

A Multimodal Deep Learning Architecture Fusing Real-Time High-Frequency Market Data, Global News Sentiment, and Macroeconomic Signals for Systemic Financial Risk Prediction

Authors

Godwin Frey, Asher Noah, Abi Cit, Abbas Ahsun, Dada Jay

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Abstract

Systemic financial risk prediction remains a critical challenge as traditional econometric models struggle with nonlinear interactions, regime shifts, and heterogeneous data sources that characterize modern financial systems. This study addresses the gap by developing and validating a multimodal deep learning architecture that fuses real-time high-frequency market data, global news sentiment, and macroeconomic signals for systemic risk prediction. The proposed architecture employs modality-specific encoders with cross-attention fusion mechanisms to capture dynamic interactions across data streams. Using a dataset spanning 2015–2024 comprising tick-level market data, FinBERT-processed news sentiment, and macroeconomic indicators, the model achieves 89.4% accuracy and 0.912 AUC-ROC in predicting systemic stress events with an average lead time of 8.3 trading days. Feature importance analysis reveals news sentiment accounts for 34.2% of predictive weight, followed by high-frequency volatility measures (28.7%) and macroeconomic signals (22.1%). These findings demonstrate that multimodal fusion significantly outperforms unimodal and traditional econometric baselines, providing a replicable framework for

real-time systemic risk monitoring with practical implications for regulators and financial institutions.

Keywords: Systemic Risk Prediction, Multimodal Deep Learning, News Sentiment Analysis, High-Frequency Financial Data

1. Introduction

1.1 Background

The global financial system has experienced increasing interconnectedness and complexity over the past two decades, culminating in systemic crises that traditional risk management frameworks failed to anticipate or mitigate effectively. The 2008 Global Financial Crisis exposed fundamental limitations in prevailing risk models, which relied predominantly on linear econometric specifications and historical correlations that broke down during extreme stress events . More recently, the COVID-19 pandemic-induced market turmoil and the 2023 regional banking crisis demonstrated that systemic risk can materialize rapidly through channels that span market microstructure, informational dynamics, and macroeconomic fundamentals simultaneously .

The proliferation of heterogeneous data sources has created new opportunities for financial risk prediction. High-frequency trading data captures market microstructure dynamics at millisecond resolution, providing early signals of liquidity deterioration and order flow imbalances . Simultaneously, the digitization of news media has generated vast unstructured textual corpora that reflect public sentiment, uncertainty, and emerging risk narratives in near-real-time . Macroeconomic indicators, though lower-frequency, anchor predictive models in fundamental economic conditions that shape system-wide vulnerability . The challenge lies in integrating these disparate modalities—which differ in sampling frequency, dimensionality, and statistical properties—into a coherent predictive framework capable of capturing cross-modal interactions that drive systemic risk emergence.

1.2 Problem Statement

Existing approaches to systemic risk prediction face three fundamental limitations. First, traditional econometric models such as logistic regression, ARIMA, and VAR specifications assume linear relationships and stationarity, which are violated during crisis periods when nonlinear feedback loops and structural breaks dominate . Second, machine learning approaches that rely solely on structured market data overlook the informational content embedded in textual sources, despite evidence that news sentiment contains predictive signal for financial stress that is not fully captured by price-based indicators alone . Third, while recent studies have begun exploring multimodal fusion for financial prediction, these efforts typically employ simple concatenation or late-fusion strategies that fail to model the dynamic, time-varying relevance of different modalities across market regimes .

The consequence of these limitations is significant. Models trained on historical data often exhibit degraded performance precisely when accurate prediction matters most—during crisis onset. The need for a validated multimodal architecture that can fuse heterogeneous data streams while respecting their temporal asynchrony and varying reliability remains unmet.

1.3 Objectives of the Study

General objective: To design, implement, and validate a multimodal deep learning architecture that integrates real-time high-frequency market data, global news sentiment, and macroeconomic signals for systemic financial risk prediction.

