OmniaScience Intangible Capital

IC, 2024 – 20(3): 513-530 – Online ISSN: 1697-9818 – Print ISSN: 2014-3214
https://doi.org/10.3926/ic.2547

Bridging sentiment and finance: An exploration of BOD statements and bank ratios in Jordan

Raed Kanakriyah[1*], Abeer Al-Faouri[1], Murad Y. Abuaddous[1], Riyad Alhindawi[2]

[1]*Al-Balqa Applied University (Jordan)*

[2]*Institute of Banking Studies (Jordan)*

[*]*Corresponding author: raedkkk1967@yahoo.com*
dr.abeeral-faouri@bau.edu.jo, Muradyousef@bau.edu.jo, Riyad@ibs.edu.jo

Received November, 2023
Accepted October, 2024

Abstract

Purpose: This study explores the intricate interplay between sentiment extracted from Board of Directors (BOD) statements and the traditional financial metrics of banks. It investigates the relationship between a bank's financial performance, measured by various financial ratios, and the sentiment expressed in BOD statements.

Design/methodology/approach: Drawing from a dataset encompassing BOD statements from 15 Jordanian banks spanning 2017 to 2021, sentiment analysis techniques are employed to derive sentiment scores. These scores are then juxtaposed with principal components distilled from financial metrics to examine their predictive relationship.

Findings: Preliminary findings reveal significant non-linear patterns between Hu and Liu's (2004) sentimental analysis (Lui_sen), the Data Science Lab's (n.d.) multilingual sentiment tool (multi_sen), and the principal components. A subsequent random-effects panel regression further elucidates these relationships, highlighting the significant influence of specific principal components on sentiment scores. This study provides a compelling case for integrating sentiment analysis with traditional financial indicators, offering a more comprehensive toolkit for evaluating bank performance.

Research limitations/implications: Future research should explore broader datasets across multiple sectors, to validate the generalisability of the findings beyond the banking sector in Jordan.

Practical implications: This research holds implications for investors, analysts, and stakeholders by combining sentiment analysis with traditional financial metrics. It offers deeper insights into the health of banks and the intentions of management. This integrated approach allows stakeholders to make informed decisions and mitigate risks based on a more comprehensive view of banks' financial situations. Additionally, the possibility of real-time sentiment analysis enables the dynamic monitoring of banking institutions' financial health as updated data becomes available.

Social implications: The study's results are valuable to users of financial information, aiding the Association of Banks and the Central Bank of Jordan in formulating policies for the banking sector. Auditors, consultants, and regulatory bodies in Jordan can also benefit from these insights.

Originality/value: This is the first study exploring the relationship between sentiment extracted from BOD statements and traditional financial metrics in Jordan. It provides novel evidence of this relationship, contributing to the literature on the integration of textual data analysis and financial performance.

Keywords: Sentiment analysis, BOD statements, Principal components, Financial metrics, Textual data in finance, Jordanian banks

Jel Codes: G21, M41, C55

To cite this article:

Kanakriyah, R., Al-Faouri, A., Abuaddous, M.Y., & Alhindawi, R. (2024). Bridging sentiment and finance: An exploration of BOD statements and bank ratios in Jordan. *Intangible Capital,* 20(3), 513-530. https://doi.org/10.3926/ic.2547

1. Introduction

In accounting and finance, obtaining accurate and reliable data on company performance is crucial. Companies communicate with their stakeholders via their annual reports and other disclosures. However, the usual focus for specialists and analysts lies in the financial declarations and their footnotes, as non-financial information is challenged by the absence of homogeneous key performance indicators (KPIs), in terms of comparability (Krasodomska, & Zarzycka 2021). Despite this, non-financial information can carry a lot of meaning, helping stakeholders draw a comprehensive view of the company under scrutiny. This view motivated our quest to search for meaning within the text itself. More precisely, we examine the sentiment of the Board of Directors' (BOD) statement in tandem with financial disclosures. In fact, we share this vision with a plethora of previous studies that have tried to capture semantics within the non-financial information found in annual reports (Haller, Link & Groß, 2017).

Thus, this research represents our quest to investigate the possible impact of sentiment in the 'BOD statement' and the banks' conventional financial performance indicators in Jordan. As a developing Middle Eastern country, Jordan shares a unique cultural setting with its neighbouring countries, which also use Arabic as their mother tongue. The use of expression and communication in this context is distinctive from other regions (Holes, 2004). Capturing sentiment analysis within this setup creates a great opportunity for research. Moreover, we focus on the banking sector as the major contributor to the Jordanian economy, making it subject to heavy regulations and rigorous monitoring. This sector is a good candidate for analysis because its disclosures are more comparable and unified than in other sectors.

Sentiment analysis is a tool used to classify and analyse the opinions expressed within texts. This tool can be utilised to quantitatively assess the emotional tone behind BOD statements, to investigate managerial sentiment and its potential implications for performance within Jordanian banks.

Accordingly, this research investigates the possible impact of the sentiment in a 'BOD statement' on a bank's performance. We aim to determine whether the sentiment expressed in these statements reflects the historical financial performance of banks. On the one hand, we believe that financial indicators can provide quantitative evidence regarding banks' performances, while the BOD statement should match those conclusions. This proposition is based on the assumption of faithful representation that stakeholders expect from management. Thus, we set forth the following question: "Can the sentiment embedded in Board of Directors' (BOD) statements provide insights into a bank's financial health and performance based on historical data?"

In previous literature, semantic analysis captured the attention of many scholars. However, the BOD statement has rarely been the focus of previous research. Recent literature has hinted at the potency of this fusion. For example, research has shown that companies nearing bankruptcy tend to use specific linguistic patterns in their management reports (Moreno & Camacho-Miñano, 2022). Likewise, the tone and content of audit committee disclosures have been linked to a company's violation risk (Guo, 2022). And yet, exploring the relationship between BOD statements and their true reflection on financial performance is a new area of investigation that we hope to expand on. Additionally, there is a general lack of evidence dealing with Arabic-speaking nations, in terms of semantic analysis. Hence, this study provides a novel exploration of the sentiment expressed in Board of Directors' (BOD) statements within Jordan's banking sector. In particular, integrating advanced sentiment analysis to analyse the nuanced linguistic patterns in BOD statements and their reflection on financial metrics results is an under-explored issue, especially in Arabic-speaking countries. This study addresses this gap by focusing on Jordan, to offer insights that can be extrapolated to similar cultural and economic contexts in the Middle East.

Based on this gap, we rely on signalling theory, which posits that voluntary disclosures act as signals to the market about the company's performance and direction. Accordingly, signalling theory provides the foundational framework for our study, as we view the BOD statements to be a form of strategic communication, signalling managerial sentiment and its predictive potential for financial outcomes.

