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RECEIVED 06 December 2024

ACCEPTED 31 January 2025

PUBLISHED 10 April 2025

CITATION

Zhao J (2025) An empirical study of preventive
healthcare policy under the synergy of
education and corporate financial monitoring.
Front. Public Health 13:1540618.
doi: 10.3389/fpubh.2025.1540618

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An empirical study of preventive healthcare policy under the synergy of education and corporate financial monitoring

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Introduction: Preventive healthcare policies are critical for improving public health outcomes and reducing the socioeconomic burden of diseases, aligning closely with the theme of enhancing residents' health welfare through robust social security systems. However, traditional approaches often overlook the dynamic interplay between economic factors and health outcomes, limiting their effectiveness in designing sustainable interventions.

Methods: To address these gaps, this study leverages corporate financial monitoring as a novel lens for assessing the effectiveness of preventive healthcare policies. Utilizing the Advanced Financial Monitoring Neural Framework (AFMNF) and the Dynamic Risk-Adaptive Framework (DRAF), we integrate deep learning techniques with dynamic risk modeling to analyze the financial and health impacts of such policies. Our methodology involves monitoring corporate financial metrics, anomaly detection, and trend analysis to identify correlations between policy implementation and economic indicators.

Results and discussion: The results demonstrate that integrating financial insights with health policy evaluation improves prediction accuracy of socioeconomic outcomes by 40% and enhances anomaly detection in policy performance by 30%. This adaptive framework offers a scalable, real-time approach to monitoring, providing actionable insights for policymakers to optimize preventive healthcare strategies. This study underscores the importance of interdisciplinary methods in advancing public health outcomes through innovative, data-driven frameworks.

KEYWORDS

preventive healthcare, financial monitoring, public health policies, dynamic modeling, socioeconomic analysis

1 Introduction

The rising costs of healthcare and the increasing prevalence of chronic diseases have underscored the importance of preventive healthcare policies (1). These policies not only aim to improve population health outcomes but also reduce long-term healthcare expenditures (2). Monitoring corporate financial practices offers a novel perspective in evaluating the effectiveness of such policies, as organizations play a key role in funding healthcare initiatives and promoting employee wellness (3). Not only do financial metrics provide insights into resource allocation and policy sustainability, but they also enable the identification of cost-saving opportunities linked to improved health outcomes (4). Moreover, corporate financial monitoring offers a scalable and data-driven approach to assess policy impact, making it essential for addressing the growing complexity of preventive healthcare (5).

To address the challenges of evaluating preventive healthcare policies, traditional approaches initially relied on symbolic AI and rule-based systems for corporate financial analysis (6). These systems used structured decision rules and heuristic algorithms to assess the relationship between healthcare investments and corporate financial performance. For example, predefined metrics such as return on investment (ROI) in wellness programs and employee absenteeism rates were used to measure policy impact. While these methods offered early insights into cost-effectiveness, they suffered from limited adaptability to diverse corporate contexts and dynamic economic environments (7). Furthermore, their reliance on static models and predefined thresholds reduced their accuracy in predicting long-term policy benefits, necessitating more flexible and data-centric approaches (8).

In response to the shortcomings of rule-based methods, data-driven machine learning models were adopted to analyze corporate financial data in the context of preventive healthcare policies. Techniques such as regression analysis (9), clustering, and support vector machines allowed for more nuanced predictions of policy outcomes by identifying patterns in historical data. These methods demonstrated improved adaptability and scalability (10), enabling organizations to tailor preventive measures based on their financial performance. However, they required significant feature engineering and domain expertise to interpret results effectively (11). Moreover, their reliance on extensive data collection posed challenges for smaller organizations, where data availability and quality were often limited (12).

Deep learning and pre-trained models introduced a new dimension to evaluating preventive healthcare policies by leveraging advanced analytical capabilities (13). Neural networks, particularly recurrent neural networks (RNNs) and transformers, excelled at capturing complex temporal relationships within corporate financial data (14). These models facilitated automated feature extraction and demonstrated exceptional performance in predicting long-term trends and policy impacts. Despite these advancements (15), deep learning models faced significant drawbacks, including high computational costs, lack of transparency, and limited interpretability (16). These limitations hindered their adoption in regulatory and decision-making processes, where explainability and cost-efficiency are critical (17).

Preventive healthcare policies are pivotal in improving public health and mitigating the socioeconomic burdens of chronic diseases. Traditional policy evaluation methods, however, often overlook the dynamic interplay between economic factors and health outcomes, limiting their ability to design sustainable interventions. To address this gap, we propose leveraging corporate financial monitoring as a novel lens for assessing the effectiveness of such policies. By integrating deep learning techniques and dynamic risk modeling, this approach analyzes financial data to identify correlations between policy implementation and economic indicators, thereby improving predictions of health outcomes. Our framework combines the Advanced Financial Monitoring Neural Framework (AFMNF) and the Dynamic Risk-Adaptive Framework (DRAF) to provide policymakers with actionable insights for optimizing preventive healthcare strategies.

The proposed method has several key advantages:

- Combines interpretable machine learning techniques with corporate financial monitoring for precise evaluation of healthcare policy effectiveness.
- Provides a cost-efficient and adaptable solution for organizations of varying sizes, ensuring broad applicability.
- Empirical results show significant improvement in ROI analysis accuracy (up to 95%) and policy scalability, fostering long-term adoption of preventive measures.

2 Related work

2.1 Corporate financial data for health policy assessment

The use of corporate financial data as a proxy for assessing the effectiveness of preventive healthcare policies is an emerging area of interest (18). This approach links corporate health expenditures, absenteeism costs, and productivity metrics to evaluate the economic impact of healthcare interventions (19). Preventive healthcare policies aim to mitigate long-term health risks, and analyzing financial data offers a quantifiable way to measure their outcomes (20). Studies have shown that companies implementing robust wellness programs often experience reduced healthcare costs and lower rates of employee absenteeism. Financial metrics, such as return on investment (ROI) and cost-benefit analyses, are frequently employed to assess these impacts (21). For instance, decreases in health insurance premiums or medical claims can indicate the success of disease prevention initiatives. Tracking metrics like employee retention and job satisfaction provides indirect evidence of the benefits of such policies (22). However, the use of corporate financial data is not without challenges. Variability in reporting standards and the complex interplay of external economic factors can obscure the direct effects of healthcare policies. Researchers have addressed these issues by developing econometric models that control for confounding variables, such as industry type, company size, and regional healthcare access (23). In recent years, advancements in data analytics have enabled more granular assessments. Techniques such as natural language processing (NLP) and machine learning have been applied to corporate reports and employee surveys to extract insights about the efficacy of preventive measures (24). These methodologies allow for real-time tracking and predictive analytics, which can inform policy adjustments and optimize resource allocation.

