# Developing a Neuro-Financial Instability Index for Early Detection of Systemic Risk during Regime shift in Stock Market

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**Abstract.** In this study, we propose a novel Neuro-Financial Instability Index (NFII) framework to identify and analyze systemic risk indicators in mixed financial markets during the period of April 2023 to March 2025. The NFII framework integrates volatility, sentiment, fear indicators, SHAP analysis, and regime-switching diagnostics to identify high impact stocks. Results of experiments highlight cryptocurrencies (BTC and ETH) as the major drivers of systemic risk rather than S&P 500. Non- linear instability and fat-tailed behavior post-2024 was observed using periodic decomposition whereas SHAP analysis highlighted significant contributions related to behavioral risk. These results support the need for adaptive surveillance systems, interpretable hybrid modeling, and revised diversification strategies using high frequency blockchain analytics and multilayer contagion networks.

**Keywords**: Systemic risk, cryptocurrency volatility, regime shifts, behavioral finance, explainable AI.

## 1. Introduction

### 1.1 Detection of Systemic Risk: Origins and Cross-Disciplinary Foundations

The evolution of systemic financial risk and work in quantification gained scholarly attention, during and post the 2008 financial crisis. Early conducted research indicates the efficacy of simplicity in designing systemic risk indicators. Research by Rodríguez-Moreno and Peña (2013) inspected the need for operationally efficient tools with parsimonious models locating interdependencies scoring over complex methods while Patro, Qi, and Sun (2013) examined co-movements in asset returns indicating systemic stress in real-time scenarios. The domain of systemic risk analytics was further analyzed with categorization of approaches such as network models, co-movement indicators, volatility-based stress measures, and macroprudential overlays (Bisias et al. ,2012), with enhanced focus on network-based models for identification of contagion and interconnectedness (Caccioli et al., 2018). Extended study by Billio et al. (2012) and Kou et al. (2019) applied econometric and machine learning frameworks, respectively, examined risk propagation across financial markets. Some studies based on diagnostics and early warning systems extracted similarities from medical diagnostics revealing the significance of prompt decision making for minimizing systemic failures (Blot and Vandewoude ,2004), in contrast to improvement in radiographic diagnosis involving sentiment, behavioral, and market signal fusion using multi-modal inputs for efficiency of systemic risk prediction (Schwendicke, Tzschoppe, and Paris, 2015). Research gaps have been identified with respect to incorporate behavioral volatility, social sentiment, and crypto-financial signals holistically for real-time detection of concealed risk states. The proposed N-FII framework integrates spike train encoding and neuromorphic fusion for structuring of a biologically inspired and computationally efficient early warning mechanism (Billio et al., 2010; Lastra, 2011; Schwaab, Lucas, & Koopman, 2010).

### 1.2 Understanding Systemic Financial Stress

Systemic risk, a constituent of financial research precedes the risk of evidence-based possibility of collapse of a financial system. Some of the early contributions include framework development for risk spillovers assessment across major institutions (Huang, Zhou, and Zhu, 2009) SRISK quantification integrating market equity values and leverage metrics to ascertain shortfall in capital market (Acharya et al. ,2017). Financial Stress Index (FSI), designed by Oet, Dooley, and Ong (2015) as a composite approach for ascertaining market dislocations, drawing from credit, equity, and funding conditions, was further complemented by integration of predictive modeling of EWS (Early Warning Systems) logic for identification of macro-financial vulnerability indicators (Duca and Peltonen ,2013) and Lo Duca and Peltonen,2011). Extended research included interdisciplinary designs in EWS that integrate complexity science and machine learning (Wever, Shah, and O’Leary, 2022). On the other hand, Network-based approaches such as the application of Granger causality and network analyze interconnectedness in the financial sector (Billio et al.,2010 and Caccioli, Barucca, and Kobayashi,2018) in addition to investigation of the structure of financial interdependencies (Montagna, Torri, and Covi ,2020). Systemic regulatory studies explored legal frameworks for systemic externalities using Systemically Important Financial Institutions (SIFIs) (Anabtawi and Schwarcz (2011) and Lastra (2011), in contrast to behavioral study of non-financial corporations (NFCs) role as systemic amplifier (Dungey et al.,2022).From a regulatory lens, Anabtawi and Schwarcz (2011) and Lastra (2011) offered legal frameworks to contain systemic externalities, especially through the regulation of Systemically Important Financial Institutions (SIFIs). The role of non-financial corporations (NFCs) was explored by illustrating how NFC stress may now act as a systemic amplifier. Hybrid AI techniques combining analytics and machine learning were used to overcome limitations of linearity in traditional models (Kou et al., 2019). Extended models used systemic risk analytics for classification of 30 metrics across categories like co-movement, exposure, and contagion. Further studies demonstrated use of cross-domain impact of non-financial shocks, such as oil price fluctuations, on systemic risk, reinforcing the argument for macro-financial coupling besides regime-switching models that capture systemic stress transitions, tackling the temporal variability lost due to static thresholds.

