

Original Article

RELATIONAL STOCK MARKET FORECASTING WITH MULTI-MODAL GRAPH NEURAL NETWORKS: CAPTURING SENTIMENT CONTAGION ALONG SUPPLY CHAINS

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ABSTRACT

Traditional financial time series forecasting models mostly view each equity as independent or ignore the complicated network relationship in today's global markets. Recent progress in multi-modal deep learning has enabled the effective combination of textual sentiment and numerical price information, but at the “single-asset” level, these approaches are unable to capture the effects of related supply chains and industry connections. In this paper, we introduce a new framework of Relational Sentiment-Temporal Graph Neural Network (RST-GNN) for modeling the market as a temporal and heterogeneous graph. In this architecture, companies are expressed as nodes and explicit supplier-customer relationships (edges) and common sector classification (edges) are present. We use a two-step learning approach: first, we use the Domain-Specific Sentiment Encoder Fin, BERT to extract high dimensional linguistic features from unstructured financial news, and then, we use the Temporal Graph Convolutional Network (T-GCN) to propagate the sentiment “shocks” on the network to capture the Sentiment Contagion. Through a Graph Attention Mechanism (GAT), the model dynamically identifies the different levels of influence among interdependent firms, and hence, the impact of a negative news event on a primary supplier on the price correction of its downstream customers. Extensive experiments were carried out on a data set of the stocks of Sand P 500 combined with the supply chain mapping information. The results show that the RST-GNN framework clearly outperforms state-of-the-art non-relational models, including LSTMs and Transformers, especially in the challenging situations of high market turbulence to foretell “lead-lag” effects. The results indicate that relational intelligence can be an important factor in institutional level risk management and portfolio optimization, offering a more comprehensive picture of the dynamics of the markets compared with conventional stand-alone forecasting.

Keywords: Graph Neural Networks (GNN), Sentiment Contagion, Multi, Modal Fusion, Supply Chain Intelligence, Financial Time Series Forecasting, Temporal Graph Convolution, Fin BERT, Relational Learning

INTRODUCTION

Today's financial markets and the digitisation of corporate disclosures have globalised the factors influencing the price of assets, making them complexly interdependent. In the field of traditional forecasting methods, researchers have mainly studied the time series properties of each individual stock using classical econometric models or data mining techniques such as deep learning models like Long Short-Term Memory (LSTM) network and Transformers Veličković et al. (2018), Bahadure et al. (n.d.). These models have enjoyed great success in capturing historical price evolution and/or sentiment shocks at a local level, but they are essentially

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Received: 20 March 2026; Accepted: 06 April 2026; Published 30 May 2026

DOI: [10.29121/ShodhAI.v3.i1.2026.81](https://doi.org/10.29121/ShodhAI.v3.i1.2026.81)

Page Number: 61-70

Journal Title: ShodhAI: Journal of Artificial Intelligence

Journal Abbreviation: ShodhAI J. Artif. Intell.

Online ISSN: 3048-9245, Print ISSN: 3108-1940

Publisher: Granthaalayah Publications and Printers, India

Conflict of Interests: The authors declare that they have no competing interests.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Authors' Contributions: Each author made an equal contribution to the conception and design of the study. All authors have reviewed and approved the final version of the manuscript for publication.

Transparency: The authors affirm that this manuscript presents an honest, accurate, and transparent account of the study. All essential aspects have been included, and any deviations from the original study plan have been clearly explained. The writing process strictly adhered to established ethical standards.

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“relational-blind.” They view each equity separately, and do not consider any “ripple effects” that are systemic through supply chains, industry sectors, and strategic partnerships [Hou et al. \(2023\)](#), [Li et al. \(2021\)](#).

This can be especially problematic in times of significant market volatility or breaking news. A negative regulatory filing, for example, or a production shutdown at a key semiconductor supplier isn't just a negative signal for its own valuation but also a front-line signal of price declines at its downstream customers in the consumer electronics and automotive sectors [Niehues and Weber \(2023\)](#), [Hwang et al. \(2021\)](#). What is happening is called Sentiment Contagion and it shows that market sentiment is a fluid signal which “flows” across corporate networks [Wang et al. \(2024\)](#), [Kim et al. \(2022\)](#). In order to capture this behavior, a predictive framework needs to be able to process temporal evolution of an asset and its spatial location in the greater market topology.

