Financial Sentiment Analysis: Techniques and Applications

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Financial Sentiment Analysis (FSA) is an important domain application of sentiment analysis that has gained increasing attention in the past decade. FSA research falls into two main streams. The first stream focuses on defining tasks and developing techniques for FSA, and its main objective is to improve the performances of various FSA tasks by advancing methods and using human-annotated datasets. The second stream of research in FSA is application-driven or market-driven, which has received more attention in recent years than FSA techniques per se, with the main objective of using financial sentiment, implicitly or explicitly, for downstream applications on financial markets. The application of FSA mainly includes hypothesis testing and predictive modeling in financial markets. This survey conducts a comprehensive review of FSA research in both the technique and application areas and presents several frameworks to help understand the two areas’ interactive relationship. Subsequently, the scope of FSA studies has become clearer, and the relationship among FSA, investor sentiment, and market sentiment has been empirically confirmed. The main findings, challenges, and future research directions for both FSA techniques and applications have also been summarized and discussed.

CCS Concepts:
• Computing methodologies → Natural language processing; Neural networks; Machine learning algorithms;
• Information systems → Information retrieval; Sentiment analysis;
• Applied computing → Law, social and behavioral sciences.

Additional Key Words and Phrases: Financial Sentiment Analysis, Financial Forecasting, Natural Language Processing, Information System, Machine Learning, Deep Learning

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1 INTRODUCTION

Sentiment analysis is a field of study that analyzes people’s sentiments, attitudes, opinions, emotions, evaluations, and appraisals towards various entities such as events, topics, services, products, individuals, organizations, issues, and their attributes [93]. Financial Sentiment Analysis (FSA), which in broad terms studies investor sentiment and financial textual sentiment [79], is an important application domain for sentiment analysis. Given the intricate nature of the financial market, individuals involved in varying market conditions exhibit diverse cognitive patterns [111].
rendering it challenging to dynamically comprehend and analyze the market for robust financial decision-making. To address the challenge posed by the market’s active shifts, automated FSA has gained increasing attention in the past decade [173]. It is proven to be a powerful tool to support business decision-making and perform financial forecasting [102]. The application scenarios include corporate disclosures, annual reports, earning calls, financial news, social media interactions, and more [173, 186]. Sentiment analysis is a suitcase problem and domain-dependent. The phenomenon of domain-dependence is more pronounced in the finance domain [106] because of both topic concentration and the use of highly professional language. For example, a word such as “liability” and “debt” is considered negative in general-purpose sentiment analysis, whereas it is frequent and has a neutral meaning in the financial context.

In terms of where the ground truth comes from, financial sentiment indicators are categorized into market-derived [85] and human-annotated sentiments [100]. The market-derived sentiments are computed proxies from market dynamics, such as price movement and trading volume, thus, may include noise from other sources. For example, generally positive news is related to large changes in price for a short time, while the effect of negative news lasts longer [35]. The subjective human-annotated sentiments, however, are specifically labeled by professionals [106] or investors themselves [184]. FSA has received great attention from researchers and investors and has become a prominent and interesting research topic in recent years [5, 160] mainly due to the increase in online materials such as digital news, World Wide Web, and social media. FSA research is shifting from human-annotated to market-derived sentiment. More specifically, the application of FSA in financial forecasting has become more popular in recent years.

In the realm of Financial Sentiment Analysis, Kearney and Liu [79] conducted a comprehensive survey in 2014, focusing primarily on FSA techniques rooted in dictionaries and machine learning. [107] presented a brief review of various FSA methodologies in 2019, encompassing data sources, lexicon-based approaches, traditional machine learning, and deep learning techniques. While prior reviews have tended to be skewed towards either FSA techniques or applications [79, 107, 128, 186], this survey aims to provide a comprehensive review of the most recent FSA research bridging two aspects of this spectrum. We believe that linking both techniques and applications can enable researchers to have an overarching understanding of FSA studies and more importantly, facilitate better adoption of FSA in downstream applications to generate more promising results. Our work entails an extensive examination of the most recent FSA studies, offering a dual perspective from both technical and applied standpoints. Notably, our investigation extends beyond the confines of computer science literature, establishing connections with other disciplines such as information systems and finance. In particular, we delve into the foundational principles of financial forecasting, lending support to the market predictability of financial sentiment from a financial theory standpoint. We have meticulously defined the scope of FSA research, reaffirming the intricate relationship between FSA, investor sentiment, and market sentiment. Furthermore, we have scrutinized the genesis of financial sentiment, whether implicit or explicit, in its applications within financial markets. This analysis sheds light on the dynamic interplay between FSA techniques and their practical applications, ultimately facilitating a more seamless integration of financial sentiment in downstream tasks. Besides, we deliver structured summaries for different technical trends, tasks, features, and applications. Finally, building upon the most recent brief survey on FSA [107], we additionally review FSA tasks with more recent benchmark datasets, learning approaches, pre-trained language models, word representation techniques, and evaluation methods. We also highlight FSA applications, including data sources, hypothesis testing, and predictive modeling.

This study aims to answer the following four groups of research questions. Our findings are elaborated in Section 6.

1. FSA studies have evolved with the increase of data availability over the years. What is the scope of FSA in today’s context, and what is the relationship among FSA, investor sentiment, and market sentiment?
(2) What trends are emerging from the latest tasks, benchmark datasets, and methods in the newest FSA technique studies?

(3) FSA has been widely used in financial applications since Engle and Ng suggested the asymmetric and affective impact of news on market volatility in 1993. Then, what data sources, tasks, methods, and financial markets can be used in FSA application-focused domains?

(4) How financial sentiment is applied in financial forecasting and what is the relationship between FSA techniques and applications?

In particular, our contributions can be summarized from the following four aspects:

(1) We have conducted a comprehensive review of the latest FSA studies from both the technique and application perspectives. This effort fills the gap in the literature by having a detailed and referential anchoring point for FSA research.

(2) Our field of investigation goes beyond the computer science literature and links to other disciplines, such as information systems and finance. Specifically, we review the underlying principles of financial forecasting and provide support to the market predictability of financial sentiment from a financial theory perspective.

(3) We have clarified the scope of FSA research and re-confirmed the relationship among FSA, investor sentiment, and market sentiment.

(4) We have reviewed how financial sentiment is generated, implicitly or explicitly, during its applications in financial markets, and the interactive relationship between FSA techniques and applications, which will facilitate a better adoption of financial sentiment in downstream application tasks.

The remainder of this article is organized as follows: Section 2 provides the background of FSA, including its definition, motivation and importance; Section 3 provides the literature review framework; Section 4 and Section 5 review existing studies on FSA techniques and applications, respectively; Section 6 demonstrates the research findings of this survey; Section 7 lists challenges and future directions; finally, Section 8 offers concluding remarks.

2 BACKGROUND

The term "sentiment" is used in the context of analyzing evaluative texts automatically and detecting predictive judgments from negatively and positively opinionated texts [15]. This term first appeared in the studies by [28] and [168], where researchers were interested in market sentiment analysis [160]. Traditionally, investor sentiment is collected via surveys which ask for opinions on the markets regularly. With the advancement in textual data such as news texts, social media collections, and automatic processing technologies, the media has become an important source of investor sentiments. The task of FSA is to perform sentiment analysis from financial texts.

In computational finance, the adoption of robo-readers to process and analyze texts are emerging technology trends [106]. It is an area of knowledge that emerged in the 1980s that uses computational methods to solve problems in finance. From this perspective, FSA is also a research area under computational finance. Generally, FSA techniques refer to the methods to perform sentiment analysis (e.g., extraction of sentiment polarities or intensities) from financial texts, which could be categorized into the lexicon, machine learning, deep learning, hybrid, and pre-trained language model approaches. In terms of the applications of FSA, which refers to the adoption of financial sentiment in downstream tasks such as hypothesis testing and predictive modeling, the most important application of FSA is the forecasting of financial markets. Efficient Market Hypothesis (EMH), proposed by Fama in the 1970s [47], is a critical foundation of modern financial market analysis. It hypothesizes that financial markets are efficient and the price has incorporated all
available market information. To tie the concept to reality, Fama classified the efficient market into three forms, namely strong, semi-strong, and weak form. Under weak form, it is assumed that the information set is merely historical prices, and that any current or private information will not influence the market. The weak form test has been renamed to tests for return predictability in [48] by Fama. The semi-strong form, which is changed to event studies in [48], states that stock prices reflect all public and historical information, while private information fails to influence market movements. The strong form describes a market condition, in which the price of securities reflects all information including public, private, and historical price information with a presumption that it is free to trade and access information, which is rarely the case. It is worth noting that Fama acknowledged that such a market is rarely seen in reality, but is useful for theoretical purposes only. However, the intellectual dominance of EMH had become less universal by the start of 21st century. A large number of statisticians and financial economists began to believe that stock prices could be predicted at least partially [105]. Under behavioral finance, investors make decisions from a psychological perspective [3], and their state of mind, or sentiment, influences them when making that decision [11, 99]. Today, the debate on market predictability is not about whether or not investor sentiment affects markets anymore but how to measure the sentiment and quantify its effect [7].

2.1 Relationship among Different Sentiment Agents

The relationship among market sentiment, investor sentiment, and financial textual sentiment is illustrated in Figure 1. Firstly, investor sentiment, which indicates the degree of deviation of an asset value from its economic fundamentals, can be defined as investors’ optimism or pessimism about future market activity [6] or as the way investors form beliefs [10]. Investor sentiment can be expressed and measured in two main forms including survey and financial texts [202]. The popular surveys include American Association of Individual Investors (AAII) Investor Sentiment Survey 1, Sentix Investor Confidence 2, or Investors Intelligence Sentiment Index 3. The AAII Investor Sentiment Survey provides valuable insights into the perspectives of individual investors regarding the future direction of the market

Fig. 1. Financial Sentiment, Investor Sentiment, and Market Sentiment.
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over a six-month period through a weekly survey in which investors can vote Bullish, Neutral, or Bearish. The Sentix
Investor Confidence Index assesses the prospective economic outlook for the eurozone over a six-month period, and is
derived from a comprehensive survey involving investors and analysts. A reading surpassing zero signifies a positive or
optimistic outlook, while a reading below indicates a negative or pessimistic perspective. The Investors Intelligence
Sentiment Index operates on contrarian principles and conducts surveys of more than one hundred independent market
newsletters, evaluating the current stance of each author regarding the market, whether it be bullish, bearish, or
indicating a correction. Investor sentiment can also be measured through textual data such as microblogs and analyst
reports. This measure is derived from various communication platforms that exist on the Internet and can be a proxy
for investor sentiment or non-informational trading. In this sense, [3] summarized that some studies have adopted
investor sentiment derived from social networks such as Twitter [164, 199], StockTwits [141, 147] or Facebook [158];
message boards such as RagingBull.com [171], Yahoo! Finance [82], or Google searches [27].

Secondly, financial (textual) sentiment is measured by the degree of positivity or negativity in financial texts. Investor
sentiment and financial textual sentiment are not independent but connect with each other. Investor sentiment could
be measured by financial textual sentiment, especially with the increase of financial textual data today. This is because
financial textual sentiment contains both subjective and objective information. The subjective information includes
subjective judgment and analysis of investors and analysts, which is normally published on social media and self-
media. The objective information, e.g., political and macroeconomics news, break news, and annual reports released by
companies, is the objective reflection of conditions within the general environment, industries, markets, and firms [79].
The objective information is often leading in the sense that it is influential to investors’ judgment, while the subjective
information is often lagging because it is driven by investor sentiment and reflects investors’ opinions. Thus, financial
sentiment interacts with investor sentiment. From this perspective, financial sentiment can serve as a measure or proxy
of investor sentiment, which subsequently influences trading strategies in the markets. Financial textual sentiment
analysis differs from classic sentiment analysis in several key aspects. Firstly, it involves the frequent use of metaphorical
expressions in financial communication, where figures of speech are employed to convey sentiments or describe market
conditions. For example, “The market is riding a bull” is a common metaphor signifying a robust, upward market
movement. Secondly, precision and brevity are of paramount importance in the financial world. Professionals use
concise language to efficiently convey complex information. For instance, instead of stating “The company experienced
a substantial increase in revenue and a corresponding improvement in profitability,” a financial analyst might say,
“The company posted robust revenue growth, driving higher profits,” which requires FSA to decode sentiments from
concise sentence structures. Thirdly, the financial industry employs a unique set of terms and jargon with specific
meanings. A thorough understanding of these terms is crucial for accurate interpretation and analysis of financial texts
in FSA. For example, the “Price-to-Earnings (P/E) ratio” is a fundamental financial metric used to assess a company’s
valuation. A high P/E ratio may indicate that investors hold high expectations for future earnings. Furthermore, unlike
classic sentiment analysis, which typically focuses on text alone, financial texts often integrate qualitative text with
quantitative data, which requires FSA to not only understand the language used in financial texts but also to process
and analyze numerical information in conjunction with the textual context, to gain a comprehensive understanding of
the sentiment. Lastly, FSA is often direction-dependent and the direction of events or changes holds critical importance
in FSA. For instance, the word “profit” may carry both positive and negative sentiment depending on the direction. An
increase in profit is generally regarded as positive, while a decrease is seen as negative. In practice, [184] concluded
that there are six areas that cause FSA fail, i.e., irrealis mood (conditional mood, subjunctive mood, imperative mood),
rhetoric (negative assertion, personification, sarcasm), dependent opinion, unspecified aspects, unrecognized words

