recognize product sales for our ophthalmic and hospital drugs and injectables business segments upon the shipment of goods or upon the delivery of goods, depending on the sales terms. The contract services segment, which produces products for third party customers, based upon their specification, at a pre-determined price, also recognizes sales upon the shipment of goods or upon delivery of the product or service as appropriate. Revenue is recognized when all of our obligations have been fulfilled and collection of the related receivable is probable. Provision for estimated doubtful accounts, chargebacks, rebates, discounts and product returns is made at the time of sale and is analyzed and adjusted, if necessary, at each balance sheet date. Allowance for Chargebacks and Rebates We enter into contractual agreements with certain third parties such as hospitals and group-purchasing organizations to sell certain products at predetermined prices. The parties have elected to have these contracts administered through wholesalers that buy the product from us and subsequently sell it to those third parties. When a wholesaler sells products to one of the third parties that are subject to a contractual price agreement, the difference between the price paid to us by the wholesaler and the price under the specific contract is charged back to us by the wholesaler. We track sales and submitted chargebacks by product number and contract for each wholesaler. Utilizing this information, we estimate a chargeback percentage for each product. We reduce gross sales and increase the chargeback allowance by the estimated chargeback amount for each product sold to a wholesaler. We reduce the chargeback allowance when we process a request for a chargeback from a wholesaler. Actual chargebacks processed can vary materially from period to period based upon actual sales volume through the wholesalers. However, our provision for chargebacks is fully reserved for at the time when sales revenues are recognized. We obtain certain wholesaler inventory reports to aid in analyzing the reasonableness of the chargeback allowance that will be paid out in the future. We assess the reasonableness of our chargeback allowance by applying the product chargeback percentage based on historical activity to the quantities of inventory on hand per the wholesaler inventory reports and an estimate of in-transit inventory that is not reported on the wholesaler inventory reports at the end of the period. In accordance with our accounting policy, our estimate of the percentage amount of wholesaler inventory that will ultimately be sold to a third party that is subject to a contractual price agreement is based on a six-quarter trend of such sales through wholesalers. We use this percentage estimate (95% as of December 31, 2006) until historical trends or new information indicate that a revision should be made. On an ongoing basis, we evaluate our actual chargeback rate experience and new trends are factored into our estimates each quarter as market conditions change. In the first quarter of 2004, we obtained more precise information from the wholesalers to estimate the amount of in-transit inventory, which lowered our estimate of in-transit inventory. This resulted in us recognizing approximately $500,000 less in chargeback expense in the first quarter of 2004. We have used this new information on a going forward basis as a more accurate estimate of in-transit inventory. Additionally, in the second quarter of 2004, we, in accordance with our policy, reduced our estimate of the percentage amount of wholesaler inventory that will ultimately be sold to a third party that is subject to a contractual price agreement. This reduction was made in reaction to a six-quarter trend of such sales being below our previous estimates, thereby confirming that the reduced percentage was other than temporary. This estimate change resulted in approximately $480,000 less in chargeback expense in the second quarter of 2004. In the fourth quarter of 2005, we reviewed our sales trends through wholesalers and revised the estimated percentage amount of wholesaler inventory that will ultimately be sold to a third party that is subject to a contractual price agreement which resulted in a $408,000 increase in chargeback expense in the fourth quarter 2005. We again reviewed and revised this same percentage estimate in the fourth quarter of 2006 which resulted in a $446,000 increase in the chargeback expense in the fourth quarter of 2006. We intend to use this revised estimate on a going forward basis until historical trends indicate that additional revisions should be made. Similarly, we maintain an allowance for rebates related to fee for service contracts and other programs with certain customers. Rebate percentages vary by product and by volume purchased by each eligible customer. We track sales by product number for each eligible customer and then apply the applicable rebate percentage, using both historical trends and actual experience to estimate our rebate allowance. We reduce gross sales and increase the rebate allowance by the estimated rebate amount when we sell our products to our rebate-eligible customers. We reduce the rebate allowance when we process a customer request for a rebate. At each balance sheet date, we analyze the allowance for rebates against actual rebates processed and make necessary adjustments as appropriate. Actual rebates processed can vary materially from period to period. However, our provision for rebates is fully reserved for at the time when sales revenues are recognized. The recorded allowances reflect our current estimate of the future chargeback and rebate liability to be paid or credited to our wholesaler and other customers under the various contracts and programs. For the years ended December 31, 2006, 2005, and 2004, we recorded chargeback and rebate expense of $26,295,000, $24,391,000 and $16,915,000, respectively. The allowance for chargebacks and rebates was $8,370,000 and $7,634,000 as of December 31, 2006 and 2005, respectively. Allowance for Product Returns Certain of our products are sold with the customer having the right to return the product within specified periods and guidelines for a variety of reasons, including but not limited to pending expiration dates. Provisions are made at the time of sale based upon tracked historical experience, by customer in some cases. In evaluating month-end allowance balances, we consider actual returns to date that are in process, the expected impact of product recalls and the wholesalers inventory information to assess the magnitude of unconsumed product that may result in a product return to us in the future. We estimate our sales returns reserve based on a historical percentage of returns to sales utilizing a twelve month look back period. One-time historical factors or pending new developments that would impact the expected level of returns are taken into account to determine the appropriate reserve estimate at each balance sheet date. The sales returns level can be impacted by factors such as overall market demand and market competition and availability for substitute products which can increase or decrease the end-user pull through for sales of our products and ultimately impact the level of sales returns. Actual returns experience and trends are factored into our estimates each quarter as market conditions change. Actual returns processed can vary materially from period to period. For the years ended December 31, 2006, 2005, and 2004, we recorded a provision for product returns of $3,861,000, $3,122,000 and $1,956,000, respectively. The allowance for potential product returns was $2,437,000 and $1,529,000 at December 31, 2006 and 2005, respectively. Allowance