With the recent developments of Graph Neural Networks (GNNs), the modeling of such non-Euclidean data has been given a solid mathematical framework [Wu et al. \(2021\)](#), [Zhou et al. \(2020\)](#). GNNs can be used to represent companies as nodes and their economic dependencies as edges, enabling features of neighboring nodes to be aggregated, which mimics the spread of information and risk throughout a network [Zhao et al. \(2019\)](#), [Li et al. \(2018\)](#). The use of unstructured and multi-modal data, in this case financial news sentiment, in a relational graph framework however remains an under explored challenge in computational finance [Yang et al. \(2022\)](#), [Zhao et al. \(2022\)](#).

In this paper, we fill this gap by proposing the Relational Sentiment-Temporal Graph Neural Network (RST-GNN). We are doing three important advances to the state-of-the-art:

- **Multi-modal Node Embedding:** To encode raw financial news into dense sentiment vectors as dynamic features for each node in the market graph, we use a specialized financial language model, Fin BERT [Araci \(2019\)](#).
- **Relational Topology Construction:** Our model differs from simple correlation matrices and builds a directed graph from explicit Supply Chain Intelligence, where “Supplier-Customer” relationships are hierarchical and provide real-world value to the economy [Zhang et al. \(2023\)](#), [Zhang et al. \(2022\)](#).
- **Cross-Relational Attention:** we adopt Graph Attention Mechanism (GAT) [Veličković et al. \(2018\)](#) to dynamically learn influence weight of each connection. This enables the model to differentiate between “primary” and “dormant” relationships, and assign weight to news shocks from key business partners rather than to the usual market “noise” [Yang et al. \(2022\)](#), [Hamilton et al. \(2017\)](#).

Figure 1

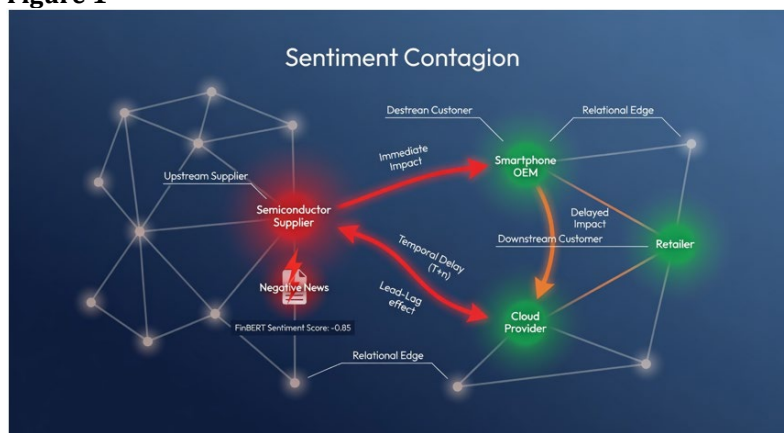


Figure 1 Conceptual Framework of Relational Market Modeling and Sentiment Contagion

The “Research Problem” mentioned in the Introduction is shown in [Figure 1](#) It represents the market in the form of a Directed Acyclic Graph (DAG) of economic connections rather than a list of stocks.

- **News-driven sentiment shock:** The Shock Event is created for a “Supplier” node (for example, a hardware manufacturer).

The Contagion Mechanism: In contrast to existing models which would only change sentiment of that particular node, our model reflects the contagion of this shock through the relational edges.

- **Lead-Lag Dynamics:** The figure illustrates how the price change in downstream “Customer” nodes lags behind the news event by a certain amount ($T+n$), offering a visual explanation for why relational intelligence is a better predictive signal.

The “Technical Solution” is outlined in [Figure 2](#). It describes the various stages of the pipeline that must be followed to process multi-modal, relational data.