To achieve the study's objective, we utilise natural language processing (NLP) to extract sentiment scores and financial ratio results from a dataset of all 15 Jordanian banks, covering the period 2017-2021. These scores are then combined with principal components, based on the financial metric, to provide a comprehensive view of sentiment and financial performance.

Therefore, we bloc quantitative information into dialogue with qualitative information, to better understand the dynamics between linguistic variations of the BOD statements and financial metrics. The objective is to develop a toolkit for the performance assessment and decision-making of bank stakeholders. The findings can also be used to advise policy-making and regulatory practices, especially in increasing the transparency and reliability of financial reporting in developing economies.

The paper is organised as follows: Section 2 describes the current state of the art on this topic and identifies the gaps. Section 3 illustrates the methods used in collecting and analysing the data. Section 4 states the findings and presents a detailed discussion of them. Section 5 synthesises the main findings of this study, with their implications, and proposes possible future research directions.

2. Literature Review and Research Gap

From a theoretical point of view, signalling theory predicts that managers credibly convey information about the company to its stakeholders through a signal. Thus, it is expected that companies communicate their intrinsic value and prospects to the market, which, in turn, reduces information asymmetry (Kharouf, Al-Khasawneh & Tarawneh, 2020). Following this logic, annual reports, including financial statements and BOD statements, serve as channels for sending information regarding the companies' financial health, operational performance, and strategic direction to stakeholders. This quantitative and qualitative communication helps reduce the information gap between company insiders and external stakeholders.

BOD statements can carry significant information that reflects the company's strategic direction and governance perspective. Thus, the signal from the BOD statement is considered a trajectory for the company's stability, responsiveness, and risk management (Shandiz, Zadeh & Askarany, 2022; Mankayi, Matenda & Sibanda, 2023). Therefore, sentiment in the report can provide meaningful indicators that signal the company's status, not explicitly detailed through financial data. Signalling theory suggests that positive sentiment might signal strong governance and optimistic future performance, and vice versa.

Within the accounting and finance literature, semantic analysis can be traced back to the early 2000s. Several attempts at textual analysis have been made to predict stock returns. For example, in their pioneering study, Antweiler and Frank (2004) attempted to predict stock market behaviour based on BOD messages. The authors employed a Naive Bayes algorithm to filter through more than 1.5 million messages posted on Yahoo! Finance and Raging Bull about the Dow Jones Industrial Average and the Dow Jones Internet Index. They then created a cluster that triggered 'buy', 'sell' or 'hold' signals. Their results looked promising as they found that the combination of BOD messages with other indicators can build an effective model able to forecast market direction. Moreover, Baker and Wurgler (2007) examined the effect of investor sentiment on the stock market. The authors targeted market behaviour as a proxy for investor sentiment. They developed a new top-down sentiment approach, revealing that sentiment affects returns for high-volatility portfolios. The effect was reversed when investors displayed low sentiment levels, resulting in higher returns for value and equal-weighted indexes. These early attempts offered key evidence of how sentiments can be considered a useful predictor.

Consequently, these early attempts triggered a series of investigations exploring the potential for semantic analysis to predict useful information in the market. In this regard, the accounting and finance literature has tried to extract useful information from unstructured data, such as message boards, annual reports, and earnings predictions. For instance, Elrod (2010) investigated the use of language (i.e. optimistic and pessimistic tones) in the Management Discussion and Analysis (MD&A) section of annual reports, to communicate expected future firm performance to investors. The research found that linguistic tone is not a reliable means of revealing information but, rather, provides a resource that is free from anything other than factual information. The research used Diction 5.0 as a tool to measure the style, tone and clarity of the words based on a predefined dictionary, which differs from sentiment analysis tools that determine the emotional tone of the text. However, the results are relevant to sentiment analysis, as the choice of words can significantly influence the sentiment conveyed by text. In addition, Kothari, Shu and Wysocki (2009) studied the impact of the dissemination of financial information by management, analysts, and news reporters. Their research conducted a content analysis of 100,000 disclosure reports by developing a unique business word classification scheme. The results revealed that a favourable assessment by this group can significantly reduce a firm's risk.

From this point onward, the availability of big data and recent AI tools, as with deep learning and neural networks, are facilitating more sophisticated text analytics in accounting research. Several investigations have analysed the textual content and delivery method of the qualitative sections of annual reports. For example, researchers used NLP technology to identify the linguistic features that distinguish authentic and fraudulent annual reports. In the 'bag of words' approach, they found that the narrative part of annual reports can provide valuable information to identify fraud that could not be detected from financial measures. Humpherys, Moffitt, Burns, Burgoon and Felix (2011) focused on linguistic cues to the deception that might be observed in fraudulent financial reports. They trained a machine learning tool to detect how deceivers craft fraudulent financial statements. The study found that textual analysis can be used to detect deception in earnings. It, also, further suggested that the deceptive models be extended to other financial documents, such as the President's letter to shareholders, public announcements, glossy annual reports, and notes.

In recent years, sentiment and textual analysis have gained prominence as tools for assessing organisational functions and evaluating a firm's performance. While the existing literature has reported two differing research avenues into the ability of textual analysis to offer insights into a firm's performance by analysing management reports and statements, the first school of thought has focused on the relationship between management statements, letters and performance. For example, Moreno and Camacho-Miñano (2022) found that, when approaching bankruptcy, firms employ more managerial language than when their finances are in a healthy condition, which provides further support to impression management theory. Buehlmaier and Whited (2018) found that the combination of accounting analyses with textual data was useful in capturing observable and difficult-to-observe firm characteristics. In a similar vein, Pengnate, Lehmberg and Tangpong (2020) found that managerial sentiment in letters to shareholders can help to identify the firm's post-crisis performance. de-Jesus and da-Nóbrega-Besarria (2023) used machine learning techniques to develop a novel measure of insolvency risk for the banks listed on the Brazilian stock exchange, by analysing bank manager sentiment. They found that the addition of sentiment analysis with a time-varying dictionary to the model enhanced its accuracy.

The second school of thought centres on the relationship between textual analysis and financial reporting. Guo (2022) carried out a textual analysis of Chinese companies, to see whether the tone of audit committee disclosure could predict instances of regulatory violations. Guo employed Python, in conjunction with machine learning and textual analysis techniques and methods, then analysed the model using STATA and conducted regression analysis. The results revealed that the tone of the text disclosed by the audit committee is an effective predictor of the violation risk of a company and helps mitigate information asymmetry. Agoraki, Aslanidis & Kouretas (2022) studied the effect of investor sentiment on bank credit and financial stability. They used two text-based sentiment measures between 1999 and 2015, from the New York Times and the Wall Street Journal. Their analysis revealed that lower sentiment in investors reduced bank lending. The study also found that the Great Financial Crisis negatively affected investor sentiment, reducing lending and increasing financial instability in the U.S. banking sector. Boudt and Thewissen (2019) argued that CEO sentiment within their letters tends to mention negative events from the past first and, when discussing unfavourable occurrences, they overwhelm these mentions with a plethora of positive terminology. The authors found that managers tend to engage in this form of impression management when they are involved in earnings management. They also found that the optimised sentiment measure tends to significantly underestimate the sentiment at the beginning and end of the text, compared to the sentiment in the middle. Asay, Libby and Rennekamp (2018) conducted two experiments and a survey on experienced managers, to inspect whether managers tend to provide reports that are considerably less readable when performance is poor than when it is favourable. The results showed that self-enhancement methods were applied and participants tended to reduce the readability of the report when performance was bad. These studies show the importance of management text narratives in financial reporting and demonstrate how sentiment analysis can be used to better comprehend corporate communication.