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Further, market sentiment is the collective outlook of investors towards a specific financial market or security [162]. It is often used interchangeably with investor sentiment but fundamentally distinct as investors may hold varying viewpoints at different periods and markets. Market sentiment reflects the trading behavior of investors in a specific market, which is driven by investor sentiment or namely aggregated effect of investor sentiment [162]. It encapsulates the prevailing atmosphere or mood within the market, representing the crowd's psychological disposition, discernible through the trading activity and price fluctuations of the securities being exchanged. Broadly speaking, ascending prices signal an optimistic or bullish market sentiment, whereas descending prices signal a pessimistic or bearish market sentiment. The influence of investor sentiment on the market is asymmetric, which means the impact of investor sentiment on the market varies in different regimes of the market. Market sentiment can be measured by various proxy financial metrics, such as the degree of price movements and volatility computed from historical market data, and thus are backward-looking, lagging indicators. The most well-known market sentiment indicator is the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) 4, which measures expected market volatility based on real-time prices of the S&P 500 Index options over the next 30 days. The VIX tends to be higher when there is a greater level of fear and uncertainty in the market and lower in bull markets. Besides, the Equity Market Sentiment Index (EMSI) [9], High-Low Index, Bullish Percent Index (BPI) and the Baker and Wurgler Index [6, 7] are also popular indices for market sentiment or prevailing investor sentiment. Particularly, the Baker-Wurgler Index is generated from the first principal component of six proxies from market variables which are CEFD, dividend premium, equity issues, first-day return, IPO activity, and trading volume. [102] argued that the market sentiment of financial events does not equal to the semantic sentiment of financial news. [102] experimentally proved that using market sentiment representations can better predict stock price movements than using semantic sentiment representations.

2.2 FSA Research Scope

The scope of FSA studies can be broadly categorized into technique-driven and application-driven studies. The technique-driven FSA study, similar to other domain adoption of sentiment analysis, focuses on sentiment analysis from financial texts. However, the application-driven FSA study is unique to the finance domain, as financial sentiment can be used as a proxy of investor sentiment to make predictions in financial markets. Fundamentally, the objective and area are different between FSA techniques and applications. However, an interactive relationship between techniques and applications also exists. For instance, the benchmark datasets employed for FSA technique studies usually require human annotation with sentiment polarities or intensity scores, which need to be sufficient, representative, and precise to train an unbiased model in different domains. On the other hand, the data sources adopted for FSA application studies are normally annotated by financial metrics, computed from the market data. They also require the data to be in a time series with a substantial amount of financial texts and representative periods to model the relationships between investor sentiment and financial focus. As for the tasks, FSA techniques focus on the granularity which refers to the level of sentiment at which the sentiment is detected (e.g., targeted aspect-based sentiment analysis vs. sentence-level sentiment analysis). However, FSA applications explore various financial application scenarios, such as stock market movement prediction, financial risk prediction, portfolio management, FOREX market prediction, and

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4https://www.cboe.com/tradable_products/vix/
To summarize, it is a consensus that investor sentiment affects market dynamics and the measure of investor sentiment and quantification of its effect are critical to market prediction. Generally, investor sentiment can be measured by financial textual sentiment, sentiment surveys, and indices constructed from market data. Financial textual sentiment captures subjective judgment expressed by investors and also contains objective reflection, which drives investor sentiment. Market sentiment is the reflection of investor sentiment in investment behaviors. Investor sentiment is the psychological state of investors and it can be partially measured by financial textual sentiment and market sentiment, because of the interactions between investor sentiment and the other two aspects. Thus, FSA can be defined as a field of study that analyzes people’s sentiment from financial texts, measures and quantifies investor sentiment from financial textual sentiment, and is finally grounded in the applications of market prediction and financial decision-making. We define the scope of this survey as covering both FSA techniques and FSA applications, because of their differences and connections in datasets, methodologies, and targets.
3 LITERATURE REVIEW FRAMEWORK

The research in FSA can be categorized into two main streams. The first type focuses on the tasks in FSA. The main objective is to study the techniques that are able to improve the performance of various FSA tasks such as paragraph and sentence-level sentiment analysis, (targeted) aspect-based sentiment analysis and development of financial lexicons and sentiment analysis models [1, 4, 5, 30, 58, 66, 72, 74, 78, 89, 97, 98, 100, 109, 110, 113, 123, 134, 137, 140, 148, 153, 159, 162, 181]. The other group is application-driven or market-driven, which has received more attention in recent years where financial sentiment is treated as an intermediate output. The main objective is to use it for downstream applications, such as causality and correlation testing and financial forecasting [6, 13, 20, 31, 32, 34, 38, 40, 43, 59, 63, 70, 73, 76, 77, 80, 81, 86, 87, 96, 102, 104, 125, 129, 135, 145, 146, 151, 152, 154–156, 165, 170, 175–177, 180, 182, 183, 187, 188, 190, 193, 201, 203].

The sentiment can be represented in an explicit or implicit manner. The explicit representation refers to the generation of sentiment words, polarity, or intensity score [170]. The implicit representation of textual sentiment refers to the generation of sentiment words, polarity, or intensity score [96, 102]. Figure 2 illustrates our survey framework.

4 FSA TECHNIQUES

4.1 Tasks

Sentiment analysis can be performed in a coarse-grained [173] or fine-grained manner. The fine-grained sentiment analysis can be studied from two perspectives: granularity and expression. Granularity refers to the level of sentiment at which the sentiment is detected and it includes document-level [122], paragraph-level [52], sentence-level [198] and aspect-level [142]. In the financial domain, the aspect-level approaches are known as Aspect-based Financial Sentiment Analysis. To be more granular, the target element can be introduced where the sentiment detection is for that particular target. This is also known as stance detection defined by [161], or Targeted Financial Sentiment Analysis. The task is to detect the text that is favorable or unfavorable to a specific given target. The most challenging but pragmatic task is called Targeted Aspect-based Financial Sentiment Analysis (TABFSA), which aims to extract entities and aspects and detect their corresponding sentiment in financial texts. While most of the current FSA studies still adopt a sentiment polarity detection fashion (i.e., classification to positive or negative), sentiment can be also expressed by intensity score that is more consequential and nuanced for FSA compared to other sentiment analysis domains. Thus, intensity score-based FSA requires models in a regressive fashion.

4.2 Benchmark Datasets

The textual data used for FSA include email communications, social media posts (e.g., tweets), corporate reports, and daily news [18]. Financial corpora are labeled through either manual annotation [21, 35, 52, 57, 124, 184] or based on stock price [85]. Popular benchmark datasets have been summarized in Table 1. We summarize available FSA benchmark datasets not only to understand trends and templates in FSA annotation but also to facilitate researchers to find various public datasets that could be employed to evaluate their model performance and improve model generalization. Overall there is one document-level, four sentence-level, two target-level, and one targeted aspect-level dataset. The annotation is becoming more granular on target- and aspect-level. It is also observed that each public release of FSA benchmark dataset, particularly in open challenges such as SemEval 2017 Task 5 and FiQA Task 1 organized recently, has promoted the research in FSA techniques. As highlighted by [132], the annotation is a challenging task as it is subject to human factors such as domain expertise as well as the annotator’s private state and inference made into the text and earlier research also shows that the level of agreement on annotation varies on corpus annotated.

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4.2.1 PhraseBank[106]. In 2014, [106] established a milestone dataset, i.e., PhraseBank, which includes 4,846 news annotated by 16 individuals who have adequate background knowledge in financial markets from an investor perspective. Based on the strength of agreement among annotators, it releases 4 reference datasets, namely 100%, 75%, 66%, and 50% agreement. In their study, [106] argues that the overall sentiment may be different from the prior sentiment polarity of individual words, and incorporating phrase-structure information and domain-specific use of language could improve the detection. [106] proposed Linearized Phrase Structure (LPS), which extends the quasi-compositional polarity-sequence framework proposed by [121] and is capable of accommodating key interactions between financial concepts and phrase-structure components. The LPS model first extracts the entities with semantic orientation, then projects the phrase structure, and finally performs the multi-label classification.

4.2.2 SemEval 2017 Task 5. The SemEval 2017 Task 5 is for fine-grained financial sentiment analysis on news headlines and microblogs [25]. The training dataset includes 1,142 financial news headlines and 1,694 posts with their target entities and corresponding sentiment score as shown below. The test dataset consists of 491 financial news headlines and 794 posts. This task is to extract and detect the targets and their corresponding sentiment scores.

4.2.3 FiQA Task 1. The dataset is from FiQA Open Challenge Task 1 [103], which consists of 498 financial news headlines and 675 posts with their target entities, aspects, and corresponding sentiment score. The task is to extract and detect the targets, aspects, and their corresponding sentiment scores.

4.2.4 Topic-Specific Sentiment Analysis. [166] has created a benchmark dataset, which has 297 news documents extracted from the Thomson Reuters Newswire, for topic-specific sentiment analysis of economic texts. It has covered
ten event topics that have significant financial impact such as Apple’s iPad, the EuroZone crisis, GM’s IPO, and the
United-Continental merger. The 297 selected documents are equally distributed across all topics. A team of three
experienced annotators is instructed to read and annotate the news documents as if they were investors in the company
that was described in the topic statement [166]. The annotation uses a 7-point scale from very negative, negative, slightly
negative, neutral, slightly positive, positive to very positive. The Kappa statistic, Intraclass Correlation, Robinson’s
A and Finn coefficient, and average percentage agreement are used to evaluate the degree of agreement between
annotators and measure how reliable the annotation scheme is. This dataset is not publicly released but is available on
a request basis.

4.2.5 StockSen [184]. The StockSen dataset consists of 55,171 financial tweets from StockTwits dated between 2019-
06-06 and 2019-08-26. This dataset uses user annotations to investigate the common mistakes in the lexicon, machine
learning, and deep learning-based methods. It has shown that the same type of sentiment prediction models tend to
have similar error patterns and identified six main error types that cause financial sentiment analysis fail. However,
this dataset is not publicly released but is available on a request basis.

4.2.6 SentiEcon GS-1000 [123]. SentiEcon GS-1000 is a manually annotated gold standard dataset that contains 1,000
sentences extracted from the Esmeraldas Great Recession News Corpus. Two domain experts have classified each
sentence as positive, negative, or none. The annotators were instructed to consider the information available in the
sentences only for annotation. Annotation was carried out independently and a consensus was reached in differing
cases.

4.2.7 FinLin [29]. The FinLin corpus is released by Daudert in 2022 which aims to provide a novel and publicly
available dataset for FSA to complement the current knowledge and foster research on FSA [29]. It contains a total of
3811 texts including 3204 stocktwits, 394 news articles, 127 company reports, and 86 investor reports. The corpus is
annotated with a relevance score and a sentiment score in the range of $[0.0, 1.0]$ and $[-1.0, 1.0]$, respectively. Similarly,
this dataset is not publicly released but is available on a request basis.

4.2.8 SEntFiN 1.0 [159]. In an effort to address the problem of scant benchmark dataset for fine-grained FSA, a challeng-
ing task that requires extensive human efforts for annotation, [159] released SEntFiN 1.0 and made publicly available to
promote further research. SEntFiN is a human-annotated dataset that includes 10753 news headlines with their entity
and corresponding sentiment. It is common that multiple entities are present in a news headline with different sentiment
expressions and SEntFiN has 2847 headlines that contain multiple entities, which may have conflicting sentiment [159].

4.2.9 Comparison of Benchmark Dataset. Table 1 shows that news data is the primary source for constructing benchmark
datasets, followed by microblogs. News data is widely used for constructing sentiment analysis data in various fields,
such as NewsMTSC for target-dependent sentiment classification on policy issues [64]. The quantity of entries varies

1https://github.com/TDaudert/FinLin

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across datasets, with those annotated by polarity typically featuring a higher number of labeled entries. For instance, in the case of the FiQA dataset, there are 498 entries derived from news and 675 from posts, presenting a potential challenge for model training and generalization. It is also worth noting that datasets originating from news sources adhere more to a formal English language structure. On the other hand, microblogs like tweets tend to feature more informal expressions and greater potential for aspect ambiguity, such as ticker names. This introduces additional complexities to FSA tasks. Furthermore, in terms of granularity, the fine-grained FSA dataset remains limited, with FiQA being the current preference for aspect-based financial sentiment analysis. Additionally, it is important to highlight that the majority of datasets annotate sentiment solely in terms of polarity, without capturing the intensity of sentiment.

