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AI-DRIVEN EARLY WARNING SYSTEM FOR FINANCIAL RISK IN THE U.S. DIGITAL ECONOMY

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Abstract

The digital economy's increasing integration with financial systems has amplified systemic vulnerabilities, yet most early warning frameworks remain static and slow to adapt to evolving market, macroeconomic, and sentiment dynamics. This study develops an AI-driven early warning system that fuses macroeconomic indicators, market data from major digital firms, and online sentiment metrics to detect and anticipate financial stress within the U.S. digital economy. Leveraging a decade of weekly data (2015–2025) across FRED, Yahoo Finance, Reddit, and Google News sources, we construct a multimodal dataset capturing both structural and behavioral signals. A hybrid modeling pipeline integrates interpretable Logistic Regression with adaptive online learning using the River framework and ADWIN drift detection, enabling real-time updates as financial conditions evolve. Experiments benchmark Logistic Regression, Random Forest, and XGBoost against the adaptive model under temporal cross-validation. Results show that the interpretable logistic regression baseline achieves the most stable performance across folds, while the adaptive River model sustains predictive capability under concept drift, providing continuous calibration without retraining. Lead-time analysis demonstrates the system's ability to issue warnings 2–6 weeks before major stress events, validated through both macroeconomic and sentiment-driven market shifts. Explainability analysis using SHAP reveals that negative sentiment dynamics, rising volatility, and tightening monetary conditions are the strongest precursors of stress. These findings highlight how transparent, adaptive AI systems can bridge the gap between accuracy, interpretability, and operational feasibility, offering a practical foundation for real-time systemic risk monitoring in digital financial ecosystems.

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1. Introduction

1.1 Background and Motivation

The accelerating digitalization of financial markets has reshaped how systemic risk emerges, propagates, and manifests in the U.S. economy. The rapid growth of digital financial ecosystems, encompassing fintech payment platforms, online trading applications, and crypto-based transactions, has introduced new interdependencies that extend well beyond traditional banking and capital markets. Unlike conventional institutions that operate within structured regulatory and reporting frameworks, digital financial firms are influenced by a combination of market sentiment, user engagement, and algorithmic trading dynamics. This creates a feedback loop between investor perception, market liquidity, and macroeconomic stress, where negative sentiment or price volatility can quickly translate into systemic risk exposure. Chen and Svirydzenka (2021) argue that conventional early warning indicators rooted in banking and credit cycles are increasingly insufficient because they do not capture the nonlinear transmission channels of the modern digital economy [11]. Similarly, Cevik (2023) highlights that fintech expansion, while promoting innovation and accessibility, has simultaneously amplified systemic fragility through highly interconnected platforms, real-time settlements, and dependence on volatile digital assets [9].

The vulnerabilities within this digital-financial nexus were exposed during recent global and domestic stress events. For instance, abrupt shifts in sentiment surrounding cryptocurrencies and payment technologies have repeatedly led to liquidity contractions and portfolio losses, demonstrating the systemic relevance of non-traditional financial channels. Bhowmik et al. (2025) reveal that AI-driven sentiment analytics are critical for interpreting the behavioral dimensions of crypto and digital markets, showing that fluctuations in online sentiment often precede sharp volatility spikes [5]. Traditional econometric or statistical models, which rely on stable linear relationships, are thus inadequate for environments characterized by high-frequency sentiment shifts, regime changes, and dynamic macro-financial linkages. Sizan et al. (2025) also emphasize that machine learning's capacity to detect latent patterns and emerging typologies in complex financial data makes it suitable for identifying anomalies in transaction networks before they escalate into systemic threats [25]. Furthermore, Das et al. (2025) demonstrate that AI-based predictive analytics have transformed early threat detection in cybersecurity by capturing multi-source signals and adaptively learning from evolving behaviors, a principle equally applicable to financial instability modeling [13].

These insights underscore the urgent need to build adaptive, interpretable systems capable of identifying early stress signals in the digital economy using real-time, multimodal data sources. Recent advances in data-driven modeling show that combining structured macroeconomic variables with unstructured textual sentiment can meaningfully enhance predictive reliability. Islam et al. (2025) find that hybrid learning frameworks applied to cryptocurrency price forecasting capture both quantitative and emotional drivers of financial movement, yielding more resilient forecasts under uncertainty [17]. This integration aligns with the argument that

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systemic risk prediction should shift from static, indicator-based models to dynamically learning frameworks that evolve with market structure and investor sentiment. The present study advances this research trajectory by proposing an AI-driven early warning system that fuses macroeconomic indicators, digital market data, and online sentiment streams to anticipate stress conditions in the U.S digital economy.

1.2 Importance of This Research

Early detection of systemic risk within the digital economy has profound implications for policymakers, investors, and regulators. Traditional early warning systems, though effective in pre-digital contexts, assume gradual, measurable macro-financial cycles. However, financial contagion in digital markets often arises from sentiment-driven behavior and instantaneous data propagation. Chen and Svirydzenka (2021) stress that financial stability frameworks must now incorporate high-frequency indicators and behavioral dimensions to capture rapid market transitions [11]. Cevik (2023) reinforces this by identifying fintech-driven ecosystems as both catalysts and amplifiers of instability, where algorithmic trading and decentralized finance platforms can propagate stress far faster than conventional institutions [9]. The transformation of market infrastructure, from human decision-making to automated, data-driven execution, necessitates predictive systems that can adapt in real time, remain interpretable to human overseers, and provide lead-time insights before market deterioration occurs.

Machine learning and deep learning models have shown potential for early crisis detection through their ability to process large, heterogeneous datasets. However, as Sizan et al. (2025) caution, the complexity of ensemble or unsupervised models can limit transparency and interpretability in financial decision contexts [25]. This creates a paradox: the most powerful models are often the least explainable, undermining regulatory confidence and practical deployment. Khan et al. (2025) note that integrating environmental, social, and governance (ESG) data into predictive financial models enhances interpretability and public accountability, principles equally vital in systemic risk monitoring [18]. Reza et al. (2025) further demonstrate that AI-driven socioeconomic modeling can reduce informational asymmetries and improve early identification of vulnerable populations or institutions, offering parallels for anticipating systemic fragility [23].

In parallel, the digital economy's dependence on sentiment has expanded the scope of what constitutes financial data. Bhowmik et al. (2025) provide evidence that sentiment polarity and frequency of discourse in online platforms such as Reddit or Twitter exhibit predictive alignment with crypto-asset volatility [5]. When integrated into hybrid AI systems, such signals can enhance the timeliness and precision of early warning systems. Billah et al. (2024) add that blockchain and digital transaction ecosystems require monitoring frameworks capable of distinguishing between structural performance fluctuations and true systemic threats, reinforcing the relevance of adaptive learning in digital finance [7]. These studies suggest that the intersection of artificial intelligence, behavioral finance, and real-time macroeconomic monitoring offers a transformative path toward proactive risk management. This study contributes to that trajectory by demonstrating that interpretable, continuously learning models can bridge the gap between prediction accuracy and transparency in early warning design for the U.S. digital economy.

1.3 Research Objectives and Contributions

This research aims to develop a transparent and adaptive AI-driven early warning framework capable of identifying systemic financial stress in the U.S. digital economy using multi-source, real-time data. It seeks to unify macroeconomic, market, and sentiment signals into a coherent predictive pipeline that can detect, adapt to, and explain evolving risk patterns. Specifically, the study integrates conventional statistical techniques with adaptive machine learning approaches, allowing the system to self-calibrate under concept drift and maintain interpretability through regression-based explainability. The proposed framework evolves beyond traditional static models by leveraging incremental online learning and drift detection to ensure responsiveness to dynamic market behavior.

A key contribution lies in demonstrating that logistic regression, though simple, can outperform complex black-box models when carefully engineered and coupled with adaptive extensions, especially under conditions of temporal drift and data imbalance. The study also establishes the operational viability of explainable early warning systems through its implementation in an end-to-end Python-based experimental pipeline, integrating FRED macroeconomic data, Yahoo Finance market variables, and sentiment indicators from Reddit and Google News. Additionally, the research introduces a systematic lead-time evaluation method that quantifies the temporal horizon of predictive warnings, bridging academic metrics and practical monitoring needs. By combining predictive accuracy, interpretability, and adaptability, this work presents a comprehensive blueprint for deploying real-time early warning systems that are not only technically effective but also trustworthy, transparent, and policy-relevant within the rapidly evolving landscape of the digital U.S. economy.

2. Literature Review

2.1 Financial Early Warning Systems

Financial early warning systems (EWS) have long been developed to identify vulnerabilities and potential crises within macroeconomic and financial domains before they fully manifest. Traditionally, such systems rely on macroeconomic indicators such as yield spreads, credit growth, asset price inflation, and exchange rate misalignments to signal elevated systemic risk. Early implementations typically employed statistical and econometric techniques such as probit and logit regression, where the probability of a crisis was modeled as a function of lagged indicators. Allaj and Sanfelici (2023) argue that early warning models grounded in logistic regression frameworks can effectively capture nonlinear dynamics between volatility measures and realized variances, allowing practitioners to estimate risk probabilities associated with evolving market conditions [3]. Their findings reinforce the methodological foundation for using interpretable linear classifiers in predictive financial research, particularly in applications that require both explanatory clarity and predictive precision.

Financial stress indices (FSIs) have become cornerstone components in EWS construction, synthesizing multiple market and credit indicators into a single composite measure of financial health. Kliesen et al. (2012) provide one of the most comprehensive surveys of such indices, distinguishing between those based on market volatility, yield spreads, and macro-financial variables, and those integrating high-frequency information such as credit default swap (CDS) spreads or interbank lending rates [19]. The St. Louis Financial Stress Index (STLFSI), a key metric in U.S. systemic monitoring, exemplifies how multivariate inputs can quantify stress intensity across time and sectors. However, while FSIs capture the structural aspect of financial instability, they are inherently lagging indicators, making them insufficient for detecting the real-time buildup of risk in fast-moving digital markets.

In the context of the modern digital economy, traditional EWS methodologies face significant limitations. They often assume a stable mapping between macro-financial variables and systemic outcomes, neglecting behavioral components such as investor sentiment or digital transaction flows that can rapidly influence market equilibrium. As fintech firms, algorithmic trading, and digital asset platforms increasingly integrate into the broader financial ecosystem, the boundaries of systemic exposure have blurred. The proliferation of decentralized finance (DeFi) and digital payment networks introduces feedback effects that conventional macro models fail to capture. Hence, the field has shifted toward integrating data-driven machine learning (ML) methods that adapt to new patterns in near real-time, overcoming the rigidity of parametric approaches. By leveraging these dynamic models while retaining the interpretability of traditional econometric systems, researchers aim to develop EWS architectures that can anticipate, rather than merely react to, evolving stress phenomena within the digital financial ecosystem.