for Doubtful Accounts Provisions for doubtful accounts, which reflect trade receivable balances owed to us that are believed to be uncollectible, are recorded as a component of SGA expenses. In estimating the allowance for doubtful accounts, we have : ##TABLE_START Identified the relevant factors that might affect the accounting estimate for allowance for doubtful accounts, including : (a) historical experience with collections and write-offs ; (b) credit quality of customers ; (c) the interaction of credits being taken for discounts, rebates, allowances and other adjustments ; (d) balances of outstanding receivables, and partially paid receivables ; and (e) economic and other exogenous factors that might affect collectibility (e.g., bankruptcies of customers, channel factors, etc.). Accumulated data on which to base the estimate for allowance for doubtful accounts, including : (a) collections and write-offs data ; (b) information regarding current credit quality of customers ; and (c) information regarding exogenous factors, particularly in respect of major customers. Developed assumptions reflecting our judgments as to the most likely circumstances and outcomes, regarding, among other matters : (a) collectibility of outstanding balances relating to partial payments ; (b) the ability to collect items in dispute (or subject to reconciliation) with customers ; and (c) economic and other exogenous factors that might affect collectibility of outstanding balances based upon information available at the time. ##TABLE_END For the years ended December 31, 2006, 2005, and 2004, we recorded a net expense/(benefit) for doubtful accounts of ($150,000), $74,000, and ($43,000), respectively. The 2005 expense was mainly due to one uncollectible account while the favorable experience in 2006 and 2004 was due to recoveries and reduced reserve requirements which exceeded write offs and reduced previously identified collectibility concerns. The allowance for doubtful accounts was $3,000 and $13,000 as of December 31, 2006 and 2005, respectively. As of December 31, 2006, we had a total of $ 196,000 of past due gross accounts receivable, of which $54,000 was over 60 days past due. We perform monthly a detailed analysis of the receivables due from our wholesaler customers and provide a specific reserve against known uncollectible items for each of the wholesaler customers. We also include in the allowance for doubtful accounts an amount that we estimate to be uncollectible for all other customers based on a percentage of the past due receivables. The percentage reserved increases as the age of the receivables increases. Allowance for Discounts Cash discounts are available to certain customers based on agreed upon terms of sale. We evaluate the discount reserve balance against actual discounts taken. For the years ended December 31, 2006, 2005, and 2004, we recorded a provision for discounts of $1,595,000, $1,003,000 and $925,000 respectively. The allowance for discounts was $236,000 and $244,000 as of December 31, 2006 and 2005, respectively. Allowance for Slow-Moving Inventory Inventories are stated at the lower of cost (average cost method) or market. See Item 8. Financial Statements and Supplementary Data, Note D Inventories. We maintain an allowance for slow-moving and obsolete inventory. For finished goods inventory, we estimate the amount of inventory that may not be sold prior to its expiration or is slow moving based upon recent sales activity by unit and wholesaler inventory information. We also analyzed our raw material and component inventory for slow moving items. For the years ended December 31, 2006, 2005, and 2004, we recorded a provision for inventory obsolescence of $652,000, $530,000 and $1,290,000, respectively. The allowance for inventory obsolescence was $ 510,000 and $916,000 as of December 31, 2006 and 2005, respectively. Warranty Liability The DTPA product warranty relates to a ten year expiration guarantee on DTPA sold to HHS. We are performing yearly stability studies for this product and, if the annual stability does not support the ten-year product life, we will replace the product at no charge. Our supplier, Hameln Pharmaceuticals, will also share this cost if we do not meet the DTPA stability requirement. If the ongoing product testing confirms the ten-year stability for DTPA we will not incur a replacement cost and this reserve will be eliminated with a corresponding reduction to cost of sales after the ten-year period. Income Taxes Deferred income tax assets and liabilities are determined based on differences between financial reporting and tax bases of assets and liabilities, and net operating loss and other tax credit carryforwards. These items are measured using the enacted tax rates and laws that will be in effect when the differences are expected to reverse. We record a valuation allowance to reduce the deferred income tax assets to the amount that is more likely than not to be realized. Intangibles Intangibles consist primarily of product licensing and other such costs that are capitalized and amortized on the straight-line method over the lives of the related license periods or the estimated life of the acquired product, which range from 3 years to 18 years. Accumulated amortization at December 31, 2006 and 2005 was $16,260,000 and $14,875,000, respectively. Amortization expense was $1,385,000, $1,508,000, and $1,372,000 for the years ended December 31, 2006, 2005, and 2004, respectively. We regularly assess the impairment of intangibles based on several factors, including estimated fair market value and anticipated cash flows. In 2004, we recorded impairment charges on certain intangible assets. See Item 8. Financial Statements and Supplementary Data, Note S Asset Impairment Charges. Stock-Based Compensation Under SFAS No. 123(R), stock compensation cost is estimated at the grant date based on the fair value of the award, and the cost is recognized as expense ratably over the vesting period. We have historically used the Black-Scholes model for estimating the fair value of stock options in providing the pro forma fair value method disclosures pursuant to SFAS No. 123 and have decided to continue using this model under SFAS No. 123(R). Determining the assumptions that enter into the model is highly subjective and requires judgment. We use an expected volatility that is based on the historical volatility of our stock. The expected life assumption is based on historical employee exercise patterns and employee post-vesting termination behavior. The risk-free interest rate for the expected term of the option is based on the average market rate on U.S. treasury securities in effect during the quarter in which the options were granted. The dividend yield reflects historical experience as well as future expectations over the expected term of the option. Also, under SFAS No. 123(R), we are required to estimate forfeitures at the time of grant and revise in subsequent periods, if necessary, if actual forfeitures differ from those estimates. After reviewing historical forfeiture information, we have decided to use 10% as an estimated forfeiture rate. RECENT ACCOUNTING PRONOUNCEMENTS In February 2006, the Financial Accounting Standard Board (FASB) issued SFAS No. 155, Accounting for Certain Hybrid Financial Instruments An Amendment of FASB Statements No. 133 and 140 . This statement amends SFAS No. 133, Accounting for Derivative Instruments and Hedging Activities , and No. 140, Accounting for Transfers and Servicing of Financial Assets and Extinguishments of Liabilities . SFAS No. 155 permits fair value remeasurement for any hybrid financial instrument that contains an embedded derivative that otherwise would require bifurcation. This statement also establishes a