In line with this, several studies have examined the relationship between the tone of the annual report text and textual analysis. Borggreve (2022) applied the textual analysis method to 1,000 annual reports from the US, the UK, Germany and the Netherlands, to examine whether the sentiment in annual reports influences the short-term cumulative abnormal stock returns for these four countries. The analysis utilised the 'bag-of-words' method and combined the pre-set dictionary by Loughran and McDonald (2011). The results revealed that text positivity, text readability, litigious text, uncertainty and text density significantly affect short-term cumulative abnormal stock returns for all four countries. Moreover, Lim, Chalmers and Hanlon (2018) investigated the board narrative in the annual report, with a focus on readability. The readability test used the FOG index and the authors argued that less readable reports are associated with greater stock return volatility; they also found that business strategy affects the readability of the annual report. In particular, prospectors report of less readable annual reports than defenders. Yadav, Jha, Sharan and Vaish (2020) examined the impact of investor sentiment on stock prices and introduced an unsupervised method based on semantic orientation to assess the sentiment intensity of financial text, which proved more effective than traditional sentiment analysis techniques. The authors noted that Turney's Algorithm, combined with the noun-verb approach, is more effective as a sentiment analysis technique than traditional techniques. Finally, Atzeni, Dridi and Reforgiato-Recupero (2018) explored the challenges and methodologies for sentiment analysis in the financial domain. After identifying bullish and bearish sentiments for companies and stocks, the authors reported a cosine similarity exceeding 72% for predicting sentiment scores of the respective company/stock in each text instance through the use of semantic resources.

With respect to the relationship between textual disclosures and earnings manipulation, the authors examined the impact of the tone of financial disclosures and managers' earnings management behaviour, using a sample of US-listed Chinese firms. Results indicate that firms that employ positive, uncertain, or modal language in their 20-F filings are more likely to engage in earnings management practices, suggesting that textual tone may serve as a valuable tool for investors in identifying earnings management. Hájek (2018) reviewed the development of textual analysis in the financial field. The author suggested that sentiment analysis and machine learning, utilising the bag-of-words approach, are highly capable of providing more accurate predictions than sentiment categories alone. Hence, many authors have focused on utilising AI tools for capturing sentiments in annual reports. For example, Chen, Wu, Chen, Li and Chen (2017) developed a novel approach for fraud detection in annual reports using natural language processing (NLP), a quantum genetic algorithm (QGA), and support vector machine (SVM) techniques. The QGA-SVM model was found to be the optimal prediction model for accuracy, providing a valuable reference for informed decision-making by investors, creditors, and other accounting information end-users.

In summary, previous literature has shown a rapid increase in interest regarding how AI and machine learning tools can be utilised for semantic analysis. The existence of vast amounts of unstructured data related to companies presents a significant challenge, in terms of filtering through this information to extract meaningful insights. Usually, readers are susceptible to various biases, such as recency bias, confirmation bias, anchoring bias, and overconfidence bias, among others. This may lead them to be misled by statements provided by the Board of Directors (BOD). In addition, signalling theory suggests that textual content should serve as a medium through which to communicate with stakeholders. Thus, it should be expected that the text be treated with a level of scrutiny similar to numerical data. In this context, we argue that the sentiment embedded in BOD statements offers predictive insights into a bank's financial health and performance. Accordingly, we hypothesise the following null hypothesis:

H01: financial performance of Jordanian banks, as measured by financial ratios, is expected to have a positive impact on the overall sentiment in Board of Directors (BOD) statements.

The following section discusses the methodology adopted in this paper.

3. Methodology and Data Analysis

To achieve the study's goal, we utilised several analytical tools, capable of handling both quantitative and qualitative data, to explore the relationship between the sentiment of BOD statements and bank ratios. The study employed data from all Jordanian commercial banks from 2017 to 2021, resulting in 75 observations (number of banks * number of years: 15 * 5 = 75 observations). Sentiment analysis techniques were used to extract sentiment scores from the BOD statements. The study data was collected from the banks' financial reports, which were obtained through the statistical reports issued by ASE on an annual basis and the Banks and directory publications available on the ASE's official website. The sentiment scores were then used in regression analyses to examine the relationship between sentiment and bank ratios. The following section expands on these procedures.

3.1. Corpus and Pre-Processing Text

The corpus was constructed via manual extraction of the BOD statements from the annual reports of 15 banks in the years 2017-2021. The extracted data were converted to the CSV format and then incorporated into the corpus. The text variables analysed were the BOD statements, resulting in a total of 75 cases.

The pre-processing of the text comprised a series of transformations, performed before the data analysis aimed to convert the data into a format that could be processed and analysed. In this project, the text pre-processing pipeline contained four main steps: text normalisation, tokenisation, filtering and POS tagging.

The first step, text normalisation, standardised the text to ensure dataset consistency. This was achieved by capitalising text and removing accents, to avoid any noise and to enhance readability. The snowball stemmer was applied to the text, to ensure that all the words were normalised and reduced into their root words. For instance, 'Bank's Annual Profits increased significantly' was converted to 'bank annual profit increase significant'.

The second step, tokenisation, involved splitting the text into individual words or tokens. In this study, a regular expression (regex) was used to tokenise the text, enabling the identification of specific patterns or characters in the text. For example, the sentence "bank annual profit increase significant" became ["bank", "annual", "profit", "increase", "significant"] (Bird, Klein & Loper, 2009).

The third step, filtering, is removing the dataset of unwanted tokens (eg, stop words, numbers, tokens with infrequent occurrences in your dataset (0.1 to 0.9 relative frequency), n-grams from 1 to 2. However, this filtered dataset is the only dataset that is only meaningful for the analysis. For example, ['bank', 'annual', 'profit', 'increas', 'significant'] in ['bank', 'annual profit', 'increas significant'] (Millstein, 2020).

The fourth step, POS tagging, identifies the syntactic relations of each token in the dataset, and is final. This study applies an average perceptron tagger on the raw data, which can guarantee high accuracy and efficiency to annotate text data. For example, ['bank', 'annual profit', 'increas significant'] turns into [('bank', 'NN'), ('annual profit', 'NN'), ('increas significant', 'JJ')].