Financial distress prediction has evolved from rule-based systems to hybrid and deep learning models. Origin work of Lee et al. (1996) established the dominance of neural networks over conventional statistical models in bankruptcy forecasting. The technique was further developed with integration of data mining techniques to evolve into a more robust distress prediction system facilitating higher accuracy and generalization across multiple financial domains (Chen and Du ,2009). Advancements highlight a combination of hybrid architectures comprising of evolutionary computation, fuzzy logic, and time-series analysis as indicated by the network-enhanced machine learning pipeline developed by Kadkhoda and Amiri (2024) for financial risk classification and a resilient optimized neuro-fuzzy inference model for handling volatile data. Further extended research encompassed deep learning integration (LSTM) with statistical forecasting (ARIMA) seeking high accuracy in volatile environments (Saâdaoui and Rabbouch, 2024) in addition to deep learning-based stress testing framework for risk assessment (Khunger, 2022). Hybrid models were also developed for trading, credit scoring, and event detection. Adaptive Neuro Fuzzy Inference System(ANFIS) model was tested and compared with conventional methods for credit analysis while logistic regression was combined with RBF networks for early crisis warning (Gutiérrez et al., 2010). Comparison of such hybrid models by Shah et al. (2022) revealed their empirical performance over traditional techniques. Hybrid models have delivered state-of-the-art tools for anticipating financial instability, supporting regulatory interventions and investor strategy formulation.

### 1.3 Motivation and Research Objectives

Current financial systems are witnessing remarkable changes, driven by the rise of decentralized digital assets with dynamic volatility resulting in nonlinear complex market structure. Traditional indicators, earlier defining systemic risks, are now being replaced by a complex mixture of digital assets and complex market behavioral patterns. Cryptocurrencies such as BTC and ETH, with independent volatility and behavioral patterns are playing a dominant role in financial market dynamics. A comprehensive NFI framework is needed (a) to understand this dynamicity that includes digital assets (b) sentiments influencing the systemic behavior.

Further, the framework shall include SHAP-based interpretability function to reveal to assert the influence of cryptocurrency assets (BTC-USD and ETH-USD) on financial instability scores and examine its significance compared to traditional market variables like S&P500 (GSPC). (Chen & Du, 2009; Khunger, 2022).

Time-series decomposition and radar visualizations included in the framework can also highlight regime shift occurring from 2023-2024 to 2024–2025 period, signifying escalating stress cycles, fat-tailed instability distributions, and expansion in the instability footprint.

**Research Objectives**: The framework investigates the use of advanced methods:

- To model the nonlinear transition from traditional financial stabilizers to crypto-driven risk factors using spiking neural networks (SNNs).
- To utilize SHAP explainability for temporal pattern recognition for systemic instability.
- To validate the correlation and decoupling trends between crypto and traditional assets (e.g., BTC-ETH vs. weak GSPC links).
- To provide interpretable neuro-financial forecasting tools for regulators and risk managers in increasingly digitalized economies.

## 2. Literature Review

The proposed NFI framework draws inspiration from different existing theories on financial risk modeling. Complexity theory deals with nonlinear, adaptive systems for tracing emergent behaviors including phase transitions. Similarly, NFII works on the principle of aggregation of combined volatility effect arising from interdependent components like cryptocurrency dynamics, behavioral sentiment, and volatility contagion. Like Complexity theory, NFII supports the use of spiking neural networks for early detection of systemic crises and indicator thresholds in existing or emerging financial ecosystems (Haldane & May 2011). The radar and SHAP-based visualizations in the proposed model handle such complex indicators using feedback loops and hidden interactions in high-dimensional market spaces. Another theory of Behavioral finance deals with the influence of cognitive biases, emotions, and social dynamics on market outcomes. The proposed NFII framework includes the integration of Reddit sentiment and Google Trends data, for introducing fear-based responses and collective behavior during crises to the systemic risk phenomenon. Herd behavior and over reaction can be traced for forecasting retail-driven bubbles (e.g., GameStop) and improving stress testing by combining sentiment volatility. This asserts the robustness and integrity of the proposed NFII model framework for real time prediction (Shiller, 2003). Market behavior evolving from principles of evolutionary psychology has also been adapted into NFII model from the well-known concept of The Adaptive Market Hypothesis (Lo, 2004). NFII includes features to adapt to structural shifts via dynamic modeling tools of SNNs reflected by time series decomposition with shifting weight distribution (SHAP scores) reflecting possible regime shifts. Some of the possible applications include portfolio rebalancing in volatile markets, regime-switching models in risk management, and AI-driven financial regulation.

## 3. Methodological Framework

The proposed NFII framework is based on the integration of traditional datasets with digital assets (S&P 500, VIX, BTC-USD, ETH-USD) with behavioral signals (Google Trends, Reddit sentiment). Normalized data of the closing prices across 2023-2024(April-March) and 2024-2025(April-March) were temporally aligned for high-frequency volatility analysis. The model presents a hybrid framework combining interpretable machine learning (SHAP) for feature attribution and Spiking Neural Networks (SNNs) for quantification of the nonlinear transitions in systemic instability. SHAP values are based on extraction from tree-based models (e.g., XGBoost) while SNN's presents temporal encoding of volatility signals to capture dynamic risk propagation and possible regime shifts. The model can be interpreted as an effort for real time detection of evolving market conditions.

This study presents a novel Neuro-Financial Instability Index (NFII) that fuses explainable AI with spiking neural networks (SNNs) to recalibrate assessment of systemic risk in increasingly digitalized markets. This is the first such study that suggests quantification of the impact of cryptocurrency dynamics (BTC, ETH) over traditional financial indicators (e.g., S&P 500, VIX) using SHAP-based attribution. Similarly, behavioral sentiments (Google Trends, Reddit) were integrated within the framework to generate a cognitively informed risk signal for real time analysis. Furthermore, SNNs enables detection of fat-tailed stress regimes and transition phases via time-series decomposition for regulators and investors facing decision dilemmas in nonlinear market volatility landscapes.