requirement to evaluate interests in securitized financial assets to identify interests that are freestanding derivatives or that are hybrid financial instruments that contain an embedded derivative requiring bifurcation. SFAS No. 155 is effective for all financial instruments acquired, issued, or subject to a remeasurement event occurring in fiscal years beginning after December 15, 2006. We do not expect that the adoption of SFAS No. 155 will have a significant impact on our consolidated financial statements. In September 2005, the EITF reached a consensus on Issue No. 05-8, Income Tax Consequences of Issuing Convertible Debt with a Beneficial Conversion Feature. Under EITF 05-8, the issuance of convertible debt with a beneficial conversion feature results in a temporary difference for purposes of applying Statement 109. The deferred taxes recognized for the temporary difference should be recorded as an adjustment to paid-in capital. EITF 98-5 Accounting for Convertible Securities with Beneficial Conversion Features or Contingently Adjustable Conversion Ratios and EITF 00-27 Application of Issue No. 98-5 to Certain Convertible Instruments require that the non-detachable conversion feature of a convertible debt security be accounted for separately if it is a beneficial conversion feature. A beneficial conversion feature is recognized and measured by allocating to additional paid-in capital a portion of the proceeds equal to the conversion features intrinsic value. A discount on the convertible debt is recognized for the amount that is allocated to additional paid-in capital. The debt discount is accreted from the date of issuance to the stated redemption date of the convertible instrument or through the earliest conversion date if the instrument does not have a stated redemption date. The U.S. Federal Income Tax Code includes the entire amount of proceeds received at issuance as the tax basis of the convertible debt security. The EITF 05-8 Consensus should be applied retrospectively to all instruments with a beneficial conversion feature accounted for under EITF 98-5 and EITF 00-27 for periods beginning after December 15, 2005. The adoption of EITF 05-8 did not had have a material impact on our financial statements. In May 2005, the FASB issued SFAS No. 154, Accounting Changes and Error Corrections (SFAS 154), which replaces APB Opinion No. 20, Accounting Changes and SFAS No. 3, Reporting Accounting Changes in Interim Financial Statements. SFAS 154 retained accounting guidance related to changes in estimates, changes in a reporting entity and error corrections. However, changes in accounting principles must be accounted for retrospectively by modifying the financial statements of prior periods unless it is impracticable to do so. SFAS 154 is effective for accounting changes made in fiscal years beginning after December 15, 2005. The adoption of SFAS 154 did not have a material impact on our financial position, results of operations or cash flows. In December 2004, the FASB issued SFAS No. 123 (revised 2004), Share-Based Payment (SFAS No. 123R), which revised and replaced SFAS No. 123, Accounting for Stock-Based Payments and superseded APB Opinion No. 25, Accounting for Stock Issued to Employees (APB 25).

SFAS 123R requires the measurement of all share-based payments to employees, including grants of employee stock options, using a fair-value based method and the recording of such expense in its consolidated statements of operations. The pro forma disclosures previously permitted under SFAS No. 123 are no longer an alternative to financial statement recognition. The provisions for SFAS No. 123R are effective for the first interim or annual reporting period beginning after June 15, 2005. We adopted SFAS No. 123R on January 1, 2006. SFAS 123R permits public companies to adopt its requirements using one of two methods. The first adoption method is a modified prospective method in which compensation cost is recognized beginning with the effective date (i) based on the requirements of SFAS 123R for all share-based payments granted after the effective date and (ii) based on the requirements of SFAS 123 for all awards granted to employees prior to the effective date of SFAS 123R that remain unvested on the effective date. The second adoption method is a modified retrospective method, which includes the requirements of the modified prospective method described above, but also permits entities to restate, based on the amounts previously recognized under SFAS 123 for purposes of pro forma disclosures, either (i) all prior periods presented or (ii) prior interim periods in the year of adoption. We elected the modified prospective method and did not restate prior year amounts. The adoption of SFAS 123Rs fair value method did have a significant impact on our results of operations, although it had no impact on our overall financial position. Had we adopted SFAS 123R in prior years, the impact of that adoption would have approximated the impact of SFAS 123, as described in the disclosure of pro forma net earnings and pro forma earnings per share. In November 2005, the FASB issued FASB Staff Position (FSP) No. 123(R)-3, Transition Election Related to Accounting for Tax Effects of Share-Based Payment Awards (FSP 123(R)-3). We elected to adopt the alternative transition method provided in FSP 123(R)-3 for calculating the tax effects of stock-based compensation pursuant to SFAS 123-(R). In June 2006, the FASB issued FASB Interpretation No. 48, Accounting for Uncertainty in Income Taxes an interpretation of FASB Statement No. 109 (FIN 48). FIN 48 clarifies the accounting for uncertainty in income taxes by prescribing a recognition threshold and measurement attribute for the financial statement recognition and measurement of a tax position taken or expected to be taken in a tax return. The interpretation also provides guidance on derecognition, classification, interest and penalties, accounting in interim periods, and disclosure. FIN 48 is effective January 1, 2007. We are in the process of evaluating the impact that FIN 48 will have on our Consolidated Financial Statements. At this time we do not believe that adoption of FIN 48 will have a material impact on our financial position, results of operations or cash flows. In September 2006 the FASB issued SFAS No. 157, Fair Value Measurements (SFAS 157), which provides guidance on how to measure assets and liabilities that use fair value. SFAS 157 will apply whenever another U.S. GAAP standard requires (or permits) assets or liabilities to be measured at fair value but does not expand the use of fair value to any new circumstances. This standard will also require additional disclosures in both annual and quarterly reports. SFAS 157 will be effective for financial statements issued for fiscal years beginning after November 15, 2007. The adoption of SFAS 157 is not expected to have a material impact on our results of operations or financial position. In September 2006, the SEC issued SAB No. 108, Considering the Effects of Prior Year Misstatements when Quantifying Misstatements in Current Year Financial Statements. This Bulletin addresses quantifying the financial statement effects of misstatements, including how the effects of prior year uncorrected errors must be considered in quantifying misstatements in the current year financial statements. This Bulletin is effective for fiscal years ending after November 15, 2006 and allows for a one-time transitional cumulative effect adjustment to beginning retained earnings in the fiscal year adopted for errors that were not previously deemed material, but are material under the guidance in SAB No. 108. The adoption of this Bulletin is not expected to have a material impact on our financial statements.