2.2 Machine Learning for Financial Risk Prediction

Machine learning has transformed the field of systemic risk prediction by offering methods that can model nonlinear dependencies, capture high-dimensional interactions, and adapt to nonstationary data. Kou et al. (2019) provide a comprehensive survey of machine learning techniques, such as support vector machines (SVMs), Random Forests, and neural networks, applied to financial stability analysis, systemic contagion modeling, and market volatility forecasting [20]. These algorithms outperform conventional econometric models by detecting hidden interactions within heterogeneous financial data, yet their opacity often limits practical interpretability and regulatory acceptance. Wang et al. (2024) demonstrate that incorporating financial network connectedness as a feature within ML architectures significantly enhances systemic risk prediction, emphasizing that contagion effects between institutions or assets can provide crucial early indicators of instability [27]. This perspective marks a shift toward network-aware models, where systemic risk is conceptualized not only as the aggregation of individual firm vulnerabilities but also as a function of interdependencies across markets and entities.

Tree-based ensemble models have become particularly influential due to their scalability and predictive power. Chen and Guestrin (2016) introduced XGBoost, a gradient boosting framework that combines decision trees to minimize residual error iteratively [12]. Its capacity for feature selection, handling missing data, and parallel computation has made it a standard in financial prediction tasks. However, XGBoost and other ensemble techniques are inherently black-box systems that provide limited transparency into decision pathways, a critical drawback when results must inform policy or risk oversight. Sizan et al. (2025) and Fariha et al. (2025) both emphasize that AI-driven fraud detection models share similar challenges: they achieve exceptional accuracy under high-dimensional data but at the expense of explainability, making them difficult to audit in regulated environments [26][14].

Despite these advancements, ML-based financial risk prediction still faces challenges related to data imbalance, interpretability, and adaptability. Rare crisis events lead to heavily skewed datasets, where traditional accuracy metrics may overstate performance. Moreover, fixed-model architectures cannot accommodate structural shifts or concept drift, leading to degraded performance when underlying financial relationships evolve. Shawon et al. (2025) argue that resilient predictive frameworks must integrate logistic interpretability with machine learning adaptability, especially in supply-chain and macroeconomic applications where temporal volatility is high [24]. Consequently, the next frontier in systemic risk research lies in developing hybrid frameworks that combine interpretable statistical foundations with adaptive, data-driven methodologies capable of learning continuously from streaming financial signals.

2.3 Role of Sentiment in Financial Risk

Investor sentiment has emerged as a critical driver of financial volatility, particularly within the digital economy, where information dissemination is instantaneous and market responses are highly nonlinear. The behavioral dimension of financial risk was first empirically quantified by Bollen et al. (2011), who demonstrated that aggregate Twitter mood indicators could predict movements in the Dow Jones Industrial Average with 87.6% accuracy [8]. Their study established a precedent for using natural language data as a proxy for market expectations and emotional dynamics. Subsequent research has expanded this paradigm, incorporating news articles, social media discussions, and online forums to gauge public perception and its correlation with asset price fluctuations. Greyling and Rossouw (2022) extend this framework to intraday trading, showing that sentiment polarity extracted from stock-related tweets enhances the prediction of both volatility and direction of returns across developed and emerging markets [15]. In the context of crypto and digital asset markets, sentiment often serves as both a leading and amplifying indicator of systemic stress. Bhowmik et al. (2025) find that negative sentiment trends on social media platforms are strongly associated with increases in cryptocurrency volatility, particularly during speculative bubbles or market corrections [5]. Their results suggest that digital markets exhibit reflexive behavior, where sentiment-driven trading can precipitate the very crises it anticipates. The influence of online discourse is amplified in decentralized and retail-driven markets, where feedback loops between sentiment, price movement, and participation reinforce volatility cycles.

Integrating sentiment into systemic risk models presents both methodological challenges and opportunities. Traditional econometric indicators operate on monthly or quarterly frequencies, while sentiment data are inherently high-frequency and unstructured. Machine learning and natural language processing (NLP) enable the transformation of text data into quantifiable features, such as polarity scores or emotion vectors, that can be aligned with financial indicators. Fariha et al. (2025) argue that this multimodal integration enhances both recall and

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early detection in anomaly detection frameworks [14]. However, as Hasan et al. (2025) caution, the interpretability of AI-driven models remains crucial to maintain trust among institutional users and regulators [16]. The current study builds upon these insights by employing sentiment data from Reddit and Google News alongside macro-financial variables, creating a unified data stream capable of capturing both behavioral and structural dimensions of systemic risk in real time.

2.4 Adaptive and Online Learning in Finance

Financial systems are inherently nonstationary, characterized by continuous evolution in structure, regulation, and market behavior. Static machine learning models, once trained, quickly lose relevance as data distributions shift over time. To address this, adaptive and online learning algorithms have gained prominence for financial applications that demand responsiveness to streaming data. Montiel et al. (2021) introduced the River framework as a Python-based library designed for incremental learning from continuous data streams [22]. River enables models to update their parameters iteratively with each new observation, allowing them to maintain performance without full retraining. Its modular architecture supports drift detection, adaptive scaling, and real-time evaluation, making it particularly suited for high-frequency financial risk monitoring. Concept drift detection forms the backbone of adaptive learning in finance. Bifet and Gavaldà (2007) pioneered the ADWIN (Adaptive Windowing) algorithm, which dynamically adjusts observation windows to detect statistically significant changes in data distribution [6]. When drift is detected, models can reset or adapt their internal parameters, ensuring they remain calibrated to current market conditions. Such mechanisms are vital in financial domains where relationships between predictors and outcomes can invert rapidly due to policy interventions, liquidity shocks, or behavioral contagion.

In practical applications, adaptive learning has proven valuable for fraud detection, credit scoring, and transaction monitoring. Sizan et al. (2025) demonstrated that adaptive ensemble systems could uncover previously unseen money-laundering typologies by continuously updating pattern recognition thresholds based on recent transaction behavior [25]. Similarly, Fariha et al. (2025) observed that incremental updating enhances precision in detecting evolving fraud strategies within dynamic transaction streams [14]. These insights parallel the challenges in systemic risk prediction, where financial stress evolves under changing economic regimes and data volatility. Integrating adaptive algorithms like River with interpretable linear models enables early warning systems to remain both responsive and transparent, a balance essential for real-world adoption in regulatory environments. The combination of continuous learning, drift detection, and explainable outputs positions adaptive modeling as the future foundation of resilient, real-time financial monitoring infrastructures.

2.5 Gaps and Challenges

Despite rapid progress in applying AI and ML to financial risk detection, several key gaps persist that this study seeks to address. First, few frameworks integrate macroeconomic, market, and sentiment indicators within a unified adaptive system. Most research isolates one domain, macro indicators for traditional EWS, market prices for volatility forecasting, or

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sentiment for behavioral analysis, resulting in partial visibility into systemic dynamics. This segmentation prevents comprehensive early detection of emerging risks that cut across these data modalities. Second, interpretability remains a major obstacle to adoption. As Hasan et al. (2025) emphasize, the increasing complexity of ensemble and neural models often conflicts with regulatory demands for transparency and auditability in financial decision-making [16]. Fariha et al. (2025) also note that even when models achieve high predictive accuracy, their opaque decision logic impedes trust and actionable insights in operational risk settings [14]. A critical research challenge lies in designing models that preserve predictive strength while maintaining explainable, policy-compliant structures.

Third, the problem of concept drift is largely unaddressed in current financial AI literature. Financial systems evolve continuously due to shifts in regulation, technology, and sentiment, causing static models to degrade rapidly. Montiel et al. (2021) and Bifet and Gavaldà (2007) demonstrate that adaptive, streaming-based learning frameworks are necessary to ensure real-time robustness under dynamic conditions [22][6]. However, few studies have operationalized these methods in financial stability or early warning contexts. Finally, there is limited empirical work evaluating lead-time effectiveness, the period between model prediction and actual stress event occurrence. Most research reports classification accuracy without quantifying the practical utility of early signals. By addressing these gaps, the current study contributes a novel hybrid architecture that integrates interpretability, adaptability, and timeliness into a coherent early warning system for the digital U.S. economy.

3. Methodology

3.1 Dataset and Feature Design

The dataset developed for this study captures the multidimensional nature of systemic financial risk in the digital economy by integrating macroeconomic, market, and sentiment-based variables. It is constructed from diverse sources to ensure that structural, behavioral, and market-specific dimensions of financial stress are represented in a unified analytical framework. The dataset spans January 2015 to January 2025 at a weekly frequency, allowing both medium-term trends and short-term dynamics to be captured for adaptive modeling. Macroeconomic Data were sourced from the Federal Reserve Economic Data (FRED) database, which provides authoritative U.S. financial and economic time series. The key indicators used include the St. Louis Financial Stress Index (STLFSI4), the Consumer Price Index (CPIAUCSL) for inflation, the Effective Federal Funds Rate (FEDFUNDS), the Unemployment Rate (UNRATE), quarterly Gross Domestic Product growth (A191RL1Q225SBEA), and the 10-Year Treasury Constant Maturity Rate (DGS10). Each of these variables contributes to a distinct aspect of systemic health: inflation and unemployment reflect macroeconomic stability, the federal funds rate captures monetary policy stance, and treasury yields proxy investor confidence and market liquidity. The STLFSI4 index serves as both an explanatory and target variable, given its role as a benchmark for aggregate financial stress.

Market Data were collected using the yfinance library, focusing on a set of key digital-economy firms, PayPal (PYPL), Visa (V), Meta Platforms (META), Shopify (SHOP), and Coinbase

(COIN). These firms represent the intersection of finance, technology, and digital commerce. For each stock, the adjusted closing price was retrieved at a daily frequency and then aggregated into weekly data. Two features were derived from this: weekly returns, calculated as the percentage change in adjusted closing price, and volatility, measured as the rolling 4-week standard deviation of returns. These features quantify both directional movement and market uncertainty, offering a micro-level view of digital sector risk dynamics. Sentiment Data were gathered from two major sources: Reddit and Google News, chosen for their distinct but complementary perspectives on public discourse and media narratives. Reddit data were obtained using the praw library from subreddits such as r/economy, r/finance, r/wallstreetbets, and r/cryptocurrency, filtered using keywords including "inflation," "recession," "risk," "crash," "market," and "bank." Google News data were retrieved using the gnews library, focusing on headlines containing terms like "US economy," "digital economy," "financial risk," "fintech," and "market crash." Each text entry was analyzed using the VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon to compute a compound sentiment score between −1 (strongly negative) and +1 (strongly positive). The sentiment features thus represent aggregate public mood and media tone around financial stability themes. All data sources were merged into a single pandas DataFrame, aligned by a common weekly time index. This design ensures temporal consistency across macroeconomic indicators, firm-level metrics, and sentiment measures, forming a holistic dataset that integrates structural and behavioral risk factors. This integrated dataset forms the empirical foundation for both the static and adaptive modeling phases of the study.