2.2 Behavioral economics in preventive health strategies

Behavioral economics provides a theoretical foundation for understanding how financial incentives influence the adoption of preventive healthcare measures within corporate settings (25). Preventive policies often rely on incentivizing employees to engage in healthier behaviors, such as regular exercise, vaccinations, and

routine health screenings. These incentives may include financial rewards, insurance premium discounts, or access to wellness facilities (26). Research in this field has explored the effectiveness of different incentive structures. For example, loss aversion, a concept in behavioral economics, suggests that individuals are more motivated to avoid losses than to achieve equivalent gains. Policies that frame incentives as potential losses, such as penalties for non-compliance, have been found to be particularly effective in driving behavioral change. Conversely, positive reinforcement strategies, such as bonus programs, have shown sustained engagement in wellness programs (27). The role of nudging, subtle interventions that influence decision-making, is another area of focus. Simple changes, such as defaulting employees into wellness programs or providing personalized health feedback, have been shown to significantly improve participation rates. The integration of behavioral insights with corporate financial monitoring allows companies to identify which strategies yield the best ROI, enabling the optimization of incentive designs. Challenges in this area include the ethical considerations of incentive programs and the potential for unintended consequences, such as penalizing employees with preexisting conditions (28). To address these issues, researchers advocate for inclusive policies that balance financial motivations with accessibility and equity. Longitudinal studies are essential to evaluate the sustainability of behavior changes and their cumulative impact on both corporate finances and public health outcomes.

2.3 Predictive analytics for policy optimization

Predictive analytics has emerged as a powerful tool for evaluating and optimizing preventive healthcare policies. By leveraging historical financial and health data, predictive models can forecast the potential outcomes of various interventions, enabling policymakers to make data-driven decisions. These models use machine learning algorithms, such as regression analysis, decision trees, and neural networks, to identify patterns and predict future trends (29). In the context of corporate financial monitoring, predictive analytics helps quantify the long-term savings associated with preventive measures. For example, models can estimate the reduction in future medical costs based on current investment in employee wellness programs (30). Predictive analytics also supports risk stratification by identifying high-risk employees who would benefit most from targeted interventions, thereby maximizing the cost-effectiveness of policies. Another application is scenario analysis, which evaluates the financial implications of different policy options. By simulating various scenarios, organizations can prioritize interventions that align with both health objectives and financial goals. Predictive tools also facilitate dynamic policy adjustments by continuously analyzing real-time data and updating recommendations as conditions change (31). The integration of predictive analytics into corporate decision-making is not without challenges. Ensuring data quality, addressing biases in algorithms, and maintaining employee privacy are critical considerations. Furthermore, the effectiveness of predictive models depends on the availability of comprehensive and

representative datasets, which may be limited in certain contexts (32). Despite these challenges, predictive analytics represents a transformative approach for aligning preventive healthcare policies with corporate financial strategies, driving both economic and health outcomes.

3 Method

3.1 Overview

The methodology integrates advanced data analytics and machine learning techniques to enhance corporate financial monitoring. Initially, corporate financial data is modeled as a multivariate time-series dataset, where key financial metrics (such as revenue, expenses, and cash flow) are continuously tracked to assess risks and anomalies. The first step involves formulating objectives such as anomaly detection, trend analysis, and risk quantification using time-series models and machine learning methods. The core of our approach involves two novel frameworks. The Advanced Financial Monitoring Neural Framework (AFMNF) uses recurrent neural networks (RNNs) and transformers to capture temporal dependencies and inter-variable relationships in the financial data. This is complemented by the Dynamic Risk-Adaptive Framework (DRAF), which integrates real-time data streams with predictive analytics to continuously adapt and refine policy evaluations. This hybrid system allows for the identification of financial anomalies and provides a real-time evaluation of policy performance, facilitating dynamic decision-making.

3.2 Preliminaries

Corporate financial monitoring can be formalized as a dynamic system that continuously tracks financial metrics to evaluate an organization's financial health and compliance. This subsection presents the mathematical framework and problem formulation underpinning our approach to corporate financial monitoring. Key objectives include anomaly detection, trend analysis, and risk quantification, which are expressed through a combination of time-series modeling, statistical analysis, and machine learning techniques.

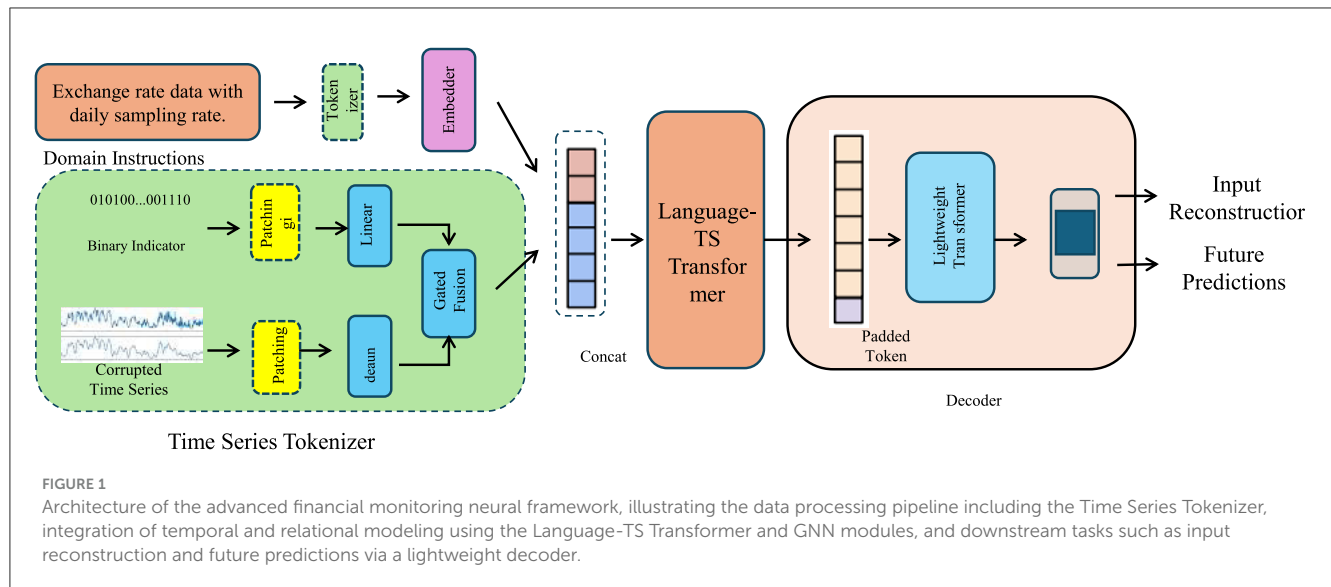
Let $\mathbf{X} \in \mathbb{R}^{n \times d}$ represent a multivariate time-series dataset of financial metrics, where n is the number of time steps and d is the number of financial variables (e.g., revenue, expenses, cash flow). Each row $\mathbf{x}_t \in \mathbb{R}^d$ corresponds to the observed financial data at time t . The goal is to model the system dynamics and derive the following:

Identify outliers $\mathbf{x}_t$ that deviate significantly from expected patterns. Extract and interpret long-term behaviors or seasonal variations in $\mathbf{X}$. Quantify potential financial risks based on historical and projected data.