### 3.1 Description of the Alternatives

Recent advancements in financial instability modeling emphasize integrating traditional economic indicators with behavioral and crypto-market signals. Billio et al. (2012) introduced econometric measures of systemic risk via interconnectedness in finance and insurance sectors. Kadkhoda and Amiri (2024) proposed a hybrid network-ML model for distress prediction. Caccioli et al. (2018) advocated for network-based models to capture cascading failures. Bahrammirzaee (2010) reviewed hybrid AI approaches in finance, highlighting their adaptability to nonlinear data. More recent studies (e.g., Saâdaoui & Rabbouch, 2024) demonstrate the power of LSTM-hybrid models in forecasting volatility—supporting the need for neuro-inspired designs.

### 3.2 Description of the Criteria

The NFII is designed around five primary criteria that includes: (a) Market Volatility: Extracted using via traditional indicators like the S&P 500 and VIX (b)Crypto-Market Dynamics: Two cryptocurrencies include BTC-USD and ETH-USD prices as agents of destabilization. (c) Behavioral Signals: Two well-known sources Google search trends and Reddit sentiment were collected to quantify fear and crowd psychology. (d) Inter-Asset Correlations: Time varying interactions between traditional assets and cryptocurrencies were used to derive correlation scores. (e) Nonlinear Regime Patterns: Patterns were detected using Spiking Neural Network (SNN) dynamics and time-series decomposition. These criteria have been included based on their documented relevance to systemic instability and capacity to reflect emerging stress in hybrid financial ecosystems.

### 3.3 Proposed Methodology

The proposed methodology integrates multi-source data with an adaptive neural framework. In the initial stage, Daily data from Yahoo Finance (S&P500, VIX, BTC-USD, ETH-USD), Google Trends, and Reddit were collected using python 3.0 on Google Colab platform using libraries of Yfinance, pytrends, asyncpraw respectively.
In the next stage of preprocessing, data was normalized using MinMaxScaler for handling missing values. The third stage included Feature Engineering for Lagged returns, volatility, and sentiment scores. In the follow up stage, neural modeling of Spiking Neural Networks was used to capture nonlinear temporal spikes in market behavior. The pre-final stage reflects the interpretation of the analyzed data using SHAP, radar plots (Explainable AI techniques) for identification of real drivers of instability and transitions in the financial regime. The final stage witnessed validation of results, with the implementation of Temporal train-test splits, correlation heatmaps, and regime shift diagnostics using spiking neural networks (Brian2 model).

## 4. Results

### 4.1 Descriptive Statistics

The descriptive statistics highlight rise in assets price from 2023-2024 to 2024-2025, including significant increase in BTC prices (108%- from $36,381 to $75,797) with heightened volatility (std rising from $12,070 to $15,799), besides Ethereum price growth by 41% % ($2,122 to $2,987) with contrasting reduced volatility indicating maturing market dynamics. Steady growth in S&P 500 prices (^GSPC) (25% increase from 4,528 to 5,646) accompanied by stable volatility was also noted besides nearly identical sentiment means (~49) and fear index distributions (mean ~5.0 both periods), signifying stable market psychology despite price fluctuations. Categorically, BTC with high-risk/high-reward profile, ETH with risk-adjusted returns, traditional assets with steady growth, sentiment and fear steadiness imply range bound design of portfolio of investments (See Table 1).

**Table 1. Descriptive Statistics**

| **PERIOD : 2023-2024** | | | | | | |
|---|---|---|---|---|---|---|
| **Period** | **Stats** | **BTC-USD** | **ETH-USD** | **^GSPC** | **sentiment** | **fear_index** |

| | | | | | | |
|---|---|---|---|---|---|---|
| **2023-2024** | count | 365 | 365 | 249 | 365 | 365 |
| **2023-2024** | mean | 36381.11 | 2121.72 | 4528.005 | 49.1547 | 4.946418 |
| **2023-2024** | std | 12069.95 | 562.9009 | 318.3779 | 29.10706 | 3.006374 |
| **2023-2024** | min | 25124.68 | 1539.612 | 4055.99 | 0.506158 | 0.108377 |
| **2023-2024** | 25% | 27530.79 | 1804.039 | 4288.39 | 24.18523 | 2.129642 |
| **2023-2024** | 50% | 30295.81 | 1892.08 | 4465.48 | 51.13424 | 4.921163 |
| **2023-2024** | 75% | 42623.54 | 2281.471 | 4746.75 | 72.90072 | 7.615106 |
| **2023-2024** | max | 73083.5 | 4066.445 | 5254.35 | 99.00539 | 9.997177 |
| **PERIOD : 2023-2024** | | | | | | |
| **Period** | **Stats** | **BTC-USD** | **ETH-USD** | **^GSPC** | **sentiment** | **fear_index** |
| **2024-2025** | count | 364 | 364 | 250 | 364 | 364 |
| **2024-2025** | mean | 75796.5 | 2987.074 | 5645.79 | 49.91394 | 5.099381 |
| **2024-2025** | std | 15798.88 | 528.746 | 309.8902 | 29.04922 | 2.980032 |
| **2024-2025** | min | 53948.75 | 1806.219 | 4967.23 | 0.463202 | 0.0494 |
| **2024-2025** | 25% | 63022.58 | 2577.818 | 5432.135 | 24.20734 | 2.295796 |
| **2024-2025** | 50% | 68248.53 | 3072.016 | 5655.645 | 50.02814 | 5.287861 |
| **2024-2025** | 75% | 93688.88 | 3390.322 | 5917.965 | 74.48621 | 7.633728 |
| **2024-2025** | max | 106146.3 | 4005.811 | 6144.15 | 99.79341 | 9.971245 |