Specific objectives:

1. To identify and characterize the optimal combination of high-frequency market features, sentiment indicators, and macroeconomic signals for systemic risk prediction.
2. To develop a cross-attention-based fusion architecture that dynamically weights modality contributions based on temporal context and signal reliability.
3. To empirically validate the proposed framework against unimodal and traditional econometric baselines using historical crisis periods.

1.4 Research Questions

1. What combination of high-frequency market data, news sentiment, and macroeconomic variables most accurately predicts systemic financial stress events?
2. How does the proposed multimodal framework compare to traditional econometric models and unimodal deep learning approaches in terms of prediction accuracy and lead time?
3. What are the dominant cross-modal interactions and feature-level contributions that drive predictive performance during different market regimes?

1.5 Significance of the Study

For practitioners and risk managers: The validated framework provides a deployable tool for real-time systemic risk monitoring, enabling proactive risk mitigation with measurable lead times.

For policymakers and regulators: Enhanced predictive capability supports macroprudential supervision by identifying emerging vulnerabilities before they crystallize into systemic events.

For academic literature: This study advances multimodal learning theory in financial applications by demonstrating effective fusion strategies for temporally asynchronous, heterogeneous data streams.

For future researchers: The framework and evaluation protocol establish a replicable benchmark for comparing multimodal architectures in financial risk prediction.

1.6 Scope and Limitations

This study focuses on systemic risk prediction for major developed markets, specifically the United States and European Union, over the period 2015–2024. Data sources include tick-level equity index futures data, news articles from major financial wire services processed through FinBERT, and monthly macroeconomic indicators from official statistical agencies.

The study excludes emerging markets and non-financial sectors from primary analysis. Key limitations include reliance on historical data that may not capture unprecedented future crisis dynamics, the assumption of consistent sentiment extraction quality across news sources, and computational constraints that necessitated sampling high-frequency data at one-minute intervals rather than tick-level.

2. Literature Review

2.1 Conceptual Review

Systemic Financial Risk. Systemic risk refers to the potential for widespread disruption in financial services caused by impairment of all or parts of the financial system, with significant negative consequences for the real economy . Unlike idiosyncratic risk, systemic risk arises from interconnectedness, common exposures, and contagion effects that propagate through the financial network.

Multimodal Deep Learning. Multimodal learning integrates information from multiple heterogeneous data sources to improve predictive performance compared to unimodal approaches . In financial applications, modalities typically include structured time-series data, unstructured text, and possibly alternative data sources such as satellite imagery or transactional records .

High-Frequency Market Data. This modality encompasses order book dynamics, trade prices, volumes, and microstructure features sampled at sub-minute intervals. Such data captures liquidity conditions, order flow toxicity, and short-term volatility patterns that precede systemic stress .

News Sentiment. Sentiment analysis of financial news extracts directional emotional content and uncertainty signals from textual sources. FinBERT, a domain-adapted language model, has demonstrated superior performance in financial sentiment classification compared to general-purpose models .

Macroeconomic Signals. These include standard indicators such as GDP growth, inflation, interest rates, credit spreads, and central bank policy variables that reflect the fundamental state of the economy and financial conditions .

2.2 Theoretical Framework

Efficient Market Hypothesis and Its Limits. While the EMH posits that prices reflect all available information, behavioral finance research and empirical anomalies demonstrate that information processing is imperfect and subject to sentiment-driven deviations, particularly during stress periods . This theoretical foundation supports the inclusion of news sentiment as a predictive modality.

Network Theory of Systemic Risk. Financial institutions and markets are interconnected through exposures, funding relationships, and common asset holdings. Systemic risk emerges from network topology and the propagation of shocks through these linkages . High-frequency data captures the dynamic evolution of these connections through correlated trading patterns.

Attention Mechanisms in Neural Networks. The transformer architecture's self-attention and cross-attention mechanisms enable models to dynamically weight information sources based on learned relevance, providing a computational analog to selective information processing in financial decision-making .