AKORN INC Risk Factors

Item 1A. Risk Factors. We have experienced recent operating losses, working capital deficiencies and negative cash flows from operations, and these losses and deficiencies may continue in the future. Our recent operating losses, working capital deficiencies and negative cash flows from operations may continue in the future and there can be no assurance that our financial outlook will improve. For the years ended December 31, 2005 and 2004, our operating losses were $7,479,000 and $368,000, respectively. We experienced negative cash flows from operations for the years ended December 31, 2005 and 2004 of $148,000 and $3,461,000, respectively. There can be no assurance that our results of operations will improve in the future. If our results of operations do not improve in the future, an investment in our common stock could be negatively affected. We have invested significant resources in the development of lyophilization manufacturing capability, and we may not realize the benefit of these efforts and expenditures . We are in the process of completing an expansion of our Decatur, Illinois manufacturing facility to add capacity to provide lyophilization manufacturing services, a manufacturing capability we currently do not have. Validation and approval of the lyophilization facility by the FDA is anticipated in the second quarter of 2006. As of December 31, 2005, we had spent approximately $19,691,000 on the lyophilization expansion and anticipate the need to spend approximately $1,000,000 of additional funds (excluding capitalized interest) which will primarily be used for testing and validation as the major capital equipment items are currently in place. In addition, we are working toward the development of an internal ANDA lyophilized product pipeline. Manufacturing capabilities for lyophilized products are projected to be in place by mid-2006. However, there is no guarantee that we will be successful in completing development of lyophilization capability, or that other intervening events will not occur that reduce or eliminate the anticipated benefits from such capability. For instance, the market for lyophilized products could significantly diminish or be eliminated, or new technological advances could render the lyophilization process obsolete, prior to our entry into the market. There can be no assurance that we will realize the anticipated benefits from our significant investment into lyophilization capability at our Decatur manufacturing facility, and our failure to do so could significantly limit our ability to grow our business in the future. We depend on a small number of distributors, the loss of any of which could have a material adverse effect. A small number of large wholesale drug distributors account for a large portion of our gross sales, revenues and accounts receivable. The following three distributors, AmerisourceBergen, Cardinal and McKesson, accounted for approximately 69% of total gross sales and 46% of total revenues in 2005, and 76% of gross trade receivables as of December 31, 2005. In addition to acting as distributors of our products, these three companies also distribute a broad range of health care products for many other companies. The loss of one or more of these distributors, together with a delay or inability to secure an alternative distribution source for end users, could have a material negative impact on our revenue and results of operations and lead to a violation of debt covenants. A change in purchasing patterns, inventory levels, increases in returns of our products, delays in purchasing products and delays in payment for products by one or more distributors also could have a material negative impact on our revenue and results of operations. Certain of our directors are subject to conflicts of interest. Dr. John N. Kapoor, Ph.D., our chairman of our board of directors, our chief executive officer from March 2001 to December 2002, and a principal shareholder, is affiliated with EJ Financial Enterprises, Inc. (EJ Financial), a health care consulting investment company. EJ Financial is involved in the management of health care companies in various fields, and Dr. Kapoor is involved in various capacities with the management and operation of these companies. The John N. Kapoor Trust dated 9/20/89 (the Kapoor Trust), the beneficiary and sole trustee of which is Dr. Kapoor, is a principal shareholder of each of these companies. As a result, Dr. Kapoor does not devote his full time to our business. Although such companies do not currently compete directly with us, certain companies with which EJ Financial is involved are in the pharmaceutical business. Discoveries made by one or more of these companies could render our products less competitive or obsolete. The Kapoor Trust has also loaned us $5,000,000 resulting in Dr. Kapoor effectively becoming a major creditor of ours as well as a major shareholder. Potential conflicts of interest could have a material adverse effect on our business, financial condition and results of operations. We may require additional capital to grow our business and such funds may not be available to us. We may require additional funds to grow our business. However, adequate funds through the financial markets or from other sources may not be available when needed or on terms favorable to us due to our recent financial history. Further, the terms of such additional financing, if obtained, likely will require the granting of rights, preferences or privileges senior to those of our common stock and result in substantial dilution of the existing ownership interests of our common stockholders and could include covenants and restrictions that limit our ability to operate or expand our business in a manner that we deem to be in our best interest. Our growth depends on our ability to timely develop additional pharmaceutical products and manufacturing capabilities. Our strategy for growth is dependent upon our ability to develop products that can be promoted through current marketing and distributions channels and, when appropriate, the enhancement of such marketing and distribution channels. We may not meet our anticipated time schedule for the filing of ANDAs and NDAs or may decide not to pursue ANDAs or NDAs that we have submitted or anticipate submitting. Our internal development of new pharmaceutical products is dependent upon the research and development capabilities of our personnel and our strategic business alliance infrastructure. There can be no assurance that we or our strategic business alliances will successfully develop new pharmaceutical products or, if developed, successfully integrate new products into our existing product lines. In addition, there can be no assurance that we will receive all necessary FDA approvals or that such approvals will not involve delays, which adversely affect the marketing and sale of our products. Our failure to develop new products, to maintain substantial compliance with FDA compliance guidelines or to receive FDA approval of ANDAs or NDAs, could have a material adverse effect on our business, financial condition and results of operations. We have entered into several strategic business alliances which may not result in marketable products. We have entered several strategic business alliances that have been formed to supply us with low cost finished dosage form products. Since 2004, we have entered into various purchase and supply agreements, license agreements, and a joint venture that are all designed to provide finished dosage