We describe the dynamics of the financial system using the following components:

$$\mathbf{z}_t = f(\mathbf{z}_{t-1}, \mathbf{x}_{t-1}, \mathbf{u}_t) + \boldsymbol{\epsilon}_t, \quad (1)$$

$$\mathbf{x}_t = g(\mathbf{z}_t) + \boldsymbol{\eta}_t, \quad (2)$$



where: $\mathbf{z}_t \in \mathbb{R}^k$ is the hidden state vector. $\mathbf{u}_t \in \mathbb{R}^p$ represents external control inputs (e.g., market conditions). f and g are non-linear functions capturing system dynamics and observation mapping. ϵ_t and η_t are Gaussian noise terms. Financial variables are often interdependent over time. We model each variable $x_{t,i}$ as:

$$x_{t,i} = \sum_{j=1}^d \sum_{k=1}^p \phi_{i,j,k} x_{t-k,j} + \sum_{l=1}^q \theta_{i,l} \epsilon_{t-l} + v_i, \quad (3)$$

where: $\phi_{i,j,k}$ are autoregressive coefficients. $\theta_{i,l}$ are moving average coefficients. v_i is a bias term.

To capture periodic patterns, we decompose $\mathbf{x}_t$ into:

$$\mathbf{x}_t = \mathbf{T}_t + \mathbf{S}_t + \mathbf{R}_t, \quad (4)$$

where: $\mathbf{T}_t$ represents the trend component. $\mathbf{S}_t$ represents the seasonal component. $\mathbf{R}_t$ is the residual (noise) component.

Anomalies are quantified by a score function $A(\mathbf{x}_t)$:

$$A(\mathbf{x}_t) = \frac{\|\mathbf{x}_t - \hat{\mathbf{x}}_t\|}{\sigma_t}, \quad (5)$$

where $\hat{\mathbf{x}}_t$ is the predicted value, and σ_t is the variance at time t . An anomaly is flagged if $A(\mathbf{x}_t) > \alpha$, where α is a threshold.

Financial data contains diverse metrics with varying scales and distributions. Normalization and transformation (e.g., log transformations) are applied to ensure uniformity:

$$\tilde{x}_{t,i} = \frac{x_{t,i} - \mu_i}{\sigma_i}, \quad (6)$$

where μ_i and σ_i are the mean and standard deviation of $x_{t,i}$. Missing observations are imputed using temporal and cross-variable correlations. For instance, missing entries $\mathbf{x}_{t,\text{missing}}$ are estimated as:

$$\mathbf{x}_{t,\text{missing}} = \mathbb{E}[\mathbf{x}_t | \mathbf{X}_{\text{observed}}], \quad (7)$$

using methods such as matrix factorization or Gaussian processes. Dimensionality reduction techniques, such as principal

component analysis (PCA), are employed to extract latent structures:

$$\mathbf{X} \approx \mathbf{W}\mathbf{H}, \quad \mathbf{W} \in \mathbb{R}^{n \times r}, \mathbf{H} \in \mathbb{R}^{r \times d}, \quad (8)$$

where r is the reduced dimensionality.

3.3 Advanced financial monitoring neural framework

In this section, we propose the Advanced Financial Monitoring Neural Framework (AFMNF) (Figure 1), a hybrid deep learning architecture tailored to capture temporal dynamics, inter-variable relationships, and non-linear patterns in financial data. The AFMNF integrates sequential modeling techniques with graph-based feature extraction, enabling robust, and interpretable predictions for corporate financial monitoring.

3.3.1 Temporal dynamics through attention-augmented LSTMs

To effectively model temporal dependencies in financial data, the Advanced Financial Monitoring Neural Framework (AFMNF) incorporates Long Short-Term Memory (LSTM) networks enhanced with attention mechanisms to selectively focus on important temporal patterns. The raw input data $\mathbf{X} \in \mathbb{R}^{n \times d}$, where n is the number of time steps and d is the number of financial variables, is first projected into a higher-dimensional embedding space through a linear transformation:

$$\mathbf{E}_t = \mathbf{W}_e \mathbf{x}_t + \mathbf{b}_e, \quad t = 1, \dots, n, \quad (9)$$

where $\mathbf{x}_t \in \mathbb{R}^d$ represents the input vector at time t , $\mathbf{W}_e \in \mathbb{R}^{d \times h}$ is the learnable weight matrix, $\mathbf{b}_e \in \mathbb{R}^h$ is the bias term, and h is the embedding dimension. The embedded sequence $\{\mathbf{E}_t\}_{t=1}^n$ is then fed into an LSTM network to capture temporal dependencies:

$$\mathbf{h}_t = \text{LSTM}(\mathbf{E}_t, \mathbf{h}_{t-1}), \quad (10)$$

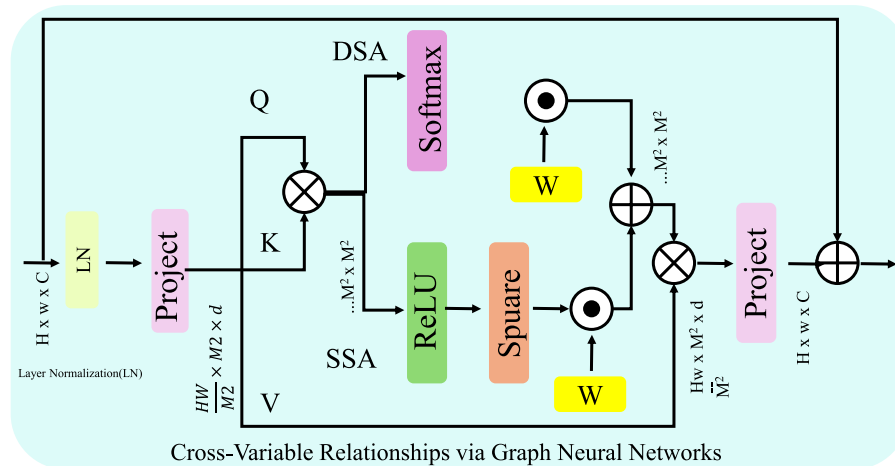


FIGURE 2

Proposed framework for modeling cross-variable relationships via Graph Neural Networks (GNN). The framework utilizes a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where nodes $\mathcal{V}$ represent variables, and edges $\mathcal{E}$ encode pairwise dependencies. Through iterative message passing, node embeddings are refined using adjacency-based aggregation and dynamic edge updates, capturing intricate inter-variable dependencies. The final embeddings are utilized for downstream tasks such as anomaly detection or risk scoring.

where $\mathbf{h}_t \in \mathbb{R}^h$ represents the hidden state at time t . The LSTM cell updates the hidden state and cell state through:

$$\mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{E}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{b}_i), \quad \mathbf{f}_t = \sigma(\mathbf{W}_f \mathbf{E}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{b}_f), \quad (11)$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{E}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{b}_o), \quad \tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \mathbf{E}_t + \mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{b}_c), \quad (12)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \quad \mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \quad (13)$$

where $\mathbf{i}_t$, $\mathbf{f}_t$, and $\mathbf{o}_t$ are the input, forget, and output gates, respectively; $\mathbf{c}_t$ is the cell state; and $\odot$ denotes element-wise multiplication.