### 4.2 Stationarity tests results

The time series was tested for stationarity with ADF test on the Rolling Instability Index, yielding an ADF Statistic of 2.0259098186377926 with p-value of 0.27532935032020056< 0.05, clearly suggesting stationarity of the included time series for analysis. Furthermore, time series decomposition of the rolling instability index exhibits deteriorating market instability, indicated by rise to severe instability (-30.0 to -500.0) from relatively mild fluctuations (-0.5 to -20.0) in the beginning phase and reaching extreme negative territory (-500.0 to -640.0) in the last phase. Patterns reflect initial period of gradual stress accumulation progressing to nonlinear breakdown in market stability, aided by non-recovery periods suggesting sustained, irreversible deterioration mirroring a systemic market failure or a highly persistent negative feedback loop in the measured financial system. Extremities in the last phase signals liquidity crisis or loss of investor confidence beyond recoverable levels due to likely complete breakdowns in normal market functioning (See Figure 1).

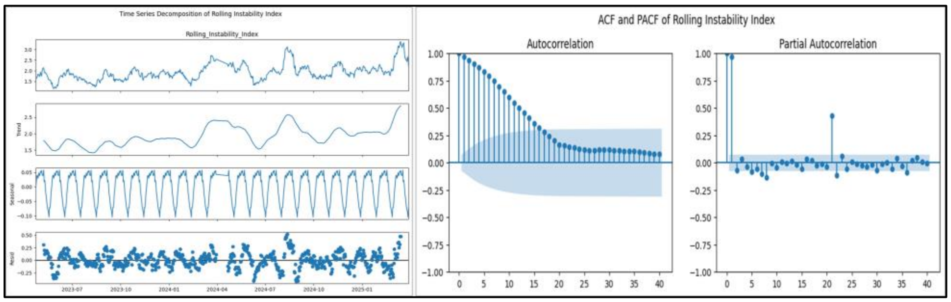



**Fig. 1** Time series decomposition of rolling Instability Index (Source: Author analysis)

### 4.3 Correlation Matrix of Instability features

Both BTC-USD and ETH-USD with strong positive relationship (0.79), reflect parallel movements with weak sentiments indicated by weak correlations with all assets (0.01–0.13), demonstrating sentiment non interdependence on price movements. Heightened fear is underlined by negative correlations with both cryptocurrencies (−0.07 for BTC-USD, −0.03 for ETH-USD) and sentiment (−0.05), that suppress prices and market optimism. Except BTC-USD and ETH-USD (0.79) linkage, other possible linkages remain insignificant or negligible (e.g., Ticker and sentiment at 0.01), revealing the predictive power between these variables. Patterns reveal the increasing impact of crypto-specific co-movements, limited by sentiment and fear as distinct, less price-sensitive factors (See Figure 2 and Appendix 2).

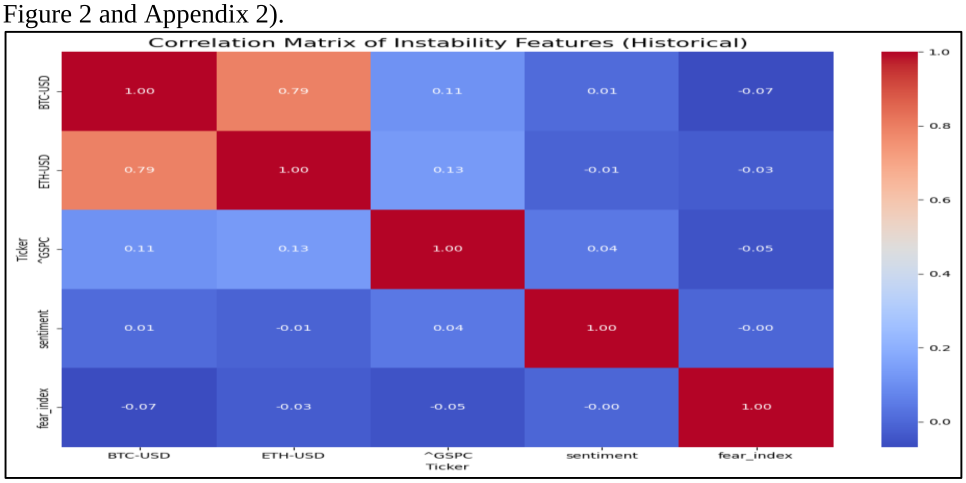



**Fig. 2** Correlation Matrix (Source: Author analysis)

### 4.4 NFI index with anomalies

Results from Z-score visualization for Neuro-Financial Instability Index (NFII) imply systemic risk anomalies observed during transition phase from historical (2023-2024) to comparison periods (2024-2025), besides volatility clustering around the regime shift date (2024-03-31/04-01). Third quarter of 2023 and first quarter 1 2024 reports intensification in anomalies while elevated Z-scores (2024-04 onward), reflect sustained instability progression to structural vulnerabilities exposed during this financial regime change in the post 2024 period. Risk accumulation was noted around the quarterly boundaries exposing higher oscillation amplitude due to deteriorating market resilience in the forecast period (See Fig. 3 and Appendix 3).