2.3 Empirical Review

Jin and Lin (2025) developed an early prediction model for systemic risk using FinBERT and Temporal Fusion Transformer, analyzing 445,500 daily observations from 162 U.S. financial companies . Their model achieved superior performance compared to LSTM and XGBoost baselines, and found that negative public confidence had particularly strong predictive impact. However, the study used daily rather than high-frequency data, potentially missing intraday dynamics.

Zhang et al. (2026) proposed UAMF-Net, an uncertainty-aware multimodal financial sensing network that achieved 0.882 accuracy and 0.941 ROC-AUC on financial risk early warning tasks . The model incorporated asynchronous temporal alignment and modality confidence weighting, addressing data asynchrony challenges. This work demonstrated the value of uncertainty quantification but did not specifically target systemic risk events.

A 2026 study on high-frequency early warning of systemic financial stress in Europe evaluated machine learning models using daily predictors including market data and sentiment indicators . The study found that logistic regression with L1 feature selection and nonlinear tree-based models performed well, with PR-AUC ranging from 0.63 to 0.90. However, the analysis was limited to daily frequency and did not integrate unstructured textual data.

Temporal Attentive Graph Networks (TAGN) applied by researchers in 2026 achieved an AUC of 0.890 for extreme volatility prediction with 1–2 week lead times over VIX during major stress events . While innovative in using graph structures for contagion modeling, TAGN focused on network topology rather than multimodal information fusion.

2.4 Research Gap

No validated multimodal architecture exists that integrates real-time high-frequency market data, news sentiment, and macroeconomic signals with explicit cross-attention mechanisms for systemic financial risk prediction. Existing studies either: (a) use daily or lower-frequency data, missing intraday risk signals; (b) focus on single modalities or employ simple fusion strategies that fail to model dynamic modality relevance; or (c) target volatility prediction rather than systemic stress events specifically. This study fills this gap by developing and empirically validating a cross-attention-based multimodal framework that addresses temporal asynchrony, modality reliability, and the specific challenge of systemic risk prediction during crisis onset.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research approach combining retrospective model development with prospective out-of-sample validation. The design is appropriate because it allows systematic comparison of the proposed architecture against established baselines using historical data while ensuring temporal integrity through strict train-test separation.

3.2 Study Area / Population

The target population comprises systemic financial stress events in developed markets. The study focuses on the United States and European Union financial systems from January 2015 through December 2024. This period encompasses multiple stress episodes including the 2018 volatility spike, the 2020 COVID-19 crisis, and the 2023 regional banking turmoil.

3.3 Sample Size and Sampling Technique

The dataset comprises 2,520 trading days across the ten-year period. High-frequency data is sampled at one-minute intervals for major equity index futures (S&P 500 E-mini, Euro Stoxx 50 futures), yielding approximately 982,800 intraday observations before feature aggregation. News sentiment is extracted from approximately 1.2 million financial news articles processed through FinBERT. Macroeconomic indicators are collected at monthly frequency (120 observations) and forward-filled to daily resolution.

Stratified temporal sampling is employed to ensure adequate representation of both crisis and non-crisis periods. The target variable—systemic stress events—is defined using the Composite Indicator of Systemic Stress (CISS) with a threshold calibrated at the 90th percentile of the training distribution.

3.4 Data Collection Methods

High-Frequency Market Data: Tick-level data for equity index futures, VIX futures, and major bank stocks was obtained from commercial market data providers. Features extracted include realized volatility, order flow imbalance, bid-ask spread, and volume-weighted price impact.

News Sentiment: Financial news articles from Reuters, Bloomberg, and major wire services were collected via API. FinBERT was employed to extract sentiment polarity scores and uncertainty measures. Following Jin and Lin , both positive and negative confidence indicators were generated.

Macroeconomic Signals: Official data from Federal Reserve Economic Data (FRED) and Eurostat included GDP growth, CPI inflation, unemployment rate, term spread, credit spreads, and central bank balance sheet measures.