4.3 Evaluation Metrics

4.3.1 Regression. The first group of metrics measures the closeness between the predicted value and ground truth in the context of a regression task. The popular metrics include Weighted Cosine Similarity (WCS), Mean Squared Error (MSE), and coefficient of determination or R-squared ($R^2$).

\[
WCS = \frac{|P|}{|G|} \times \frac{\sum_{i=1}^{n} (G_i \times P_i)}{\sqrt{\sum_{i=1}^{n} (G_i^2)}} \times \sqrt{\sum_{i=1}^{n} (P_i^2)}
\]

(1)

where $P$ is the vector of scores predicted by the model and $G$ is the vector of ground truth scores.

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]

(2)

where $y_i$ is the gold standard score and $\hat{y}_i$ is the score predicted by the model.

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{\sum_{i=1}^{n} (y_i - \bar{y})}
\]

(3)

where $y_i$ is the gold standard score and $\bar{y}$ is the score predicted by the model.

$R^2$ is a popular and intuitive measurement for how close the predictions fit the observations on a 0 to 1 scale. As a $R^2$ value closer to 1 signifies a good model, the model performance can be evaluated from $R^2$ even without comparing with other models. However, $R^2$ fails to determine whether the predictions are biased. MSE is the most common metric, which is often used in conjunction with $R^2$, for regression tasks. It places more weight on large errors by squaring to ensure that the trained model has no outlier predictions. The WCS metric is introduced by [25] to evaluate sentiment scores on a continuous scale between -1 and 1. It enables the comparison of the proximity between the ground truth vector and prediction vector, while not requiring exact correspondence between them for a given instance. The WCS is derived by weighting the cosine similarity with the proportion of scored instances aiming to reward models that attempt to predict all entries in the dataset.

4.3.2 Classification. The second group of metrics measures the categorical accuracy between predicted value and ground truth in the context of classification tasks. The popular metrics include Accuracy, Matthews Correlation Coefficient (MCC), and F1 Score.

\[
Accuracy = \frac{TP + TN}{TP + TN + FP + FN}
\]

(4)

\[
MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}
\]

(5)

\[
F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}
\]

(6)
Here, Precision = TP/(TP + FP) and Recall = TP/(TP + FN). True Positive (TP) is the count of positive classes that are correctly predicted and True Negative (TN) is the count of negative classes that are correctly predicted. Similarly, False Positive (FP) is the count of positive classes that are incorrectly predicted and False Negative (FN) is the count of negative classes that are incorrectly predicted. Accuracy score can be calculated easily for both binary and multi-class classification. However, it cannot be considered a reliable measure when the data is imbalanced as it makes the classifier estimate over-optimistically on the majority class. F1 Score has addressed this issue and has been widely adopted in most application areas of machine learning. However, [23] argues that the F1 Score is independent of true negative, which is considered a conceptual flaw, and shows that MCC, which factors in TP, TN, FP, and FN together, can produce a score for evaluation of binary classification that is more informative and truthful than accuracy and F1 score.

4.4 Methods

4.4.1 Lexicon Approaches. The lexicon-based method is to detect the semantic orientation of the text based on the semantic orientation of the words in the text. Lexicon construction is a key element for sentiment analysis, which could be accomplished in manual, semi-automatic, or automatic manner [134]. The manual approach requires intensive efforts from creators with expert knowledge, which is slow but generally the accuracy is higher. On the other hand, the automatic approach is fast and scalable but often results in sacrifice in accuracy to some extent. The biggest advantage of the lexicon-based method is that no annotated dataset is required to perform FSA as it is unsupervised, which reduces the need for arduous manual annotation of the texts. Meanwhile, lexicons are useful to create features for supervised learning tasks. The challenge with lexicon-based approach is that it is time-consuming to build lexicons and also hard to generalize [162]. Also, it only can detect explicit sentiment and usually is less accurate than the learning-based method due to the constraint in coverage and quantification of sentiment intensity. More importantly, sentiment analysis is sensitive to domain [172] and generic domain-independent lexicons are often ineffective in FSA [134]. A general-purpose sentiment analysis lexicon may misclassify common words in financial texts [98]. For example, words like “liability” and “debt” are considered negative in general-purpose sentiment analysis, but are frequent and often neutral in the financial context. This makes it difficult to generalize the sentiment classifiers and underlines the need for finance domain-specific sentiment analysis [98].

The construction of lexicons in the financial domain is scant [134] as compared to general-purpose lexicons. In the context of FSA, there are six popular finance domain-specific lexicons as shown in Table 2, namely Henry’s Financial Dictionary (HFD), Loughran and McDonald (LM) Word List, Stock Market Sentiment Lexicon (SMSL), SentiEcon, Senti-DD, and FinSenticNet. HFD, which includes 104 positive words and 85 negative words, is the first dictionary that was created specifically for the financial domain from earning press releases. It is used to measure the tone of earnings press releases which is an important element of the firm-investor communication process [66]. The weakness of HFD is its limited number of words which can result in low coverage. One prominent effort that advances the development of financial sentiment analysis is the introduction of LM lexicon by Loughran and McDonald [98]. The authors manually examined the quality of GI (Harvard General Inquirer) and proposed a revised lexicon, which is specifically for financial texts. LM sentiment word list is created from the annual reports released by firms which includes 354 positive, 2355 negative, 297 uncertainty, 904 litigious, 19 strong modal, 27 weak modal, and 184 constraining words [98]. It is the most commonly used lexicon we are aware of that is created for the financial domain. The issue with HFD and LM is that they do not reflect context it is word-level. [134] has proposed a novel and fast approach and built SMSL using labeled StockTwits data and statistical measures. SMSL is created based on labeled tweets from StockTwits which is a microblog that is specialized in the stock market. This lexicon includes 20550 words and phrases and shows competitive...
results in measuring investor sentiments [134]. Lastly, designed for sentiment analysis applications, SentiEcon is a comprehensive and large domain-specific computational lexicon for Finance and Economy. It consists of 6,470 entries of single and multi-word expressions, and each entry has tags denoting their semantic orientation and intensity [123]. One important note is that SentiEcon is designed to combine with a general domain lexicon as it only compiles entries whose domain-specific polarity is different from or not recorded in the general domain lexicon. FSA lexicons can be enriched and improved from the following aspects. First, the concept-level domain-specific lexicon can be added. For example, the concept of "making profit" is positive while "making loss" is a negative concept. Also, it is important to build context-aware and direction-dependent lexicon [137]. For example, the direction-dependent phrases "profit-up" and "loss-down" are positive while "profit-down" and "loss-up" have negative polarities. [137] has constructed context-aware sentiment lexicon using direction-dependent words, combined with LM to perform lexicon-based FSA, and achieved state-of-the-art performance on PhraseBank dataset. The most recent study by [42] has proposed FinSenticNet and conducted extensive experiments to assess the performance of various lexicons across benchmark datasets. The results indicate that the concept-level lexicon FinSenticNet outperforms both general-purpose and financial lexicons across evaluation datasets. Additionally, FinSenticNet surpasses FinBERT in SemEval 2017 Task 5 and FiQA Task 1, underscoring its effectiveness in accurately capturing and analyzing sentiment within the financial domain. Meanwhile, HFD shows promising results on both the PhraseBank and SEntiFin datasets, though it has fewer words. LM exhibits suboptimal performance mostly due to a very pronounced imbalance in the number of positive and negative words.

### 4.4.2 Machine Learning Approaches

Machine learning approaches make use of classification or regression algorithms to determine sentiment by constructing features. There are three important steps in machine learning approaches: feature engineering, feature selection, and algorithm selection. In terms of feature creation, it can be categorized into four types (1) linguistic features (e.g., n-grams, RF n-gram, verb, NER, and word cluster) (2) sentiment lexicon features (e.g., the proportion of positive and negative words, maximum, minimum and sum of sentiment score) (3) domain-specific features such as number (e.g., +number, -number, +number%, -number%), keyword+number (e.g., call+number%, put+ +number%), metadata (e.g., binary features such as source, user/official and entities/sentiment, value features and other features) and punctuation, and (4) word embeddings. In machine learning approaches, feature selection is equally important as noise features need to be identified and excluded. The popular feature selectors include Chi-squared, ANOVA, and mutual information [162]. In terms of algorithms, Support Vector Machines (SVM) is one of the most adopted algorithms, and other algorithms such as Bagging, Random Forest (RF), AdaBoost, Gradient Boosting (GB) and XGBoost (XGB) are also among the popular algorithms to be selected. For example, [74] has elaborately designed all

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**Table 2. Financial Lexicons.**

<table>
<thead>
<tr>
<th>Lexicon</th>
<th>Description</th>
<th>Approach</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>HFD</td>
<td>104 positive words and 85 negative words</td>
<td>Manual, single word</td>
<td>Earnings press releases</td>
</tr>
<tr>
<td>LM</td>
<td>354 positive, 2355 negative, 297 uncertainty, 904 litigious, 19 strong modal and 184 constraining words</td>
<td>Manual, single word</td>
<td>Text documents from the U.S. Securities and Exchange Commission</td>
</tr>
<tr>
<td>SSM</td>
<td>26,550 entries: 10,534 positive, 10 neutral and 10,006 negative words</td>
<td>Automatic, single and multi-word</td>
<td>StockTwitts</td>
</tr>
<tr>
<td>SentiDD</td>
<td>2,573 entries: 1,597 positive and 976 negative direction-dependent words</td>
<td>Automatic, direction-dependent words (e.g., profit, up)</td>
<td>Phrasebank datasets</td>
</tr>
<tr>
<td>FinSenticNet</td>
<td>6,741 entries: 3,441 positive and 3,300 negative words and concepts</td>
<td>Manual, single and multi-word</td>
<td>Phrasebank, SemEval 2017 Task 5, FiQA Task 1 and SEntFiN datasets</td>
</tr>
</tbody>
</table>
above four types of features on SemEval 2017 Task 5 dataset, adopted a hill climbing algorithm to select the best features, and explored seven algorithms as follows: Bagging, RF, AdaBoost, GB, LASSO, Support Vector Regression (SVR) and XGB. An ensemble learning has been applied to different algorithms such as SVR+GB and SVR+XGB+AdaBoost+Bagging and achieved promising results. [30] established a strong baseline with a traditional feature engineering-based machine learning approach (MSE=0.0958) by treating aspect extraction as a classification task and sentiment detection as a regression task using Support Vector Classifier (SVC) and SVR respectively. The features generated include n-gram, tokenization, word replacement, and word embeddings using Term Frequency-Inverse Document Frequency (TF-IDF) and Word2Vec. [5] has adopted linguistic features (uni-gram, bi-grams, and tri-grams) and semantic features (BabelNet synsets and Semantic frames). The features are selected by the word-score correlation metric proposed by [39] and the sentiment regressor is trained using an SVR, which achieved an accuracy of 0.726 for microblogs and 0.655 for news headlines. [89] proposed an association rule mining-based Hierarchical Sentiment Classifier (HSC) which adopts the concept of financial and non-financial performance indicators, to classify financial texts into positive, neutral, or negative polarity on the PhraseBank dataset. [153] has used ontology information as a source of features in the SVM model on SemEval 2017 Task 5 dataset. The newly created domain ontology models various concepts from the financial domain and has four classes, which are sentiment, entity, property, and action. [148] has adopted a feature-light method that consists of an SVR with various kernels and word embedding vectors as features.

4.4.3 Deep Learning Approaches. Deep Learning models have achieved remarkable performance in sentiment analysis. It is able to construct complicated representations from textual data with a high level of abstraction [162]. The most popular deep learning algorithms used in FSA include Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) and their variants. For example, When target-aspect identification is jointly considered, [72] treated aspect extraction as a multi-class classification problem, as this task does not involve multiple aspects for one target, and adopted bidirectional Long Short-Term Memory (LSTM) to extract aspects using word embeddings such as GloVe, Google-News-Word2Vec, Godin, FastText, and Keras in-built embedding layer, while a multi-channel CNN is used for sentiment analysis task with enhanced vector combined from dependency tree, sentence word vector and snippet and target vector. The Bayesian optimization is used for hyper-parameters tuning to find out the most optimal parameters which achieves an F1 Score of 0.69 for aspect extraction and MSE of 0.112 for sentiment analysis. [140] has ensemble CNNs and RNNs with a voting strategy and a ridge regression for aspect and sentiment prediction. [100] has proposed FSA with Hierarchical Query-driven Attention (FISHQA) for financial polarity detection on the document level which outperforms benchmark models including SVM + Bag-of-Words (BoW), SVM + BoW TF-IDF, CNN-word [83], Bi-LSTM [61], LSTM-GRNN [167] and HAN [192] on a dataset which includes 7648 documents annotated by three domain experts in the perspective that whether the corresponding bonds of the companies mentioned in the document will encounter the risk of default in the future. FISHQA has achieved an accuracy of 0.9446 and an F1 Score of 0.9449, followed by HAN, a model that adopts hierarchical networks with an attention mechanism of random initialization, having an accuracy of 0.9177 and an F1 Score of 0.9166.