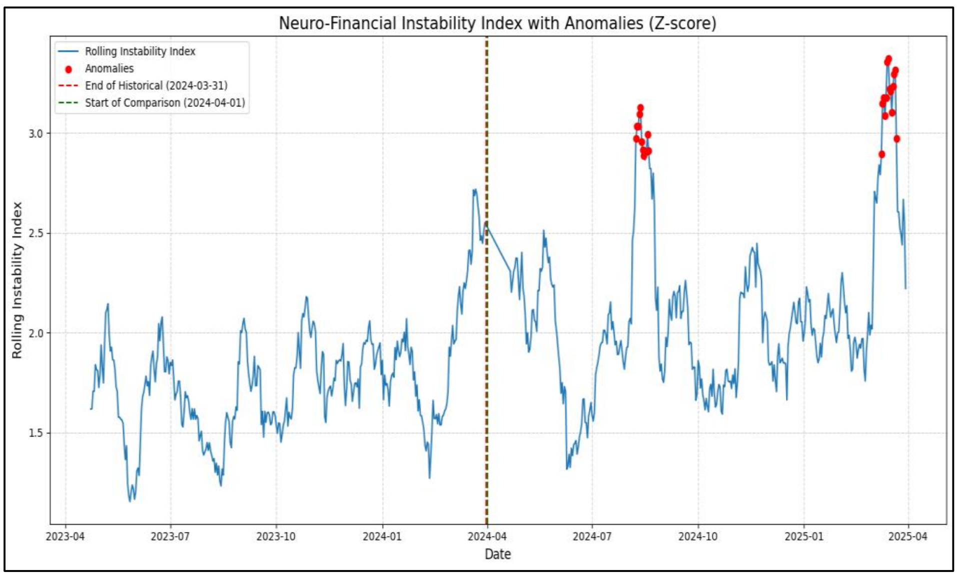



**Fig. 3** Neuro Financial Instability Index with anomalies (z-score) (Source: Author analysis)

### 4.5 NFI Distribution

The historical index (2023-2024) represents a concentrated, left-skewed distribution (values clustered at lower instability levels), in contrast to a rightward shift with a fatter tail (0-10 range), for the comparison period (2024-2025) suggesting distinctiveness with respect to higher typical instability and more frequent extreme events. Patterns reveal transition from low-risk state to an environment prone state indicated by elevated baseline instability and periodic crises. Furthermore, emerging values across the full 0-10 spectrum in the comparison period particularly signals collapse in the historical stability patterns indicated by right-tail events (6-10 range) due to unprecedented stress levels not observed in the earlier period (See Figure 4).

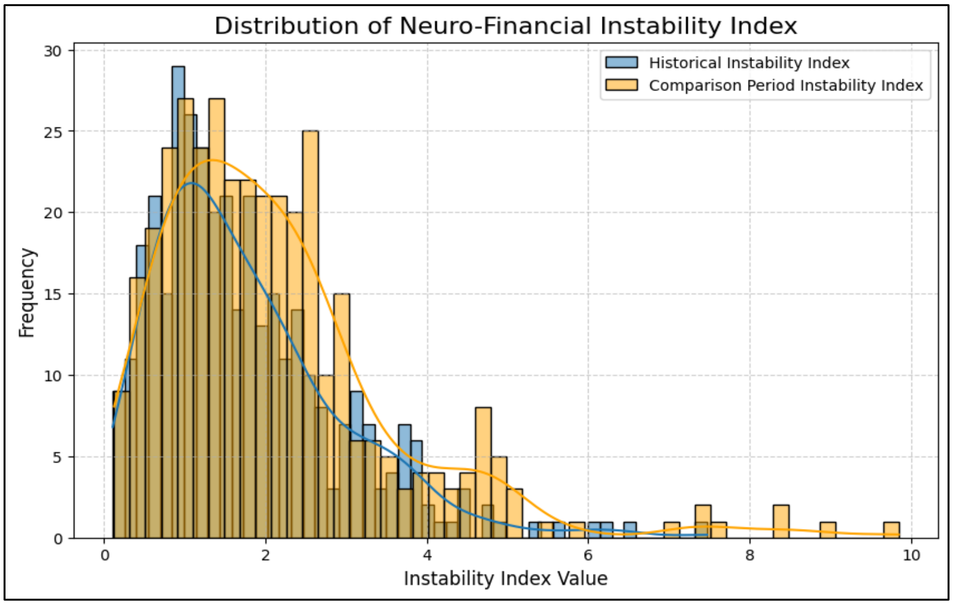



**Fig. 4** NFI index distribution (Source: Author analysis)

### 4.6 Sentiment or behavioral analysis

Sentiment or behavioral analysis of components is highlighted, with BTC-USD (SHAP: 0.6) and ETH-USD (0.4) proving as dominant factors besides sentiment (-0.2) and fear_index (-0.4) as mitigating factors, with lesser influence of GSPC (0.2). Similarly, increase in systemic instability (40%) is clearly amplified by the spikes in the chart geometry for crypto assets. Both visualizations confirm the dominance of cryptocurrencies in terms of source and amplification of financial instability in the forecast period, not perturbed by the movements of traditional markets (GSPC) and behavioral indicators, suggesting a new regime of digital asset volatility increasingly dictating systemic risk patterns (See Figure 5 and Appendix 1).

