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A Review of Social Media Sentiment Analysis in Financial Risk Control: Based on Natural Language Processing Technologies

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Abstract

This review examines the application of social media sentiment analysis, driven by Natural Language Processing (NLP) technologies, within financial risk control. It outlines the four-stage evolution of NLP, from traditional methods to pre-trained models. Using credit risk control as an example, it elaborates on its application across the entire loan lifecycle: pre-loan, in-loan, and post-loan. The study identifies limitations such as data scarcity, insufficient model generalization and interpretability, and high implementation costs. It also explores potential breakthroughs, including dataset construction and model optimization, aiming to provide a framework for related research and practice.

Keywords

natural language processing (NLP), social media sentiment analysis, financial risk control, pre-trained language models, credit risk control

1. Introduction

The financial sector is undergoing profound transformation amidst the digital wave, where the integration of technology and finance is reshaping the industry landscape. The rapid development and widespread adoption of social media have turned platforms like Twitter and StockTwits into real-time indicators of financial market sentiment, providing a new dimension of unstructured data for financial risk control research.

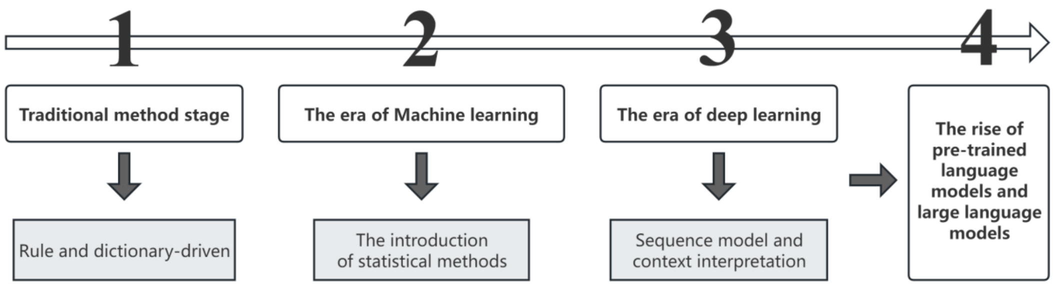
Traditional methods, such as the Loughran-McDonald dictionary, can capture sentiment in financial vocabulary but struggle with resolving contextual ambiguity (Loughran and McDonald, 2011). Advances in Natural Language Processing (NLP) have effectively addressed the gap in handling unstructured text within finance: the development of the Transformer architecture and domain-specific pre-trained models, the application of adversarial training in fused models, and the emergence of financially fine-tuned models like GPT-4o all demonstrate the potential value of NLP technologies in financial risk control (Du et al., 2025, Duan and Xue, 2024, Liu et al., 2024, Bollen et al., 2011). However, existing applications still face multiple challenges: difficulties in cross-lingual and multi-modal information fusion limit their deployment in risk control scenarios (Ardekani et al., 2024); slang, ambiguity, and the context-dependency of financial terminology lead to insufficient robustness in general-purpose models (Todd et al., 2024), among others. Against this backdrop, in-depth research into the application of social media sentiment analysis in financial risk control can provide insights for the deeper adaptation of NLP technologies within the financial domain, refining relevant theoretical frameworks. It also offers a rational basis and scientific guidance for different financial entities to use social media data to optimize their risk control systems, supporting the stable development of the financial industry in a complex and changing market environment.

From the perspective of Natural Language Processing (NLP), this paper systematically reviews the literature spanning the two intersecting fields of financial risk control and text sentiment analysis, conducting a comprehensive study on the application limitations and technical breakthroughs of social media sentiment analysis in financial risk control. Specifically, this paper aims to: (1) outline the developmental trajectory of fundamental NLP applications in processing financial social text in recent years; (2) explore the existing application models and practical effectiveness of social media sentiment analysis in financial risk control; (3) identify the core limitations and risks of sentiment analysis in financial risk control, and propose targeted development suggestions conducive to technological breakthroughs, thereby providing a clear framework for theoretical research and practical application in this field.

2. Fundamental Applications of NLP Technology in Financial Social Text Processing

The application of Natural Language Processing (NLP) technology in financial social text processing has shown a clear developmental trajectory alongside different phases of technological iteration. From a technological evolution perspective, the fundamental applications of NLP in this domain, as figure 1 illustrated below, have primarily undergone four major stages: the Traditional Methods stage, the Machine Learning era, the Deep Learning era, and the rise of Pre-trained Language Models and Large Language Models.