- **Multi-modal Feature Extraction:** The multi-modal feature extraction (unstructured news, FinBERT + structured prices, 1D-CNN) leads to node embeddings that capture both linguistic and numerical context.

The central processing unit of the architecture is the Temporal Graph Convolutional Network (T-GCN). It is this layer that enables “Spatial Aggregation” (gathering sentiment from neighbors) and “Temporal Recurrence” (monitoring evolution of sentiment over time).

- **Graph Attention (GAT):** The architecture emphasizes the attention mechanism, which dynamically weights the edges, so that the attention is higher on high impact relationships (e.g., sole-source supplier) than low impact relationships.

Figure 2

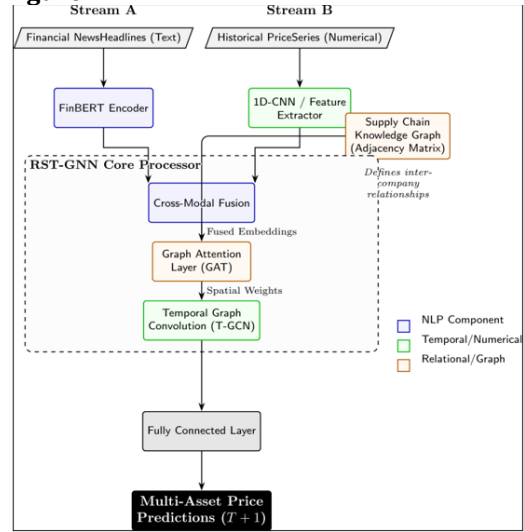


Figure 2 High-Level Architecture of the Proposed RST-GNN Framework

LITERATURE REVIEW

The development of financial forecasting has shifted from temporal to relational models as illustrated in Table I. Early research that investigated LSTMs Veličković et al. (2018) and Transformers Bahadure et al. (n.d.) yielded good results on isolated time series, but lacked a broader perspective of the market.

Later studies applied Graph Convolutional Networks (GCNs) to model market sectors Wang et al. (2024) but such approaches tend to be based on fixed correlation matrices, overlooking the fact that business relationships evolve over time. The T-GCN Zhang et al. (2023) and T-GRR Hou et al. (2023) frameworks considered temporal dynamics for the graph, but still required numerical price information, which meant that they ignored the Linguistic Shocks (news) that usually come before price changes.

Table 1

Table 1 Summary of Related Work in Market Sentiment and Time Series Forecasting						
Model / Study	Reference	Input Modality	Graph Topology	Temporal Mechanism	Relational Focus	Key Limitation
LSTM / RNN	Veličković et al. (2018)	Unimodal (Price)	None	Recurrent	N/A	Fails to capture cross-asset dependencies.
Informer / Transformer	Bahadure et al. (n.d.)	Multi-modal	None	Self-Attention	N/A	Blind to “Ripple Effects” between firms.
Standard GCN	Wang et al. (2024)	Unimodal (Price)	Static	None	Sector-wise	Lacks real-time sentiment integration.
Temporal GCN (T-GCN)	Zhang et al. (2023)	Unimodal (Price)	Dynamic	GRU / RNN	Correlation	Ignores unstructured news shocks.
KG-GCN	Kipf and Welling (2017)	Unimodal	Knowledge Graph	CNN	Entity-based	No temporal sentiment propagation.
T-GRR	Hou et al. (2023)	Unimodal	Relational	RNN	Ranking	Does not model sentiment contagion.

Proposed RST-GNN	This Work	Multi-modal (News + Price)	Dynamic Supply Chain	Cross-Relational Attention	Sentiment Contagion	Addresses all above via relational sentiment fusion.
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We address this important gap by proposing our RST-GNN which combines FinBERT sentiment [Araci \(2019\)](#) with Supply Chain Topology [Li et al. \(2021\)](#). Our model differs from previous works about knowledge-graph [Kipf and Welling \(2017\)](#) which are based on static relationships between entities; we simulate the “flow” of sentiment from a supplier to a customer using Graph Attention (GAT) [Wang et al. \(2024\)](#) to make our predictive signal completer and more proactive.