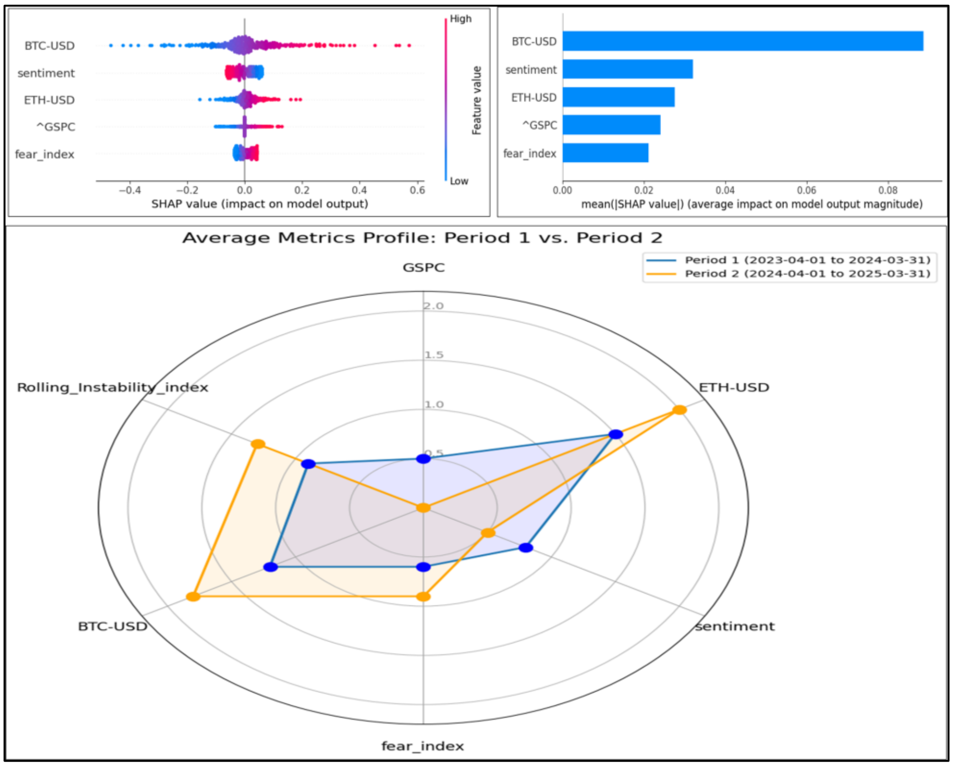
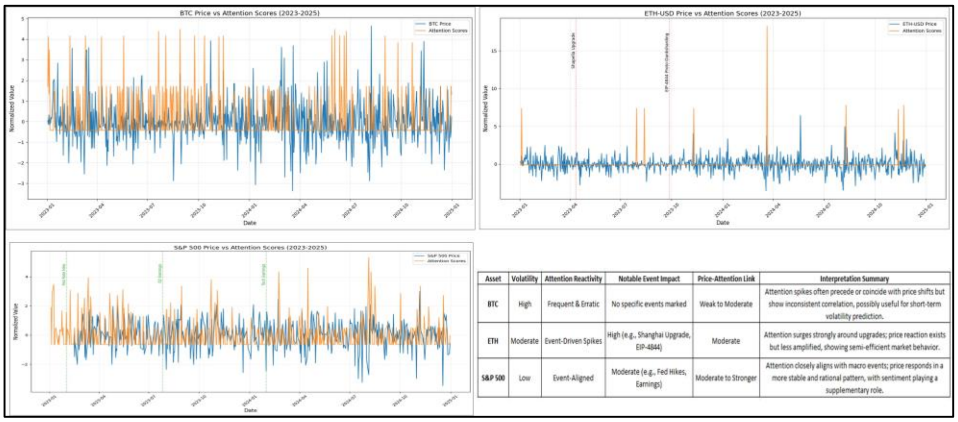



**Fig. 5** SHAP and radar analysis for NFII (Source: Author analysis)

Calculated attention scores across the three assets emphasize varying degrees of alignment with existing price behavior. As observed, Crypto assets (BTC, ETH) indicate spiky and sentiment-driven attention being partially predictive but highly noisy while S&P 500 echoes a more structured and event dependent sentiment profile with stronger market discipline. Attention scores provide greater potential for forecasting around major events for crypto assets beside acting as a confirmatory or amplifying signal in traditional markets (See Fig. 6).




| Asset | Volatility | Attention Reactivity | Notable Event Impact | Price-Attention Link | Interpretation Summary |
|---|---|---|---|---|---|
| BTC | High | Frequent & Erratic | No specific events marked | Weak to Moderate | Attention spikes often precede or coincide with price shifts but show inconsistent correlation, possibly useful for short-term volatility prediction. |
| ETH | Moderate | Event-Driven Spikes | High (e.g., Shanghai Upgrade, EIP-4844) | Moderate | Attention surges strongly around upgrades; price reaction exists but less amplified, showing semi-efficient market behavior. |
| S&P 500 | Low | Event-Aligned | Moderate (e.g., Fed Hikes, Earnings) | Moderate to Stronger | Attention closely aligns with macro events; price responds in a more stable and rational pattern, with sentiment playing a supplementary role. |

**Fig. 6** BTC, ETH and S&P 500 with attention spikes (Source: Author analysis)

## 5. Discussions

Valuable insights into the causes of present financial instability were obtained during an extensive review of results of analysis. Cryptocurrency assets of BTC and ETH have more positive influence (0.4 to 0.6) as compared to traditional market indicator of GSPC (0.2). The instability footprint progressed to 40 % during the 2nd period of the year 2024 to 2025, as indicated by the polygon for BTC and ETH in the radar chart (see Figure 5). Other factors such as fear (-0.4) and rolling instability index (-0.2) also reflect higher negative movements, driven by cyclical stress patterns and increasing instability. This was confirmed by the right fat tail (range of 6 to 10) observed in the second period, highlighting collapse in the historical stability patterns (see Figure 4). Stronger correlation between crypto assets (BTC-ETH: 0.79) compared to traditional assets, indicate parallel movements of both cryptocurrencies dominating their influence on the right fat tail. This phenomenon suggests that cryptocurrency risks are far higher than traditional assets during periods of growing instability. Therefore, our NFSI model truly identifies the growing challenges in risk management of multi class asset investments.