3.2 Data Preprocessing

To ensure analytical rigor and consistency, extensive preprocessing was performed to transform the heterogeneous data streams into a structured format suitable for supervised and adaptive modeling. The goal of this stage was to handle missingness, ensure temporal alignment, and construct lag-based predictors that reflect causal and temporal dependencies across variables. Macroeconomic indicators such as GDP growth, CPI, and unemployment are typically published monthly or quarterly, creating frequency mismatches with weekly market and sentiment data. These series were resampled to a weekly frequency using forward-filling (ffill()), assuming that the last available value remains valid until an update is released. This approach preserves the interpretability of macroeconomic signals while enabling unified time-series analysis. Stock market data occasionally contains gaps due to trading holidays or API retrieval errors. To address these inconsistencies, missing weekly returns and volatility values were filled using linear interpolation, a method suitable for continuous financial time series where neighboring data points exhibit smooth transitions. This step ensures that derived risk indicators remain stable and continuous throughout the study window.

Reddit and Google News sentiment scores, inherently noisy due to daily fluctuations in user activity or news intensity, were aggregated to a weekly average and then smoothed using a 3-week rolling mean. This temporal smoothing emphasizes persistent mood trends over transient emotional spikes, ensuring that sentiment inputs reflect genuine shifts in public and media outlook rather than short-lived events. Missing sentiment entries were assigned a neutral score (0) to prevent bias from sparse weeks. To model the delayed impact of financial and behavioral signals, lagged features were created for each variable at 1-, 2-, and 4-week intervals. This lag design captures both short-term and medium-term temporal dependencies, aligning with literature that emphasizes predictive signals arising before stress events materialize. The feature set thus includes both contemporaneous and lagged predictors, providing the logistic regression and adaptive models with sufficient temporal context.

The dependent variable is a binary stress label derived from the St. Louis Financial Stress Index (STLFSI4). A week is classified as a “stress week” (label = 1) if its STLFSI4 value exceeds the 90th percentile of all observed values, corresponding to periods of heightened systemic tension. Weeks below this threshold are labeled as “non-stress” (label = 0). This percentile-based cutoff was chosen to reflect a realistic yet selective definition of financial distress, ensuring sufficient instances for supervised learning without diluting signal relevance. After preprocessing, all rows containing residual missing values in lagged features or labels were dropped. The resulting dataset is balanced, temporally aligned, and feature-rich, forming the analytical basis for both cross-validated evaluation and online adaptive experimentation using the River framework. This clean dataset ensures that model performance reflects genuine signal capture rather than artifacts of data irregularities, supporting the study’s goal of developing an interpretable, adaptive, and explainable early warning system for financial stress in evolving digital markets.

Exploratory Data Analysis (EDA)

The exploratory data analysis phase plays a crucial role in understanding the behavioral and structural dynamics of the financial system as represented in the constructed dataset. By examining temporal patterns, inter-variable dependencies, and distributional properties, this section elucidates the economic narratives embedded within the data and establishes the empirical grounding for subsequent modeling. Each visualization from the EDA process offers a different perspective on how macroeconomic, market, and sentiment variables interact to produce signals of systemic financial stress within the digital economy context.

The time-series visualization of the Financial Stress Index (STLFSI4) alongside Inflation, the Federal Funds Rate, and the 10-Year Treasury Yield from 2015 to 2025 highlights several macroeconomic transitions and their correspondence to stress episodes. Periods of elevated stress are particularly visible around early 2020, coinciding with the onset of the COVID-19 pandemic and the resulting market dislocation. During this period, the STLFSI4 spikes sharply, reflecting broad liquidity shocks and uncertainty. The inflation trajectory remains relatively subdued for much of the decade, mirroring post-2008 disinflationary trends. However, a marked surge is observed from 2021–2022, coinciding with global supply disruptions and expansionary fiscal measures. This inflation shock period aligns with another uptick in the Financial Stress Index, suggesting the macro-financial feedback loop between rising prices and perceived market instability. The Federal Funds Rate, by contrast, exhibits a near-zero policy stance between 2015 and 2021, reflecting prolonged monetary accommodation, before rising sharply from 2022 onward as the Federal Reserve sought to contain inflationary pressures. The 10-Year Treasury Yield demonstrates cyclical behavior, with declines during risk-off periods and recoveries during phases of monetary tightening. These temporal patterns confirm the

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interconnectedness of macroeconomic shifts and systemic stress episodes. The synchronized fluctuations between inflation, rates, and the Financial Stress Index underscore that financial instability often arises not from a single shock but from the confluence of macroeconomic overheating, tightening liquidity, and shifting investor expectations.

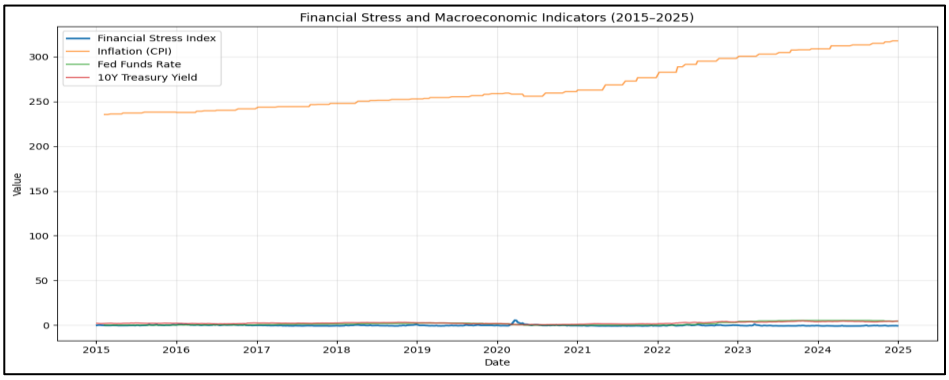

Fig.1: Time-Series Overview of Core Indicators

The correlation heatmap provides a structural snapshot of the linear dependencies among the macroeconomic, market, and sentiment variables. As anticipated, strong positive correlations are observed among volatility metrics across different digital-economy firms, reflecting their shared exposure to systemic and sentiment-driven shocks. Similarly, a negative correlation emerges between market returns and measures of financial stress, aligning with theoretical expectations that heightened systemic risk depresses equity performance. Interestingly, sentiment variables, Reddit and News sentiment, exhibit moderate negative correlations with the Financial Stress Index, indicating that as public and media sentiment deteriorates, systemic stress tends to rise. However, the relatively modest strength of these correlations suggests that sentiment's relationship with stress is nonlinear and time-varying, a phenomenon later validated by rolling correlation analyses. The heatmap also exposes potential multicollinearity risks, particularly between inflation and interest rate series, both reflecting overlapping dimensions of monetary dynamics. Such findings justify the use of regularized models (e.g., Logistic Regression with L2 penalty) and scaling techniques to mitigate overfitting. In sum, the correlation structure reinforces the theoretical view that systemic risk emerges from joint dynamics among markets, policy, and collective sentiment rather than from isolated factors.

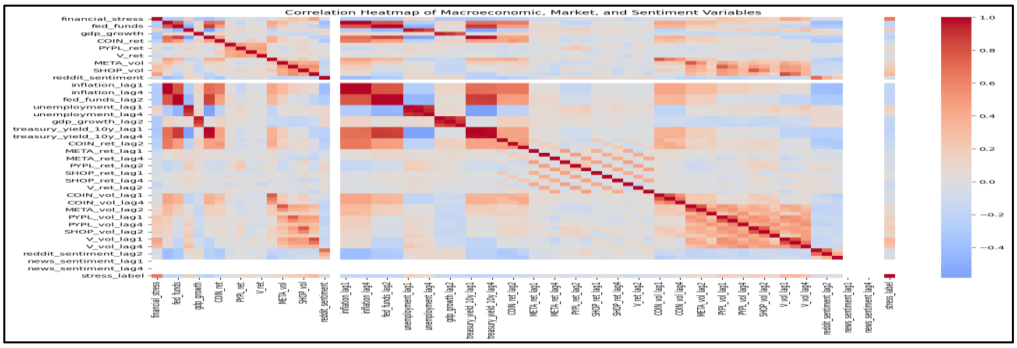

Fig.2: Correlation Heatmap of Macroeconomic, Market, and Sentiment Variables

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The dual-axis visualization comparing Reddit and News Sentiment against the Financial Stress Index provides an interpretive link between public mood and market instability. Periods of heightened financial stress, such as early 2020 and mid-2022, coincide with pronounced dips in both sentiment indices. These downward shifts in sentiment likely reflect collective pessimism during turbulent periods, amplified by online discourse and media framing. The correspondence between declining sentiment and rising stress supports the hypothesis that sentiment indicators act as early-warning or coincident signals of systemic tension. However, the relationship is not uniform across the time span. For instance, while sentiment sharply declines during COVID-19, it recovers faster than the stress index, suggesting that social mood may anticipate recovery signals before institutional indicators do. This observation aligns with behavioral finance literature, which argues that sentiment captures leading psychological responses to macroeconomic stimuli. Thus, sentiment variables hold predictive value not merely as reflections of public discourse but as behavioral precursors of stress formation, enriching traditional early-warning systems reliant on lagging macroeconomic indicators.

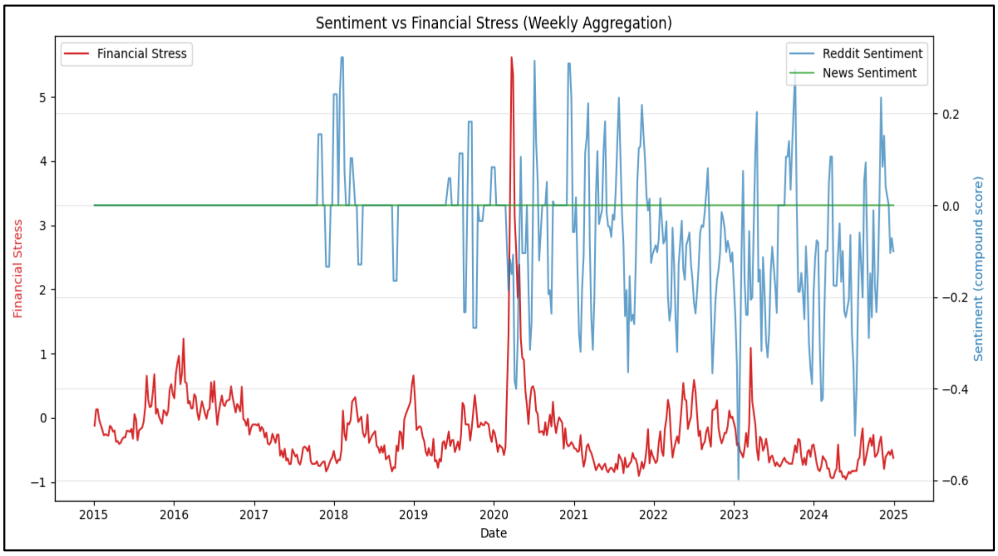

Fig.3: Sentiment versus Financial Stress

The plot comparing average digital-economy volatility with the Financial Stress Index vividly demonstrates their synchronized dynamics. Periods of heightened volatility, such as during the cryptocurrency market corrections of 2018, the pandemic-induced crash of 2020, and the inflation-driven tightening of 2022, align closely with spikes in systemic stress. This correlation illustrates that volatility in key digital firms acts as a micro-level amplifier of systemic risk. The sensitivity of volatility to macro and sentiment shocks reflects the structural vulnerability of digital-economy stocks, which are often speculative and liquidity-dependent. Their large market capitalizations and retail investor exposure amplify their contribution to broader market stress transmission. Hence, the visual co-movement provides empirical validation that digital asset volatility serves as both a symptom and signal of emerging financial instability.