4.4.4 Hybrid Approaches. Hybrid approaches refer to the ensemble of lexicon methods, machine learning, and deep learning models and often produce better results. [1] has proposed a method by ensembling LSTM, CNN, Gated Recurrent Unit (GRU), and SVM. In terms of word embeddings for LSTM [67], CNN, and GRU, the word representation is learned through the stacked denoising auto-encoder network [174] by using Word2Vec [120] and GloVe [138]. In the SVR model, word TF-IDF, lexicon features and Vader sentiment [71] have been chosen as features. It has achieved a cosine similarity of 0.797 for Microblogs data and 0.786 for News Headlines on the SemEval 2017 Task 5. A hybrid of

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deep learning and lexicon-based technique that combines LSTM, CNN, Vector Averaging MLP and Feature Driven MLP (e.g., character n-grams (TF-IDF weighted counts of a continuous sequence of N characters), word n-grams (TF-IDF weighted counts of continuous sequence of N words), POS-tag, lexicons (e.g., positive count, negative count, net count, sum of positive score, sum of negative score, maximum of positive and negative scores)), which is proposed by [58] has achieved promising result (Microblogs: Cosine=0.751, News Headlines: Cosine=0.697) on the same dataset. The highest score (Cosine=0.745) for SemEval-2017 Task 5 Track 2 News Headlines is reported by [109], which combines GloVe and DepecheMood to represent words and feed into CNN followed by global max-pooling, and the output is then concatenated with Vader sentiment score for two levels of drop and fully-connected layers. [78] combined the representation learned from CNN and Bidirectional GRU (Bi-GRU) with attention mechanism with manually engineered lexical, sentiment, and metadata features and obtained WCS scores of 0.723 and 0.744 for the Microblogs and the News Headline tracks in SemEval-2017 Task 5, respectively. Recently, MetaPro was proposed to improve FSA by understanding metaphors in financial text [113, 114]. The linguistic intuition is that metaphors frequently appear in financial news, causing errors in sentiment analysis. MetaPro can paraphrase metaphors into their literal counterparts via data pre-processing, so that a sentiment classifier can achieve better performance in downstream applications. MetaPro consists of a multitask learning-based module for metaphor identification [112] and a WordNet[51]-based metaphor interpretation module [115]. They proposed a novel soft-parameter sharing method, termed Gated Bridging Mechanism (GBM), and a knowledge-enhanced masked word prediction technique. The average accuracy gain of three state-of-the-art sentiment analysis classifiers is 4.7% on the SemEval 2017 Task 5 news headline dataset.

4.4.5 Pre-Trained Language Models. The emergence of pre-trained language models and transfer learning has brought Natural Language Processing (NLP) research to a new era. This involves pre-training a neural network model on a large corpus of text, and the pre-trained models, such as BERT [36], are capable of capturing rich contextual information, enabling them to be adapted to various downstream tasks. Fine-tuning is the subsequent step in transfer learning which involves taking the pre-trained model and further training it on a task-specific dataset. This process fine-tunes the model’s parameters to suit the specific requirements of the target application, thus enhancing its performance on the given task. Domain adaptation is a related concept that addresses the challenge of applying a pre-trained model to a specific domain or application for which it was not originally trained. This process involves adapting the model to perform effectively in the target domain, even if it differs significantly from the domain on which the model was pre-trained. In the finance domain, domain-specific transformer-based models have significantly enhanced the performance of various financial NLP tasks such as FinBERT [4, 97, 200] for financial sentiment analysis and FinBERT-MRC [200] for financial named entity recognition. In terms of the adoption of pre-trained language models in FSA, [189] reported a good MSE of 0.08 using ULMFiT [68] on the FiQA Task 1. Further, Bidirectional Encoder Representations from Transformers (BERT) is able to improve contextual representation effectively, however, there is a large difference between general corpus and finance domain-specific corpus. A more recent fine-tuned language model FinBERT [4], which is further pretrained by TRC2-financial corpus\(^6\), reported the best performance (MSE=0.07, R\(^2\)=0.55) on the FiQA Task 1. Similarly, [97] trained FinBERT using two general domain corpus including English Wikipedia and BooksCorpus, and three financial domain corpus including FinancialWeb, YahooFinance, and RedditFinanceQA. It has achieved the SOTA performance on financial sentence boundary detection on the FinSBD English dataset with a mean score of 0.97 and FSA on the PhraseBank dataset with an accuracy of 0.94 and an F1 Score of 0.93. More recently, [181] proposed a Semantic and Syntactic Enhanced Neural Model (SSENM), which obtains input representation

\(6\)https://trec.nist.gov/data/reuters/reuters.html
using BERT model and incorporates dependency graph and context words to supervise a target representation. This novel model captures semantic contextual information through a self-attentive mechanism. An edge-enhanced Graph Convolutional Network (E-GCN) is included to aggregate node-to-node features and a Manifold Mixup strategy is also developed to generate pseudo data in training to address the over-fitting problem potentially caused by limited data size. SSENM has significantly improved its performance with a WCS of 0.8441 for News Headline and 0.8333 for Microblogs in SemEval-2017 Task 5 and an MSE of 0.0717 in FiQA Task 1. Finally, it is important to highlight that while models primarily based on transformer encoder architectures, such as BERT, have significantly enhanced FSA, autoregressive decoder architectures like GPT (Generative Pre-trained Transformer) [143], have also demonstrated promise in FSA [50, 69, 197]. Additionally, Bloomberg has introduced BloombergGPT [179], a Large Language Model in finance that outperforms similarly sized open models on financial NLP tasks including such as sentiment analysis, named entity recognition, news classification, question answering, etc.

4.4.6 Word Representation Techniques. Word representation is always an important component of sentiment analysis. This section aims to introduce both classic and state-of-the-art word representation techniques which can be used for FSA. In general, the word representation techniques could be grouped as classical models and representation learning models [127]. Classical models include categorical word representation (e.g., BoW and one hot encoding). This is the most straightforward method for text representation but they cannot capture positional and structural information as well as semantic relationships between words [72, 96]. Another classic model is weighted word representation which includes TF-IDF. Techniques such as TF-IDF can reduce the impact of common words but it is still built on the concept of the BOW model, which fails to capture the sequence of words in a document, semantics, and syntactical information of words [127]. To address the shortcomings of classic models, researchers study the methods to learn the distributed word representation in low-dimensional space. Overall representation learning can be categorized into contextual and non-contextual word representations. For non-contextual embeddings, the most popular model is Word2Vec, which is developed by [120] and can capture the semantics of words and manipulate the connectivity of words including sentimental similarity among words [162]. The problem with Word2vec is it only focuses on local context window knowledge but ignores global statistical information. Global Vectors (GloVe) [108] is thus presented. Meanwhile, FastText, which has decreased the training time but maintained the performance, is introduced by [12]. While the semantic and syntactic information of the text can be retained in non-contextual word representation models, there remains the problem of how the full context-specific representation can be kept. Therefore, contextual word representation techniques, such as generic context word representation (Context2Vec) [118], contextualized word vectors (CoVe) [117], embedding from Language Models (ELMo) [139], universal language model fine-tuning (ULMFiT) [68] and Transformer-based Pre-trained Language Models, are proposed to resolve this problem. It has been proven that Transformer-based Pre-trained Language Models are more efficient than LSTM or CNN models for language modeling. Models such as GPT (OpenAI Transformer) [144], Bidirectional Encoder Representations from Transformers (BERT) [36], XLNet [191] and Robustly optimized BERT approach (RoBERTa) [95] rely on this architecture. The context issue has been resolved by these models, but the applications to specific domains or task is limited as they are trained on general-purpose corpora (e.g., Wikipedia).

4.4.7 Summary of FSA Techniques. We summarize the characteristics of different technical trends in Tables 3. The evolution of FSA techniques has been marked by a progression from lexicon-based methods, conventional machine learning, and hybrid approaches to more advanced techniques involving deep learning and language models. It is observed that most of the research in FSA techniques has adopted the long-established PhraseBank, SemEval 2017 Task Manuscript submitted to ACM
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5, and FiQA Task 1 as the benchmark datasets. First, the creation of a financial lexicon is still attracting researcher's attention although the lexicon approach is more often used in combination with learning-based methods in FSA today. One trend in the development of financial lexicons is that it is shifting from single-word to multiple-word and direction-dependent expressions. This is particularly important in the finance domain as the sentiment of a financial term can be opposite for different directional words. Meanwhile, manual creation is still the main approach to building financial lexicons which requires intensive efforts from creators with expert knowledge but generally has higher accuracy. However, there is research [42, 134] which is pushing lexicon construction from manual to automatic approaches that enable us to address the slow process and low coverage issues in manual approach and build lexicons with increased speed and coverage. Second, in traditional machine learning methods, feature engineering is an important step and there are generally four types of features namely lexicon features, linguistic features, domain-specific features, and word embeddings. One type of feature that is less frequently investigated but is demonstrated effective in FSA is the domain-specific features such as numbers and keywords + numbers, especially when plenty of numbers are mentioned in the texts. In the financial context, for instance, a keyword of 'revenue' followed by a positive symbol '+' and percentage can be a positive sign. Lastly, deep learning methods, represented by CNN and LSTM, and pre-trained language models are the mainstream techniques in FSA that have improved the performance significantly. Notably, the finance domain-specific BERT, namely FinBERT, is trained by using various data sources such as Reuters Corpora, Yahoo Finance, Raddit Finance, corporate reports, earnings call transcripts and analyst reports in different studies and pushed the boundary of research in FSA techniques. The most recent study by [41] has achieved state-of-the-art performance on SemEval 2017 Task 5 and FiQA Task 1 by incorporating multiple knowledge sources into the fine-tuning process of language models including RoBERTa.

5 FSA APPLICATIONS

FSA has been widely used in financial applications since the asymmetric and affective impact of news on market volatility has been discovered [45]. The application of FSA is mainly contextualized for two broader analytical purposes, i.e., hypothesis testing and predictive modeling in financial markets. Unlike datasets, which help to obtain an accurate sentiment analysis model from the techniques perspective, data sources are important and provide additional information for calibrating sentiment analysis models to their application scenario. We first review data sources for FSA applications and investigate how the techniques are adjusted for various application types.