### 5.1 Research Limitations and future scope

Experimental results suggest the NFSI as a trustworthy approach for managing financial risk modeling and market stability during periods of instability. Findings also identify cryptocurrencies as risky assets whose movements needs to be continuously monitored in macroeconomic studies or volatility studies in multi class asset management. NFII model is a promising model which can be used in speculative trading, liquidity constraints for studying structural weaknesses in decentralized markets. The proposed model can also be combined with other models, as it introduces sentiment and fear index which are vital in

high frequency trading environments. A consistent long right fat tail observed in the study indicates a regime shift during second period of 2024- 2025, which is another benefit of using NFSI model. This model also studies nonlinearity in uncertain and volatile markets, indicated by cyclical anomalies during regime shifts. With markets becoming unpredictable and more uncertain, NFSI machine learning approach easily adopts the application of the extreme value theory, highlighting its future prospects of integration with gaussian based risk assessments. These results highlight the need for interdisciplinary approaches (finance, behavioral science and computer science) as the next generation structural model redefining assessment of highly complex multi asset investment markets.
The present work highlights many benefits of the proposed NFII approach, but needs to be used on more experimental datasets due to constraints such as (1) the design predicts the role of only two cryptocurrencies although in reality more cryptocurrencies may be involved (2) SHAP values are based on nonlinear interdependencies among financial variables and can fluctuate due to higher complexity or presence of more variables (3) NFSI approach combined with other models can give better results as compared to NFSI standalone model. Therefore, possible suggestions for improvement in usage NFII may include (1) Integration with high frequency block chain metrics (e.g., on-chain liquidity flows, decentralized finance leverage ratios) can improve model specificity; (2) Using multiple layers for measurement of complex nonlinear stress or shock flows among multi-class assets. (3) More experimentation against extreme volatility regimes for setting higher threshold conditions Future work in theses directions can strengthen the theoretical foundations of systemic risk assessment in hybrid financial systems.

## 6. Conclusion

This study provides understanding of the role of two major cryptocurrencies (BTC and ETH) in resulting financial instabilities during the financial year (2024-2025). The results of the experiment highlight the rapid co-movements of BTC and ETH as compared to GSPC (traditional stock) during the second period of the financial year 2024-2025. The NFII framework can capture different patterns of instability that includes (1) a 40% increase in risk formation in 2024-2025 compared to the baseline (2) the growing influence of psychological emotional factors on financial behavior (3) emerging long right fat tail leading to financial regime shift. This model suggests that financial decision making should involve use of machine learning approaches (1) to increase monitoring of risks related to cryptocurrencies (2) restructure diversification tools to minimize increasing such risks. (3) to study the influence of behavioral and psychological factors on financial investment patterns. The NFII model is an addition to the existing group of machine learning models suggesting increased utility of machine learning adaptive models in future. It provides a new foundational framework which can be developed further with addition of more behavioral factors besides more traditional and crypto based stocks. The findings suggest the need for machine learning based advanced financial surveillance systems which can track high frequency mixed asset and stock movement for financial regime shift prediction in future (see Figure 7).

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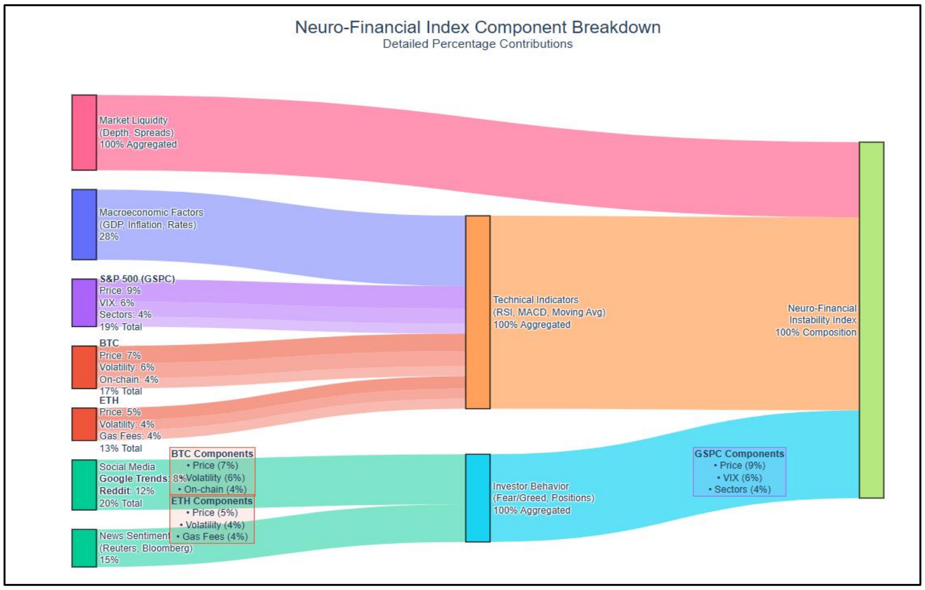