The text pre-processing pipeline described above aims to transform the raw text data into a structured, clean, and consistent dataset which is suitable for further analysis.

3.2. Sentiment Analysis

Sentiment analysis is a widely used technique in data science, and is used for understanding people's attitudes and opinions expressed in textual data. We discuss four popular methods for sentiment analysis: VADER, Liu Hu, SentiArt, and Multilingualsentiment.

VADER, developed by Hutto and Gilbert (2014), is a rule-based model that employs a lexicon-based approach. The sentiment score is calculated based on the intensity of sentiment-expressing words in the lexicon, and the review is classified as positive or negative depending on the score. VADER's sentiment lexicon is larger and of a higher quality than traditional sentiment lexicons like LIWC, and it outperforms other sentiment analysis benchmarks, including machine learning techniques. For example, the sentence "The bank's profits have increased significantly" would be scored as positive, due to the presence of words like "increased" and "significantly" (Hutto & Gilbert, 2014).

Liu Hu, introduced by Liu (2012), is an aspect-based sentiment analysis method that focuses on mining product features and opinions from customer reviews. Liu's Sentiment (Liu_Sen) extracts product features and the associated sentiment of customers towards those features. Liu Hu proposes several techniques for feature mining, which are highly effective in achieving experimental results. The method also uses an algorithm that summarises customer reviews by selecting representative sentences that capture the most important aspects of the product. In our analysis, we used Liu Hu to extract specific features from BOD statements, such as mentions of financial performance, management decisions, and market conditions, and then analysed the sentiment associated with these features Liu (2012).

SentiArt is a heuristic tool for computing Emotional Figure Profiles and Figure Personality Profiles, as described by Jacobs (2019). It is based on vector space models and computes the valence of words in text by using theory-guided, empirically validated label lists. SentiArt is accurate in predicting the emotional potential of text passages and in classifying figures as 'good' or 'bad'.

Multilingualsentiment is a sentiment analysis engine that analyses text. It can analyse non-Latin-based and Latin-based languages. Multilingualsentiment uses state-of-the-art machine learning to determine if the text it analyses is positive, negative or neutral, based on keyword phrases found in the text and, optionally, whether the word is used positively or negatively. Multilingualsentiment currently analyses text in more than 80 languages. Multilingualsentiment is very accurate and has fundamental applications for monitoring social media sentiment, while also identifying complaints or complimentary messages about a business or service in customer feedback. Data Science Lab offers Multilingualsentiment through a cloud API but it can also install the engine on your premises (Data Science Lab, n.d.)

3.3. Financial ratios

The present study relied on metrics used for conventional banks, as they used the most pervasively employed financial ratios. Stakeholders tend to scan through a heterogeneous set of financial ratios to assess the whole picture of a bank's soundness and efficiency (Krasodomska & Zarzycka, 2021). The Non-Performing Loans (NPL) ratio reveals the quality of a bank's loan portfolio (Abuaddous, 2023). The Earnings Per Share (EPS) and Book Value per Share (BVShare) indicate the profitability and the value of underlying assets, respectively (Al-Naimi, Alshouha, Kanakriyah, Al-Hindawi & Alnaimi, 2021). The yield ratio portrays the income-generating capacity of the bank's assets. The Debt to Equity (DE) ratio offers a perspective on the bank's financial leverage. ROA and ROE are employed to assess efficiency, to ensure that banks utilise their assets for generating returns. The income ratio is also used to gauge operational efficiency and profitability. The Quick Ratio serves to assess the bank's short-run liquidity by the extent to which it can satisfy immediate liabilities with liquid assets.

Taken together, these ratios provide an unambiguous signal for decision-makers to assess the healthiness of banks' financial, operational and risk-management efficacies. Table A in the Appendix provides the operational definition for each of the ratios adopted in the present study.

4. Empirical Results and Analysis

4.1. Financial Ratios

Table 1 presents the descriptive statistics for the variables considered in this study. The table summarises observations, mean values, standard deviations, and the minimum and maximum values for each of the studied variables.

In Table 1, the results indicate that NPL has a low average (mean) of 0.052 with little variability (SD = 0.027), suggesting relative consistency across the dataset. EPS and Bvshare show more variation, indicating diverse financial health among Jordanian banks. ROA and ROE display modest averages with minimal negative values, which can indicate a generally positive profitability. The sentiment analysis variables, such as Art sen and Lui sen, exhibit a broad spread, as evidenced by their higher standard deviations, reflecting varied sentiment in BOD statements.

Variable	Obs	Mean	Std. Dev.	Min	Max
npl	75	0.052	0.027	0.001	0.110
EPS	75	0.181	0.132	-0.030	0.680
Bvshare	75	2.310	1.232	1.120	6.010
yelid	75	0.045	0.037	0	0.127
DE	75	0.579	0.551	0	3.527
ROA	75	0.009	0.005	-0.002	0.018
ROE	75	0.078	0.040	-0.010	0.217
incomeratio	75	0.039	0.007	0.021	0.060
QuickRatioTimes	75	0.258	0.071	0.120	0.410
Art sen	75	0.357	0.184	-0.635	0.575
Lui sen	75	2.191	1.487	-0.360	7.054
vad sen	75	0.972	0.162	0.000	1.000
multi sen	75	2.200	1.497	-0.270	7.054

Note: non-performing loans (npl), earnings per share (EPS), book value per share (Bvshare), yield (yelid), debt-to-equity ratio (DE), return on assets (ROA), return on equity (ROE), income ratio (incomeratio), Liu's Sentiment (Lui sen), SentiArt (Art sen), Vader (vad sen), Multilingualsentiment(multi sen)

Table 1. Descriptive Statistics

Table 2 provides a Pearson correlation matrix which examines the interrelations between the studied variables. The results include all of the adopted financial indicators, along with the sentiment analysis variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) npl	1.000												
(2) EPS	0.046	1.000											
(3) Bvshare	0.424*	0.606*	1.000										
(4) yelid	0.148	0.017	-0.052	1.000									
(5) DE	0.131	-0.121	0.288*	0.533*	1.000								
(6) ROA	0.016	0.728*	0.153	0.230*	-0.138	1.000							
(7) ROE	-0.249*	0.708*	0.000	0.139	-0.194*	0.823*	1.000						
(8) incomeratio	0.553*	0.295*	0.240*	0.229*	0.015	0.548*	0.156	1.000					
(9) QuickRatioTimes	0.077	0.521*	0.515*	0.150	0.294*	0.483*	0.417*	0.331*	1.000				
(10) Art_sen	-0.117	0.176	0.170	-0.110	0.008	0.053	0.102	-0.140	0.164	1.000			
(11) Lui_sen	-0.360*	0.386*	0.000	-0.059	-0.150	0.319*	0.573*	-0.153	0.201*	0.436*	1.000		
(12) vad_sen	-0.018	0.050	0.077	-0.078	0.008	0.013	-0.011	-0.071	0.061	0.900*	0.244*	1.000	
(13) multi_sen	-0.359*	0.390*	0.002	-0.052	-0.144	0.324*	0.575*	-0.151	0.198*	0.432*	0.999*	0.244*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2. Pearson Correlation Matrix

Table 2 reveals several important relationships. In this regard, a moderate positive correlation exists between BVShare and NPL, and a strong positive correlation between EPS and ROE, indicating that, as earnings per share increase, return on equity tends to rise. Conversely, ROE shows a negative correlation with NPL, suggesting that higher non-performing loans are associated with lower returns on equity. The sentiment variables, particularly Lui_sen and multi_sen, display strong positive correlations with each other and with several financial variables, implying a significant relationship between board sentiment and financial performance.