3.5 Research Instruments

The architecture is implemented using PyTorch with Hugging Face Transformers for FinBERT inference. Key preprocessing steps include:

- **Temporal alignment:** Following Zhang et al. , asynchronous modalities are aligned using absolute time encoding with relative interval modeling to preserve temporal relationships.
- **Normalization:** Z-score standardization is applied per-feature using training-set statistics only to prevent information leakage.
- **Sequence construction:** Sliding windows of 60 trading days are constructed for each prediction target, with multi-scale features aggregated at daily, hourly, and minute resolutions.

The cross-attention fusion mechanism is implemented following the LANISTR framework , with modality-specific encoders projecting into a shared latent space before cross-attention layers compute dynamic modality weights.

3.6 Validity and Reliability

Content validity: Feature selection was informed by established literature on systemic risk indicators and multimodal financial prediction .

Predictive validity: Out-of-sample testing uses strict temporal separation with a five-trading-day embargo to prevent leakage from feature construction windows.

Reliability: All experiments were repeated with five random seeds, reporting mean performance with standard deviations. Model checkpointing and early stopping based on validation PR-AUC ensure reproducibility.

3.7 Data Analysis Techniques

Baseline Models:

- Logistic regression with L1 regularization
- Random Forest (500 trees)
- XGBoost (gradient boosting)

- Unimodal LSTM (high-frequency only)
- FinBERT-TFT (news sentiment only)

Proposed

Architecture:

The multimodal model employs:

1. **High-frequency encoder:** 1D-CNN with temporal attention for intraday pattern extraction
2. **Sentiment encoder:** FinBERT embeddings with temporal aggregation
3. **Macro encoder:** Dense network for low-dimensional indicator processing
4. **Fusion module:** Multi-head cross-attention with modality confidence weighting

Performance Metrics:

- Accuracy, Precision, Recall, F1-score
- ROC-AUC and PR-AUC (primary metrics given class imbalance)
- Lead time (trading days between prediction and stress event)
- Brier score for calibration assessment

Cross-validation: Expanding-window time-series cross-validation with three ordered folds is used for hyperparameter tuning. The final 20% of data (2022–2024) is reserved as a holdout test set never used during development.

3.8 Ethical Considerations

All data used in this study is publicly available or obtained through standard commercial licenses. No personally identifiable information or protected health information was accessed. The research protocol was reviewed and determined to be exempt from IRB oversight under institutional guidelines for studies using publicly available financial data.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Market Regime (2015–2024)

Indicator	Tranquil (n=1,842)	Stress (n=678)	p-value
Realized Volatility (annualized, %)	12.4 (3.8)	31.7 (12.4)	<0.001

Indicator	Tranquil (n=1,842)	Stress (n=678)	p-value
News Sentiment (polarity, -1 to 1)	0.12 (0.18)	-0.24 (0.31)	<0.001
Term Spread (10y-3m, %)	1.84 (0.62)	0.97 (0.71)	<0.001
Credit Spread (BAA-AAA, %)	0.89 (0.21)	1.87 (0.84)	<0.001
Order Flow Imbalance	0.02 (0.15)	-0.11 (0.28)	<0.001

Note: Values shown as mean (SD). Stress periods defined as CISS > 90th percentile.

Table 1 presents descriptive statistics comparing tranquil and stress periods. All indicators exhibit statistically significant differences, with stress periods characterized by elevated volatility, negative sentiment, flattened yield curves, and widened credit spreads.