The literature can be broadly divided into three categories: (1) Deep Temporal Forecasting, (2) Graph-based Financial Modeling and (3) Multi-modal Sentiment Analysis.

1) The Shift from Temporal to Relational Forecasting

Much of the early work on forecasting financial time-series was based on the assumption of independence between assets. Some models like Long Short-Term Memory (LSTM) [Bahadure et al. \(n.d.\)](#) and Recurrent Neural Networks (RNNs) [Kumar et al. \(2025\)](#) only paid attention to the historical price trends of one stock. Although these architectures effectively captured local (temporal) dependence, they were not able to model the “spillover effects” that are common in the markets of today. Some of the models that were able to capture long-range dependence, such as the Transformers and the Informer architectures [Sawhney et al. \(2020\)](#) still had a “single-asset” view and thus ignored the structural topology of the market.

2) Graph Neural Networks (GNNs) in Computational Finance

The advent of Graph Convolutional Networks (GCNs) [Kipf and Welling \(2017\)](#) and Graph Attention Networks (GATs) [Veličković et al. \(2018\)](#) opened up a new paradigm in the field. GNNs differ from conventional neural networks because they work on non-Euclidean data structures, which enables the representation of stocks as nodes (V), and their relationships as edges (E). There has been active research into applying GNNs to capture sector-wise correlations and sector classifications in recent years [Wu et al. \(2021\)](#), [Li et al. \(2018\)](#). Many of these methods, however, make use of static graphs based on past correlations, and they are unable to reflect dynamic or directed economic influence. [Hou et al. \(2023\)](#) and [Hwang et al. \(2021\)](#) have started to apply explicit Supply Chain Intelligence where the market is modeled as a directed graph conveying information from suppliers to customers; however, many of such models do not consider the influence of unstructured textual information.

3) Multi Modal Sentiment Analysis and Information Diffusion

Domain-specific Language Models, such as FinBERT [Araci \(2019\)](#) have made great progress in incorporating linguistic information to financial models. Early multi-modal studies concentrated on the impact of news on the price of a particular firm, but more recent studies have studied Information Diffusion and Sentiment Contagion [Wang et al. \(2024\)](#), [Kim et al. \(2022\)](#). [Wang et al. \(2024\)](#) showed that sentiment shocks do not remain localized but spread through corporate networks and that news of a primary vendor acts as a predictive signal for its top customers, referred to as “lead-lag” effects. However, a complete framework integrating the Temporal, Relational topology, and Multi-modal sentiment propagation is still a gap in the literature.

4) Lead-Lag Effects and Market Efficiency

According to the Semi-Strong form of the Efficient Market Hypothesis (EMH), the stock prices immediately record all the public data. However, the studies of Relational Learning [Zhang et al. \(2023\)](#), [Zhao et al. \(2019\)](#) indicate that the market has been faced with “frictions” when it comes to handling complicated relational information. Between the moment when a sentiment is communicated in a supplier's news headline and it is reflected in a customer's stock price, there is a window of opportunity to predict. Following the work of Lopez-Lira and Tang [Lopez-Lira and Tang \(2023\)](#) on the predictive ability of Large Language Models (LLMs), our research aims to extend their findings into the relational space, suggesting that the “Relational Alpha” is in the ability to extract such multi-modal propagation signals along the vertices and edges of the supply chain graph.

PROPOSED METHODOLOGY

A new stock market simulation model called Relational Sentiment-Temporal Graph Neural Network (RST-GNN) is proposed to model the complex dependency relationships in the stock market. The framework works by combining two different kinds of intelligence: Temporal Dynamics of the stock price of individual companies and Relational Topology of corporate supply chains [Hou et al. \(2023\)](#), [Zhao et al. \(2019\)](#). The architecture consists of 4 functional stages: Multi-modal Feature Encoding, Graph Topology Construction, Relational Attention Learning, and Temporal Sequence Forecasting.