form products that can be marketed through our distribution pipeline. However, there can be no assurance that any of these agreements will result in FDA-approved ANDAs or NDAs, or that we will be able to market any such finished dosage form products at a profit. In addition, any clinical trial expenses that we incur may result in adverse financial consequences to our business. Our success depends on the development of generic and off-patent pharmaceutical products which are particularly susceptible to competition, substitution policies and reimbursement policies. Our success depends, in part, on our ability to anticipate which branded pharmaceuticals are about to come off patent and thus permit us to develop, manufacture and market equivalent generic pharmaceutical products. Generic pharmaceuticals must meet the same quality standards as branded pharmaceuticals, even though these equivalent pharmaceuticals are sold at prices that are significantly lower than that of branded pharmaceuticals. Generic substitution is regulated by the federal and state governments, as is reimbursement for generic drug dispensing. There can be no assurance that substitution will be permitted for newly approved generic drugs or that such products will be subject to government reimbursement. In addition, generic products that third parties develop may render our generic products noncompetitive or obsolete. There can be no assurance that we will be able to consistently bring generic pharmaceutical products to market quickly and efficiently in the future. An increase in competition in the sale of generic pharmaceutical products or our failure to bring such products to market before our competitors could have a material adverse effect on our business, financial condition and results of operations. Further, there is no proprietary protection for most of the branded pharmaceutical products that either we or other pharmaceutical companies sell. In addition, governmental and cost-containment pressures regarding the dispensing of generic equivalents will likely result in generic substitution and competition generally for our branded pharmaceutical products. We attempt to mitigate the effect of this substitution through, among other things, creation of strong brand-name recognition and product-line extensions for our branded pharmaceutical products, but there can be no assurance that we will be successful in these efforts. We can be subject to legal proceedings against us, which may prove costly and time-consuming even if meritless. In the ordinary course of our business, we can be involved in legal actions with both private parties and certain government agencies. To the extent that our personnel may have to spend time and resources to pursue or contest any matters that may be asserted from time to time in the future, this represents time and money that is not available for other actions that we might otherwise pursue which could be beneficial to our future. In addition, to the extent that we are unsuccessful in any legal proceedings, the consequences could have a negative impact on our business, financial condition and results of operations. See Item 3. Legal Proceedings. Our revenues depend on sale of products manufactured by third parties, which we cannot control. We derive a significant portion of our revenues from the sale of products manufactured by third parties, including our competitors in some instances. There can be no assurance that our dependence on third parties for the manufacture of such products will not adversely affect our profit margins or our ability to develop and deliver our products on a timely and competitive basis. If for any reason we are unable to obtain or retain third-party manufacturers on commercially acceptable terms, we may not be able to distribute certain of our products as planned. No assurance can be made that the manufacturers we use will be able to provide us with sufficient quantities of our products or that the products supplied to us will meet our specifications. Any delays or difficulties with third-party manufacturers could adversely affect the marketing and distribution of certain of our products, which could have a material adverse effect on our business, financial condition and results of operations. Dependence on key executive officers. Our success will depend, in part, on our ability to attract and retain key executive officers. We are particularly dependent upon Dr. John N. Kapoor, Ph.D., chairman of our board of directors, and Mr. Arthur S. Przybyl, our chief executive officer. The inability to attract and retain key executive officers, or the loss of one or more of our key executive officers could have a material adverse effect on our business, financial condition and results of operations. We must continue to attract and retain key personnel to be able to compete successfully. Our performance depends, to a large extent, on the continued service of our key research and development personnel, other technical employees, managers and sales personnel and our ability to continue to attract and retain such personnel. Competition for such personnel is intense, particularly for highly motivated and experienced research and development and other technical personnel. We are facing increasing competition from companies with greater financial resources for such personnel. There can be no assurance that we will be able to attract and retain sufficient numbers of highly skilled personnel in the future, and the inability to do so could have a material adverse effect on our business, operating results and financial condition and results of operations. We are subject to extensive government regulations that increase our costs and could subject us to fines, prevent us from selling our products or prevent us from operating our facilities. Federal and state government agencies regulate virtually all aspects of our business. The development, testing, manufacturing, processing, quality, safety, efficacy, packaging, labeling, record keeping, distribution, storage and advertising of our products, and disposal of waste products arising from such activities, are subject to regulation by the FDA, DEA, FTC, the Consumer Product Safety Commission, the Occupational Safety and Health Administration and the Environmental Protection Agency. Similar state and local agencies also have jurisdiction over these activities. Noncompliance with applicable United States regulatory requirements can result in fines, injunctions, penalties, mandatory recalls or seizures, suspensions of production, recommendations by the FDA against governmental contracts and criminal prosecution. Any of these could have a material adverse effect on our business, financial condition and results of operations. New, modified and additional regulations, statutes or legal interpretation, if any, could, among other things, require changes to manufacturing methods, expanded or different labeling, the recall, replacement or discontinuation of certain products, additional record keeping and expanded documentation of the properties of certain products and scientific substantiation. Such changes or new legislation could have a material adverse effect on our business, financial condition and results of operations. See Government Regulation. FDA regulations. All pharmaceutical manufacturers, including us, are subject to regulation by the FDA under the authority of the FDC Act. Under the FDC Act, the federal government has extensive administrative and judicial enforcement powers over the activities