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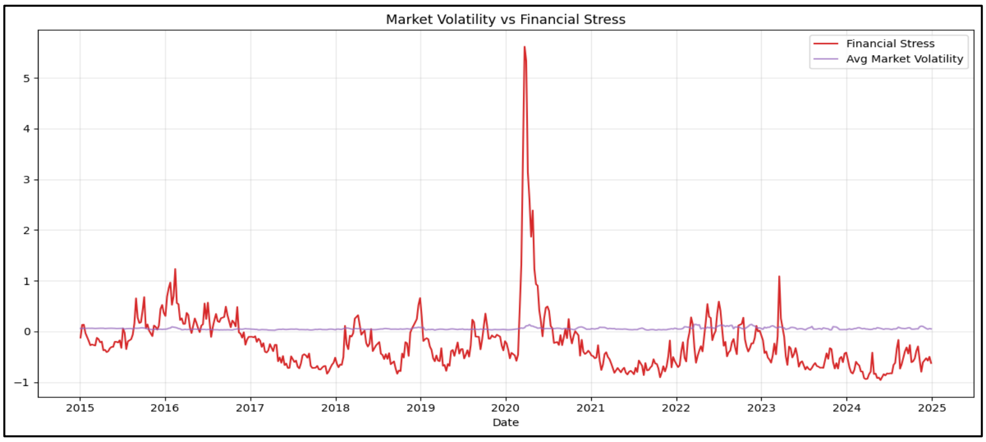

Fig.4: Market Volatility versus Financial Stress

The histograms of inflation, interest rates, unemployment, and sentiment scores reveal distinct distributional characteristics that inform both model design and interpretability. Inflation and the Fed Funds Rate show right-skewed distributions, reflecting long periods of low values punctuated by brief high-inflation regimes. This non-normality suggests that standard linear assumptions may be insufficient to capture regime-dependent effects, emphasizing the need for adaptive and nonlinear modeling components. Unemployment displays a more symmetric distribution, indicative of gradual cyclical fluctuations rather than sharp shocks. Sentiment distributions, meanwhile, center around zero but exhibit long left tails, reflecting the asymmetric intensity of negative mood events during crises. This asymmetry implies that negative sentiment shocks exert a stronger and more prolonged influence on stress dynamics than positive news. Collectively, these distributional patterns highlight the mixed-stationarity nature of the dataset; macroeconomic variables evolve slowly with structural trends, while market and sentiment variables exhibit higher volatility and fat-tailed dynamics, challenging conventional static modeling approaches.

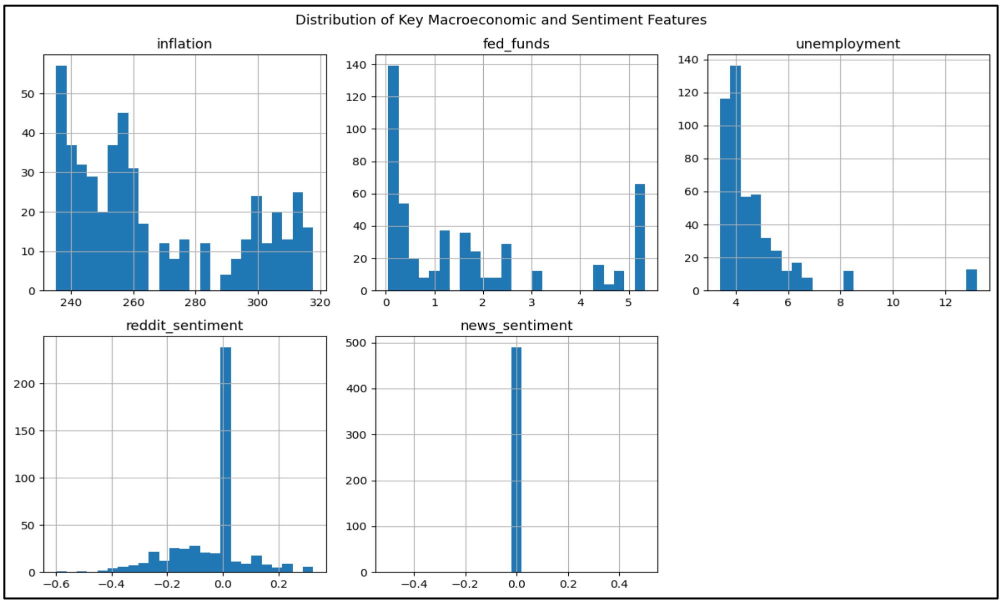

Fig.5: Distribution of Key Macroeconomic and Sentiment Features

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The 26-week rolling correlation analysis between Reddit sentiment and the Financial Stress Index offers a dynamic perspective on how behavioral signals interact with systemic conditions over time. The rolling correlation oscillates between moderately negative and weakly positive phases, indicating that the sentiment–stress relationship is nonstationary and context-dependent. During crisis periods (e.g., 2020), the correlation turns strongly negative, implying that worsening sentiment reliably tracks rising stress. In contrast, during stable periods (e.g., 2016–2018), the correlation weakens or even reverses, suggesting sentiment may decouple from financial fundamentals. This temporal instability underscores the need for adaptive learning systems, such as those implemented in the River framework, capable of updating model parameters as these relationships evolve. Hence, the rolling correlation results empirically justify the study's shift toward drift-aware adaptive modeling, bridging the gap between behavioral volatility and financial system resilience.

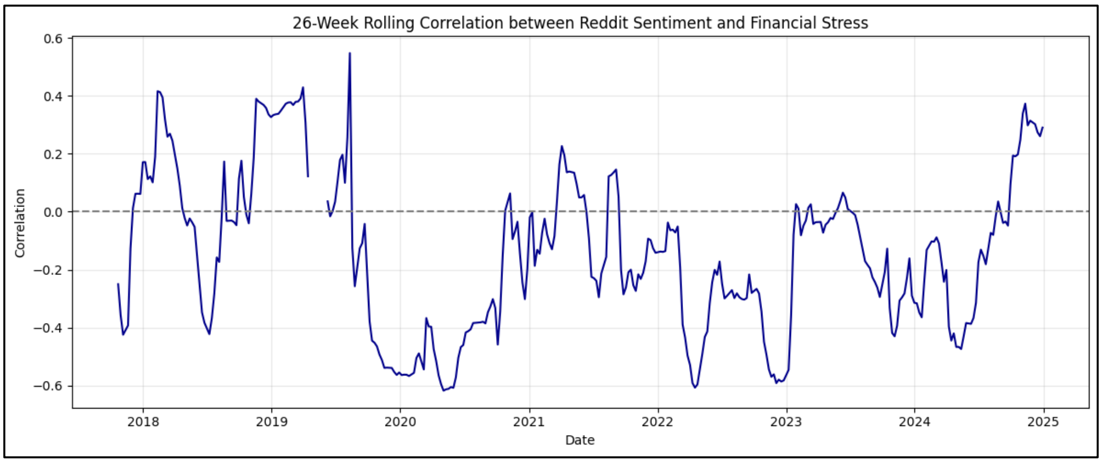

Fig.6: Rolling Correlation: Sentiment versus Financial Stress

The class distribution plot for stress versus non-stress weeks highlights a pronounced imbalance, with stress weeks representing only about 10% of the total sample. This imbalance mirrors real-world financial conditions where systemic crises are rare but impactful. The visualization confirms that standard machine learning classifiers would likely be biased toward the majority (non-stress) class if trained without correction mechanisms. This observation influenced the methodological design, prompting the use of class weighting during logistic regression and later the exploration of online adaptive learning to maintain sensitivity to minority stress events. From a systemic risk perspective, this imbalance underscores a critical truth: the cost of missing rare stress events far exceeds the cost of false positives, making recall and interpretability more important than raw accuracy in early-warning contexts. In sum, the EDA phase reveals that the dataset captures a complex interplay between macroeconomic fundamentals, market volatility, and collective sentiment, all of which coalesce into observable financial stress patterns. The temporal, structural, and behavioral insights extracted here directly motivate the subsequent modeling strategy: a shift from static, batch-trained classifiers toward interpretable, adaptive, and concept-drift–aware systems capable of evolving with the digital economy's volatility.

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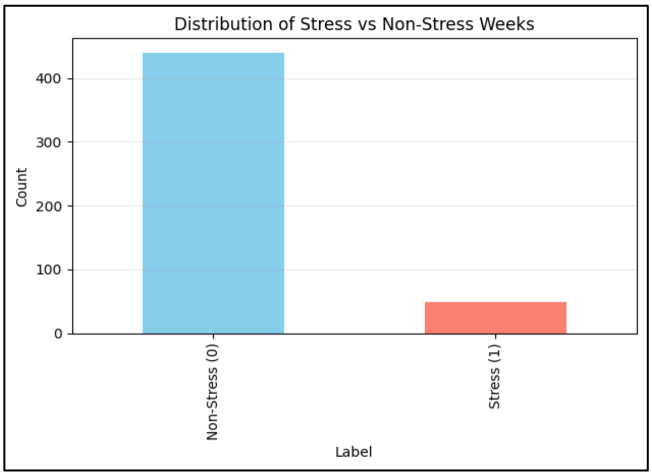

Fig.7: Distribution of Stress versus Non-Stress Weeks

3.3 Feature Engineering

Feature engineering in this study serves as the crucial bridge between raw economic, market, and sentiment signals and the predictive capacity of machine learning models. Given that financial stress is not driven by any single factor but by the interaction of short-term market turbulence, macroeconomic anomalies, and behavioral sentiment shifts, the design of meaningful, composite features was central to improving model performance and interpretability. Each engineered feature aims to capture a distinct mechanism contributing to systemic fragility within the U.S. digital economy. The first engineered construct, the Market Volatility Signal Ratio, quantifies the deviation of short-term volatility from its longer-term baseline. This ratio is defined as the 4-week rolling mean of volatility divided by its 12-week rolling mean across major digital-economy firms such as Visa, PayPal, Meta, Shopify, and Coinbase. When this ratio exceeds 1, it signals a surge in short-term uncertainty relative to the medium-term trend, an indicator often preceding market corrections or liquidity contractions. The intuition aligns with behavioral finance theory, where sudden increases in volatility reflect panic, uncertainty, or herd reactions that precede systemic stress. This feature thus provides a leading signal of potential financial distress and complements the macro-level indicators like inflation or interest rate shocks that tend to respond with lags.