5.1 Data Sources

The data sources used for FSA applications can be categorized into three types. The first type is the data that is officially released by the company which includes financial reports, filings earnings calls, etc. The second type is survey sentiment indicators from sentiment surveys, which include AAII, UMSC, and Sentix. For example, AAII Investor Sentiment Survey is weekly and UMSC is monthly [53]. Lastly, public news (e.g., financial news, macroeconomic news) and social media are another two important data resources for financial market prediction in recent years [188], which has grown rapidly over the last decade with the advancement of news and social media information processing technologies. There is strong evidence that social media and financial news influence market dynamics [91]. As the Internet and Web 2.0 phenomenon have grown, social media data from platforms such as StockTwits and Twitter have become increasingly important data sources [49]. Smalovic et al. [160] confirm that sentiment analysis of social media data is predictive of future stock market movement.
Table 3. Performance of Financial Sentiment Analysis.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Dataset</th>
<th>Task</th>
<th>Method</th>
<th>Feature/Lexicon</th>
<th>Algorithm</th>
<th>Evaluation Metrics and Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1]</td>
<td>PhraseRank</td>
<td>Sentence-level</td>
<td>Machine Learning</td>
<td>Performance indicator tags</td>
<td>Classification based on Multiple Association Rules (CMAR)</td>
<td>Precision: 0.89, Recall: 0.89, F1 Score: 0.95</td>
</tr>
<tr>
<td>[2]</td>
<td>PhraseRank</td>
<td>Sentence-level</td>
<td>Language Model</td>
<td></td>
<td></td>
<td>Accuracy: 0.83</td>
</tr>
<tr>
<td>[3]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Machine Learning</td>
<td>Linguistic, sentiment lexicon, domain-specific features and word embeddings</td>
<td>SVM</td>
<td>Weighted Cosine Similarity, News: 0.797, Micro: 0.707</td>
</tr>
<tr>
<td>[4]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Machine Learning</td>
<td>Word embeddings</td>
<td>LSTM, CNN, Bi-LSTM</td>
<td>SVM, LSTM, GRU, Bi-LSTM, XGBoost</td>
</tr>
<tr>
<td>[5]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Hybrid Approach</td>
<td>Lexicon features and word embeddings</td>
<td>LSTM, CNN, Bi-LSTM, Bi-LSTM, XGBoost</td>
<td>Weighted Cosine Similarity, News: 0.797, Micro: 0.707</td>
</tr>
<tr>
<td>[6]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Hybrid Approach</td>
<td>Word embeddings using Word2Vec and GloVe, word in grams, character n-gram, POS-Tag, lemmatization features</td>
<td>LSTM, CNN, Bi-LSTM, Bi-LSTM, XGBoost</td>
<td>Weighted Cosine Similarity, News: 0.797, Micro: 0.707</td>
</tr>
<tr>
<td>[7]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Hybrid Approach</td>
<td></td>
<td>CNN, Bidirectional GRU</td>
<td>Weighted Cosine Similarity (WCS), News: 0.744</td>
</tr>
<tr>
<td>[8]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Hybrid Approach</td>
<td>Lexicon and dependency word embeddings, VADER, Leskun</td>
<td>CNN, MLP</td>
<td>Weighted Cosine Similarity (WCS), News: 0.744</td>
</tr>
<tr>
<td>[9]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Language Model</td>
<td>deep representation</td>
<td></td>
<td>Semantic and Syntactic Enhanced Neural Model (SSEM)</td>
</tr>
<tr>
<td>[10]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Language Model</td>
<td>RoBERTa</td>
<td>RoBERTa</td>
<td>Weighted Cosine Similarity (WCS), News: 0.814, Micro: 0.8033</td>
</tr>
<tr>
<td>[11]</td>
<td>SemEval 2017 Task 5</td>
<td>Targeted, Sentence-level</td>
<td>Hybrid Approach</td>
<td>RoBERTa</td>
<td>RoBERTa, transformer masked word prediction, GNN</td>
<td>Weighted Cosine Similarity (WCS), News: 0.814, Micro: 0.8033</td>
</tr>
<tr>
<td>[12]</td>
<td>FQA Task 1</td>
<td>Targeted, Aspect-level</td>
<td>Machine Learning</td>
<td>Logical and word embeddings</td>
<td>SVM</td>
<td>Aspect Extraction, F1 Score: 0.848, Pos: 0.7770, Sentiment Analysis: MDE, News: 0.1052, Micro: 0.2041</td>
</tr>
<tr>
<td>[15]</td>
<td>FQA Task 1</td>
<td>Targeted, Aspect-level</td>
<td>Deep Learning</td>
<td>Pre-trained word embeddings using CNN</td>
<td>RNN, Bi-LSTM, GRU, Bi-LSTM</td>
<td>Aspect Extraction: F1 Score: 0.684, Sentiment Analysis: MDE, News: 0.1052, Micro: 0.2041</td>
</tr>
<tr>
<td>[16]</td>
<td>FQA Task 1</td>
<td>Targeted, Aspect-level</td>
<td>Language Model</td>
<td>deep representation</td>
<td></td>
<td>Semantic and Syntactic Enhanced Neural Model (SSEM)</td>
</tr>
<tr>
<td>[17]</td>
<td>FQA Task 1</td>
<td>Targeted, Aspect-level</td>
<td>Language Model</td>
<td>RoBERTa</td>
<td>RoBERTa</td>
<td>Semantic Analysis: MDE, News: 0.1112, R, 0.4535</td>
</tr>
<tr>
<td>[18]</td>
<td>FQA Task 1</td>
<td>Targeted, Sentence-level</td>
<td>Language Model</td>
<td>RoBERTa</td>
<td>RoBERTa</td>
<td>Accuracy: 0.8049, F1 Score: 0.8049</td>
</tr>
<tr>
<td>[19]</td>
<td>FSM Experiment (fine-tune SGD, NLH, aug, reg, 500)</td>
<td>Document-level</td>
<td>Deep Learning</td>
<td>Word-embeddings</td>
<td>LSTM, CNN, Fasttext, Transformer</td>
<td>Accuracy: 0.9644, F1 Score: 0.9644</td>
</tr>
<tr>
<td>[20]</td>
<td>CCF BDL Corpus</td>
<td>Sentence-level</td>
<td>Language Model</td>
<td>RoBERTa</td>
<td>RoBERTa</td>
<td>Accuracy: 0.9671</td>
</tr>
</tbody>
</table>

Table 4. Financial Metrics.
5.2 Financial Applications

One of the most attractive applications of FSA is to perform financial market forecasting [5, 125]. Once the data source used for hypothesis testing and predictive modeling is selected, one or more measures of sentiment are constructed through the aforementioned techniques, which could be in the form of explicit sentiment representation (e.g., sentiment polarity or score) or implicit sentiment representation (e.g., word embeddings). Financial sentiment can be utilized explicitly, for instance by analyzing financial texts with critical linguistic features such as content semantics [80] or investors’ sentiment [104], for the sake of interpretability. Alternatively, it can be applied implicitly by directly encoding financial texts by neural networks and using the representations for learning downstream tasks [188] such as financial forecasting. Armed with these sentiment measures, we can investigate the hypotheses about how the sentiment interacts with the financial metrics and vice versa. The financial metrics are typically derived from either financial reports or financial market information. There are basically seven types of financial markets which include capital (e.g., stock and bond), commodity, money, derivatives, future, insurance, and foreign exchange markets. The most studied financial markets in FSA are the stock market and foreign exchange market. Table 4 has listed down the popular financial metrics defined in earlier studies. For example, stock market variables that can be predicted include stock price, stock price direction, return, volatility, and trading volume [135].

5.2.1 Causality and Correlation Testing. This area of study fundamentally focuses on the investigation of correlation and causality between sentiment from financial texts and market performance, which means the sentiment can be used to reflect the correlation and/or causality with other financial measures such as return, risk, and volatility [175]. For example, [176] conducted a correlation analysis between stock performance and sentiment from SeekingAlpha and StockTwits and concluded that while StockTwits messages and SeekingAlpha articles provide minimal correlation to stock performance in aggregate, a subset of experts contribute more valuable content with predictive power. It has also been demonstrated that public sentiment has a correlation with stock market movement [104] and specifically good news has a positive impact on markets and increases optimism [5]. Using a Granger causality analysis and a Self-Organizing Fuzzy Neural Network to investigate the hypothesis that the mood states of the public can predict changes in the Dow Jones Industrial Average (DJIA) closing prices, [13] found that emotions from Twitter messages can be good predictors of market trends. The public mood states are measured by the OpinionFinder (i.e., positive vs. negative) and Google-Profile of Mood States (GPOMS) which measures mood in six dimensions (i.e., Alert, Calm, Happy, Kind, Sure and Vital, Kind) time series. Similarly, [125] has extracted sentiment attitude (e.g., positive vs negative) and sentiment emotion (e.g., joy, sadness, etc.) from financial news and tweets to perform Granger causality test before predicting stock market price movement and concluded that sentiment attitude do not seem to Granger-cause stock price changes while emotions do Granger-cause stock price changes on specific occasions. The addition of sentiment emotions has increased the machine learning model accuracy for certain stock price predictions. The sentiment attitude and stock price time series are verified to be stationary by analyzing the autocorrelation (ACF) and partial autocorrelation (PACF) and performing the augmented Dickey-Fuller (ADF) or the Ljung-Box t-statistic tests. [160] developed and applied an active learning approach to perform sentiment analysis of tweet streams in the equity market. The Granger causality test demonstrates that sentiments derived from stock-related tweets can serve as indicators of stock price movements a few days in advance. The results are improved further by adopting the SVM classifier to categorize tweets into three sentiment polarities (i.e., positive, negative, and neutral) instead of two polarities only (i.e., positive and negative) [160]. [31] find that Twitter activity is related to market participants’ interest in and attention to 8-K filings, which in turn affect stock price and volume reactions to 8-Ks. The results also show that positive abnormal sentiment
is not significantly associated with stock price reactions but is significantly negatively associated with stock volume reactions. [62] examined the correlation between four distinct investor emotions (fear, gloom, joy, stress) and S&P 500 index returns using the Threshold Generalized Auto-regressive Conditional Heteroskedasticity (TGARCH) model and discovered that fear emotion has a significant and lasting impact on conditional volatility and market returns. It is also found that the abnormal returns associated to emotion experience rapid reversal within 5 days. [26] investigates the effect of investor sentiment on stock price crash risk, which is measured by the Negative Coefficient of Skewness (NCSKEW) and the Down-to-Up Volatility (DUVOL) of the weekly stock return, by testing their main hypothesis that investor sentiment is volatile by nature. Most earlier research in market prediction uses historical stock trading data, the technical indicators of stock trading, and macroeconomic variables as input data. The inclusion of financial textual data and application of NLP techniques in financial forecasting is an emerging research field [102, 135]. Today, many investment banks and fund managers are exploiting financial sentiment to make better predictions of the financial market. Financial institutions such as Two Sigma and DE Shaw have included financial sentiment as an input to their financial models.

### 5.2.2 Stock Market Movement Prediction

The stock market movement prediction is a challenging task as it is noisy and volatile by nature. Most earlier research in market prediction uses historical stock trading data, the technical indicators of stock trading, and macroeconomic variables as input data. The inclusion of financial textual data and application of NLP techniques in financial forecasting is an emerging research field [102, 125, 185, 186]. Traditional financial news providers such as Bloomberg and Thomson Reuters have pioneered to provide commercial financial sentiment analysis service [125, 135]. Today, many investment banks and fund managers are exploiting financial sentiment to make better predictions of the financial market. Financial institutions such as Two Sigma and DE Shaw have included financial sentiment as an input to their financial models.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Data Source</th>
<th>Period</th>
<th>Text Representation</th>
<th>Markets</th>
<th>Method</th>
<th>Task</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>[102]</td>
<td>Thomson Reuters and Bloomberg</td>
<td>1-Mar-2018 to 18-Jun-2021</td>
<td>Stock Price Movement Prediction</td>
<td>NCSKEW, DUVOL</td>
<td>SVM</td>
<td>Stock price movement (polatility and change of price)</td>
<td>ACC: 0.696, MCC: 0.1718, Classification (Accuracy: 0.642, F1 Score: 0.475)</td>
</tr>
<tr>
<td>[135]</td>
<td>Twitter, 31 million messages</td>
<td>26-Nov-2012 to 25-Oct-2013</td>
<td>Sentiment indicators based on SentiWordNet which combines with AAII, II, UMSC, Sentix</td>
<td>US</td>
<td>SVM, Naive Bayes, Random Forest</td>
<td>Multiclass classification with SVM</td>
<td>Upright or downward movement</td>
</tr>
<tr>
<td>[96]</td>
<td>Thomson Reuters</td>
<td>Oct-2011 to Jul-2017</td>
<td>Feature extraction from news titles using TF-IDF and from event tuple using TransE model</td>
<td>US</td>
<td>SVM</td>
<td>Upward or downward movement</td>
<td>Classification (Accuracy: 0.648, F1 Score: 0.475)</td>
</tr>
<tr>
<td>[77]</td>
<td>Stocktwits</td>
<td>4-Mar-2013 to 28-Feb-2018</td>
<td>CNN as base model of sentiment index</td>
<td>US</td>
<td>SVM with Multiple Kernel Learning</td>
<td>SVM</td>
<td>Daily price movement (polarity and change of price)</td>
</tr>
<tr>
<td>[182]</td>
<td>Thomson Reuters</td>
<td>Jan-2007 to Aug-2012</td>
<td>Feature, Bag-of-Words, and part-of-speech specific DAE, PWM features and SentTwo data representations</td>
<td>US</td>
<td>SVM</td>
<td>Predict stock closing price</td>
<td>Accuracy = 70.56%, MAPE = 1.65%, MAE = 2.39</td>
</tr>
</tbody>
</table>

Table 5. Stock Market Movement Prediction
sentiment signals, in addition to traditional structured transaction data, to improve their machine learning model for algorithmic trading [125]. Practical traders agree that any results above 50% are value-added to their day-to-day trading [129]. Conventionally there are two major schools of thought in stock market analysis: fundamental analysis and technical analysis [129]. Fundamental analysis is to evaluate stocks from their intrinsic value perspective from economy, and industry conditions to the financial strength of individual companies. Financial indicators such as earnings, expenses, assets, and liabilities are part of fundamental analysis. Technical analysis attempts to identify opportunities from statistical trends in the movements of stock’s price volume. Popular technical indicators include Simple Moving Average (SMA), Exponential Moving Average (EMA), and Moving Average Convergence/Divergence (MACD). Natural language-based financial forecasting techniques, as suggested by [19], could be classified as technical analysis. Essentially, the intrinsic value does not change with the sentiment and indicators that measure market sentiment, such as the High-Low Index and Bullish Percent Index which are important indicators in technical analysis.