However, given these observed correlations, there are clear interdependencies between the variables. Such multicollinearity can be challenging for various statistical analyses, as it can inflate variances and make it difficult to determine the individual effect of predictors (Shrestha, 2020). Moreover, the results may become sensitive to small changes in the model, thereby reducing the reliability and interpretability of the statistical outputs.

To address this issue, Table 3 shows the results of a Principal Component Analysis (PCA) conducted to obtain the key components from the multivariate dataset. This analysis identifies the eigenvalues and the explained variance proportion of each component, along with their cumulative contribution to the data's total variance.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.352	1.385	0.373	0.373
Comp2	1.967	0.596	0.219	0.591
Comp3	1.371	0.188	0.152	0.743
Comp4	1.184	0.669	0.132	0.875
Comp5	0.515	0.240	0.057	0.932
Comp6	0.275	0.052	0.031	0.963
Comp7	0.224	0.146	0.025	0.988
Comp8	0.077	0.042	0.009	0.996
Comp9	0.035	0.002	0.004	1.000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Unexplained
ROA	0.474	-0.225	0.103	0.244	-0.021	-0.166	0.173	-0.772	-0.021	0
ROE	0.393	-0.411	0.215	0.031	0.126	0.275	0.404	0.416	0.449	0
QuickRatio~s	0.402	0.114	0.083	-0.333	-0.659	0.446	-0.242	-0.008	-0.128	0
EPS	0.474	-0.164	-0.147	-0.211	0.401	-0.163	-0.112	0.269	-0.641	0
Bvshare	0.299	0.330	-0.348	-0.464	0.264	-0.185	-0.180	-0.128	0.559	0
yelid	0.141	0.290	0.636	0.259	0.361	0.150	-0.514	0.009	0.080	0
incomeratio	0.327	0.235	-0.171	0.543	-0.367	-0.473	-0.090	0.369	0.104	0
npl	0.126	0.494	-0.375	0.344	0.226	0.552	0.320	-0.057	-0.140	0
DE	0.043	0.498	0.468	-0.298	-0.059	-0.293	0.573	0.047	-0.148	0

Table 3. PCA analysis

Table 3 shows that the financial dataset under examination includes several metrics that often display inherent correlations (Li, Wang & Luo, 2022). This is expected to lead to multicollinearity, potentially complicating further analysis. To address this issue, PCA was utilised to transform these correlated variables into a set of linearly uncorrelated principal components. The decision to focus on the first four principal components was based on their cumulative explained variance, which accounts for 87.5% of the dataset's total variance. Therefore, adopting these components strikes a balance between simplifying the dataset, preserving its informational integrity, and minimising the risk of multicollinearity. Figure 1 provides a visual representation of the principal components' cumulative explained variance.

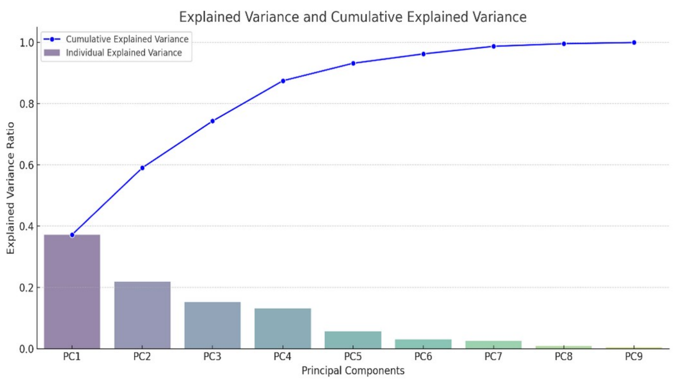

Figure 1. PCA analysis and Explained Variance Ratio

4.2. BOD Sentiment and Financial Ratio Analysis

Many methods are followed in sentiment analysis, each method utilising a unique rationale that is subject to strengths and limitations (Camacho, Panizo-LLedot, Bello-Orgaz, Gonzalez-Pardo & Cambria, 2020). Therefore, this study relies on the most used methods to enable a well-founded interpretation of the information extracted from BOD speeches. By considering the diverse applications of sentiment analysis methods in various fields, determining the most suitable method is a sophisticated issue. Choosing an approach that can have a substantial impact on the sentiment analysis of the BOD should be based on a solid foundation. With this in mind, this study began by using the VADER tool because it is widely used in academic discourse and is well known for its ability to convey the difference between sentiment polarity and intensity (Hutto & Gilbert, 2014).

However, further analysis suggests several problems with its implementation in a financial research context. Primarily, the fact that VADER is tuned to social media language is a valid ground for concern. Social media posts are verifiably very different from financial statements; for example, the vocabulary, tone, and argument structure are dramatically different. Thus, the lexicon and valence rules associated with VADER are likely to miss the precision in BOD.

Furthermore, the study's analysis revealed that this was equally evident in the study's context, with preliminary analyses demonstrating possible differences in the output of VADER when applied to the dataset. These differences, along with those observed by other methods of sentiment analysis, indicate a possibility of misrepresentation or simplification that can occur with emotions derived from financial narratives that are not inherently simple.

Thus, a decision was reached to exclude VADER, on the premise that the measurements should align as closely as possible with the linguistic and contextual characteristics of the board's statements, to ensure that any sentiments in the text reflect the original intent of the source more accurately.

In empirical financial studies, understanding the relationships between qualitative metrics, such as sentiment extracted from board statements (BOD), and traditional quantitative financial metrics, is both challenging and valuable. Historical analogies illustrate that these emotional dynamics fluctuate with evolving performance, strategic initiatives, and overall economic conditions (Borggreve, 2022; Brundin, Liu & Cyron, 2022). Therefore, linear approximation may not fully encompass the magnitude and richness of this relationship.

Linear regression, whilst essential in econometric methodologies, primarily assumes a constant rate of change, which is likely to oversimplify the complex interrelationship between emotions and financial performance. Although more detailed nonlinear models provide depth, they can also present complexities, sometimes obscuring clearer explanations (Jeffrey, 2020).