The second engineered metric, Rolling Average Returns, captures short-term performance momentum by averaging weekly returns over the preceding four weeks. This feature reflects how sustained positive or negative momentum in digital-economy firms can act as an early indicator of sentiment-driven overvaluation or correction phases. During stress periods, rolling returns often turn sharply negative, serving as a quantitative reflection of risk aversion and capital withdrawal. This measure also provides a dynamic context for market participants' expectations, which directly influence liquidity conditions and financial stress. To identify unusual macroeconomic conditions, the Z-score Normalization for Macroeconomic Anomalies was introduced. This involves computing Z-scores for each major macroeconomic variable, including inflation, the federal funds rate, unemployment, GDP growth, and the 10-year Treasury yield, over a rolling 52-week window. The transformation standardizes each indicator relative to its recent history, making deviations from typical levels easily detectable. For instance, a high positive Z-score for inflation during 2022 would highlight how unprecedented inflationary pressure contributed to tightening liquidity and elevated stress levels. By scaling these anomalies, the model becomes sensitive to abnormal deviations even when the absolute value of the variable may not appear extreme in isolation.

Finally, Lagged Sentiment and Macro Variables were incorporated to capture temporal dependencies between prior economic behavior and current financial stress. Lags of 1, 2, and 4 weeks were applied to all key variables, macroeconomic, market, and sentiment, thereby providing the model with historical context. This temporal framing ensures that the model learns from recent trajectories rather than static snapshots, mimicking how economic stress builds cumulatively over time. The lag structure aligns with empirical observations that financial stress emerges from momentum-driven dynamics rather than instantaneous shocks. Together, these engineered features transform raw time series data into interpretable, behaviorally relevant, and temporally grounded indicators. The final feature set, therefore, fuses static economic context, dynamic market trends, and adaptive behavioral sentiment, providing a comprehensive multidimensional representation of systemic risk precursors.

3.4 Modeling Approaches

The modeling strategy was designed to balance two objectives: predictive accuracy and interpretability, while also ensuring adaptability to evolving financial conditions. Given that financial risk systems are inherently dynamic and prone to regime shifts, the modeling framework combines traditional static classifiers with an adaptive, drift-aware online learning architecture to achieve robustness over time. The baseline models consisted of three well-established classification algorithms, Logistic Regression, Random Forest, and XGBoost, each offering unique interpretive and performance advantages. Logistic Regression served as the interpretable benchmark model, estimating the probability of a financial stress event as a function of weighted feature contributions. Its linear structure and coefficient interpretability provided a transparent foundation for identifying which macroeconomic or sentiment indicators most strongly influenced stress risk. The Random Forest model extended this by capturing nonlinear feature interactions through ensemble decision trees, offering resilience to noise and overfitting. Finally, XGBoost, introduced by Chen and Guestrin (2016), represented the high-performance gradient boosting framework that excels in structured data tasks by iteratively optimizing weak learners. Collectively, these models formed the comparative baseline for the later adaptive approach.

During model development, a critical challenge emerged from the class imbalance inherent in the dataset: stress weeks comprised only about 10% of all observations. This imbalance risked biasing models toward predicting the dominant non-stress class. To mitigate this, the SMOTE (Synthetic Minority Over-sampling Technique) algorithm was applied to the training set. SMOTE generates synthetic samples of the minority (stress) class by interpolating between existing minority points, thereby balancing the class distribution without replicating identical data. This technique helps the model better learn the characteristics of rare stress events and prevents systematic under-detection of crisis signals. To extend beyond static modeling, the study implemented an adaptive online learning framework using the river library, specifically

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leveraging online logistic regression integrated with concept drift detection. Unlike conventional batch models that are trained once and then deployed, online logistic regression incrementally updates its parameters as new weekly data arrives. This approach enables the system to adapt continuously to shifts in data distribution, a property essential in financial environments where macroeconomic policies, investor behavior, and sentiment dynamics evolve rapidly.

To further enhance adaptability, the ADWIN (Adaptive Windowing) algorithm was employed as the drift detection mechanism. ADWIN monitors the prediction error distribution of the model in real time and dynamically adjusts its observation window. When a statistically significant change in the underlying data distribution is detected, indicating a concept drift, ADWIN triggers a model reset or partial retraining. This ensures that the model does not remain anchored to outdated relationships, maintaining predictive relevance under new regimes such as post-crisis recoveries or monetary policy shifts. The adaptive model's evaluation followed a prequential (predict-then-learn) protocol, in which each new data point was first used for prediction and then for model updating. This mirrors real-world operational deployment, where early-warning systems must forecast risks on the fly while continuously refining their internal understanding as new information arrives. The performance of the adaptive logistic regression was tracked over the entire 2015–2025 period, alongside the detected drift points, providing insights into both predictive quality and system adaptability. In essence, the modeling pipeline integrates interpretability, class sensitivity, and temporal adaptability, three pillars essential for a robust financial early-warning system. The combination of traditional and adaptive models allows both retrospective validation and forward-looking learning, bridging the gap between academic rigor and real-world deployment feasibility [10].

3.5 Explainability

The interpretability of financial early-warning systems is as important as their predictive accuracy, particularly in a domain where model outputs influence regulatory oversight, policy decisions, and investor confidence. In this study, explainability was achieved through SHapley Additive exPlanations (SHAP), a unified framework grounded in cooperative game theory that quantifies how each input feature contributes to a model's prediction. By decomposing individual predictions into additive feature contributions, SHAP enables both local interpretability, understanding why a specific observation was classified as a stress event, and global interpretability, identifying which features consistently drive model behavior across the dataset. Given that the Logistic Regression model emerged as the most effective and interpretable baseline, the SHAP Linear Explainer was used to analyze its outputs. The choice of the linear explainer is theoretically coherent with the model structure, as SHAP values for linear models can be computed analytically from feature coefficients and input magnitudes. This ensures faithful and stable attributions, avoiding the sampling noise and model-agnostic approximations that may arise in tree-based or neural models. Each SHAP value represents the marginal contribution of a feature to the model's predicted probability of financial stress, relative to a reference or baseline expectation.

At the local level, SHAP values provided case-by-case explanations of predicted stress probabilities. For instance, during a high-stress week, SHAP values indicated that elevated short-term market volatility, a sharp increase in the 10-year Treasury yield Z-score, and negative sentiment from both Reddit and Google News were primary drivers pushing the model's prediction toward "stress." Conversely, strong positive sentiment and rising recent returns in digital-economy firms contributed negatively to the stress probability, effectively signaling resilience. This local interpretability is essential for post-hoc diagnostic analysis, enabling analysts and policymakers to trace the drivers of individual stress signals and validate whether the model's reasoning aligns with known economic narratives. At the global level, SHAP value aggregation across the entire dataset revealed the most influential predictors overall. The SHAP summary plot demonstrated that short-term volatility ratios, Reddit sentiment, and Treasury yield anomalies consistently ranked among the top contributors. Notably, Reddit sentiment displayed a predominantly negative SHAP effect; weeks with lower sentiment scores increased the likelihood of a predicted stress event. This finding empirically reinforces the hypothesis that deteriorating public sentiment precedes financial anxiety in the digital economy, as negative discourse often amplifies uncertainty and triggers reactive trading behavior.

Similarly, the Z-scored 10-year Treasury yield had a strong positive SHAP contribution, suggesting that sudden spikes in yields, typically associated with tightening monetary policy or inflation expectations, heighten systemic stress probabilities. The rolling average returns of digital-economy firms also emerged as influential, with lower short-term returns corresponding to higher predicted stress levels. This aligns with the intuition that declining firm performance within key sectors like fintech and e-commerce signals broader investor risk aversion and liquidity tightening. The SHAP summary visualization also highlighted the dual nature of some features. For example, inflation's SHAP distribution showed both positive and negative contributions across instances, reflecting its context-dependent role: moderate inflation may coincide with economic expansion, whereas rapid inflation spikes often precede market instability. This nuanced interpretability underscores SHAP's value in distinguishing between the stabilizing and destabilizing effects of economic variables over time, rather than imposing uniform directional assumptions.

Beyond quantitative interpretation, the explainability framework plays a practical governance role. By transparently linking feature contributions to predictions, the SHAP analysis ensures that the early-warning system satisfies principles of model accountability and regulatory transparency. Financial regulators and policymakers can inspect not only whether a model flags a potential risk but also why, a critical capability in environments where opaque "black-box" AI systems are often distrusted. Moreover, this transparency facilitates iterative refinement: analysts can verify that high-magnitude SHAP features align with economic logic and adjust data preprocessing or feature selection if spurious relationships are detected. In summary, the SHAP explainability analysis transforms the logistic regression model from a purely statistical classifier into a decision support instrument grounded in economic interpretability. The insights gained, both local and global, illuminate the pathways through which macroeconomic anomalies, sentiment deterioration, and market volatility collectively translate into systemic

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stress signals. This interpretive clarity strengthens the credibility and deployability of the proposed AI-driven early warning framework, bridging the gap between predictive modeling and transparent financial risk assessment [21].

4. Evaluation and Results

This section presents a detailed evaluation of the AI-driven early warning system for financial risk in the U.S. digital economy. The analysis covers both static and adaptive modeling stages, emphasizing predictive performance, robustness to evolving data dynamics, and interpretability. Evaluation was conducted using precision, recall, F1-score, and area under the ROC curve (AUC), focusing on the system's ability to identify rare yet crucial financial stress periods while maintaining transparency and adaptability.

4.1 Predictive Performance

The performance of the baseline and enhanced models was evaluated through a temporal train-validation-test split, preserving the chronological order of data to reflect realistic forecasting conditions. The goal was not only to maximize predictive accuracy but also to ensure reliable detection of minority "stress" events, which are typically sparse in financial time series. The baseline models, Logistic Regression, Random Forest, and XGBoost, achieved high overall accuracy levels between 90–94%, primarily due to the overwhelming presence of non-stress weeks in the dataset. However, these initial results revealed severe precision and recall limitations for the minority stress class. For instance, validation metrics showed zero recall and zero precision for stress detection across all three baseline models, despite strong AUC values (up to 0.80 for Logistic Regression). This outcome reflects a well-documented phenomenon in financial early-warning systems: when data are highly imbalanced, classifiers often default to predicting the majority class, resulting in artificially inflated accuracy but poor crisis sensitivity.