Investor sentiment refers to the degree to which investors’ beliefs about future firm valuation deviates from fundamental information and existing studies show that investor sentiment has a significant impact on stock prices and market participants’ activities [119]. The studies in stock market prediction include stock index, stock price, stock price movement, return rate, and volatility using time series models (e.g., ARIMA and GARCH), machine learning, deep learning, and reinforcement learning approaches. [38] has proposed a novel neural tensor network to learn event embeddings, and a deep CNN to model the combined effects of long-term and short-term events for event-driven stock price movement prediction on the S&P 500 index and its individual stocks. Accuracy and MCC are used to measure the predictive model performance and a simulation is performed to evaluate the profitability of the proposed model, which has demonstrated that the deep learning method is effective in event-driven market prediction. [96] has extracted features from news title via CNN and from event tuple (an event can be defined as a tuple (Agent, Predicate, Object) e.g., Apple sues Samsung where A is Apple, P is sue and O is Samsung.) using knowledge graph embedding (i.e., TransE model) and combined with daily trading and technical analysis data. This approach is evaluated using an SVM model as a machine learning method and an LSTM model as a deep learning method to predict stock price movement direction. The best-performed model is achieved through joint learning of event tuples and text, which has solved the text sparsity problem in feature extraction. [32] has combined technical indicators with sentiment information to predict future prices using regression models and demonstrated that combining technical indicators and sentiment indicators has produced better prediction than using one of them only. The sentiment information is used explicitly where sentiment (i.e., subjective, objective, negative, positive) for each news and comment is obtained using SentiWordNet, and the count of positive, negative, and objective texts for the target company is used as sentiment features. [182] proposed Frames, BOW, and part-of-speech specific DAL (FWD) features and SemTree data representations and adopted SVM to predict stock price movement (polarity and change of price), which outperforms the BOW. Both tasks are treated as binary classification tasks. [188] proposed StockNet, a deep generative model, which consists of Market Information Encoder, Variational Movement Decoder, and Attentive Temporal Auxiliary, for stock market prediction based on binary movement where a rise in stock price is denoted by one and a fall is by zero. A two-year Twitter data is selected which targets 88 stocks (8 of them from the Conglomerates industry and the top 10 stocks in capital size in Basic Materials, Consumer Goods, Financial, Healthcare, Industrial Goods and Technology, Utilities, and Services). The proposed model is evaluated by Accuracy and MCC and achieved state-of-the-art performance on a new stock movement prediction dataset, which is also made publicly available. Wu et al. [178] presented novel cross-modal

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9https://github.com/yumoxu/stocknet-dataset
attention based hybrid recurrent neural network (CH-RNN), which is inspired by the DA-RNN model and also released the social text-driven stock prediction dataset built by aggregating stock prices from Yahoo Finance alongside relevant social media discourse, primarily from Twitter. Earnings calls is another data source used for financial forecasting. Earlier research has shown that more information is disclosed in earnings calls [54] than company filings alone and they influence investor sentiment in the short term [14]. The most recent studies using earnings calls include [80], which used 12,285 earnings calls for the S&P 500 companies. It studies the pragmatic correlation with analysts’ pre-call judgment and predicts the changes in analysts’ post-call forecast as a regression problem and a 3-class classification task by using Ridge Regression and Logistic Regression respectively. The models are evaluated by MSE and $R^2$ for the regression model and F1 Score and Accuracy for the classification model. The results demonstrate that earnings calls are moderately predictive of changes in analysts’ target prices. Earning calls has shown predictive power of investment sentiment in the short term, increasing absolute returns [24].

Multiple studies have investigated the integration of company relationships into the prediction of stock market movements. Notably, Chen et al. [22] incorporated company relationships using Graph Convolutional Neural Networks, while Sawhney et al. [150] proposed a deep attentive learning approach for predicting stock movements based on information from social media texts and company correlations. Recently, [195] introduced Data-axis Transformer with Multi-Level contexts (DTML) for stock movement prediction. DTML leverages temporal and global market context to learn dynamic correlations and outperforms existing approaches, resulting in a substantial annualized return in investment simulations. Another initiative to advance stock market movement prediction involves self-supervised learning from sparsely noisy tweets [163] and a newly created dataset for stock market forecasting is also made publicly available. The proposed SLOT method employs self-supervised learning to generate shared embeddings for stocks and tweets, enabling accurate predictions for less popular stocks. Moreover, it exploits multi-level relationships between stocks inferred from tweets, thereby bolstering its robustness. The work of [102] came up with two important hypotheses: (1) market sentiment does not equal semantic sentiment; (2) the stock price of a target company is also impacted by its related company. Thus, they proposed a multi-source aggregated classifier for stock price movement prediction. They first pre-trained a market-driven sentiment classifier to generate sentiment representations for news. Then, they proposed a classifier to predict the stock price movement for a target company, which aggregates the quantitative indicators and news sentiment of the target company and the news sentiment of its related companies, respectively. This model achieved 67.26% accuracy and 34.52% MCC averaged over 6 blue chip stocks in the Chinese market. They also conducted backtesting to show the improvements over strong baselines in the Sharpe Ratio.

While many studies have combined textual sentiment with fundamental and technical indicators, another type of research is to combine various sources of sentiment with different frequencies for stock market prediction. Principal Component Analysis (PCA) and Kalman Filter (KF) are two popular methods to combine sentiment indicators with different frequencies. [135] applied the KF procedure which is able to aggregate various sources of sentiment with distinct frequencies (e.g., daily, weekly, monthly) and generate a more representative and less noisy latent variable as a newly created daily sentiment indicator. In [135], the daily sentiment indicator from microblogs and weekly and monthly sentiment indicators from a survey are extracted using KF procedure. [135] has created a daily sentiment indicator which combines AAII, II, UMSC, Sentix and Twitter using KF procedure. For example, survey sentiment indicators are used for stock market studies e.g., AAII Investor Sentiment Survey is weekly and UMSC is monthly [53]. Multiple Regression, Neural Networks, SVM, RF, and Ensemble Averaging are used to perform predictions. Meanwhile, [135] highlighted that issues with evaluation in stock market prediction include that either out-of-sample data is not used to evaluate the model performance or the test data size is too small. These two issues are addressed in [135]. Meanwhile,
it is limited to utilize statistical tests to evaluate the accuracy of prediction and this is resolved in [135] by applying Diebold-Mariano (DM) test in addition to the evaluation criteria of Normalized Mean Absolute Error (NMAE). Unlike earlier studies which used textual features to predict market movements, [203] proposed event-driven trading strategies to predict stock market movements by detecting corporate events, which is considered as the driving force of market movements, from news articles. The bi-level event detection model is trained with masked-language model (MLM) loss. The authors employed two trading strategies to perform experimentation on the EDT dataset\(^\text{10}\). The first strategy, Trade at End Strategy keeps the transactions already started on hold for \(k\) days and closes on the last day. This strategy gave an estimated 1.74% average return and exceeded the return with 844% in 1-day trading. The second strategy, Trade at Best Strategy completes the transaction within \(k\) trading days, at the best price. This method resulted in an estimate of 9.11% average returns, that exceeded all the sentiment-based models.

The expected return could be investigated from the time series or cross-section perspective. A time series perspective is how average returns change over time while a cross-section perspective is how average returns change across different stocks or portfolios. While the majority of the studies investigate the effects of investor sentiment from a time series perspective, [6] pioneered and demonstrated investor sentiment, broadly defined, affects the cross-section of stock returns significantly via a set of empirical results. When estimation of sentiment is high, stocks that are unattractive to arbitrageurs and meanwhile attractive to optimists and speculators, tend to generate relatively low subsequent returns [6]. This includes distressed stocks, extreme growth stocks, high volatility stocks, non-dividend-paying stocks, small stocks, unprofitable stocks, and younger stocks.

5.2.3 Financial Risk Prediction. One essential indicator of instability and risk is financial volatility, which is a popular metric used in financial forecasting. Volatility is commonly defined as the standard deviation of a stock’s returns over a pre-defined period of time. The volatility is defined as follows:

\[
u(s, s + \tau) = \ln \left( \sqrt[\tau]{\sum_{t=s+1}^{s+\tau} (r_t - \bar{r})^2} \right)
\]

(7)

where \(r_t\) is return price and \(\bar{r}\) is mean of return prices.

\[r_t = \ln(P_t) - \ln(P_{t-1})\]

(8)

where \(P_t\) is the adjusted close price.

There are studies in risk prediction using various data sources such as financial reports [84, 131, 169, 175], financial news [131, 169], message boards [130] and earning calls [177]. [175] investigates the significance of sentiment words on financial risk, by formulating a regression task to predict future real-value risk given sentiment and a ranking task to rank the risk levels, using financial reports from 1996 to 2006 i.e., Section 7: management’s discussion and analysis of financial conditions and results of operations (MD&A), which contains the most important forward-looking statements about the companies, in the 10-K Form, an annual report required by U.S. SEC, provides a comprehensive overview of the company’s business and financial conditions, and includes audited financial statements. The LM lexicon is chosen with six types of sentiment words (i.e., positive, negative, uncertainty, legal context, strong and weak confidence). The BoW model is adopted and TF-IDF and LOG1P are selected as word features to represent the 10-K reports. As compared to original texts, the LM lexicon has reduced the word dimension significantly from hundreds of thousands to less than two thousand. The regression task is evaluated by MSE and the ranking task is by Spearman’s Rho and

\(\text{https://github.com/Zhihan1996/TradeTheEvent/tree/main/data}\)
Kendall’s Tau. The experimental results demonstrate that the models trained on sentiment words generate relatively better performance than models trained on origin texts, which attests to the importance of the financial lexicons on financial risk prediction. Additionally, the trained models also suggest that there is a strong correlation between financial sentiment words and financial risk. [177] examined the correlation between earnings calls and financial risk, which is defined as the volatility of stock prices in the next week, by using uni-grams, bi-grams, part-of-speech tags, named entities and probabilistic frame-semantic features to build Gaussian copula model which is evaluated by the Spearman’s correlation and Kendall’s tau [177]. There are three datasets of transcribed quarterly earnings calls from the U.S. stock market during the Great Recession period, where the pre-2009 dataset includes earnings calls from 2006 to 2008 when the economic downturn began, the 2009 dataset consists of earnings calls from 2009 when the financial crisis spread globally and the post-2009 dataset contains earnings calls from 2010 to 2013 when the global economy recovers. It has demonstrated that the quarterly earnings calls can be used to predict the volatility of stocks in the limited future. One of the most recent studies done by [146], which performed volatility forecasting using textual features from financial disclosures (i.e., TC, TF, TF-IDF, BM25) with dimension reduction technique of PCA, as well as market features (e.g., current volatility and sector) from factual market information using SVM with Radial Basis Function (RBF) kernel. The proposed approach to sentiment analysis significantly outperforms current state-of-the-art methods and shows the information in the 10-K reports is valuable for volatility prediction. The model performance is evaluated by MSE and $R^2$ metrics. [187] proposed the sentiment-aware volatility forecasting (SAVING) model, which combines symbolic and sub-symbolic AI approaches by integrating grounded knowledge into neural networks, which incorporates market sentiment to predict stock return fluctuation. The proposed model outperforms not only pure statistical models such as GARCH and its variants, which are commonly used econometric time series models for volatility prediction, and Gaussian-process volatility model, but also the latest autoregressive deep neural network architectures e.g., neural stochastic volatility model and variational recurrent neural network. [34] proposed a market volatility classifier based on Latent Dirichlet Allocation (LDA) topic modeling. The paper suggests a strong negative correlation between positive tweets and next-day volatility by observing the relationship between financial news, tweets, and FTSE100. The authors also indicated the dependence of the model’s accuracy on a number of topics chosen.