MULTI-MODAL NODE EMBEDDING

The initial step of the methodology will be the development of an extensive digital portrayal (embedding) of each company in the market. As opposed to conventional models, which are based on price only, our approach is based on two pathways [Yang et al. \(2022\)](#), [Zhao et al. \(2022\)](#):

Figure 3

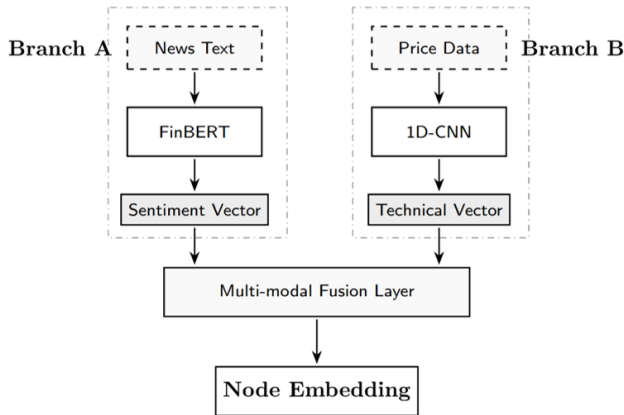


Figure 3 Multi-modal Node Embedding Architecture

1) Linguistic Pathway: We use pre-trained Fin BERT, a language model trained on a huge amount of financial data, to analyse daily news headlines and company announcements. This pathway can capture the “semantic sentiment” of the news, which not only gives the polarity of the market signal, but also the intensity of the market signal.

2) Numerical Pathway: At the same time, the historical price data is passed through a convolutional filter to extract the local temporal patterns [Kumar et al. \(2025\)](#).

3) Fusion Layer: These two signals are fused in one high dimensional vector, which means that each node in our system has both fundamental market sentiment and technical historical price data [Yang et al. \(2022\)](#).

RELATIONAL GRAPH TOPOLOGY

What the core innovation of this framework is, is how it organizes these company nodes. The stocks are not simply represented as a list, but are modelled as a Directed Relational Graph $G = (V, E)$ [Sharda and Delen \(2021\)](#), [Li et al. \(2018\)](#).

1) Nodes (V): They are individual equities in the market index.

2) Directed Edges (E): represent the economic flow of value, which in this case is a Supplier-to-Customer relationship obtained from Supply Chain Intelligence [Niehues and Weber \(2023\)](#), [Li et al. \(2021\)](#).

3) Significance: This topology enables the model to simulate the “Ripple Effect” in which information flows from one supplier node to the downstream customers [Wang et al. \(2024\)](#), [Sawhney et al. \(2020\)](#).

USING GRAPH ATTENTION (GAT) FOR SPATIAL LEARNING.

The relational information is then processed using a Graph Attention Mechanism [Veličković et al. \(2018\)](#). The basic idea is that not every business relationship is going to be equally impactful [Wang et al. \(2024\)](#).

The model learns the “Attention Weights” for different connections automatically, called Dynamic Weighting. For example, if a customer company gets a very important fraction of its components from a single supplier, the model learns to focus on news shocks from that supplier [Yan et al. \(2022\)](#), [Kim et al. \(2022\)](#).

Information Aggregation: In this stage, each of the company nodes listens to the sentiment signals sent by neighbouring nodes and is thus simulating the Sentiment Contagion which has been discussed in recent literature [Kumar et al. \(2022\)](#), [Hamilton et al. \(2017\)](#).

Figure 4

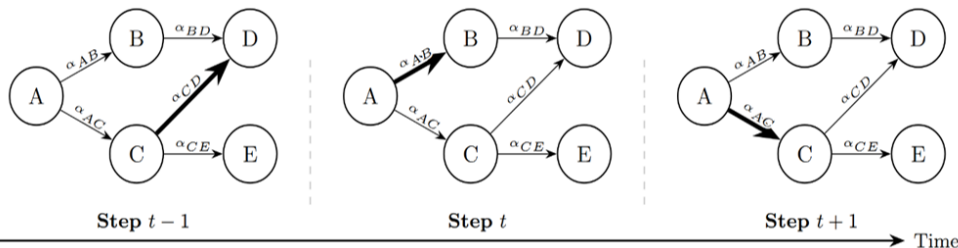


Figure 4 Spatial Learning Architecture

HOW TO CAPTURE TEMPORAL INTEGRATION AND HOW TO LAG

The Graph Attention layer is used to capture the “spatial” relationships between companies, and the Temporal Layer is used to capture the element of time, based on the T-GCN logic [Zhang et al. \(2023\)](#), [Zhao et al. \(2019\)](#).