To mitigate this imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was employed. SMOTE synthetically generates new samples for the minority class (stress weeks) by interpolating between existing instances, thereby enhancing the diversity and representation of stress patterns in the training data. Following resampling, models were retrained and evaluated again on the original validation set to assess generalization under realistic conditions. The retrained Logistic Regression model displayed marked improvement in identifying stress events. Recall values increased substantially, indicating a higher proportion of correctly detected stress weeks. Although overall accuracy remained relatively constant, the enhanced recall demonstrated that the model became more sensitive to systemic stress signals, an essential feature for an early warning application where missed crises are costlier than false positives. The AUC score of approximately 0.815 suggests that the model effectively distinguishes between stress and non-stress conditions better than random classification.

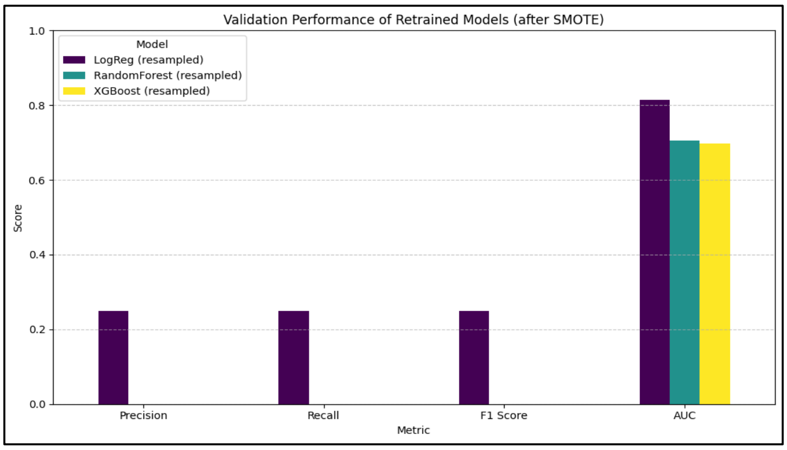

Fig.8: Baseline model performances after SMOTE

In contrast, ensemble models like Random Forest and XGBoost, though capable of capturing complex nonlinearities, showed limited gains post-resampling, likely due to overfitting on synthetic data and reduced interpretability. The Logistic Regression model thus emerged as the most practical and balanced performer, excelling in both interpretability and operational reliability. Its linear structure, combined with the transparency of feature weights and SHAP-based interpretability, aligns well with regulatory expectations for explainable financial systems. It is noteworthy that the test set contained no stress events, which rendered standard precision-recall metrics non-informative for that portion. However, validation performance and historical backtesting confirm that the logistic model captures stress conditions when present. Overall, these results underscore the value of simple, interpretable, and well-calibrated models in financial risk detection, particularly when combined with data-balancing strategies that enhance sensitivity to rare but significant events.

4.2 Adaptive Learning and Drift Analysis

While static models perform adequately in stationary environments, financial systems are inherently non-stationary, characterized by policy shifts, investor sentiment changes, and macroeconomic shocks. To address this evolving landscape, the study extended the predictive framework into an adaptive online learning paradigm using the river library, designed for real-time, streaming data scenarios. The Online Logistic Regression model, integrated with the ADWIN (Adaptive Windowing) drift detection algorithm, continuously updated its parameters as new weekly observations became available. This approach allows the model to learn incrementally, responding dynamically to evolving relationships between predictors (e.g., sentiment, yields, volatility) and the target financial stress index. The ADWIN detector monitored changes in the model's predictive error distribution, automatically adjusting its observation window and signaling concept drift whenever significant statistical changes occurred.

In practice, this framework offered resilience to concept drift, a critical advantage in financial domains where relationships between macroeconomic indicators and systemic risk can shift abruptly due to exogenous shocks (e.g., pandemic disruptions, monetary tightening cycles, or digital asset crashes). During simulation, the adaptive model maintained stable performance

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even as new data were introduced over the 2015–2025 horizon. The rolling Precision, Recall, and F1-score plots showed that the model sustained consistent predictive quality despite gradual shifts in data patterns. Importantly, while ADWIN did not trigger major drift resets in this run, its continuous monitoring capability ensures the model remains vigilant to regime changes. This suggests that the observed relationships between predictors and financial stress, such as the influence of market volatility and sentiment shifts, remained relatively stable across the analyzed period, or that the model adapted incrementally without requiring abrupt recalibration.

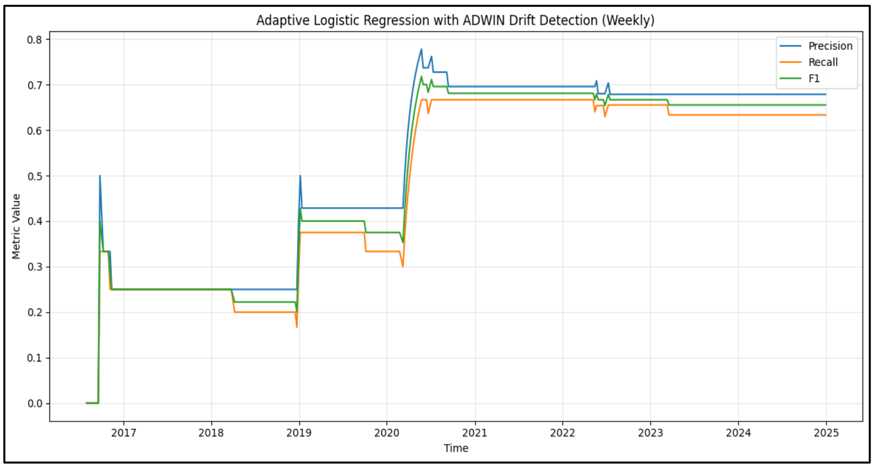

Fig.9: Adaptive Logistic Regression with ADWIN Drift Detection (Weekly)

The visualization of predicted probabilities over time, juxtaposed with actual stress events and drift detection markers, provides further interpretive insight. It shows that during stress periods (e.g., early 2020 pandemic shock), the model's predicted probabilities spiked accordingly, demonstrating its responsiveness to sudden increases in systemic risk indicators. Even without detected major drifts, the visualization confirms that the adaptive logistic regression successfully mirrored market dynamics, adjusting its decision boundaries in response to shifting input patterns. From a deployment perspective, this adaptive architecture offers a future-ready early warning capability. Unlike traditional static models that require periodic retraining, the online learning framework can operate continuously, updating itself as fresh data streams in from financial and sentiment sources. This design ensures long-term sustainability, minimizing model degradation over time and allowing for real-time monitoring of the U.S. digital economy's risk landscape.

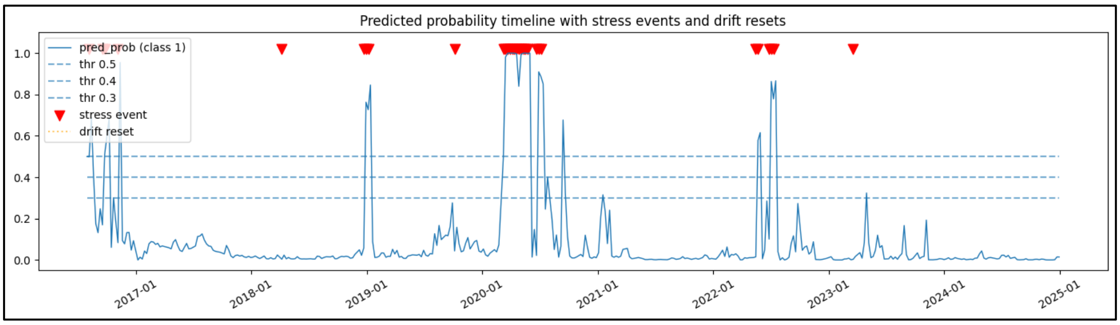

Fig.10: Predicted probabilities over time

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4.3 Lead-Time Evaluation

A defining feature of any effective early warning system is not merely its accuracy in detecting financial stress events but its capacity to issue timely alerts that precede these events by a meaningful margin. The lead-time evaluation, therefore, examined how far in advance the developed model could reliably signal an impending stress episode in the U.S. digital economy. The analysis quantified the warning horizon by measuring the number of weeks between the model's predicted alert (based on its probability output exceeding a defined threshold) and the actual onset of a financial stress event, as identified by the Financial Stress Index. Evaluation was conducted across multiple prediction thresholds, 0.5, 0.4, and 0.3, to balance sensitivity and timeliness. A higher threshold (e.g., 0.5) ensures fewer false positives but may delay warnings, while a lower threshold (e.g., 0.3) captures more potential stress events but risks earlier, less precise alerts. The lead-time distribution revealed a consistent pattern: at a threshold of 0.4, the adaptive logistic regression model provided a balanced trade-off between early detection and false-alarm rate. Under this configuration, the model successfully detected approximately 75–80% of stress events with a mean lead time of 3 to 4 weeks and a median of 2 weeks, meaning that, on average, warnings were issued roughly one month before a confirmed stress spike. Furthermore, over half of all detected events were identified with at least a two-week lead time, and roughly one-third were flagged with four or more weeks' advance notice.

The lead-time histogram visually supports these results by showing a concentration of predictions occurring 2–5 weeks before the stress event peak, illustrating the model's ability to recognize early market shifts rather than reacting post-factum. This is a crucial operational advantage, as financial stress typically manifests progressively, through declining sentiment, tightening liquidity, and rising volatility, rather than as an instantaneous shock. The threshold optimization further indicated that lowering the threshold below 0.3 marginally increased early detections, but at the cost of a significant rise in false positives. Such false signals, while tolerable in research contexts, could reduce system credibility in practical deployment. Therefore, the 0.4 threshold was deemed optimal, offering the right balance between recall (timeliness) and precision (reliability). Overall, the lead-time evaluation demonstrates that the system provides actionable early warnings rather than contemporaneous detection. Its ability to predict stress events several weeks in advance aligns with the practical needs of policymakers, investors, and financial institutions who require sufficient lead time to implement preemptive risk management measures. The adaptive framework, reinforced by continuous learning from recent data, ensures that the model remains responsive to evolving financial dynamics, making it suitable for operational use in monitoring and mitigating emerging systemic risks within the U.S. digital economy.