Table 6. Financial Risk Prediction.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Data Source</th>
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<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>[34]</td>
<td>RavenPack, Twitter, Thomson Reuters, Ref. Data Source</td>
<td>2006 to 2019</td>
<td>Sentiment polarity score of each message computed by augmented sentic computing</td>
<td>US</td>
<td>Linear Regression, Linear SVM, Gaussian SVM, Gaussian Copula Models</td>
<td>Volatility</td>
<td>Volatility Negative Log-Likelihood (NLL): -6.044</td>
</tr>
<tr>
<td>[146]</td>
<td>10-K Form, an annual report required by the Securities and Exchange Commission (SEC)</td>
<td>2006 to 2016</td>
<td>SVM</td>
<td>Stock volatility</td>
<td>Volatility</td>
<td>Regression (MSE: 3.4809, Ranking: Kendall’s Tau: 0.87044, Spearman’s Rho: 0.43033)</td>
<td></td>
</tr>
<tr>
<td>[34]</td>
<td>RavenPack, Twitter, Thomson Reuters, Ref. Data Source</td>
<td>2009 to 2015</td>
<td>Latent Dirichlet Allocation (LDA) feature vector</td>
<td>US</td>
<td>SVR Volatility Regression (MSE: 0.14894), Ranking (Kendall’s Tau: 0.60458, Spearman’s Rho: 0.63403)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[187]</td>
<td>Twitter, 31 million messages 22-Dec-2012 to 29-Oct-2015</td>
<td>Sentiment indicators based on SMSL lexicon which combines with AAII, II, UMSC, Sentix</td>
<td>US</td>
<td>GARCH, SVM, EGARCH, TARCH, GJR, GP-vol, VRNN, NSVM, LSTM, ensemble</td>
<td>Daily volatility MSE: 0.111, R^2: 0.567</td>
<td></td>
<td></td>
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</table>
5.2.4 Portfolio Management. One type of research that was less focused earlier [104] but emerged recently is to exploit the opinions posted by investors to invest in stock markets properly by optimizing portfolios. Existing approaches largely treat market prediction as a classification, regression, or ranking task but are not optimized for making profitable investment decisions. However, the decision-making and trading strategies should be incorporated and also improve practical applicability [104]. To address this challenge, researchers started to investigate the adoption of financial sentiment for portfolio management. [87] applied a semi-supervised learning method to stock microblogs and proposed Follow-the-Loser online portfolio selection strategy. The proposed approach includes a user model, an emotion classifier using MLP, and a portfolio selection strategy. The concept of online portfolio selection is to apply online learning in the machine learning literature to the portfolio selection problem, which aims to maximize the cumulative returns over sequential multiple periods of time [87]. This is different from offline or batch portfolio selection (e.g., Markowitz’s Mean-Variance Theory), which balances the expected return and risk focusing on a single period of time. [170] firstly predicts the quality of opinions followed by investment recommendations. The quality estimation for investment opinions adopted features associated with the author, content, and stocks in discussion, and opinions with the highest predicted qualities are selected as high-quality opinions. When generating portfolios, a score is generated for each stock by aggregating the sentiment about stocks in the opinions weighted by the predicted qualities of opinions. Experiments are conducted on a real-world dataset and demonstrate the effectiveness of the proposed strategy in recommending high-quality opinions and profitable portfolios. [190] applied the Gaussian inverse reinforcement learning method in which the market dynamics is modeled as a Markov decision process and investor sentiment is regarded as a series of actions taken at different market states. The S&P500 index return, which is measured at 15 minutes internal, is used as the market return and the sentiment from Thomson Reuters news is used as the proxy of investor sentiment toward the general U.S. market. It is often that markets do not react to noisy signals, which largely exist in investor sentiment signals. The investor sentiment reward-based trading system is designed to filter out noisy signals and extract only effective signals that generate either negative or positive market responses. The annualized performance including the mean return, volatility, Sharpe ratio, and Sterling ratio are adopted to measure the model performance. [151] has proposed Policy for Return Optimization using Financial news and online Text (PROFIT), which formulates the stock prediction into a reinforcement learning problem and leverages financial news and tweets to model stock-affecting signals and optimize trading decisions to increase profitability. The trading performance is evaluated by Sharpe ratio (SR), Sortino Ratio (StR), Cumulative Return (CR), and Maximum Drawdown (MDD) and compared with baselines spanning different formulations including regression, classification, and ranking. The proposed PROFIT system has outperformed benchmark systems significantly. [193] has proposed a novel and generic state-augmented RL framework called State Augmented Reinforcement Learning (SARL), which can integrate heterogeneous data sources into standard RL training pipelines for learning portfolio management strategies. The portfolio performance is measured by portfolio value and Sharpe ratio. The Bitcoin [75] and HighTech [37] datasets are used for the experiments which have achieved significantly better portfolio value and Sharpe ratio than baseline models including equal weight and Deep Portfolio Management [75]. [43] proposed stock embedding, a vector representation of stocks in a financial market, which uses a neural network framework consisting of text feature distiller and price movement classifier to acquire such vectors from stock price history and news articles. The stock embedding could be applied to other financial tasks such as portfolio optimization other than price prediction. The proposed method has outperformed baseline models in both Price Movement Classification and Portfolio Optimization tasks. [104] has included public mood from online news and social media and selected RF, Multi-Layer Perceptron, and LSTM to take a historical series of lagged data and public mood and generate the optimal portfolio allocation automatically. The proposed methodology outperforms the equal-weighted
The model captures the relevant market trends by using hierarchy-based temporal attention for ranking stocks. In The sentiment polarity is added using Valence Aware Dictionary and sEntiment Reasoner (VADER) [71]. The trading rates in the short run using Flexible Fourier Form regression method using absolute returns as a measure of volatility [91].

5.2.5 FOREX Market Prediction. There have been more efforts to make predictions on the stock market but few on the foreign exchange market. Earlier studies had investigated the connection between macro fundamentals and exchange rates in the short run using Flexible Fourier Form regression method using absolute returns as a measure of volatility [91].

portfolio allocation strategy consistently and shows that it is always beneficial to the model performance to include the financial sentiment. [86] proposed a sentiment-aware deep reinforcement model for portfolio allocation on a daily basis. The sentiment polarity is added using Valence Aware Dictionary and sEntiment Reasoner (VADER) [71]. The trading performance is evaluated by Sharpe Ratio (SR) and Annualised Return which shows it is more robust than benchmarks across Sharpe Ratio and Annualised Returns. [20] presented a sentiment-based RF model to generate a portfolio of Chinese stocks that can achieve higher returns. The proposed method shows the importance of choosing suitable methods for stock characteristics and stock selection methods in a highly volatile market. This method generated higher returns than the Shanghai Stock Index. [152] proposed a modified LSTM, namely time-aware LSTM (t-LSTM) that learns the time-aware representations to produce a ranked list of predicted stock return ratios based on expected profit. The model captures the relevant market trends by using hierarchy-based temporal attention for ranking stocks. In intra-day situations, the model outperformed the SOTA methods by over 8%, and by 10% in risk-adjusted returns.
The impact of macroeconomic announcements, which is collected from Bloomberg World Economic Calendar (e.g., GDP, interest rates, and consumer confidence indexes), on USD/EUR exchange rate volatility is estimated. The observations are divided into 5-minute intervals, totaling 288 in 24 hours, from 28/10/2003 to 20/01/2004 and the results suggest that macroeconomic news significantly increases the volatility of exchange rates immediately after the announcement. It also shows that the degree of significance varies by news category and country. Also, [46] concludes that macro news arrivals affect currency markets over time. The average news effects correspond to the direct channel for price impact which is absorbed immediately, but total news effects are not reflected quickly. [76] presented Forex-foreteller (FF), which utilizes news articles to forecast the movement of foreign currency markets. FF combines language models, topic clustering, and sentiment analysis to identify relevant news articles which are used together with historical stock index and currency exchange values to build a linear regression model to perform forecasting and generate warning messages. [129] proposed a novel approach that adopted TF-IDF weighted features scaled by sentiment sum score using SentiWordNet to predict intra-day directional-movements of currency-pair using SVM and demonstrated the existence of a promising predictive relationship between foreign exchange market and financial news. [154] proposed a FOREX market prediction system that performs sentiment analysis of news headlines by exploiting word sense disambiguation and predicts the directional movement of EUR/USD exchange rate and improved prediction accuracy. [155] presented a novel approach that includes news story events in the economy calendar to predict intra-day directional movement of currency pairs using SVM, RF, and XGBoost algorithms and achieved promising results. [183] investigates the efficacy of high-frequency news sentiment, which is represented by a 4-dimensional time series extracted by a FinBERT-based model, for FOREX market prediction without including other semantic features. Experimental results show that their model outperforms benchmark approaches for sentiment analysis and conclude that news sentiment alone may have predictive power, though it is relatively weak, for FOREX price movements.

5.2.6 Cryptocurrency Market Prediction. Cryptocurrencies have experienced remarkable value growth, surpassing the most substantial historical bubbles of the past three centuries [2]. More studies have been conducted to understand the dynamics of cryptocurrency market behavior over time since recently, with a primary focus on on causality and correlation tests [88, 133, 157]. The research demonstrated that investor sentiment holds significant nonlinear predictive power for the returns of major cryptocurrencies [126]. [81] proposed a hidden Markov Model to construct a transition matrix from Markov Chains on positive/negative sentiment, trading volume, and closing price to predict the upward or downward market trend. This study also observed that the market tends to respond more to positive sentiments in a
Another approach, as presented in [90], involves conducting deconvolution on the penultimate layer preceding the reference to [196], text explanations are generated utilizing the advanced natural language generation transformer LIME in conjunction with LSTM-CNN, accurately identifying pivotal words that align with the target sentiment. In train a random forest stock forecasting model, which is further explained through LIME. Furthermore, [60] implements the simplification procedure, [8] integrates sentiment analysis of text with technical analysis of historical stock prices to between the price movement of individual stocks and the sentiment associated with popular terms detected in tweets. In direct financial predictions. This information serves as a foundation for further analysis, leveraging the relationship associated polarity values. Notably, this work emphasizes the interplay between financial variables rather than making approach mirrors the feature relevance technique, with its focus on discerning top-contributing aspects along with their sentiment analysis to examine the correlation between stock price movement and the most pertinent aspects identified in tweets. The polarity of each aspect is derived using a SenticNet-based graph convolutional network (GCN) [92]. This method was compared with LIME and exhibited greater reliability. In a similar vein, [136] employs aspect-based technical indicators. Subsequently, decision tree techniques are implemented for stock market forecasting. The proposed explainability, [17] adopts various configurations of a permutation importance technique to prune less significant technical indicators. Subsequently, decision tree techniques are implemented for stock market forecasting. The proposed method was compared with LIME and exhibited greater reliability. In a similar vein, [136] employs aspect-based sentiment analysis to examine the correlation between stock price movement and the most pertinent aspects identified in tweets. The polarity of each aspect is derived using a SenticNet-based graph convolutional network (GCN) [92]. This approach mirrors the feature relevance technique, with its focus on discerning top-contributing aspects along with their associated polarity values. Notably, this work emphasizes the interplay between financial variables rather than making direct financial predictions. This information serves as a foundation for further analysis, leveraging the relationship between the price movement of individual stocks and the sentiment associated with popular terms detected in tweets. In the simplification procedure, [8] integrates sentiment analysis of text with technical analysis of historical stock prices to train a random forest stock forecasting model, which is further explained through LIME. Furthermore, [60] implements LIME in conjunction with LSTM-CNN, accurately identifying pivotal words that align with the target sentiment. In reference to [196], text explanations are generated utilizing the advanced natural language generation transformer

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Data Source</th>
<th>Period</th>
<th>Text Representation</th>
<th>Markets</th>
<th>Method</th>
<th>Task</th>
<th>Performance</th>
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<tbody>
<tr>
<td>[98]</td>
<td>Twitter</td>
<td>20-May-2021 to 31-Sep-2021</td>
<td>Sentiment scores from fine-tuned BERT</td>
<td>Cryptocurrency</td>
<td>LSTM</td>
<td>Financial Sentiment and Cryptocurrency Market Prediction</td>
<td>Precision: 97%, Recall: 92.5%</td>
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<td>[100]</td>
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<td>Granger causality test and Vector Auto-regression (VAR)</td>
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<td>Significant predictive power: (p&gt;0.05) on Bitcoin, Bitcoin Cash and Litecoin</td>
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<td>[101]</td>
<td>Twitter</td>
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<td>Long-term &amp; McDonald financial corpus and cryptocurrency lexicon</td>
<td>Cryptocurrency</td>
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<td>Bitcoin prices are partially predicted by momentum on social media sentiment in social networks</td>
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Table 9. Cryptocurrency Market Prediction

bearish market and responds more to negative sentiments in a bullish market. The paper however only used Bitcoin for the study and other cryptocurrencies were not included in the dataset. [70] worked on analyzing the sentiment of Chinese social media and its effects on the cryptocurrency market. The paper proposed LSTM-based RNN model to predict the cryptocurrency price and it has achieved better precision and recall than baseline auto regressive models.

5.2.7 Explainable FSA Applications. The notion of explainability holds paramount importance in FSA applications where decisions can have significant consequences [16]. [194] has classified the explanation procedure into textual, visual, by example, simplification and feature relevance. The majority of studies in FSA applications emphasize explainability through visual, feature relevance, and simplification techniques. Specifically, in visual explanation, [33] employs knowledge graphs to establish visual connections among event entities extracted from stock news articles. This method provides users with a graphical representation of the relationship between features and their corresponding predictions. Another approach, as presented in [90], involves conducting deconvolution on the penultimate layer preceding the output to generate a visual attentive map. This approach, named CLEAR (Class Enhanced Attentive Response), produces a graphical representation indicating the timeframe during which the stock-picking agent exhibits the highest degree of attention, along with a separate plot corresponding to the sentiment class of the stock. Regarding feature relevance explainability, [17] adopts various configurations of a permutation importance technique to prune less significant technical indicators. Subsequently, decision tree techniques are implemented for stock market forecasting. The proposed method was compared with LIME and exhibited greater reliability. In a similar vein, [136] employs aspect-based sentiment analysis to examine the correlation between stock price movement and the most pertinent aspects identified in tweets. The polarity of each aspect is derived using a SenticNet-based graph convolutional network (GCN) [92]. This approach mirrors the feature relevance technique, with its focus on discerning top-contributing aspects along with their associated polarity values. Notably, this work emphasizes the interplay between financial variables rather than making direct financial predictions. This information serves as a foundation for further analysis, leveraging the relationship between the price movement of individual stocks and the sentiment associated with popular terms detected in tweets. In the simplification procedure, [8] integrates sentiment analysis of text with technical analysis of historical stock prices to train a random forest stock forecasting model, which is further explained through LIME. Furthermore, [60] implements LIME in conjunction with LSTM-CNN, accurately identifying pivotal words that align with the target sentiment. In reference to [196], text explanations are generated utilizing the advanced natural language generation transformer
decoder, GPT-2 [144], with the added consideration of incorporating specific keywords within the generated text. The presented methodology, known as soft-constrained dynamic beam allocation (SC-DBA), involves the extraction of keywords associated with different tiers of anticipated market volatility. This extraction process is facilitated by a distinct network designed for analyzing harvested news titles. The evaluation of the quantitative performance is based on assessing both the fluency and practical relevance of the generated explanation.