**Fig. 7** Neuro-Financial Index Component breakdown using Sankey diagram (Source: Author analysis)

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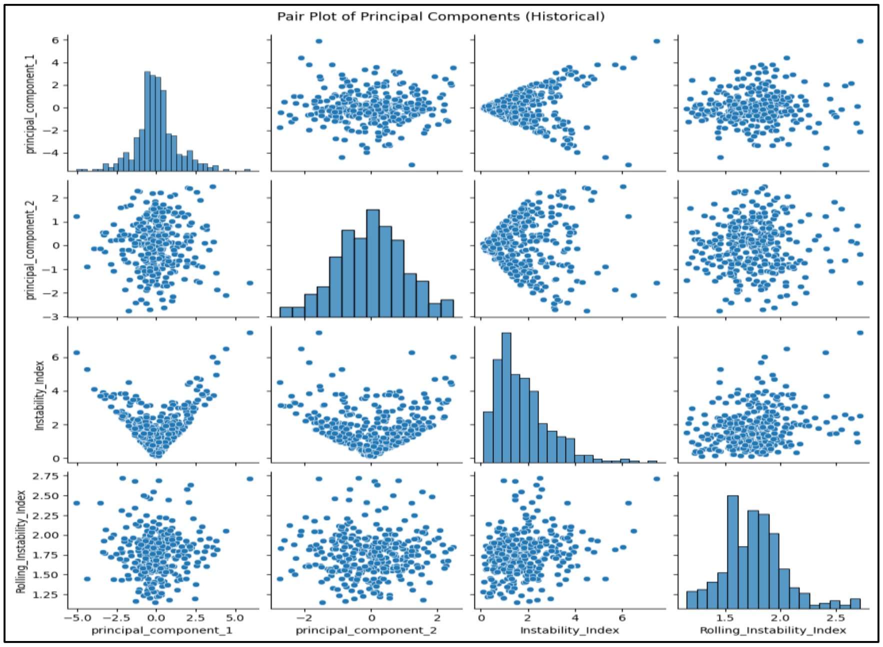
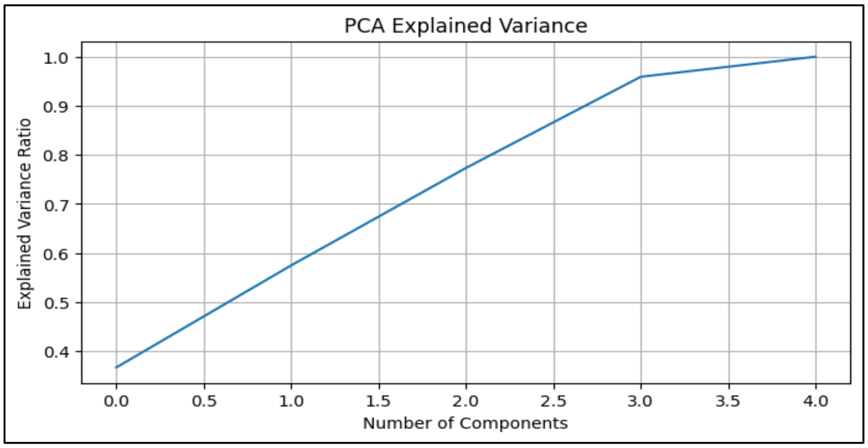
**Appendices:**

**1. PCA plots**



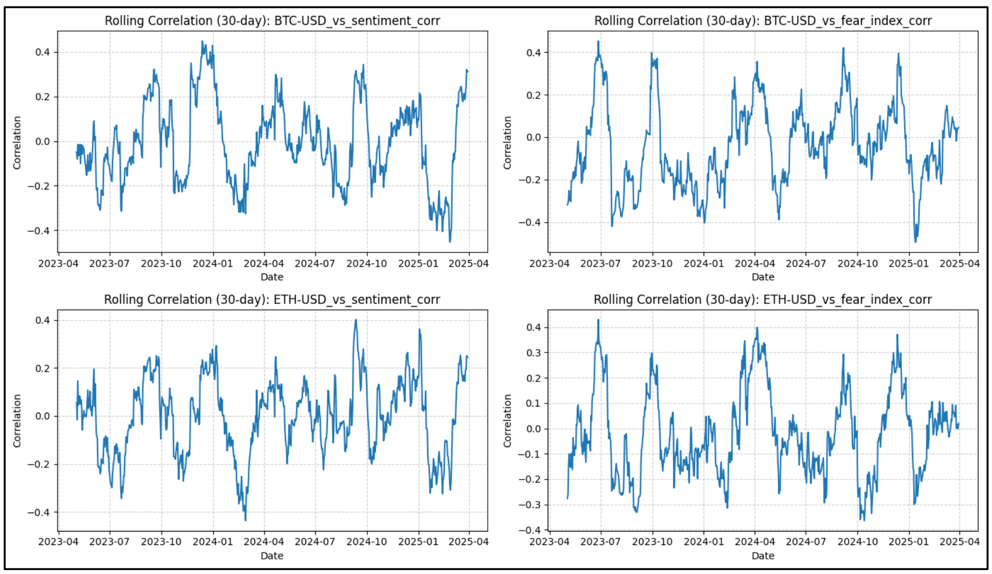

Appendix 1. PCA Plots for principal components
for Instability Index
(Source: Author analysis)

**2. PCA explained Variance**




Appendix 2. PCA explained variance for Instability Index (Source: Author analysis)

## 3. Rolling correlation




Appendix 3. Rolling correlation for (BTC-USD, ETH-USD) vs (Sentiment, Fear) for Instability Index (Source: Author analysis)