Linear regression assumes a relatively constant rate of change that is potentially overly straightforward in characterising the complex relationship between emotions and financial performance. While more granular nonlinear models could provide nuance, they can also lead to complications that sometimes mask more straightforward interpretations. To overcome this issue, the study used quadratic polynomials including second-order terms; it is highly effective in capturing potential curved patterns without overcomplicating the model's structure (Fan, 2018).

Figure 2 illustrates the polynomial regression analysis between the sentiment analyses models and the four main components extracted from financial ratios.

To understand the relationships between key components derived from financial scales and different emotion scores, polynomial quadratic regression was used, as illustrated in Figure 2. This type of regression allows for modelling nonlinear relationships, which are often found in complex datasets where linear models are limited. Visualisations represent scatter plots of the first four main components (PC1, PC2, PC3, and PC4) versus degrees of emotion (Art_sen, Lui_sen, and multi_sen), accompanied by quadratic regression curves. After examining the regression curves, it is evident that, while Lui_sen and multi_sen exhibit distinct nonlinear patterns with key components, the relationship between Art_sen and the components seems more ambiguous. Specifically, the quadratic curves of Art_sen are relatively flat and do not capture the obvious differences observed in other emotion scores.

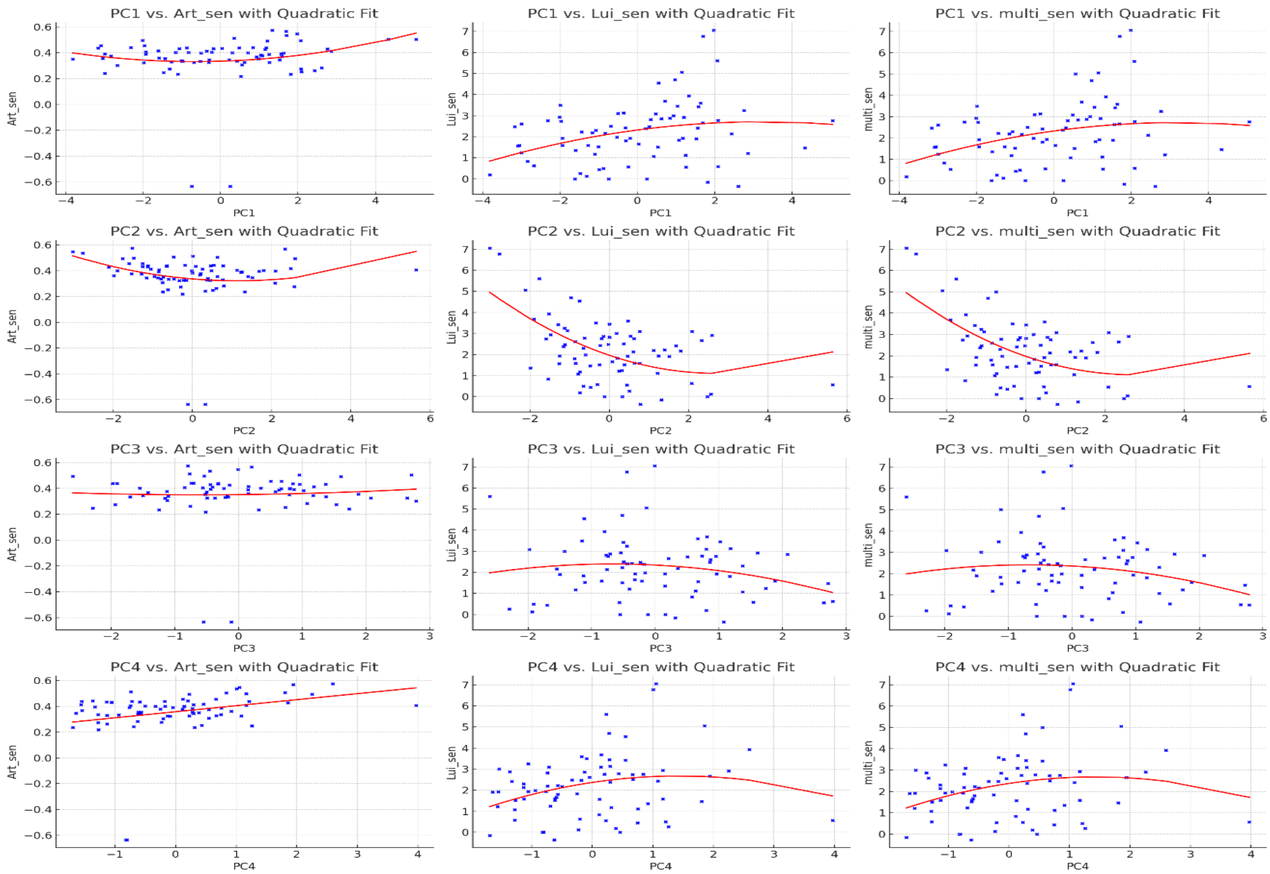

Figure 2. Polynomial regression

This observation raises concerns about the effectiveness of Art_sen in reflecting the underlying complexities between sentiment and financial metrics captured within key components. It is plausible that the methodology or lexical resources used to derive the degree of Art_sen may not be as consistent with the nuances of financial discourse as other sentiment analysis techniques. Alternatively, the nature of the information embedded in key components may not strongly resonate with the aspects of emotion captured by Art_sen. In light of the above, while Lui_sen and multi_sen have shown their potential as indicators of media sentiment, in relation to key financial components, the usefulness of Art_sen seems more limited in this context. Hence, researchers and analysts should be cautious when using Art_sen and consider complementary or alternative sentiment scales to ensure a thorough understanding of the interaction between emotions and financial variables.

Another noteworthy observation from Figure 2 emerges from the relationships between the main derived components of financial metrics and the scores of Lui_sen and multi_sen sentiment. Distinct nonlinear patterns can be distinguished, suggesting complex fundamental relationships between these sentiment metrics and the financial information encapsulated within key components. Such nonlinear correlations highlight the multifaceted dynamics between sentiment and financial metrics, suggesting potentially unnoticed heterogeneity between entities (in our case, Jordanian banks) over time. This variation can be attributed to the unique characteristics inherent in each bank, which remain constant over time (fixed effects) or specific unobservable factors that vary across banks and over time (random effects). Ignoring this heterogeneity can lead to biased and inconsistent estimates within the framework of simple linear regression (Abuaddous, 2023). Given this backdrop, using panel data regression techniques or specifically fixed effects or random effects models, becomes compelling. Panel data models are specifically designed to handle data spanning multiple entities over multiple time periods, capturing both noticeable and unnoticed heterogeneity.