of pharmaceutical manufacturers to ensure compliance with FDA regulations. Those powers include, but are not limited to, the authority to initiate court action to seize unapproved or non-complying products, to enjoin non-complying activities, to halt manufacturing operations that are not in compliance with cGMP, to recall products, to seek civil and monetary penalties and to criminally prosecute violators. Other enforcement activities include refusal to approve product applications or the withdrawal of previously approved applications. Any such enforcement activities, including the restriction or prohibition on sales of products we market or the halting of our manufacturing operations, could have a material adverse effect on our business, financial condition and results of operations. In addition, product recalls may be issued at our discretion, or at the request of the FDA or other government agencies having regulatory authority for pharmaceutical products. Recalls may occur due to disputed labeling claims, manufacturing issues, quality defects or other reasons. No assurance can be given that restriction or prohibition on sales, halting of manufacturing operations or recalls of our pharmaceutical products will not occur in the future. Any such actions could have a material adverse effect on our business, financial condition and results of operations. Further, such actions, in certain circumstances, could constitute an event of default under the terms of our various financing relationships. We must obtain approval from the FDA for each pharmaceutical product that we market. The FDA approval process is typically lengthy and expensive, and approval is never certain. Our new products could take a significantly longer time than we expect to gain regulatory approval and may never gain approval. Even if the FDA or another regulatory agency approves a product, the approval may limit the indicated uses for a product, may otherwise limit our ability to promote, sell and distribute a product or may require post-marketing studies or impose other post-marketing obligations. We and our third-party manufacturers are subject to periodic inspection by the FDA to assure regulatory compliance regarding the manufacturing, distribution, and promotion of sterile pharmaceutical products. The FDA imposes stringent mandatory requirements on the manufacture and distribution of sterile pharmaceutical products to ensure their sterility. The FDA also regulates drug labeling and the advertising of prescription drugs. A finding by a governmental agency or court that we are not in compliance with FDA requirements could have a material adverse effect on our business, financial condition and results of operations. We were previously subject to an FDA Warning Letter which the FDA issued to us in October 2000 following a routine inspection of our Decatur manufacturing facility. An FDA Warning Letter is intended to provide notice to a company of violations of the laws administered by the FDA and to elicit voluntary corrective action. The Warning Letter cited violations of regulatory requirements identified during the 2000 inspection and requested that we take corrective actions. Under the terms of the Warning Letter, we were unable to obtain any approvals to market new products and government agencies were notified of our non-compliant status. Additional FDA inspections in 2002, 2003 and 2004 identified additional and recurring violations resulting in continuance of the Warning Letter. During this time, the FDA initiated no enforcement action. Since 2000, and in response to the violations cited by the FDA, we implemented a comprehensive systematic corrective action plan at our Decatur manufacturing facility. We maintained regular communications with the FDA and provided periodic progress reports. On December 13, 2005, the FDA notified us that we had satisfactorily implemented corrective actions and that the FDA had determined that our Decatur manufacturing facility was in substantial compliance with cGMP regulations. Consequently, the restrictions of the 2000 Warning Letter were removed and we became eligible for new product approvals for products manufactured at our Decatur manufacturing facility. If the FDA changes its regulatory position, it could force us to delay or suspend indefinitely, our manufacturing, distribution or sales of certain products. While we believe that all of our current pharmaceuticals are lawfully marketed in the United States under current FDA enforcement policies or have received the requisite agency approvals for manufacture and sale, such marketing authority is subject to withdrawal by the FDA. In addition, modifications or enhancements of approved products are in many circumstances subject to additional FDA approvals which may or may not be granted and which may be subject to a lengthy application process. Any change in the FDAs enforcement policy or any decision by the FDA to require an approved NDA or ANDA for one of our products not currently subject to the approved NDA or ANDA requirements or any delay in the FDA approving an NDA or ANDA for one of our products could have a material adverse effect on our business, financial condition and results of operations. A number of products we market are grandfathered drugs that are permitted to be manufactured and marketed without FDA-issued ANDAs or NDAs on the basis of their having been marketed prior to enactment of relevant sections of the FDC Act. The regulatory status of these products is subject to change and/or challenge by the FDA, which could establish new standards and limitations for manufacturing and marketing such products, or challenge the evidence of prior manufacturing and marketing upon which grandfathering status is based. We are not aware of any current efforts by the FDA to change the status of any of our grandfathered products, but there can be no assurance that such initiatives will not occur in the future. Any such change in the status of our grandfathered products could have a material adverse effect on our business, financial condition and results of operations. We are subject to extensive DEA regulation, which could result in our being fined or otherwise penalized. We also manufacture and sell drugs which are controlled substances as defined in the federal Controlled Substances Act and similar state laws, which impose, among other things, certain licensing, security and record keeping requirements administered by the DEA and similar state agencies, as well as quotas for the manufacture, purchase and sale of controlled substances. The DEA could limit or reduce the amount of controlled substances which we are permitted to manufacture and market. See Item 1. Business DEA Regulation. We may implement product recalls and could be exposed to significant product liability claims; we may have to pay significant amounts to those harmed and may suffer from adverse publicity as a result. The manufacturing and marketing of pharmaceuticals involves an inherent risk that our products may prove to be defective and cause a health risk. In that event, we may voluntarily implement a recall or market withdrawal or may be required to do so by a regulatory authority. We have recalled products in the past and, based on this experience, believe that the occurrence of a recall could result in significant costs to us, potential disruptions in the supply of our products to our customers and adverse publicity, all of which could harm our ability to market our products. There were no product recalls in 2004 or 