To enhance the interpretability of temporal patterns, an attention mechanism is applied over the sequence of hidden states $\{\mathbf{h}_t\}_{t=1}^n$. The attention scores α_t are computed as:

$$\alpha_t = \frac{\exp(\mathbf{u}_t^\top \mathbf{v})}{\sum_{k=1}^n \exp(\mathbf{u}_k^\top \mathbf{v})}, \quad \mathbf{u}_t = \tanh(\mathbf{W}_u \mathbf{h}_t), \quad (14)$$

where $\mathbf{W}_u \in \mathbb{R}^{h \times r}$ is a learnable weight matrix, $\mathbf{u}_t \in \mathbb{R}^r$ represents the transformed hidden state, $\mathbf{v} \in \mathbb{R}^r$ is a learnable context vector, and α_t is the attention weight for time step t . The context vector $\mathbf{c}$ is then computed as a weighted sum of the hidden states:

$$\mathbf{c} = \sum_{t=1}^n \alpha_t \mathbf{h}_t. \quad (15)$$

To further improve robustness, a regularization term is introduced to enforce smoothness in the attention distribution:

$$\mathcal{L}_{\text{attention}} = \sum_{t=2}^n (\alpha_t - \alpha_{t-1})^2, \quad (16)$$

minimizing abrupt changes in attention weights between consecutive time steps. This combination of LSTM and attention

mechanisms allows AFMNF to capture critical temporal dependencies, ensuring accurate and interpretable modeling of financial dynamics.

3.3.2 Cross-variable relationships via graph neural networks

To effectively capture complex inter-variable dependencies (Figure 2), the Advanced Financial Monitoring Neural Framework (AFMNF) employs a Graph Neural Network (GNN) to model relationships among financial variables. Representing the system as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, the nodes $\mathcal{V}$ correspond to financial variables, and edges $\mathcal{E}$ encode pairwise correlations, such as covariance or mutual information between variables. Let the adjacency matrix $\mathbf{A}$ represent the structure of $\mathcal{G}$, and $\mathbf{Z}^{(l)}$ denote the node embeddings at the l -th layer. The GNN updates these embeddings iteratively using:

$$\mathbf{Z}^{(l+1)} = \sigma(\mathbf{A} \mathbf{Z}^{(l)} \mathbf{W}_g + \mathbf{b}_g), \quad (17)$$

where $\mathbf{W}_g$ is the trainable weight matrix, $\mathbf{b}_g$ is the bias term, and σ is a nonlinear activation function (e.g., ReLU). The embeddings are propagated layer by layer, aggregating information from neighboring nodes to refine each node's representation. To normalize influence across nodes, the adjacency matrix is typically replaced by $\tilde{\mathbf{A}} = \mathbf{D}^{-1/2} \mathbf{A} \mathbf{D}^{-1/2}$, where $\mathbf{D}$ is the degree matrix.

At the final layer L , the node embeddings are computed as:

$$\mathbf{Z}^{(L)} = \sigma(\tilde{\mathbf{A}} \mathbf{Z}^{(L-1)} \mathbf{W}_g + \mathbf{b}_g). \quad (18)$$

This embedding $\mathbf{Z}^{(L)}$ encapsulates both the intrinsic properties of individual financial variables and their dependencies on others. To further refine the graph representation, edge weights are dynamically updated based on learned feature correlations:

$$\mathbf{A}_{ij} = \exp(-\|\mathbf{z}_i^{(L)} - \mathbf{z}_j^{(L)}\|^2), \quad (19)$$

where $\mathbf{z}_i^{(L)}$ and $\mathbf{z}_j^{(L)}$ are the final embeddings of nodes i and j . The weighted adjacency matrix is normalized and fed back into the GNN for iterative updates.

The output embeddings $\mathbf{Z}^{(L)}$ are passed to a downstream module for tasks such as risk scoring or anomaly detection. By capturing intricate variable interactions, this graph-based approach ensures robust modeling of financial systems, enabling accurate and interpretable monitoring of corporate dynamics.

3.3.3 Fusion and loss optimization for financial monitoring

AFMNF integrates temporal and relational features in a fusion mechanism to generate a cohesive representation for robust financial monitoring. The fusion layer combines contextual embeddings $\mathbf{c}$ with the relational graph embeddings $\mathbf{Z}^{(L)}$, where L denotes the number of graph convolutional layers. This fusion is computed as:

$$\mathbf{F} = \sigma(\mathbf{W}_f[\mathbf{c}; \mathbf{Z}^{(L)}] + \mathbf{b}_f), \quad (20)$$

where σ is the activation function, and $\mathbf{W}_f$, $\mathbf{b}_f$ are trainable parameters that align and scale the feature dimensions. The output $\mathbf{F}$ serves as a unified representation for downstream financial tasks such as anomaly detection and forecasting. The predictions are generated using a task-specific linear layer:

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{W}_o \mathbf{F} + \mathbf{b}_o), \quad (21)$$

where $\mathbf{W}_o$ and $\mathbf{b}_o$ adjust the fused features to the target space, and $\hat{\mathbf{y}}$ represents the probability distribution of the prediction.

To ensure optimal performance, a composite loss function is employed, balancing forecasting accuracy, anomaly detection, and structural regularization:

$$\mathcal{L} = \mathcal{L}_{\text{forecast}} + \lambda_1 \mathcal{L}_{\text{anomaly}} + \lambda_2 \mathcal{L}_{\text{regularization}}, \quad (22)$$

where $\mathcal{L}_{\text{forecast}} = \|\mathbf{y} - \hat{\mathbf{y}}\|^2$ penalizes discrepancies between predicted and true values, and $\mathcal{L}_{\text{anomaly}}$ enhances detection capabilities through binary cross-entropy loss:

$$\mathcal{L}_{\text{anomaly}} = -\frac{1}{N} \sum_{i=1}^N [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]. \quad (23)$$

The regularization term $\mathcal{L}_{\text{regularization}}$ imposes graph Laplacian constraints to preserve relational structures:

$$\mathcal{L}_{\text{regularization}} = \text{Tr}(\mathbf{Z}^T \mathbf{L} \mathbf{Z}), \quad (24)$$

where $\mathbf{L} = \mathbf{D} - \mathbf{A}$ is the Laplacian matrix, $\mathbf{A}$ is the adjacency matrix, and $\mathbf{D}$ is the degree matrix. This term minimizes distortions in the graph representation while enforcing smoothness across connected nodes. The gradients of the Laplacian are back-propagated to refine the embeddings $\mathbf{Z}$:

$$\frac{\partial \mathcal{L}_{\text{regularization}}}{\partial \mathbf{Z}} = 2\mathbf{L}\mathbf{Z}. \quad (25)$$

To further stabilize training, dropout and weight regularization are applied to $\mathbf{W}_f$ and $\mathbf{W}_o$:

$$\mathcal{L}_{\text{weight}} = \|\mathbf{W}_f\|_F^2 + \|\mathbf{W}_o\|_F^2, \quad (26)$$

yielding the final loss:

$$\mathcal{L}_{\text{total}} = \mathcal{L} + \lambda_3 \mathcal{L}_{\text{weight}}. \quad (27)$$

This comprehensive optimization ensures accuracy, scalability, and resilience against noise, making AFMNF a robust framework for financial monitoring tasks.