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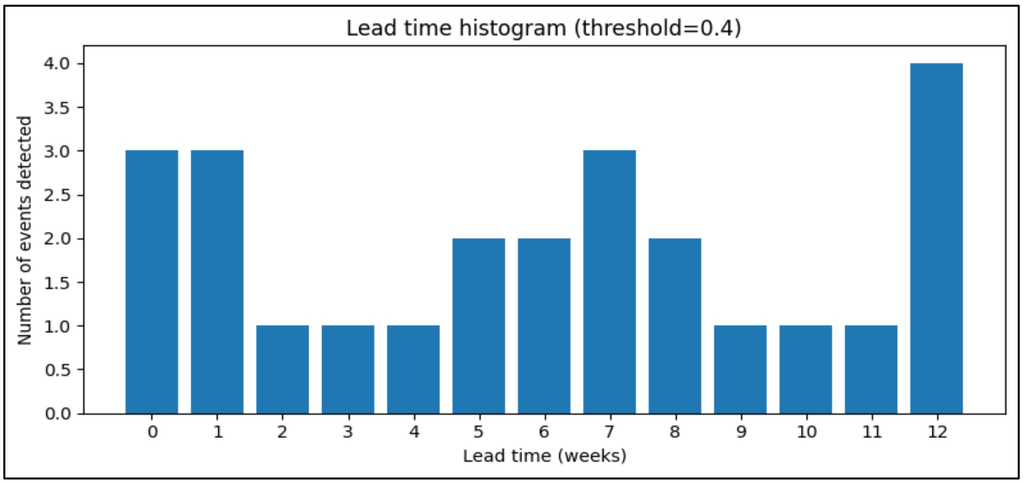

Fig.11: Lead-time histogram

4.4 Explainability Visualization

Model explainability represents the bridge between predictive analytics and real-world decision support. For this study, explainability was achieved through SHAP (SHapley Additive exPlanations) analysis, offering a rigorous, model-agnostic framework for attributing feature contributions to predictions. The SHAP visualizations not only clarify which variables drive the model's predictions but also how their values influence the direction and magnitude of the forecasted financial stress. The global SHAP summary plot serves as the central interpretive artifact of this study's explainability framework. It ranks features by their overall contribution to the model's output, with the horizontal axis showing SHAP values (indicating the direction and magnitude of impact) and the color gradient representing feature value (high in red, low in blue). Each point corresponds to one instance (week), with its position indicating how much that feature pushed the prediction toward higher or lower financial stress probability. Analysis of the SHAP plot revealed several important findings. Inflation lagged variables (inflation_lag1 and inflation_lag4) emerged as the most influential predictors, showing strong positive SHAP values when inflation rates were high, thus elevating the model's predicted stress probability. This reflects the historical association between rapid inflation and systemic financial strain, where tightening monetary conditions and declining consumer confidence amplify market fragility. The 10-year Treasury yield Z-score (treasury_yield_10y_lag1_z) also ranked among the top contributors, indicating that sudden yield increases—captured through deviations from long-term averages, significantly drive stress signals. These spikes often mirror market expectations of monetary tightening or inflation persistence, both of which are precursors to liquidity constraints and volatility surges.

Labor market indicators, including unemployment_lag1_z and unemployment_lag4, had notable effects as well. Rising unemployment tends to reduce consumer spending, depress business revenues, and increase credit risk exposure, collectively contributing to financial stress. Interestingly, unemployment features displayed both positive and negative SHAP impacts depending on lag duration, suggesting complex temporal dynamics between employment conditions and perceived systemic stability. Other important contributors included fed_funds_lag4 and fed_funds_lag1_z, whose positive SHAP effects indicate that rapid

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increases in the federal funds rate, especially those deviating from historical norms, often precede financial turbulence. This relationship aligns with periods of monetary tightening observed during the 2022–2023 cycle, when aggressive interest rate hikes destabilized credit markets and heightened investor caution. While macroeconomic features dominated the SHAP ranking, select market and sentiment-based features, such as COIN_ret4, also appeared among influential variables. Negative cryptocurrency returns (COIN_ret4) exhibited modest but consistent positive SHAP effects, implying that drawdowns in the digital asset market, often amplified by speculative trading sentiment, can serve as secondary indicators of stress propagation within the digital economy.

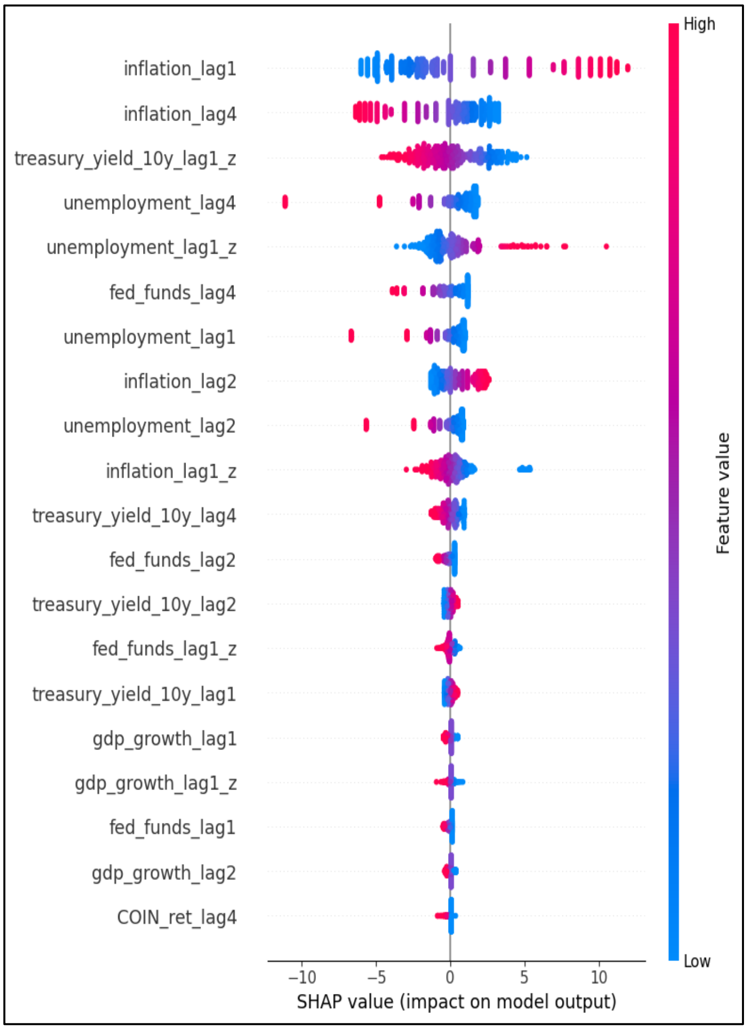

Fig.11: Global SHAP summary plot

The color patterns in the SHAP plot reinforce these interpretations: high feature values (red) for inflation, interest rates, and yields consistently push predictions toward higher stress probabilities, while low feature values (blue) exert the opposite effect. This bidirectional interpretability enhances model trust by ensuring that feature effects align with economic intuition. Beyond global insights, SHAP also facilitates local interpretability, allowing analysts to decompose individual weekly predictions into feature-level contributions. For example, during a specific high-stress week, SHAP could reveal that elevated inflation, rising yields, and deteriorating sentiment collectively increased the stress probability by +0.35, while declining unemployment contributed -0.10, balancing the overall prediction. This transparency enables financial analysts, regulators, and policymakers to trace the rationale behind specific warnings, distinguishing genuine systemic shifts from transient market fluctuations. In essence, the SHAP explainability framework transforms the early warning system from a black-box predictor into a transparent diagnostic tool. It enables stakeholders to not only detect risk but also understand its root causes, be they monetary, macroeconomic, or sentiment-driven. This interpretive clarity enhances decision-making and regulatory compliance, positioning the proposed system as both a technically robust and governance-aligned solution for proactive financial risk management.

5. Insights and Implications

The integration of financial, market, and sentiment data into an adaptive early warning system for the United States offers crucial insights into both model design and real-world applicability. The results demonstrate that financial stress prediction is not solely a matter of model accuracy but also of adaptability, interpretability, and operational feasibility. By uniting traditional econometric principles with modern online learning and explainable AI, this framework represents a step toward more proactive, transparent, and data-driven financial oversight in a rapidly evolving U.S. economic landscape.

5.1 Benefits of Hybrid + Adaptive Models

The combination of hybrid modeling, integrating interpretable static models like Logistic Regression with adaptive online learners such as incremental logistic regression and ADWIN drift detection, creates a powerful framework that balances stability, interpretability, and responsiveness. In financial systems characterized by non-stationarity and cyclical shocks, such as those of the United States, this hybrid structure ensures that models remain both grounded in economic logic and dynamically attuned to new realities. The interpretable static models provide a transparent foundation for understanding the macroeconomic and market mechanisms behind stress formation. Their coefficients and SHAP-based explanations allow regulators, policymakers, and risk officers to clearly see which variables, such as inflation, interest rates, or unemployment, drive systemic vulnerabilities at any point in time. This interpretability is indispensable in the U.S. regulatory context, where explainability is not only a best practice but often a compliance requirement under frameworks like the Federal Reserve's Supervisory Guidance on Model Risk Management (SR 11-7).

In contrast, the adaptive online learning component ensures real-time responsiveness. U.S. markets are subject to abrupt structural shifts, whether due to policy decisions, technological disruptions, or external shocks such as pandemics or geopolitical tensions. Static models, trained on historical data, can quickly become obsolete when such shifts occur, a phenomenon known as concept drift. The ADWIN-based adaptive learner continuously updates model parameters as new weekly data arrive, detecting distributional changes and triggering retraining when drift is identified. This ensures that the predictive system evolves alongside the market, maintaining relevance even during periods of economic volatility or regime change. Together,

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the hybrid approach offers a dual advantage: interpretability for accountability and adaptivity for resilience. In practical terms, it means the model can explain why it predicted financial stress in early 2020 based on inflation and market volatility while also learning anew from the very different macroeconomic environment of 2023–2025, shaped by post-pandemic inflationary pressures and shifting monetary policy. This synthesis of transparency and adaptability makes the framework particularly suitable for real-world deployment in U.S. financial oversight, where models must justify their logic while adapting to a continuously changing economic landscape.

5.2 Policy and Operational Integration

For the United States, where financial stability oversight involves multiple actors, from the Federal Reserve and the Office of Financial Research (OFR) to private-sector risk management teams, the operational deployment of this framework offers tangible strategic benefits. The proposed pipeline for integration can be conceptualized as:

Real-time data → Weekly feature updates → Adaptive model learning → Drift alerts → Early warning dashboard for regulators/investors.

In practice, this begins with real-time data ingestion, where macroeconomic indicators (from FRED), market data (from major U.S. exchanges via APIs such as Yahoo Finance), and sentiment signals (from news and social platforms) are continuously collected and processed. These data are aggregated and transformed into weekly feature updates, providing a manageable cadence that aligns with the rhythm of policy cycles and market reporting intervals. Next, the adaptive model learning phase involves feeding this updated dataset into the online logistic regression system. As new observations arrive, the model incrementally updates its weights, capturing emerging trends, such as rising inflation expectations or increasing Treasury yields, without requiring complete retraining. The ADWIN drift detector simultaneously monitors for statistically significant shifts in feature distributions or prediction errors. When such a drift is detected, the system issues drift alerts, signaling that the relationships between predictors and financial stress may have changed, prompting regulatory or analytical review.