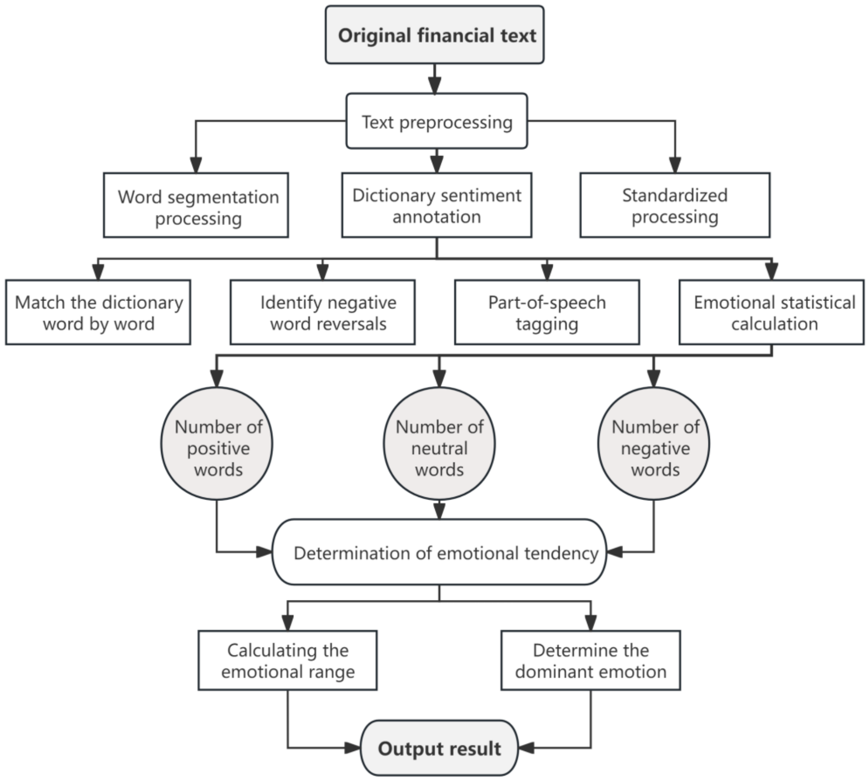
Figure 1: Development Path of NLP Technology Stages



2.1 Traditional Methods Stage: Rule and Dictionary-Driven

In the early stages of NLP application, researchers primarily relied on rule-based and dictionary-based methods to process financial text. As shown in Figure 2, the Loughran-McDonald dictionary is a highly representative, finance-specific lexicon for English. It identifies sentiment or specific information in text through predefined keyword lists and linguistic rules.

Figure 2: Operational Logic of the Loughran-McDonald Dictionary



These methods laid the foundation for the subsequent development of financial text sentiment analysis and achieved certain results. However, the limitation of such methods lies in their rigidity, making it difficult to capture complex and variable linguistic phenomena. Particularly in finance, the meaning of some words can vary depending on context, causing general-purpose dictionaries to perform poorly in domain-specific sentiment analysis (Todd et al., 2024).

2.2 Machine Learning Era: Introduction of Statistical Methods

Against the backdrop of the rise of machine learning techniques, text processing entered a new phase. Traditional machine learning algorithms, such as Support Vector Machines (SVM), Random Forests, and Naïve Bayes, were widely introduced into financial text sentiment classification tasks. The significant achievements of this stage were evident in the enhancement of processing scale and generalization capability. By learning features from large volumes of financial text data, the ability to handle large-scale datasets improved, partially overcoming the limitations of rule and dictionary methods.

2.3 Deep Learning Era: Sequence Models and Contextual Interpretation

Entering the deep learning era, NLP technology made breakthrough progress in the field of financial social text processing. Recurrent Neural Networks (RNNs) and their variants, especially Long Short-Term Memory networks (LSTMs), became the core tools of this stage due to their advantages in processing sequential data, helping to better capture contextual information and long-range dependencies in text (Cao, 2024). Precisely because of the significant advantage of LSTM models in understanding textual context, they could more accurately identify the sentiment expressed in text, playing a key role in tasks requiring sentiment analysis, such as market analysis and public relations management (Cao, 2024).

2.4 The Rise of Pre-trained Language Models and Large Language Models

In recent years, pre-trained language models, particularly Large Language Models (LLMs) represented by

BERT and GPT, have rapidly risen, completely transforming the landscape of financial text analysis. These models undergo unsupervised pre-training on massive corpora, enabling them to learn universal language representations. They can then be fine-tuned for specific tasks, significantly enhancing their ability to handle complex linguistic information (Lu, 2025).

As shown in the table 1, different models at this stage vary in prediction time and cost (Nasiopoulos et al., 2025). Nonetheless, financial social text processing in this new developmental phase is generally exploring directions towards multimodality and knowledge enhancement.