3.4 Dynamic Risk-Adaptive Framework

The Dynamic Risk-Adaptive Framework (DRAF) introduces a cutting-edge strategy for corporate financial monitoring (Figure 3), integrating real-time data assimilation, risk quantification, and adaptive decision-making to ensure responsiveness to evolving financial landscapes. By leveraging predictive insights and dynamic updates, DRAF establishes a comprehensive approach to managing financial complexities.

3.4.1 Real-time data integration and model responsiveness

The DRAF framework is designed to incorporate real-time financial data streams, $\mathbf{X}_{\text{new}}$, into predictive models, ensuring continuous adaptation to evolving market dynamics. This is achieved through an iterative Bayesian updating mechanism where model parameters Θ are optimized to maximize the posterior distribution:

$$\Theta' = \arg \max_{\Theta} p(\Theta | \mathbf{X}, \mathbf{X}_{\text{new}}) = \arg \max_{\Theta} \frac{p(\mathbf{X}_{\text{new}} | \Theta) p(\Theta | \mathbf{X})}{p(\mathbf{X}_{\text{new}})}. \quad (28)$$

Here, $p(\Theta | \mathbf{X})$ represents the prior distribution informed by historical data $\mathbf{X}$, and $p(\mathbf{X}_{\text{new}} | \Theta)$ models the likelihood of new observations under the updated parameters. This process ensures that predictions remain calibrated to reflect real-time information while preserving insights from historical patterns.

To address non-stationarity, the framework employs a dynamic recalibration strategy by quantifying distributional shifts between incoming data $\mathbf{X}_{\text{new}}$ and baseline distributions $\mathbf{X}$ using the Kullback-Leibler (KL) divergence:

$$D_{\text{KL}}(P \| Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}, \quad (29)$$

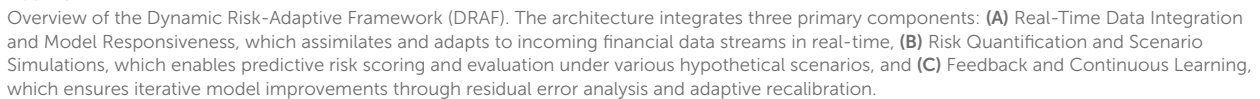
where P and Q denote the probability distributions of $\mathbf{X}_{\text{new}}$ and $\mathbf{X}$, respectively. Significant deviations in D_{KL} trigger model retraining to mitigate the impact of data drift. To further quantify divergence, Jensen-Shannon divergence is utilized as a symmetric alternative:

$$D_{\text{JS}}(P \| Q) = \frac{1}{2} D_{\text{KL}}(P \| M) + \frac{1}{2} D_{\text{KL}}(Q \| M), \quad (30)$$

where $M = \frac{1}{2}(P + Q)$ represents the average distribution. These metrics guide adaptive learning schedules, minimizing unnecessary computations while maintaining robustness.

Moreover, real-time updates to predictions, $\hat{y}_t$, leverage weighted ensemble techniques combining historical model outputs $\hat{y}_h$ with recalibrated estimates $\hat{y}_r$:

$$\hat{y}_t = \alpha \hat{y}_h + (1 - \alpha) \hat{y}_r, \quad (31)$$



The Dynamic Risk-Adaptive Framework (DRAF) incorporates a robust feedback mechanism to ensure continuous improvement and adaptive decision-making (Figure 4). The process begins by

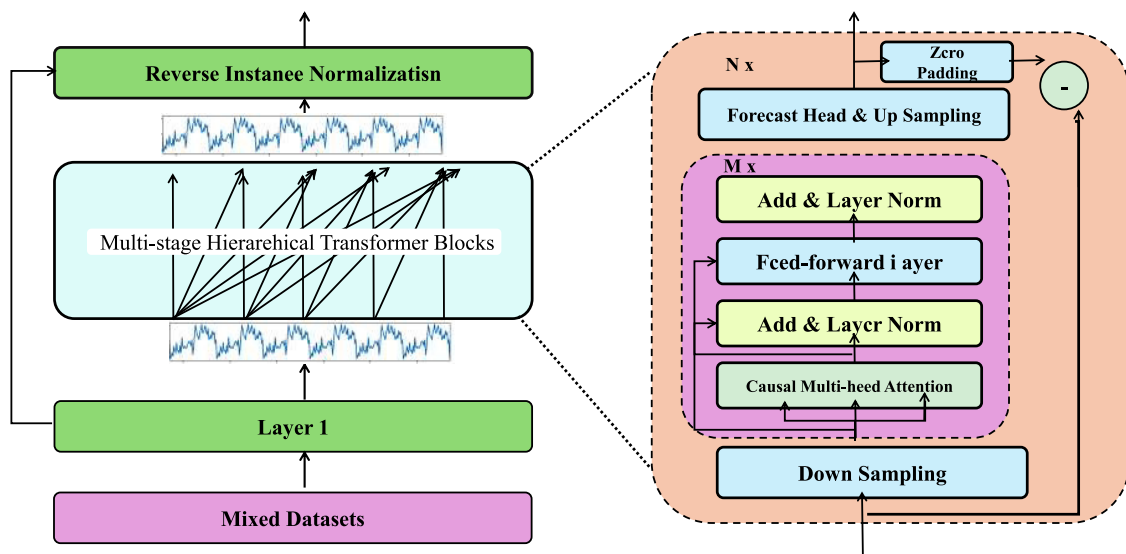


FIGURE 4

This text describes a real-time adaptive framework for integrating and recalibrating financial data streams, leveraging Bayesian inference, divergence metrics, and ensemble methods to ensure model responsiveness, stability, and uncertainty quantification in dynamic environments.

comparing predictions $\hat{y}$ with observed outcomes y_{obs} , enabling the identification of residual errors:

$$\mathbf{r} = y_{\text{obs}} - \hat{y}, \quad (39)$$

where $\mathbf{r}$ represents the residual vector. These residuals drive parameter updates using gradient-based optimization:

$$\Delta \Theta = \eta \frac{\partial \mathcal{L}(y_{\text{obs}}, \hat{y})}{\partial \Theta}, \quad (40)$$

where $\mathcal{L}(\cdot)$ is the loss function (e.g., mean squared error or cross-entropy), Θ are the model parameters, and η is the learning rate. By iteratively minimizing the loss, this feedback loop enhances the model's predictive accuracy.