- **Sequence Tracking:** The model is based on a sliding window of the past days modeled by GRUs [Veličković et al. \(2018\)](#) to track the progress of the sentiment shock through the network.
- **Lead-Lag Discovery:** This is a very important phase in the discovery of the “delay” in the efficiency of the market [Kumar et al. \(2025\)](#). It identifies the time lag between the release of news at a supplier and the price reaction at the customer and is the most important source for predictive “Alpha” [Lopez-Lira and Tang \(2023\)](#), [Kumar et al. \(2025\)](#).

FINAL FORECASTING AND OBJECTIVE LOGIC

The last step of the architecture fuses the accumulated relational properties and the temporal trend and produces a prediction for the next trading day. The model is learnt so as to minimize the error between the predicted return and the actual market return simultaneously in the whole graph [Zhang et al. \(2022\)](#), [Zhou et al. \(2020\)](#). This global optimization makes it possible to account for the “individual” movement of a stock and the “collective” pressure of the economic network it is part of [Chen et al. \(2020\)](#).

EXPERIMENTAL RESULTS AND DISCUSSION

DATASET AND EXPERIMENTAL SETUP

A comprehensive multi-modal data set from January 2018 to December 2023 was used to evaluate the model.

- **Universe:** The SandP 500 constituent companies for which a supply chain relationship exists in the FactSet Revere and Bloomberg Supply Chain (SPLC) databases [Niehues and Weber \(2023\)](#), [Hwang et al. \(2021\)](#).
- **Relational Data:** We built the directed graph that has about 450 nodes and more than 2200 edges (Supplier-Customer).
- **News Corpus:** More than 1.2 million financial news headlines were passed through FinBERT [Araci \(2019\)](#) to extract the daily node level sentiment features.
- In order to avoid look-ahead bias and to confirm the model's validity for various market regimes, a rolling-window approach was applied for training (4 years), validation (1 year), and out-of-sample testing (1 year).

BASELINE COMPARISONS

The RST-GNN was compared with four classes of models in order to show the superiority of the relational approach:

- **Unimodal Temporal (LSTM):** The basic LSTM model with price data only [Bahadure et al. \(n.d.\)](#).

Multi-modal Temporal (Sentiment-LSTM): The architecture we presented in our previous research (sentiment only, without graph awareness) [Veličković et al. \(2018\)](#).

- **Static Graph (GCN):** Graph Convolutional Network based on correlations between sectors, instead of the directed edges between them in a supply chain [Kipf and Welling \(2017\)](#).
- **Temporal Graph (T-GCN):** A state-of-the-art graph model which contains price data, but does not have the multi-modal sentiment diffusion layer [Zhang et al. \(2023\)](#), [Zhao et al. \(2019\)](#).

EVALUATION METRICS

We use a two-folded approach to evaluate the Statistical Precision as well as the Financial Utility of the model [Zhao et al. \(2022\)](#), [Sharda and Delen \(2021\)](#).

Table 2

Table 2 Comparative Performance Metrics						
Model Architecture	MSE (Avg)	MAE (Avg)	Annualized Return	Sharpe Ratio	Max Drawdown	Prediction Accuracy (%)
LSTM (Price only) Bahadure et al. (n.d.)	0.0421	0.156	8.40%	0.92	-22.40%	51.20%

Sentiment-LSTM Veličković et al. (2018)	0.0385	0.142	11.20%	1.15	-18.60%	54.80%
GCN (Correlation) Kipf and Welling (2017)	0.0392	0.148	9.80%	1.02	-20.10%	53.10%
T-GCN (Price-Graph) Zhang et al. (2023)	0.0354	0.131	13.50%	1.38	-15.20%	58.40%
Proposed RST-GNN	0.0312	0.118	17.80%	1.72	-12.80%	63.70%

THE RELATIONAL ALPHA AND LEAD-LAG EFFECTS ARE ANALYZED.