4.2 Analysis of Results

Table 2. Model Performance Comparison (Holdout Test Set, 2022–2024)

Model	Accuracy	PR-AUC	ROC-AUC	Lead Time (days)
Logistic Regression	0.742	0.518	0.724	2.1
Random Forest	0.768	0.547	0.751	3.4
XGBoost	0.791	0.583	0.778	4.2
LSTM (HF only)	0.774	0.561	0.762	3.8
FinBERT-TFT	0.812	0.634	0.801	5.6
Proposed Multimodal	0.894	0.847	0.912	8.3

The proposed multimodal architecture achieves 89.4% accuracy and 0.912 ROC-AUC, substantially outperforming all baselines. The improvement over the strongest unimodal baseline

(FinBERT-TFT) is 8.2 percentage points in accuracy and 0.111 in ROC-AUC. Lead time extends to 8.3 trading days, compared to 5.6 days for the best baseline.

Feature Importance Analysis:

The cross-attention mechanism's learned weights reveal the following modality contributions during stress prediction:

1. **News Sentiment:** 34.2% (negative confidence weighted most heavily)
2. **High-Frequency Volatility Measures:** 28.7%
3. **Macroeconomic Signals:** 22.1% (credit spreads and term spread dominant)
4. **Order Flow Dynamics:** 15.0%

Ablation studies confirm that removing any modality degrades performance, with news sentiment removal causing the largest single-modality drop (accuracy decreases to 0.823).

5. Discussion

5.1 Interpretation

The finding that the multimodal architecture achieves 89.4% accuracy with 8.3-day lead time substantially exceeds prior benchmarks. This aligns with Jin and Lin's observation that public confidence indicators carry significant predictive power for systemic risk, but extends their work by demonstrating that sentiment's value is maximized when dynamically fused with high-frequency market signals rather than used in isolation.

The dominance of news sentiment in feature importance (34.2%) supports behavioral theories of systemic risk, where narrative dynamics and confidence effects can propagate through markets faster than fundamental deterioration becomes visible in macroeconomic data . The substantial contribution of high-frequency volatility (28.7%) confirms that market microstructure contains early warning signals that daily data misses .

The cross-attention mechanism's ability to dynamically weight modalities addresses a key limitation of static fusion approaches . During tranquil periods, macroeconomic signals receive relatively higher weight; as stress builds, the model shifts attention toward sentiment and high-frequency indicators, reflecting the changing information content of different modalities across regimes.

5.2 Implications

Academic Implications: This study extends multimodal learning theory by demonstrating that cross-attention fusion with modality confidence weighting effectively addresses the challenge of temporal asynchrony and varying reliability in financial data. The finding that sentiment and

market microstructure exhibit complementary predictive roles advances understanding of information flow in systemic risk emergence.

Practical Implications: Financial regulators should incorporate news sentiment monitoring alongside traditional market surveillance. The 8.3-day average lead time provides an actionable window for supervisory intervention. Risk managers can implement the framework for daily systemic risk scoring, with alerts triggered when predicted probability exceeds calibrated thresholds.

5.3 Limitations

1. **Generalizability:** Findings are based on U.S. and EU markets; performance in emerging markets with different information environments remains unverified.
2. **Historical Dependence:** The model is trained on historical patterns that may not capture unprecedented crisis dynamics.
3. **Sentiment Quality:** FinBERT's performance may vary across news sources and languages not represented in training data.

5.4 Future Research Directions

1. Extension to emerging market financial systems with distinct institutional characteristics.
2. Integration of additional modalities including social media sentiment and central bank communication analysis.
3. Development of explainability interfaces that provide regulators with interpretable risk narratives.
4. Real-time deployment studies examining operational latency and decision-making integration.

6. Conclusion

This study developed and validated a multimodal deep learning architecture that fuses high-frequency market data, news sentiment, and macroeconomic signals for systemic financial risk prediction, achieving 89.4% accuracy and 0.912 ROC-AUC with 8.3-day average lead time. The cross-attention fusion mechanism successfully captures dynamic modality relevance, with news sentiment emerging as the single most important predictor during stress periods. The framework provides a replicable benchmark for multimodal financial risk prediction and offers practical utility for regulators seeking early warning capabilities. As financial systems continue to generate increasingly diverse data streams, architectures that can dynamically integrate heterogeneous information will become essential tools for maintaining systemic stability.

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