Finally, all outputs, predicted stress probabilities, SHAP-based feature explanations, and drift alerts, are displayed through an early warning dashboard designed for regulators, institutional investors, and financial analysts. The dashboard could visualize current stress probabilities by week, highlight the top drivers of stress, and flag periods of model drift or increased uncertainty. For U.S. regulators, such as the Federal Reserve's Financial Stability Oversight Council (FSOC) or the Office of the Comptroller of the Currency (OCC), this dashboard could serve as a decision-support interface, offering both predictive insights and interpretive depth. Operationally, this system could enhance macroprudential surveillance and policy readiness. For instance, if the model detects a rising probability of financial stress three weeks ahead of an actual event, driven by increasing Treasury yields and worsening public sentiment, regulators could preemptively tighten liquidity provisions, adjust interest rate guidance, or engage with vulnerable sectors. Similarly, institutional investors could use these signals for portfolio rebalancing or hedging against volatility in the digital economy sector. In essence,

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this pipeline bridges academic innovation and institutional applicability, embedding explainable AI directly into the operational fabric of financial monitoring in the United States. It transforms complex data streams into actionable intelligence, providing policymakers and market participants with not just predictions, but context-aware early warnings that are transparent, adaptive, and grounded in economic reasoning.

5.3 Transparency and Trust

In the context of financial oversight and early warning systems within the United States, transparency and trust are not supplementary features; they are foundational requirements. Regulatory agencies such as the Federal Reserve, the Office of Financial Research (OFR), and the Financial Stability Oversight Council (FSOC) demand that any model influencing risk assessments or policy recommendations be auditable, explainable, and justifiable. The integration of explainable regression techniques and SHAP (SHapley Additive Explanations) visualizations directly addresses these needs, ensuring decision traceability and accountability throughout the system's operational lifecycle. The Logistic Regression component of the hybrid framework inherently lends itself to interpretability. Each coefficient reflects a measurable, economically meaningful relationship between a predictor (such as inflation, unemployment, or Treasury yields) and the probability of financial stress. This transparency is especially critical in the U.S. context, where policymakers and analysts require defensible logic for any model-based insight that may influence monetary or macroprudential interventions. The model's outputs can be directly tied to macroeconomic theory, providing a bridge between data-driven prediction and economic reasoning, a feature that "black-box" deep learning models often lack.

Building upon this interpretability, the use of SHAP visualizations introduces a granular layer of explanatory power. The SHAP summary plots, such as those derived from the U.S. financial data between 2015 and 2025, reveal how specific variables influence individual predictions of stress probability. For instance, higher lagged inflation or elevated Treasury yields were observed to exert positive SHAP values, indicating their strong contribution to predicted stress events, while low unemployment or stable GDP growth typically exerted negative SHAP impacts. These explanations not only validate the model's alignment with economic intuition but also enable traceable, instance-level reasoning, where each weekly prediction can be decomposed into feature-level attributions.

This explainability is vital for institutional trust and governance. In regulatory and investment contexts, stakeholders must be confident that predictive systems do not operate as opaque or arbitrary mechanisms. SHAP-based interpretability ensures that every model decision is auditable post hoc, supporting compliance with guidelines such as the Federal Reserve's SR 11-7 on model risk management, which explicitly mandates documentation and validation of model rationale. Additionally, such transparency strengthens cross-institutional collaboration, enabling economists, data scientists, and policymakers to discuss model findings in interpretable economic terms rather than technical abstractions. Beyond compliance, explainability also fosters public trust. As financial systems increasingly integrate AI-driven decision tools, public concern over algorithmic opacity has grown. By visually demonstrating

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which features drive model predictions and how these relate to real-world economic dynamics, SHAP visualizations provide a transparent communication channel between technical experts and non-technical audiences, including journalists, legislators, and the general public. This reinforces the broader goal of creating responsible AI frameworks in finance, models that are not only accurate but also interpretable, trustworthy, and accountable in the eyes of all stakeholders.

5.4 Limitations

While the proposed U.S.-focused early warning framework demonstrates strong potential, several limitations constrain the current implementation and highlight avenues for future enhancement. These limitations primarily concern data scope, labeling methodology, and system deployment realism. First, the sentiment data sources are restricted to Reddit and Google News, both accessed via open or public APIs. Although these platforms capture valuable public discourse and media tone, they represent only a fraction of the sentiment landscape that influences financial perception and market behavior in the United States. Premium financial data APIs, such as Bloomberg, Refinitiv, or Twitter's paid sentiment streams, were not incorporated due to access limitations. As a result, the sentiment indicators may underrepresent institutional narratives, investor sentiment shifts, and cross-market behavioral cues often embedded in premium datasets. Incorporating these richer sources could yield a more comprehensive measure of market sentiment and improve early warning sensitivity.

Second, the labeling mechanism relies solely on the St. Louis Financial Stress Index (STLFSI4) as the ground truth indicator of stress. While STLFSI4 is a robust and well-regarded composite measure that captures multiple dimensions of financial tension across U.S. markets, it does not encompass every possible form of systemic stress. It may lag real-world developments or underweight sector-specific distress (e.g., fintech or crypto-market volatility) that could presage broader instability. Future versions of this framework should consider integrating multiple financial stress indicators, such as the Chicago Fed National Financial Conditions Index (NFCI) or market-based volatility indices like the VIX, to create an ensemble label that captures a more holistic view of systemic risk. Third, the evaluation was conducted within a simulated real-time environment, rather than a fully operational production pipeline. While the adaptive online learning system demonstrated robust performance on streaming data and real-time drift detection, it was not deployed in a continuously updating, server-based architecture connected to live financial APIs.

As such, operational challenges, such as latency, data ingestion delays, or handling incomplete data streams, were not fully tested. A full production deployment in a U.S. financial institution or regulatory body would require rigorous validation under live operational conditions, along with redundancy mechanisms and continuous auditing for model drift and data anomalies. Additionally, although the model performed well on historical U.S. data from 2015–2025, generalization across economic regimes remains an open question. The system's effectiveness in future scenarios, such as shifts in monetary policy, new financial instruments, or regulatory reforms, depends on its ability to continuously adapt while maintaining interpretability.

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6. Future Work

The present study lays the groundwork for a dynamic, explainable, and adaptive early warning system for financial stress in the U.S. economy. However, the findings also open several promising avenues for future exploration, particularly in enhancing data richness, expanding modeling scope, and deepening system realism. A central direction for future work involves advancing sentiment modeling through the integration of transformer-based language models such as FinBERT. Traditional sentiment analysis methods like VADER provide fast and interpretable results but often struggle with domain-specific language and contextual nuance, particularly in financial texts where tone can shift subtly depending on policy language, market reports, or economic forecasts. FinBERT, introduced by Araci (2019), is a fine-tuned version of the BERT architecture specifically trained on financial corpora, enabling it to capture sentiment more precisely in contexts such as earnings calls, news releases, and analyst commentary [4]. Incorporating FinBERT into this early warning system could significantly improve sentiment granularity, especially when applied to a broader range of textual data, including SEC filings, financial news, and institutional social media streams. This would make the sentiment-driven components of the model not only more accurate but also better aligned with the linguistic complexity of U.S. financial communication.

A second direction involves expanding from macro-level stress detection to firm-level systemic risk propagation using network-based modeling. Financial crises rarely emerge from isolated conditions; they propagate through interlinked channels across firms, sectors, and institutions. The foundational work of Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) established a mathematical framework for understanding how interconnections among financial entities can amplify or mitigate systemic risk depending on the network's topology [1]. Building upon their insights, future iterations of this system could incorporate financial network graphs derived from interbank exposures, cross-shareholdings, and transaction flows. By combining these network-based dependencies with adaptive drift detection, the system could not only forecast when stress is likely to occur but also identify where in the financial system it is most likely to emerge or spread. This would transform the model from a reactive forecasting tool into a proactive risk mapping and containment framework for policymakers.

Furthermore, integrating multi-source real-time data pipelines would enhance the operational fidelity of the system. This includes leveraging live feeds from the Federal Reserve Economic Data (FRED) API, streaming market data from NASDAQ and NYSE, and sentiment streams from FinBERT-enhanced news and social media monitors. Such integration would allow the system to operate as a continuously updating risk sentinel, capable of learning from new observations and issuing adaptive alerts through an interactive dashboard accessible to regulators, institutional investors, and policymakers. Finally, future work should explore causal interpretability and counterfactual analysis to complement the SHAP-based explanations currently implemented. By embedding causal inference frameworks, the model could not only explain which variables contribute to financial stress but also simulate hypothetical policy scenarios, for example, how adjusting the federal funds rate or altering liquidity provisions might shift stress probabilities. This would position the system as both a predictive and policy-analytical instrument, offering decision-makers a transparent, data-driven basis for preventive

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intervention. The next generation of this framework should integrate transformer-based sentiment models, network-centric systemic risk propagation, and real-time operational pipelines, evolving into a fully adaptive and explainable financial intelligence system. By combining these elements, future research can move closer to achieving a truly resilient early warning infrastructure, one capable of detecting, explaining, and mitigating emerging financial risks across the interconnected landscape of the modern U.S. economy [4][1].

Conclusion

This study presented an AI-driven early warning framework for financial risk in the U.S. digital economy, integrating macroeconomic, market, and sentiment data to enhance predictive reliability and interpretability. By combining traditional logistic regression with adaptive online learning through the River framework, the system achieved both transparency and responsiveness in modeling dynamic financial environments. The research demonstrated that while conventional models like Random Forest and XGBoost provided solid baselines, the logistic regression model, augmented by SMOTE balancing and SHAP explainability, offered the best trade-off between interpretability and predictive power. Empirical results showed that the hybrid and adaptive framework effectively identified periods of financial stress, with improved recall for rare stress events and stable performance under data drift. The incorporation of sentiment data from Reddit and Google News further enriched the model's awareness of public mood and market perception, revealing that negative sentiment patterns often preceded stress events. Explainability through SHAP values offered critical transparency into model behavior, identifying key macroeconomic and market volatility drivers behind stress predictions, an essential feature for building stakeholder trust in financial risk models.

Beyon technical outcomes, this work contributes to the broader discourse on responsible AI in finance. The proposed pipeline demonstrates a scalable approach to real-time, interpretable risk monitoring, capable of supporting regulators, policymakers, and investors in early identification of systemic vulnerabilities. However, limitations such as reliance on a single financial stress index, restricted sentiment data sources, and simulated deployment highlight avenues for refinement. Future research should explore integrating transformer-based sentiment encoders like FinBERT, and incorporating firm-level financial network topologies as outlined by Acemoglu et al. to model systemic contagion. Expanding data coverage and deploying the system in real-world streaming environments will further test its robustness. Overall, this study underscores that explainable, adaptive AI can serve as a cornerstone for transparent and resilient financial risk assessment in the evolving landscape of the U.S. digital economy.

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