2005. In February 2003, we recalled two products, Fluress and Fluoracaine, due to container/closure integrity problems resulting in leaking containers. The recall was classified by the FDA as a Class II Recall, which means that the use of, or exposure to, a violative product may cause temporary or medically reversible adverse health consequences or that the probability of serious health consequences as a result of such use or exposure is remote. In March 2003, as a result of the December 10, 2002 to February 6, 2003 FDA inspection, we recalled twenty-four lots of product produced from the period December 2001 to June 2002 in one of our production rooms at our Decatur manufacturing facility. The majority of the lots recalled were for third party contract customer products. Subsequent to this decision and after discussions with the FDA, eight of the original twenty-four lots were exempted from the recall due to medical necessity. The recall was classified by the FDA as a Class II Recall. Although we are not currently subject to any material product liability proceedings, we may incur material liabilities relating to product liability claims in the future. Even meritless claims could subject us to adverse publicity, hinder us from securing insurance coverage in the future and require us to incur significant legal fees and divert the attention of the key employees from running our business. Successful product liability claims brought against us could have a material adverse effect on our business, financial condition and results of operations. We currently have product liability insurance in the amount of $5,000,000 for aggregate annual claims with a $50,000 deductible per incident and a $250,000 aggregate annual deductible. However, there can be no assurance that such insurance coverage will be sufficient to fully cover potential claims. Additionally, there can be no assurance that adequate insurance coverage will be available in the future at acceptable costs, if at all, or that a product liability claim would not have a material adverse effect on our business, financial condition and results of operations. The FDA may authorize sales of some prescription pharmaceuticals on a non-prescription basis, which would reduce the profitability of our prescription products. From time to time, the FDA elects to permit sales of some pharmaceuticals currently sold on a prescription basis, without a prescription. FDA approval of the sale of our products without a prescription would reduce demand for our competing prescription products and, accordingly, reduce our profits. Our industry is very competitive. Additionally, changes in technology could render our products obsolete. We face significant competition from other pharmaceutical companies, including major pharmaceutical companies with financial resources substantially greater than ours, in developing, acquiring, manufacturing and marketing pharmaceutical products. The selling prices of pharmaceutical products typically decline as competition increases.

Further, other products now in use, under development or acquired by other pharmaceutical companies, may be more effective or offered at lower prices than our current or future products. The industry is characterized by rapid technological change that may render our products obsolete, and competitors may develop their products more rapidly than we can. Competitors may also be able to complete the regulatory process sooner, and therefore, may begin to market their products in advance of our products. We believe that competition in sales of our products is based primarily on price, service and technical capabilities. There can be no assurance that : (i) we will be able to develop or acquire commercially attractive pharmaceutical products ; (ii) additional competitors will not enter the market ; or (iii) competition from other pharmaceutical companies will not have a material adverse effect on our business, financial condition and results of operations. Many of the raw materials and components used in our products come from a single source. We require a supply of quality raw materials and components to manufacture and package pharmaceutical products for ourselves and for third parties with which we have contracted. Many of the raw materials and components used in our products come from a single source and interruptions in the supply of these raw materials and components could disrupt our manufacturing of specific products and cause our sales and profitability to decline. Further, in the case of many of our ANDAs and NDAs, only one supplier of raw materials has been identified. Because FDA approval of drugs requires manufacturers to specify their proposed suppliers of active ingredients and certain packaging materials in their applications, FDA approval of any new supplier would be required if active ingredients or such packaging materials were no longer available from the specified supplier. The qualification of a new supplier could delay our development and marketing efforts. If for any reason we are unable to obtain sufficient quantities of any of the raw materials or components required to produce and package our products, we may not be able to manufacture our products as planned, which could have a material adverse effect on our business, financial condition and results of operations. Our patents and proprietary rights may not adequately protect our products and processes. The patent and proprietary rights position of competitors in the pharmaceutical industry generally is highly uncertain, involves complex legal and factual questions, and is the subject of much litigation. There can be no assurance that any patent applications or other proprietary rights, including licensed rights, relating to our potential products or processes will result in patents being issued or other proprietary rights secured, or that the resulting patents or proprietary rights, if any, will provide protection against competitors who : (i) successfully challenge our patents or proprietary rights ; (ii) obtain patents or proprietary rights that may have an adverse effect on our ability to conduct business ; or (iii) are able to circumvent our patent or proprietary rights position. It is possible that other parties have conducted or are conducting research and could make discoveries of pharmaceutical formulations or processes that would precede any discoveries made by us, which could prevent us from obtaining patent or other protection for these discoveries or marketing products developed there from. Consequently, there can be no assurance that others will not independently develop pharmaceutical products similar to or obsoleting those that we are planning to develop, or duplicate any of our products. Our inability to obtain patents for, or other proprietary rights in, our products and processes or the ability of competitors to circumvent or obsolete our patents or proprietary rights could have a material adverse effect on our business, financial condition and results of operations. Concentrated ownership of our common stock and our registration of shares for public sale creates a risk of sudden changes in our share price. The sale by any of our large shareholders of a significant portion of that shareholders holdings could have a material adverse effect on the market price of our common stock. We registered 64,964,680 shares held by certain of our investors for sale under a registration statement on a Form S-1 and a Form S-3 filed with the Securities and Exchange Commission (SEC). Sales