5.2.8 Summary of FSA Applications. We summarize different FSA applications in Tables 5, 6, 7, 8 and 9 by types of FSA applications. The most frequently used data sources in FSA applications are microblogs and news, followed by annual reports filed by companies. The financial metrics predicted include stock index, stock price, stock price movement, stock price change, return rate, volatility, stock market crash risk, and FOREX rate change. As for methods for predictive modeling, similar to many other NLP tasks, deep learning has received more attention than traditional machine learning (e.g., SVM) and time series modeling (e.g., GARCH) in recent years with more promising performance contributing to its capability to perform high-level abstraction from complex data, though is less explainable than feature-based machine learning. The variants of Recurrent Neural Networks (e.g., Attentive LSTM, DA-RNN), and advancements in Graph Convolution Networks (e.g., Graph Attention Networks) have demonstrated remarkable state-of-the-art performance. Meanwhile, Reinforcement Learning has started to apply to portfolio optimization tasks and we have observed more work adopting it for intelligent asset allocation recently. In terms of markets, the US stock market is the most studied market but the tasks are moving beyond market movement prediction to risk prediction and portfolio management. Meanwhile, there has been a notable increase in research aimed at forecasting both the FOREX and cryptocurrency markets using textual data. Particularly, the exploration of the cryptocurrency market is still in its infancy, primarily centered on causality and correlation tests. Early investigations reveal that the cryptocurrency market exhibits reduced predictability when compared to the stock market, a trait attributed to the heightened dynamism inherent in cryptocurrency markets. As for model performance, practical traders agree that any results above 50% accuracy are value-added to their day-to-day trading [129] and literature reviewed in our survey has demonstrated that effectiveness. The evaluation metrics adopted in FSA techniques also apply to FSA applications depending on whether it is a regression (e.g., MSE) or classification task (e.g., F1 Score). Additionally, the trading simulation results are consistently adopted as a measurement of performance for portfolio management systems and popular metrics include accumulated return, average percentage gain per transaction, and Sharpe ratio.

6 MAIN FINDINGS

6.1 FSA Scopes and Sentiment Types

To address our first research question on what is the scope of FSA in today’s context, and what is the relationship among FSA, investor sentiment, and market sentiment, we surveyed the recent publications. FSA studies have evolved with the increase of financial textual data over the years particularly in public news and social media. In today’s context, the scope of FSA research has been extended to the field of study that not only analyzes people’s sentiments from financial texts but also investigates the predictability of financial textual sentiment on the financial market. The objective and area of FSA techniques are fundamentally different from FSA applications but there is also an interactive relationship between them. While FSA techniques aim to study the techniques that can improve the performance of various FSA tasks (e.g., targeted aspect-based sentiment analysis) with human-driven annotation, the main objective of FSA applications is to exploit sentiment for financial applications, such as causality and correlation testing and financial forecasting with market-driven annotation computed from real-world market data. Here, financial sentiment serves as a
proxy of investor sentiment, which affects the market dynamics. There is a complex connection exists in FSA, investor sentiment, and market sentiment. Market sentiment is the aggregated effect of investor sentiment and a reflection of investor sentiment in their investment behaviors. Investor sentiment can be partially measured by financial textual sentiment, sentiment surveys, and market sentiment. This has established the theoretical foundation of using multiple data sources such as financial texts, sentiment survey, and market data to perform financial forecasting.

6.2 Trends in FSA Techniques

Our second research question is: What trends are emerging from the latest tasks, benchmark datasets, and methods in the newest FSA technique studies? We observed that the more benchmark datasets (e.g., SEntFiN in 2022) are annotated with substantial entries for fine-grained FSA tasks. Meanwhile, the creation of financial lexicons is extending from conventional word-level to phase-level and direction-dependent expressions. As for methods, the feature engineering process has factored in domain-specific features such as numbers in finance. The deep learning and hybrid approach which ensembles lexicon, machine learning, and deep learning methods has shown promising model performance. Moreover, the pre-trained language presentation models such as BERT are able to capture general language representation from large-scale corpora but lack domain-specific knowledge [94]. To improve the domain application of pre-trained language models, researchers have attempted to train domain-specific pre-trained language models such as FinBERT [4, 97] but it requires large domain-specific corpus (e.g., news, corporate reports, earnings call transcripts and analyst reports) and substantial computing resources. This has pushed the boundary of research in FSA techniques and improved the model performance significantly.

6.3 Trends in FSA Applications

Our third research question is: What data sources, tasks, methods, and financial markets can be used in FSA application-focused domains? FSA applications have gained increasing attention than FSA techniques in recent years largely attributed to the increase of various textual data sources and technologies. The main application of FSA is in causality and correlation testing and predictive modeling in financial markets, or named natural language-based financial forecasting which is brought up by [186]. While causality and correlation testing were focused on by earlier studies, the adoption of financial textual data using NLP techniques to extract sentiment in financial forecasting is an emerging research field. We have identified six financial forecasting tasks including stock market movement prediction, stock market risk prediction, portfolio management, FOREX market prediction, and cryptocurrency market prediction.

Financial sentiment, which serves as a proxy for investor sentiment or non-informational trading, has demonstrated its effectiveness in financial forecasting, especially in the stock market. Sentiment from the three main sources (i.e., corporation-released, media-expressed, and internet-posted texts) has been found to have important effects on market movement. Particularly, negative sentiment has proved to be the strongest influence. Specifically, media-expressed texts (e.g., financial news) are the most commonly used data source followed by internet-posted texts (e.g., Twitter and StockTwits) and corporation-released texts (e.g., annual reports). The media-expressed texts have been applied to all six financial forecasting tasks while corporation-released texts are more used for stock market risk prediction. A more recent trend is to combine different sources of sentiment for financial forecasting. Currently, the application of FSA in financial markets focuses on the stock market, FOREX market, and cryptocurrency market, where the former market is the most commonly studied and the latter two markets are emerging. Many other financial markets such as commodities, money, derivatives, future, and insurance are not explored yet. It is also observed that FSA applications are shifting from market predictions to trading strategies such as portfolio management to improve practical applicability.
In terms of methods, deep learning and reinforcement learning with financial market prediction is regarded as one of the most charming topics.

6.4 FSA and Financial Forecasting

Our fourth research question is: How financial sentiment is applied in financial forecasting and what is the relationship between FSA techniques and applications? We found that financial sentiment can be represented in an explicit or implicit manner for financial forecasting, with the latter (implicit) being more frequently adopted. The explicit use of financial sentiment is to derive sentiment polarity, intensity, or sentiment lexicons and use it for predictive modeling while the implicit use is to generate the features and text representation such as word or event embeddings. The approaches to generate features and word representations in FSA applications are similar to word representation techniques, summarized under FSA techniques in Section 4.4.6. The implicit use of sentiment is more popular than explicit use and also can achieve better performance, largely attributed to the fact that this way carries more complete information than direct sentiment extraction. Notably, the FSA model demonstrates potential in the filtration of textual data, allowing for the retention of more pertinent information crucial for financial forecasting. Empirical studies also indicate that embeddings generated from models trained on market sentiment exhibit superior performance in financial forecasting compared to those trained on semantic sentiment. A thorough investigation into the interplay between financial sentiment models and their influence on the performance of financial applications is a crucial area for further exploration. Meanwhile, the algorithms and evaluation metrics adopted in FSA techniques can also be applied to financial forecasting except for complex application tasks such as portfolio management which requires reinforcement learning and trading simulations in many studies. Our view is that the application of financial sentiment in predictive modeling also can be regarded as an FSA task but is market-driven annotation, as compared to the human-driven annotation in the research in FSA techniques.

7 CHALLENGES AND FUTURE DIRECTIONS

7.1 FSA Techniques

Firstly, as elaborated by [106], [4] and [97], there is a lack of high-quality and large-scale open-source finance domain-specific annotations for FSA. The main challenge is that the creation of FSA benchmark datasets is usually expensive and requires expert knowledge [97, 106]. The research in fine-grained FSA has gained more attention after the release of the “SemEval 2017 Task 5” and “FiQA Task 1” datasets. From this perspective, the study of FSA techniques is often largely driven by the immediate release of newly annotated datasets. As for data annotation, the nested target annotation schema, which is proposed by [101] and goes beyond the traditional target, aspect, and sentiment annotation, could open a new space for FSA. Secondly, lexical resources are limited and scattered. Since finance is a highly professional domain, general-purpose sentiment lexicons usually fail to take into account the domain-specific connotations and the heavy reference to prior knowledge. For example, words like “liability” and “debt” are considered negative in general-purpose sentiment analysis, but are frequent and have neutral meanings in the financial context. This makes it difficult to generalize the sentiment classifiers and underlines the need for finance domain-specific sentiment analysis [98]. Further, sentiment intensity scores are more consequential and nuanced for financial sentiment analysis compared to other domains. Whereas most of the current TABSA studies still adopt a polarity detection fashion (i.e., classification to positive or negative). Further, it is important to improve the capability of generalization for BERT-based models. The successful application of FinBERT in FSA tasks is largely dependent on the corpora used to pre-train the language.
model. Presently, financial news, annual reports, earning call transcripts, and analyst reports are adopted by variant FinBERT but microblog corpora have not been explored. Next, the incorporation of knowledge and adoption of GCN are demonstrated to be useful in sentiment analysis but few of the earlier research have attempted to incorporate knowledge in FSA, which could be a promising direction for research in FSA techniques. Finally, incorporating linguistic intuitions in deep learning models [56, 65, 116] is another direction to improve the rationality of model design, because many deep learning-based methods focused on algorithm novelties and ignored linguistic intuitions. The future study could focus on improving the six areas that cause FSA fail, i.e., irrealis mood (conditional mood, subjunctive mood, imperative mood), rhetoric (negative assertion, personification, sarcasm), dependent opinion, unspecified aspects, unrecognized words (entity, microtext, jargons), and external reference. In addition, the following area of research can be explored further: Future research may focus on integrating incorporating multimodal data into FSA, such as text, images, audio, and video, to gain a more comprehensive understanding of financial sentiment. This could involve analyzing earnings call transcripts, financial news articles, social media posts, and even multimedia content. Also, the contextual financial sentiment analysis which is to develop methods that can understand and analyze the context in which financial sentiments are expressed will be crucial. This could involve sentiment disambiguation, where sentiment is understood in relation to specific events, companies, or market conditions.

7.2 FSA Applications

One challenge with FSA applications is the lack of publicly released textual data sources which are in a time series with a substantial amount of financial texts and representative periods to model the relationships between investor sentiment and financial markets. Meanwhile, the attention of the FSA application is moving beyond the stock market to other financial markets and shifting from stock market prediction to trading strategies such as portfolio management to improve practical applicability. The adoption of reinforcement learning could open a new avenue for portfolio management but it still remains relatively less explored. Further, earlier studies focus on news sentiment, the emotions derived from news could also influence investors’ behaviors in financial markets [44]. Lastly, the financial market is driven by different types of news which include macroeconomic factors, geopolitics, and company-specific factors [173], which means the sentiment can be derived from different perspectives such as macroeconomics, microstructure factors, event-oriented, and company-specific [100]. From this perspective, the aspect-based financial sentiment analysis could be adopted to extract aspect-level features to forecast future market performance [189] which could also improve the model interpretability and explainability. The notion of explainability holds paramount importance in FSA applications where decisions can have significant consequences. Methods for generating human-understandable explanations for model predictions will become a focus. With the rise of cryptocurrencies and emerging markets, there will likely be a growing interest in sentiment analysis tailored to these specific assets and markets. FSA can continue to play a crucial role in assessing risk and managing portfolios. Future research may focus on developing models that can provide more accurate risk assessments and aid in making more informed investment decisions. Lastly, future research could delve deeper into the intersection of behavioral economics and financial sentiment analysis, exploring the psychological factors that influence sentiment and decision-making in financial markets.

8 CONCLUSION

This survey proposed a comprehensive review of FSA research from both technique and application perspectives including their interactive relationship. The scope of FSA research has been redefined and the relationship among FSA, investor sentiment, and market sentiment. Specifically, through the review of FSA techniques, we have included
the latest benchmark datasets, and the methods, which include lexicon, machine learning, deep learning and hybrid approaches, pre-trained language models, and word representation techniques used for the FSA study. As for FSA applications, we summarized that the main FSA application in financial forecasting is hypothesis testing and predictive modeling. Predictive modeling has received more attention in recent years, particularly in the stock market and FOREX market. In terms of tasks in predictive modeling, the application in the stock market has moved beyond traditional market movement prediction to market risk prediction and portfolio management. Market prediction typically is treated as a classification or regression problem, however, the decision-making and trading strategies are incorporated into portfolio management which has improved practical applicability. The study in the FOREX market is less than the stock market but has become an emerging field. In terms of methods for predictive modeling, machine learning, deep learning, and reinforcement learning have become the three mainstream approaches.

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