Moreover, the motivation for constructing a fixed effect versus random effects model, after a non-linear regression, is based on the nuanced nature of the data and the specific characteristics of the banking sector in

Jordan. On one hand, non-linear regression revealed significant but complex patterns between sentiment scores (Lui_sen and multi_sen) and the principal components derived from financial ratios, indicating that the relationships might not be linearly proportional across the entire dataset. On the other hand, the non-linearity suggests dynamics between the variables that cannot be fully captured by a straightforward linear regression model. The choice between fixed effects and random effects will also depend on the nature of the unobserved heterogeneity. If we believe that unobserved effects are related to predictors, a fixed effects model would be appropriate. Conversely, if these unobservable effects are assumed to be random and unrelated to predictors, a random effects model would be appropriate.

In the polynomial regression analysis, the quadratic fit lines exhibit two distinct patterns: some show maximum values (n-shaped or inverted U-shaped), while others show minimum values (U-shaped). These patterns can be understood through the following theoretical and empirical insights. An n-shaped curve suggests that, as the principal component (PC) increases, the sentiment score initially rises to a peak and then begins to decline. This pattern could indicate a threshold effect, where moderate levels of the financial metric correlate with positive sentiments but, beyond a certain point, further increases may be associated with negative sentiments due to potential risks or diminishing returns. Conversely, a U-shaped curve suggests that the sentiment score initially decreases as the PC increases, reaches a minimum, and then starts to rise. This pattern might indicate that low levels of the financial metric are initially perceived negatively but, as the metric improves beyond a certain threshold, sentiment becomes positive, reflecting improved financial stability or performance.

Signalling theory posits that companies send signals to the market through disclosures, with positive signals typically being associated with good performance (Kharouf et al., 2020). In the context of n-shaped curves, moderate financial improvements might initially send strong positive signals. However, excessive growth could signal potential overextension or unsustainable practices, leading to negative sentiment. The observed n-shaped and U-shaped patterns align with the broader literature on financial performance and sentiment analysis. For instance, studies like Moreno and Camacho-Miñano (2022) and Borggreve (2022) highlight how sentiment scores derived from management reports exhibit complex relationships with financial performance, often showing non-linear dynamics.

Therefore, Tables 4 and 5 present the outcomes of the fixed effects panel data analysis, with multi_sen and Lui_sen as the dependent variables, and the first four principal components, representing financial ratios, as independent variables. The choice of a fixed effects model was informed by the Hausman test, which indicated a preference for the fixed model over a random effects model.

Therefore, we established the following two fixed effect regression models:

$$\text{Multi\_Senit}=\alpha+\beta1(\text{pc1it}) + \beta2\ (\text{pc2it}) + \beta3\ (\text{pc3it}) + \beta4\ (\text{pc4it}) + \mu\text{i}+\epsilon\text{it} \tag{1}$$

$$\text{Lui\_Senit}=\alpha+\beta1(\text{pc1it}) + \beta2\ (\text{pc2it}) + \beta3\ (\text{pc3it}) + \beta4\ (\text{pc4it}) + \mu\text{i}+\epsilon\text{it} \tag{2}$$

where:

- Multi_Senit and Lui_Senit represent the dependent variable sentiment scores for each bank i at time t, derived from two different sentiment analysis methods (Multi_Sen and Lui_Sen).
- α is the intercept, a constant term.
- B1, $\beta2$, $\beta3$, and $\beta4$ are the coefficients estimating the impact of each predictor (pc1, pc2, pc3, and pc4) on the sentiment score.
- pc1it, pc2it, pc3it, pc4it are the predictor variables for bank i at time t, based on the principal component results.
- μi captures the fixed effects.
- ϵit is the error term for each observation.

multi_sen	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pc1	0.240	0.078	3.08	0.002	0.087	0.392	***
pc2	-0.494	0.102	-4.87	0.000	-0.694	-0.295	***
pc3	0.191	0.122	1.57	0.117	-0.048	0.0429	
pc4	-0.288	0.131	-2.20	0.028	-0.545	-0.032	**
Constant	2.200	0.141	15.55	0.000	1.923	2.478	***
Mean dependent var	2.200		SD dependent var		1.497		
Overall r-squared	0.367		Number of obs		75		
Chi-square	40.503		Prob > chi2		0.000		
R-squared within	0.348		R-squared between		0.928		

*** p<.01, ** p<.05, * p<.1

Table 4. Fixed Effect Panel Regression Results for Multi_Sen

Lui_sen	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pc1	0.235	0.077	3.050	0.002	0.084	0.387	***
pc2	-0.494	0.101	-4.900	0.000	-0.692	-0.296	***
pc3	0.183	0.121	1.520	0.129	-0.053	0.420	
pc4	-0.289	0.13	-2.230	0.026	-0.544	-0.035	**
Constant	2.191	0.14	15.600	0.000	1.916	2.467	***
Mean dependent var	2.191		SD dependent var		1.487		
Overall r-squared	0.367		Number of obs		75		
Chi-square	40.523		Prob > chi2		0.000		
R-squared within	0.348		R-squared between		0.936		

*** p<.01, ** p<.05, * p<.1

Table 5. Fixed Effect Panel Regression Results for Lui_Sen

5. Discussion and Conclusions

In examining the relationship between the sentiment score multi_sen and the principal components derived from financial metrics, we employed a random-effects panel regression model. The results in Table 4 offer a wealth of insights. The coefficient for pc1 is positive, statistically significant at the 1% level, with an estimated value of 0.24. This indicates that as pc1 increases by one unit, the multi_sen score rises by an average of 0.24 units, all else being equal. In contrast, pc2 is negatively associated with multi_sen, significant at the 1% level, with a coefficient of -0.494. This suggests that a one-unit increase in pc2 corresponds to a decline of approximately 0.494 units in the multi_sen score. While pc3 exhibits a positive relationship with multi_sen, it does not reach conventional levels of statistical significance. Conversely, pc4 has a negative relationship with multi_sen, significant at the 5% level, with a coefficient of -0.288. The model's constant term is 2.2, which represents the predicted value of multi_sen when all predictors are nullified. The overall R^2 of 0.367 indicates that the model explains approximately 36.7% of the variance in multi_sen.

Shifting focus to Lui_sen and its relationship with the principal components, several patterns emerge from Table 5. The coefficient for pc1 is 0.235, statistically significant at the 1% level, indicating a positive association. A one-unit increase in pc1 is associated with an average increase of 0.235 units in the Lui_sen score, holding other variables constant. Furthermore, pc2 exhibits a negative relationship with Lui_sen, significant at the 1% threshold, with a coefficient of -0.494. Mirroring the pattern observed with multi_sen, pc3 in the Lui_sen model shows a positive but statistically non-significant relationship. However, pc4 maintains a negative relationship, with a coefficient of -0.289, significant at the 5% level. The model's constant is 2.191, indicating the expected Lui_sen score when the predictors are zeroed out. Similar to the multi_sen model, the R^2 of 0.367 suggests that the model accounts for 36.7% of the variability in Lui_sen.