of these shares on the open market could cause the price of our stock to decline. Exercise of warrants and the conversion of subordinated debt and preferred stock may have a substantial dilutive effect on our common stock. If the price per share of our common stock at the time of exercise or conversion of any preferred stock, warrants, options, convertible subordinated debt, or any other convertible securities is in excess of the various exercise or conversion prices of such convertible securities, exercise or conversion of such convertible securities would have a dilutive effect on our common stock. As of December 31, 2005, holders of our convertible securities would receive 44,425,407 shares of our common stock upon conversion and holders of our outstanding warrants and options would receive 15,028,256 shares of our common stock at a weighted average exercise price of $1.79 per share. The amount of such dilution that may result from the exercise or conversion of the foregoing, however, cannot currently be determined as it would depend on the difference between our common stock price and the price at which such convertible securities were exercised or converted at the time of such exercise or conversion. For example, on January 13, 2006, all 241,122 outstanding shares of our Series A 6.0% Participating Convertible Preferred Stock (Series A Preferred Stock) were converted into 36,796,755 shares of common stock. See Item 7. Managements Discussion and Analysis of Financial Condition and Results of Operations Financial Condition and Liquidity Preferred Stock and Warrants. Any additional financing that we secure likely will require the granting of rights, preferences or privileges senior to those of our common stock and which result in substantial dilution of the existing ownership interests of our common shareholders. The terms of our preferred stock may reduce the value of our common stock. We are authorized to issue up to a total of 5,000,000 shares of preferred stock in one or more series. As of December 31, 2005, we had 241,122 shares outstanding of Series A Preferred Stock and on January 13, 2006, all of those shares, including the related accrued and unpaid dividends, were converted into 36,796,755 shares of common stock . On December 31, 2005, we had 106,600 shares of Series B 6.0% Participating Convertible Preferred Stock (Series B Preferred Stock) outstanding, and 4,601,828 additional shares of preferred stock remained authorized for issuance. Our board of directors may determine whether to issue additional shares of preferred stock and the terms of such preferred stock without further action by holders of our common stock. If we issue additional shares of preferred stock, it could affect the rights or reduce the value of our common stock. In particular, specific rights granted to future holders of preferred stock could be used to restrict our ability to merge with or sell our assets to a third party. These terms may include voting rights, preferences as to dividends and liquidation, conversion and redemption rights, and sinking fund provisions. We continue to seek capital for the growth of our business, and this additional capital may be raised through the issuance of additional preferred stock. Our obligations to pay dividends on our preferred stock decrease the returns available to our common shareholders. Our Series B Preferred Stock bears cumulative dividends at the rate of 6.0%. These dividends are payable in cash, or in our discretion, in additional conversion rights. If dividends are paid in cash, this decreases our working capital available for operations. If dividends are paid in additional conversion rights, this results in further dilution of our common shareholders. In either case, the equity per outstanding common share declines, which can cause a decrease in the value of our common stock. See Item 7. Managements Discussion and Analysis of Financial Condition and Results of Operations Financial Condition and Liquidity Preferred Stock and Warrants. We experience significant quarterly fluctuation of our results of operations, which may increase the volatility of our stock price Our results of operations may vary from quarter to quarter due to a variety of factors including, but not limited to, the timing of the development and marketing of new pharmaceutical products, the failure to develop such products, delays in obtaining government approvals, including FDA approval of NDAs or ANDAs for our products, expenditures to comply with governmental requirements for manufacturing facilities, expenditures incurred to acquire and promote pharmaceutical products, changes in our customer base, a customers termination of a substantial account, the availability and cost of raw materials, interruptions in supply by third-party manufacturers, the introduction of new products or technological innovations by our competitors, loss of key personnel, changes in the mix of products sold by us, changes in sales and marketing expenditures, competitive pricing pressures, expenditures incurred to pursue or contest pending or threatened legal action and our ability to meet our financial covenants. There can be no assurance that we will be successful in avoiding losses in any future period. Such fluctuations may result in volatility in the price of our common stock. Penny Stock rules may make buying or selling our common stock difficult. Trading in our common stock is subject to the penny stock rules. The SEC has adopted regulations that generally define a penny stock to be any equity security that has a market price of less than $5.00 per share, subject to certain exceptions. These rules require that any broker-dealer that recommends our common stock to persons other than prior customers and accredited investors, must, prior to the sale, make a special written suitability determination for the purchaser and receive the purchasers written agreement to execute the transaction. Unless an exception is available, the regulations require the delivery, prior to any transaction involving a penny stock, of a disclosure schedule explaining the penny stock market and the risks associated with trading in the penny stock market. In addition, broker-dealers must disclose commissions payable to both the broker-dealer and the registered representative and current quotations for the securities they offer. The additional burdens imposed upon broker-dealers by such requirements may discourage broker-dealers from effecting transactions in our common stock, which could severely limit the market price and liquidity of our common stock. The requirements of being a public company may strain our resources and distract management. As a public company, we are subject to the reporting requirements of the Securities Exchange Act of 1934 (the Exchange Act) and the Sarbanes-Oxley Act of 2002 (the Sarbanes-Oxley Act). These requirements are extensive. The Exchange Act requires that we file annual, quarterly and current reports with respect to our business and financial condition. The Sarbanes-Oxley Act requires that we maintain effective disclosure controls and procedures and internal controls for financial reporting. In order to maintain and improve the effectiveness of our disclosure controls and procedures and internal control over financial reporting, significant resources and management oversight is required. This may divert managements attention from other business concerns, which could have a material adverse effect on our business, financial condition and results of operations.