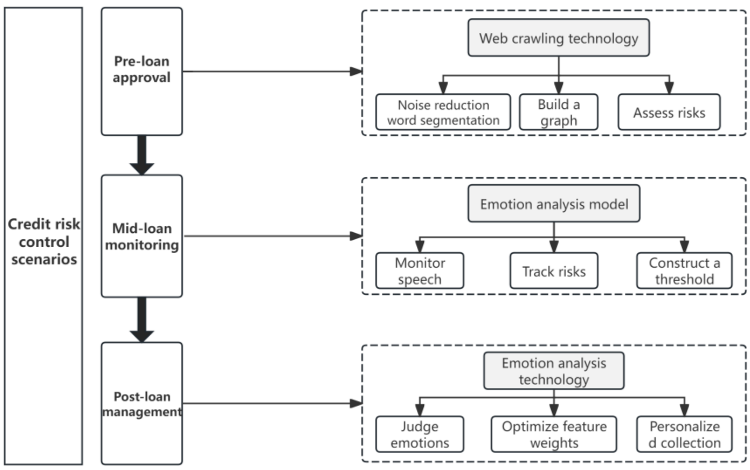
Table 1: Model Prediction Time and Cost Comparison

Model	Average prediction time for a single sentence (in seconds)	Total time for 516 sentences (in seconds)	Predicted cost (in US dollars)
GPT-4o(After fine-tuning)	1.89	976.28	0.25
GPT-4o-mini (After fine-tuning)	0.78	404.15	0.03
FinBERT	0.01	6.05	0
SVM	0.002	0.92	0

3. Integration of Social Media Sentiment Analysis into Financial Risk Control Scenarios

In the financial sector, the accuracy and timeliness of risk control are crucial for the stability and development of the entire industry, making it a field of study that cannot be overlooked. Social media is increasingly becoming a hub for information, and the market sentiment, corporate creditworthiness, and potential risks contained within are drawing more attention from both the industry and researchers. This section uses the credit risk control scenario as an example for elaboration.

Figure 3: Credit Risk Control Process Flowchart



As can be seen in Figure 3. The core of credit risk control is assessing a borrower's repayment capacity and willingness while balancing risk and return. Social media sentiment analysis forms a dual-dimensional evaluation system of "hard data + soft information" by mining behavioral patterns and risk tendencies in users' social media discourse, covering the entire process of pre-loan, in-loan, and post-loan.

3.1 Pre-loan Approval and Risk Assessment

In the preprocessing stage, credit institutions use crawler technology to collect text data of borrowers from social platforms, financial forums, etc., which includes content such as loan purpose descriptions, repayment promises, and interpersonal interactions (Zhou et al., 2025). After noise reduction and word segmentation via multimodal preprocessing techniques, entity linking technology is then used to associate related entities in the user's social network, constructing an associated risk graph (Xiao et al., 2021), thereby enabling a preliminary assessment of the borrower's financial behavior risk.

3.2 In-loan Monitoring and Early Warning

Sentiment changes on social media can reflect a borrower's various states in real-time and indicate potential risks in credit activities. Institutions conduct real-time monitoring of the social media dynamics of customers who have obtained credit qualifications. They use natural language processing techniques and sentiment analysis models to locate and track risk factors embedded in their statements, combining this with repayment behavior data to construct dynamic warning thresholds (Xiao et al., 2021).

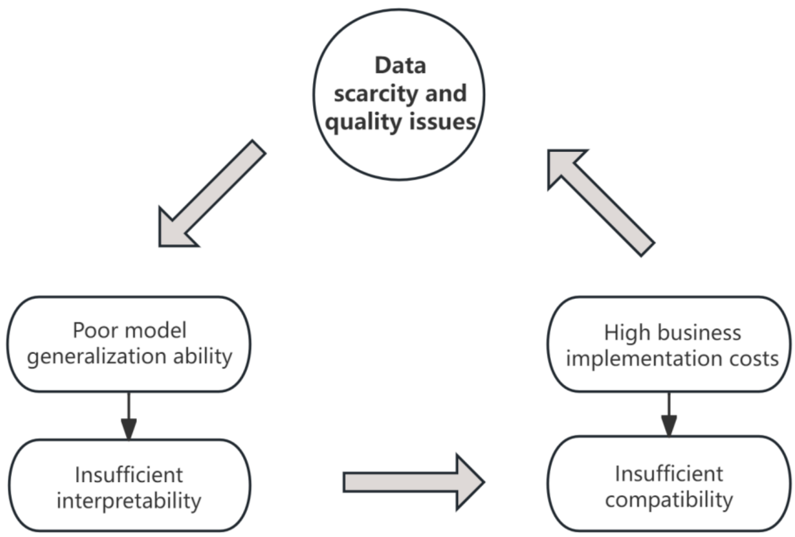
3.3 Post-loan Management and Collection Optimization

Social media sentiment analysis also plays a positive role in post-loan risk control. Research finds that positive expectation reminders help prompt repayment when the borrower's emotional intensity is high (whether anger or happiness), whereas negative consequence reminders might lead to a higher probability of default for overdue borrowers with high immediate happiness (Zhou et al., 2025). This also reflects that personalized, differentiated collection strategies based on emotional analysis can reduce default risk.