The polynomial regression analysis further highlighted distinct nonlinear patterns between Lui_sen and multi_sen versus the principal components. The quadratic curve shapes reveal complexities that are not captured by simplistic linear models. Notably, the polynomial curvature suggests that fluctuations in key components do not translate into linear shifts in the sentiment scores. This delicate relationship is particularly notable for Lui_sen and multi_sen, suggesting their intricate interaction with the financial metrics within the key components. As we moved to the panel regression, the coefficients for PC1, PC2, and PC4 across the sentiment scores reflected patterns observed in the polynomial regression. The positive coefficient for PC1 in both models mirrored the upward trajectory observed in the polynomial regression charts, while the negative curvature for PC2 aligned with the downward trend observed. Similarly, the negative slope for PC4 in both models corresponded with the downward trajectory in the polynomial regression. However, the lack of statistical significance for PC3 in the panel regression, despite the curve in the polynomial regression, suggests an underlying relationship that lacks sufficient strength to be statistically clear at conventional significance levels.

Since the early 2000s, sentiment analysis has gained significant attention in accounting and finance research (Antweiler & Frank, 2004). Our research contributes to this growing body of knowledge by revealing that the sentiment expressed in BOD statements subtly interacts with traditional financial measures. The results support the existing evidence on the predictive power of BOD messages for forecasting future financial outcomes. For instance, the finding that BOD messages influence stock trends and bankruptcy predictions aligns with the research of Antweiler and Frank (2004) and Moreno and Camacho-Miñano (2022). Our study adds further nuance to this literature by uncovering the fluctuating relationship between sentiment and financial performance, as evidenced by the polynomial regression results for Lui_sen and multi_sen. These results reflect the complexities noted in previous research on the relationship between management reports and corporate performance (Buehlmaier & Whited, 2018; Pengnate et al., 2020).

The significant coefficients for PC1, PC2, and PC4 in our panel regression correspond with findings from prior studies that confirm the complex dynamics between linguistic elements in annual reports and financial metrics (Borggreve, 2022; Guo, 2022). Furthermore, the high correlation between Lui_sen and multi_sen highlights both the challenges and opportunities that arise when integrating sentiment analysis with traditional financial indicators, a sentiment echoed by Luo (2022) and Hájek (2018).

Based on the findings, we can specify that the hypothesis supports both positive and negative relationships. Specifically, positive financial performance (e.g., increases in PC1) correlates with positive sentiment, while metrics such as PC2 and PC4 correlate with negative sentiment, as reflected in the BOD statements.

The findings from our research offer valuable insights into the synthesis of sentiment and financial analysis. Combining textual emotions with financial metrics can enhance the application of sentiment analysis in understanding organizational behavior and financial performance. This ability to capture a broad spectrum of information—viewing the firm through the eyes of its managers and the general public—provides a more holistic toolkit for stakeholders, including investors, analysts, and policymakers, to evaluate bank performance. One promising avenue for future exploration is the integration of sentiment analysis into real-time financial decision-making platforms, allowing for dynamic monitoring and adjustments based on updated data flows.

However, our study is not without limitations. First, the dataset's relatively narrow scope—comprising 15 Jordanian banks over five years—limits the generalizability of the findings and may not fully capture the dynamic nature of sentiment and financial performance. Future research could enrich this study by including banks from other regions and refining sentiment analysis tools to better account for the cultural and linguistic nuances in Arabic-language BOD statements. Second, the static nature of our data may overlook the potential of longitudinal analyses that could track changes in sentiment and financial performance over longer intervals or in response to extreme economic events.

While our research offers a novel perspective on the fusion of sentiment and financial analysis, future studies could improve our understanding by advancing the use of artificial intelligence and machine learning tools (Goel, Gangolly, Faerman & Uzuner, 2010; Humphreys et al., 2011). Integrating sentiment analysis with financial metrics promises to yield deeper insights into organizational behavior and performance. Another compelling research direction would involve the creation of hybrid models that combine sentiment analysis with other forms of unstructured data, such as social media posts or news articles, to provide a more comprehensive view of market sentiment and its implications for financial performance.

In conclusion, blending textual emotions with financial metrics, as demonstrated in our study and from prior studies, presents a promising path for future research inquiry. Embracing the complexities and challenges inherent in this integration can lead to richer and more comprehensive insights into the world of finance and accounting.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

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Appendix

Non-Performing Loans (Npl)	The borrower is in default and has not made any scheduled payments of principal or interest.
Earnings Per Share (EPS)	Measure of a company's profitability.
Book Value Per Share (Bvshare)	This figure represents the minimum value of a company's equity and measures the book value of a firm on a per-share basis.
Yield	How much income an investment generates.
Debt-To-Equity Ratio (DE)	To evaluate a company's financial leverage.
Return On Assets (ROA)	Measures the profitability of a business in relation to its total assets.
Return On Equity (ROE)	Measure of a company's net income divided by its shareholders' equity.
Income Ratio (Incomeratio)	Provides insight into how much of each dollar in revenue is converted into profit.
Quick ratio times	Current Assets/Current Liabilities
VADER	Developed by Hutto and Gilbert (2014), it is a rule-based model that employs a lexicon-based approach. The sentiment score is calculated based on the intensity of sentiment-expressing words in the lexicon, and the review is classified as positive or negative depending on the score. VADER's sentiment lexicon is larger and of higher quality than traditional sentiment lexicons like LIWC, and it outperforms other sentiment analysis benchmarks, including machine learning techniques.
Lui sen	Introduced by Hu and Liu (2004), it is an aspect-based sentiment analysis method that focuses on mining product features and opinions from customer reviews. It extracts product features and the associated sentiment of customers towards those features. Liu Hu proposed several techniques for feature mining, which are highly effective in experimental results. The method also uses an algorithm that summarises customer reviews by selecting representative sentences that capture the most important aspects of the product..
Art sen	SentiArt is a heuristic tool to compute Emotional Figure Profiles and Figure Personality Profiles, as described by Jacob (2019). It is based on vector space models and computes the valence of words in a text by using theory-guided, empirically validated label lists. SentiArt is accurate in predicting the emotional potential of text passages and in classifying figures as 'good' vs 'bad'.
Multi Sen	Multilingualsentiment is a sentiment analysis engine that analyses text. It can analyse non-Latin-based and Latin-based languages. Multilingualsentiment uses state-of-the-art machine learning to determine if the text it analyses is positive, negative or neutral, based on keyword phrases found in the text, and (optionally) whether the word is used positively or negatively. Multilingualsentiment currently analyses text in more than 80 languages. Multilingualsentiment is very accurate and has fundamental applications for monitoring social media sentiment, while also identifying complaints or complimentary messages about a business or service in customer feedback. Data Science Lab offers Multilingualsentiment through a cloud API, it can also install the engine on your premises.