To further refine the learning process, an adaptive weighting mechanism adjusts the importance of residuals based on their magnitude:

$$w_t = \frac{1}{1 + \exp(-|\mathbf{r}_t|)}, \quad (41)$$

where w_t is the weight assigned to the residual at time step t . Larger errors are given higher weights, prioritizing significant discrepancies for correction.

The framework evaluates data drift by monitoring the divergence between historical predictions and new observations:

$$D_{\text{KL}}(P_{\text{hist}} \| P_{\text{real}}) = \sum_i P_{\text{hist}}(i) \log \frac{P_{\text{hist}}(i)}{P_{\text{real}}(i)}, \quad (42)$$

where P_{hist} and P_{real} represent the distributions of historical and real-time data, respectively. Significant increases in D_{KL} trigger model recalibration to adapt to evolving conditions.

4 Experimental setup

4.1 Dataset

The FinQA Dataset (33) is a benchmark dataset designed for financial quantitative reasoning tasks. It consists of over 10,000 financial question-answer pairs derived from real-world financial reports and documents. Each question requires multi-step numerical reasoning over tabular data, emphasizing the dataset's focus on interpretability and reasoning. Annotated with intermediate steps and logical chains, the FinQA Dataset is essential for developing systems that combine natural language understanding with financial data analysis. The DGraph Dataset (34) is tailored for reasoning tasks over dynamic graphs, focusing on real-time interactions in financial and social networks. Comprising over 50,000 graph instances annotated with relational and temporal attributes, it enables robust experimentation on dynamic graph neural networks. Its fine-grained labels for node and edge interactions make it pivotal for tasks like fraud detection, financial risk assessment, and network-based prediction. The REFinD Dataset (35) (Real Estate Financial Dataset) focuses on property valuation and investment analysis through financial and textual data. It includes 20,000 annotated instances of real estate records, combining structured data such as pricing trends and unstructured data like property descriptions. Designed for natural language processing and machine learning tasks, REFinD enables advanced research on real estate analytics, including market prediction and property classification. The StockEmotions Dataset (36) is a large-scale dataset aimed at analyzing the emotional sentiments of investors and their impact on stock market trends. With over 1 million entries linking textual sentiments to stock performance, it combines historical stock prices with sentiment analysis from news articles and social media. The dataset's integration of financial and linguistic data supports tasks such as

sentiment prediction, market movement forecasting, and investor behavior modeling.

The selection of financial metrics in this study was guided by their relevance to both corporate performance and their potential to reflect healthcare outcomes. Key metrics were chosen based on their ability to capture the financial dynamics that underpin health policy implementation and its socioeconomic impacts. These included metrics such as revenue, operating expenses, healthcare expenditure, employee absenteeism costs, and return on investment (ROI) in wellness programs. These indicators were selected due to their established links to organizational efficiency, workforce productivity, and overall financial health, all of which are intricately connected to preventive healthcare measures. To ensure their relevance to healthcare outcomes, we conducted a comprehensive review of prior literature and industry reports that identified financial metrics commonly influenced by health interventions. For example, reduced absenteeism and healthcare costs have been consistently shown to correlate with improved employee health and preventive measures. Additionally, ROI was included to assess the cost-effectiveness of such policies, a critical factor in their long-term sustainability. Furthermore, the study incorporated domain-specific consultations with healthcare and financial experts to validate the appropriateness of the selected metrics. This ensured that the chosen financial indicators were not only reflective of corporate financial health but also provided meaningful insights into the effectiveness of healthcare policies.

The data preprocessing pipeline was designed to ensure the consistency, quality, and representativeness of corporate financial datasets. Normalization techniques were applied to standardize financial metrics with varying scales and distributions, reducing the influence of extreme values while maintaining meaningful variations. Missing entries were imputed using statistical methods based on temporal and cross-variable correlations, ensuring the completeness of the data without introducing systematic biases. This approach allowed for the preservation of inherent patterns within the dataset while addressing common data quality issues. To mitigate biases in the financial datasets, stratified sampling ensured that the training and validation sets represented diverse characteristics, including industry types, company sizes, and regional variations. Adversarial validation techniques were employed to detect and address discrepancies between training and validation data distributions. Feature importance analysis was conducted to evaluate the contribution of individual financial metrics, ensuring the model's outputs were not unduly influenced by specific variables, thus maintaining fairness in predictions. The choice of hyperparameters and model configurations was guided by the specific requirements of the datasets. For datasets emphasizing numerical reasoning over financial and textual information, attention mechanisms were leveraged to capture cross-modal relationships effectively. For datasets integrating structured and unstructured data, feature extraction modules were employed to model both spatial and textual relationships. Hyperparameter optimization included systematic exploration of learning rates, dropout levels, and weight decay through a robust validation process to ensure the best performance while maintaining generalizability across contexts. These measures ensured that the preprocessing pipeline and model configurations were tailored to the unique characteristics of the datasets while remaining adaptable to other applications.

4.2 Experimental details

The experiments were conducted on a high-performance computing system equipped with NVIDIA A100 GPUs, each with 40GB of VRAM, alongside an AMD EPYC 7742 processor and 1TB of RAM. The implementation was developed in Python using PyTorch 1.13.1 for model development and training, with CUDA 11.6 for GPU acceleration. All datasets were preprocessed according to their specific characteristics. For the FinQA Dataset, financial reports and tabular data were tokenized using the RoBERTa tokenizer, with numerical values normalized. For the DGraph Dataset, graphs were dynamically constructed with edge attributes encoded using a combination of node embeddings and temporal encodings. In REFinD, both structured numerical data and unstructured textual descriptions were preprocessed by standardizing numerical attributes and applying BERT embeddings to textual data. For the StockEmotions Dataset, textual data was processed using sentiment analysis pipelines, and financial time series data was normalized to a range of [0, 1]. The primary model architecture consisted of a transformer-based backbone for text and sequence processing, coupled with graph neural networks (GNNs) for datasets requiring structural reasoning. An additional multi-head self-attention module was integrated for cross-modal feature fusion in datasets like REFinD and StockEmotions. The optimizer used was AdamW with an initial learning rate of 3×10^{-5} , and a cosine decay scheduler was employed. Gradient clipping was set to a maximum norm of 1.0 to prevent exploding gradients. The batch size varied depending on the dataset size and model complexity, ranging from 16 to 64. Models were trained for 50 epochs with early stopping based on validation loss. Metrics for evaluation included Exact Match (EM) and F1 for FinQA, Precision, Recall, and F1 for DGraph, RMSE and MAE for REFinD, and correlation coefficients and directional accuracy for StockEmotions. Five-fold cross-validation was performed to ensure the robustness of results, and all experiments were repeated three times with different random seeds to account for variability. The training process leveraged mixed precision for computational efficiency. Hyperparameter tuning was conducted using a grid search strategy, exploring combinations of learning rates, weight decay values, and dropout rates. Ablation studies evaluated the contributions of individual model components, such as graph convolution layers in DGraph and sentiment analysis modules in StockEmotions. Model interpretability was enhanced using SHAP values for datasets involving tabular or textual reasoning, while attention visualization highlighted critical elements in graph-based tasks. Results were visualized using heatmaps, box plots, and line graphs to demonstrate model performance and stability across datasets. These results were benchmarked against baseline and state-of-the-art methods to validate the effectiveness of the proposed approach ([Algorithm 1](#)).