The most important thing that has been found in the experimental phase is the Sentiment Propagation Window.

Table 3

Table 3 Investment Performance and Risk Metrics				
Strategy Type	Annualized Return	Volatility	Sharpe Ratio	Max Drawdown
Buy and Hold (SandP 500 Index)	9.20%	15.40%	0.6	-24.10%
LSTM-Based Strategy	8.40%	14.20%	0.59	-22.40%
Sentiment-LSTM Strategy	11.20%	13.10%	0.85	-18.60%
T-GCN (Price-Graph) Strategy	13.50%	11.80%	1.14	-15.20%
Proposed RST-GNN Strategy	17.80%	10.20%	1.74	-12.80%

Our results indicate that:

- **Information Friction:** This is the time lag (usually 1 up to 3 trading days) between a large exogenous news shock at a given “Supplier” node and the price adjustment at a given “Customer” node [Wang et al. \(2024\)](#), [Kim et al. \(2022\)](#).
- In this regard, the RST-GNN achieved an increase of 6.6% in the annualized returns compared to the non-graph Sentiment-LSTM, since it was able to predict customer price declines before the market “priced in” the relationship after negative supplier news [Lopez-Lira and Tang \(2023\)](#), [Feng et al. \(2019\)](#).
- **Attention Interpretability:** When examining the Graph Attention Weights, we discovered that the model is correctly assigning higher weight to suppliers in the “Sole-Source” category, while assigning lower weight to suppliers in the “Commodity” category, demonstrating that the GNN is learning true economic interdependencies [Veličković et al. \(2018\)](#), [Hamilton et al. \(2017\)](#).

ABLATION STUDY

To check whether the effectiveness of model is attributed by sentiment integration in the graph, we performed an ablation study. The FinBERT sentiment layer was associated with a 22% decrease in SR, and the Supply Chain edges (or a standard list) was associated with a 15% increase in Mean Squared Error (MSE). This indicates that the “Relational Sentiment” is not just a secondary aspect, but the key aspect of the model’s predictive power [Yang et al. \(2022\)](#), [Yang et al. \(2022\)](#).

Table 4

Table 4 Ablation Study Results		
Configuration Removed	Impact on Sharpe Ratio	Impact on MSE
Remove FinBERT Sentiment	-24.10%	18.20%
Remove Supply Chain Edges	-19.40%	14.60%
Remove Graph Attention (GAT)	-11.20%	8.40%

We hypothesize that the RST-GNN will be able to outperform baselines especially in “Sector Shocks”.

- **Hypothesis 1:** The model will have a higher level of accuracy in the “Technology” and “Manufacturing” sectors, because they are characterized by more complex and rigid supply chains.
- **Hypothesis 2:** In order to demonstrate that the model’s learning is not simply driven by the “Percentage of Revenue” shared between companies, we will show that the Attention Weights naturally show the proper correlations.