4. Common Limitations in Technology Integration and Business Implementation

In financial risk control scenarios, the integrated application of social media sentiment analysis and NLP technology has demonstrated substantial practical value. However, As shown in Figure 4, specific scenario applications face some common challenges and limitations.

Figure 4: Common Limitations



4.1 Data Scarcity and Quality Issues

Although the volume of text data on various social media platforms is vast, high-quality, annotated datasets tailored for specific financial risk control tasks, particularly in Chinese context, are actually quite scarce (Xu et al., 2021). The inherent characteristics of social media text—high noise, colloquialism, and informal expression—also make data cleaning and preprocessing a time-consuming and complex task.

4.2 Insufficient Model Generalization and Interpretability

The context dependency of terminology in the financial field increases the risk of model misjudgment of words. General-purpose models fail to distinguish the different meanings of the same word in ordinary text versus financial text, indicating weak generalization capability. For example, "利空" (bad news) is clearly negative in a financial context but might be misclassified as neutral by a general sentiment model (Sheetal and Aithal, 2025). Lack of model interpretability is another core limitation. In a field like financial risk control, which requires high transparency, traceability, and compliance, insufficient interpretability undoubtedly poses a significant obstacle. This issue becomes particularly prominent with the application of advanced technologies like Large Language Models (LLMs) (Lin and Sun, 2025).

4.3 Business Implementation Costs and Compatibility Issues

The need for customized annotation for model training and the regular maintenance of real-time processing architectures contribute to high technology implementation costs. Beyond this, effectively embedding social media sentiment analysis technology into the complex existing business processes of financial institutions is not straightforward. This involves not just technical integration but also the reshaping of business models, the transformation of data flows, and the coordination of cross-departmental collaboration. Specifically, practical challenges such as data and platform integration, and process integration require robust data ingestion and preprocessing pipelines, as well as compatibility with existing IT infrastructure (Du et al., 2025).

5. Conclusion and Outlook

5.1 Summary

Driven by the rapidly evolving digital wave, Natural Language Processing (NLP) technologies, particularly social media sentiment analysis, have demonstrated significant potential and value in their application within the field of financial risk control. However, it is crucial to note that the technological integration and business implementation of social media sentiment analysis in financial risk control still face multiple common limitations. Firstly, the scarcity of high-quality, annotated datasets tailored to specific financial scenarios is a core constraint on improving model performance. The inherent noise and colloquial characteristics of social media text further increase the complexity of data processing. Secondly, advanced models, represented by LLMs, commonly exhibit "black box" problems, leading to insufficient model interpretability, which constitutes a major obstacle in financial decision-making environments requiring high transparency and traceability. Additionally, high technology implementation costs and poor compatibility with existing business systems also hinder the scalable application of sentiment analysis technology. Finally, regulatory compliance and ethical risks, particularly concerning data privacy protection and algorithmic bias, are challenges that financial institutions must cautiously address when utilizing social media data.

5.2 Outlook

Looking ahead, to fully unleash the potential of social media sentiment analysis in the financial risk control domain, the following directions merit in-depth exploration: First, collaborative efforts from industry, academia, and research are needed to construct high-quality, multimodal, domain-specific datasets. Second, enhancing model interpretability and generalization capability are the main technical barriers that future research needs to break through. Third, reducing implementation costs and fostering cross-scenario synergy are also highly worthy of attention.

In summary, although this review systematically collates and summarizes previous literature intersecting the fields of financial risk control and natural language processing, achieving certain results, it still possesses some limitations. Firstly, while it integrates the application logic from scenarios like credit risk control and market risk control, it lacks empirical validation targeting specific sub-fields, failing to fully demonstrate the details of scenario adaptability in technical applications or completely reveal commonalities. Future work should supplement this with more diverse scenarios to enhance persuasiveness. Secondly, constrained by the perspective of a review study, the discussion of specific implementation paths and parameter optimization logic for NLP technology in financial risk control remains relatively macro, and detailed analysis requires further depth.

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Conflicts of Interest

The authors declare no conflict of interest.

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