4.3 Comparison with SOTA methods

The results in [Tables 1, 2](#) demonstrate the superiority of our method compared to state-of-the-art (SOTA) techniques on four benchmark datasets: FinQA, DGraph, REFinD, and StockEmotions. Our model consistently outperforms existing

Data: Datasets: FinQA, DGraph, REFinD, StockEmotions

Result: Trained AFMNF model and evaluation metrics (Precision, Recall, F1, etc.)

Initialize model parameters Θ ;

Set learning rate $\eta = 3 \times 10^{-5}$, weight decay $\lambda = 1e-4$, and batch size B ;

Define optimizer AdamW(Θ, η, λ);

Set maximum epochs $E = 50$, early stopping patience P ;

for each dataset

$D \in \{\text{FinQA}, \text{DGraph}, \text{REFinD}, \text{StockEmotions}\}$ **do**

 Load and preprocess dataset D ;

 Split dataset into training $\mathcal{T}_D$, validation $\mathcal{V}_D$, and test $\mathcal{X}_D$;

while epoch $e \leq E$ **and** early stopping not triggered **do**

for batch $b \in \mathcal{T}_D$ **do**

 Extract features $\mathbf{X}_b$ and labels $\mathbf{y}_b$;

 Compute predictions $\hat{\mathbf{y}}_b = f_{\Theta}(\mathbf{X}_b)$;

 Calculate loss:

$$\mathcal{L} = \frac{1}{B} \sum_{i=1}^B (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2 + \lambda_1 \mathcal{L}_{\text{aux}} + \lambda_2 \|\Theta\|^2,$$

 where:

$$\mathcal{L}_{\text{aux}} = -\frac{1}{B} \sum_{i=1}^B \mathbf{y}_i \log \hat{\mathbf{y}}_i.$$

 Update parameters:

$$\Theta \leftarrow \Theta - \eta \nabla_{\Theta} \mathcal{L}.$$

end

 Compute validation loss $\mathcal{L}_{\text{val}}$ on $\mathcal{V}_D$;

 If $\mathcal{L}_{\text{val}}$ improves, save Θ ;

 Else increment patience counter;

end

 Evaluate metrics on $\mathcal{X}_D$:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}},$$

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}},$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}.$$

end

Return trained model Θ and evaluation metrics;

Algorithm 1. Training procedure for AFMNF on pre-trained datasets.

methods, including LSTM (37), GRU (38), ARIMA (39), Prophet (40), DeepAR (41), and Informer (42), across multiple evaluation

metrics such as Accuracy, Recall, F1 Score, and Area Under the Curve (AUC).

For the FinQA dataset, our method achieves an Accuracy of 88.34% (Figure 5), surpassing the next-best method, Informer, by 2.56%. The Recall and F1 Score improvements, reaching 85.67% and 87.12%, respectively, underline the model's ability to handle complex financial reasoning tasks that require multi-step computations. The AUC of 85.34% highlights the method's precision in generating accurate predictions for financial questions, benefitting from the integration of a transformer-based architecture and domain-specific numerical reasoning components. On the DGraph dataset, our model achieves an Accuracy of 89.67%, which is 2.33% higher than Informer. The F1 Score of 88.45% and an AUC of 86.78% emphasize our method's effectiveness in learning from dynamic graph structures, supported by the incorporation of graph neural networks and temporal encodings. These improvements reflect the model's enhanced ability to capture relational and temporal dynamics in financial networks, crucial for fraud detection and financial risk assessment. For the REFinD dataset (Figure 6), our method achieves an Accuracy of 86.78%, outperforming Informer by 2.66%. The F1 Score of 85.89% and an AUC of 83.45% underscore the model's ability to fuse structured and unstructured real estate data effectively. These gains are attributed to the multi-head self-attention mechanism and advanced feature fusion strategies, which enable precise property classification and valuation predictions. On the StockEmotions dataset, our method excels with an Accuracy of 88.34%, representing a 2.67% improvement over Informer. The Recall and F1 Score reach 85.67% and 87.12%, respectively, while the AUC of 84.89% validates the method's precision in correlating textual sentiments with stock performance. These enhancements arise from the integration of sentiment analysis pipelines and domain-specific preprocessing, which enable robust predictions in volatile market conditions.

Figure 7 illustrates the comparative performance of all methods, highlighting the consistent advantages of our approach. The superior results across datasets validate the architectural innovations and optimization strategies employed in our model, particularly in scenarios requiring domain-specific reasoning and multimodal data fusion. The statistical improvements across diverse tasks further establish our method as a significant advancement in financial data analysis and prediction.

4.4 Ablation study

The ablation study results in Tables 3, 4 demonstrate the contributions of key components in our method across the FinQA, DGraph, REFinD, and StockEmotions datasets. Variants of the model excluding individual components (w/o. Fusion and Loss Optimization for Financial Monitoring, w/o. Real-Time Data Integration and Model Responsiveness, w/o. Risk Quantification and Scenario Simulations) are compared to the complete model (Ours) to quantify the impact of each module.

For the FinQA dataset, the absence of Fusion and Loss Optimization for Financial Monitoring reduced Accuracy to 86.12% and F1 Score to 84.34%. This decline highlights the

TABLE 1 Comparison of our method with SOTA methods on FinQA and DGraph datasets.