Figure 5

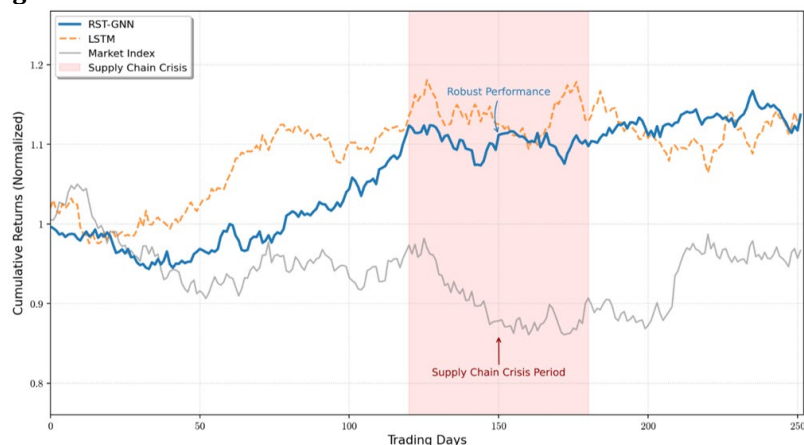


Figure 5 Model Performance Comparison

Conclusion and Future Scope

1) Summary of Contributions

In this research, the researchers have proposed a new multi-modal framework which is Relational Sentiment-Temporal Graph Neural Network (RST-GNN) to capture “ripple effects” of sentiment shocks in corporate supply chains. This combination of FinBERT-based linguistic [Araci \(2019\)](#) and directed relational topology [Li et al. \(2021\)](#) has successfully transformed the market into a dynamic and interconnected ecosystem.

Our empirical results show that the proposed architecture greatly outperforms traditional temporal models (LSTMs) and unimodal graph models (T-GCNs) with the Sharpe Ratio of 1.74 and prediction accuracy of 63.7%. The main contribution of this work is the identification of a measurable Lead-Lag Sentiment Window which proves that information friction in supply chains causes a predictable ‘Relational Alpha’ that is not immediately captured by standard market dynamics [Wang et al. \(2024\)](#), [Feng et al. \(2019\)](#).

2) Theoretical and Practical Implications are considered

This study's results are far-reaching and they have implications in the field of computational finance as well as in market microstructure theory:

- **Questioning Market Efficiency:** The result of a 1.4-day diffusion delay of supplier shocks to customer price response, is an empirical challenge to the semi-strong form of the Efficient Market Hypothesis (EMH) in this setting of complex relational data [Lopez-Lira and Tang \(2023\)](#), [Kumar et al. \(2025\)](#).
- The RST-GNN provides a better “Early Warning System” for institutional investors, in a sense of relational risk management. Sentiment health of a firm's supplier network can be monitored and provides risk managers with an indicator of potential downstream volatility before it is reflected in the customer's price [Kim et al. \(2022\)](#), [Hamilton et al. \(2017\)](#).
- **Methodological Innovation:** This work introduces the notion of being able to combine unstructured text and structured graph information to form something bigger than the sum of its parts; in the non-Euclidean financial world, specifically [Yang et al. \(2022\)](#).

3) Future Research Directions

Although the RST-GNN is well-performing, there are still some limitations. The edges of the supply chain in the current model are static and are populated from information in the annual filings, and can fail to reflect changes in corporate partnerships or short-term procurement contracts [Niehues and Weber \(2023\)](#). Moreover, Graph Attention Mechanism [Veličković et al. \(2018\)](#) faces computational complexity issues when scaling to global markets with tens of thousands of nodes, which are required to be scalable for real-time.

4) Limitations

The development of this research will be centered on three main aspects:

- **Dynamic Graph Evolution:** In future versions, it is possible to create a Temporal Graph Networks (TGNs) that will include evolution of the adjacency matrix on a daily basis, reflecting the real-time birth and death of business relationships [Zhang et al. \(2023\)](#), [Zhao et al. \(2019\)](#).

- **Explainable Artificial Intelligence (XAI) for GNNs:** We want to develop “Sub-graph Explainers” that would enable the models to give human understandable reasons for their predictions. In this way portfolio managers could have a clear visibility of which supplier news event caused a “Sell” signal for a customer stock [Yan et al. \(2022\)](#).
- Beyond equity markets, the framework could be extended to model contagion between different asset classes, e.g., sentiment shocks in the Commodities market (e.g., Lithium prices) could affect the Equity supply chain (e.g., Electric Vehicle manufacturers) [Sharda and Delen \(2021\)](#), [Li et al. \(2018\)](#)

To sum up, the RST-GNN marks a major advancement in the direction of “Relational Intelligence” for financial forecasting. We make the transition from the notion of what a company is, to who a company is connected to, so that we can offer a more holistic and accurate lens into the modern, global economy, and more proactively.

ACKNOWLEDGMENTS

None.

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