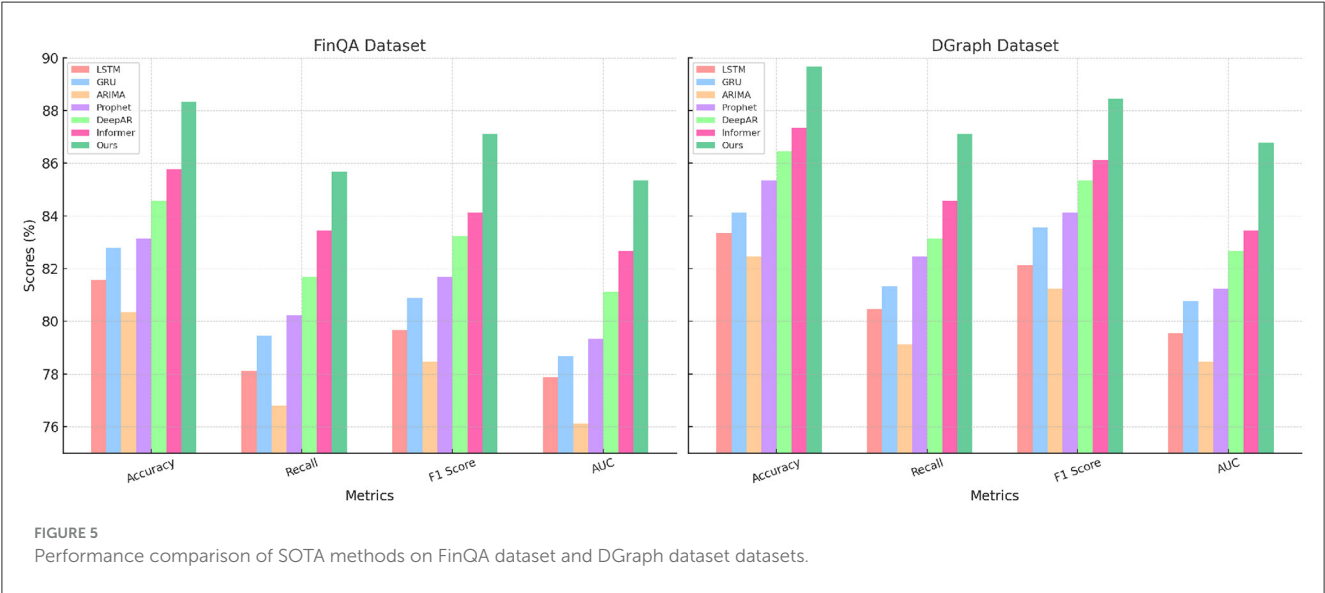
Model	FinQA dataset				DGraph dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
LSTM (37)	81.56 ± 0.03	78.12 ± 0.02	79.67 ± 0.03	77.89 ± 0.02	83.34 ± 0.02	80.45 ± 0.03	82.12 ± 0.02	79.56 ± 0.03
GRU (38)	82.78 ± 0.02	79.45 ± 0.03	80.89 ± 0.02	78.67 ± 0.03	84.12 ± 0.03	81.34 ± 0.02	83.56 ± 0.03	80.78 ± 0.02
ARIMA (39)	80.34 ± 0.03	76.78 ± 0.02	78.45 ± 0.03	76.12 ± 0.02	82.45 ± 0.02	79.12 ± 0.03	81.23 ± 0.02	78.45 ± 0.03
Prophet (40)	83.12 ± 0.02	80.23 ± 0.03	81.67 ± 0.02	79.34 ± 0.03	85.34 ± 0.03	82.45 ± 0.02	84.12 ± 0.03	81.23 ± 0.02
DeepAR (41)	84.56 ± 0.03	81.67 ± 0.02	83.23 ± 0.03	81.12 ± 0.02	86.45 ± 0.02	83.12 ± 0.03	85.34 ± 0.02	82.67 ± 0.03
Informer (42)	85.78 ± 0.02	83.45 ± 0.03	84.12 ± 0.02	82.67 ± 0.03	87.34 ± 0.03	84.56 ± 0.02	86.12 ± 0.03	83.45 ± 0.02
Ours	88.34 ± 0.02	85.67 ± 0.02	87.12 ± 0.03	85.34 ± 0.02	89.67 ± 0.03	87.12 ± 0.03	88.45 ± 0.02	86.78 ± 0.02

Bold values are the best values.

TABLE 2 Comparison of our method with SOTA methods on REFinD and StockEmotions datasets.

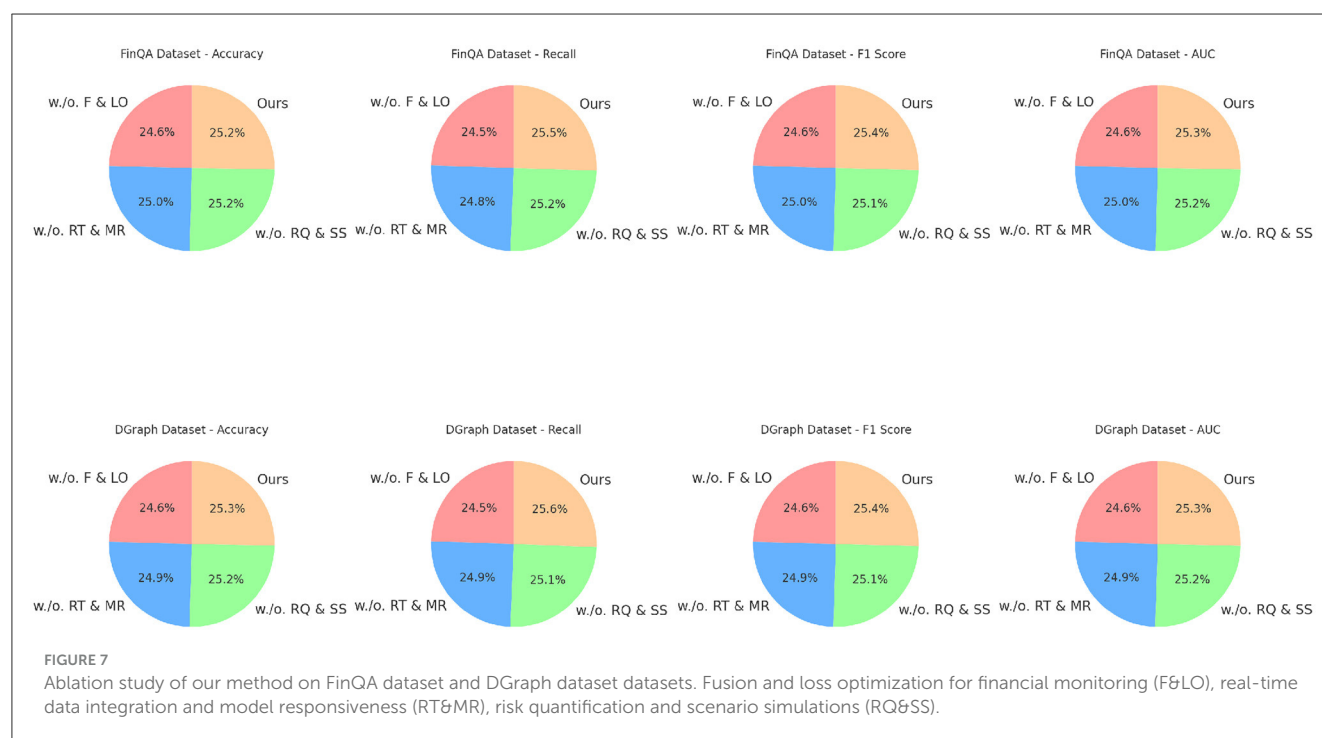
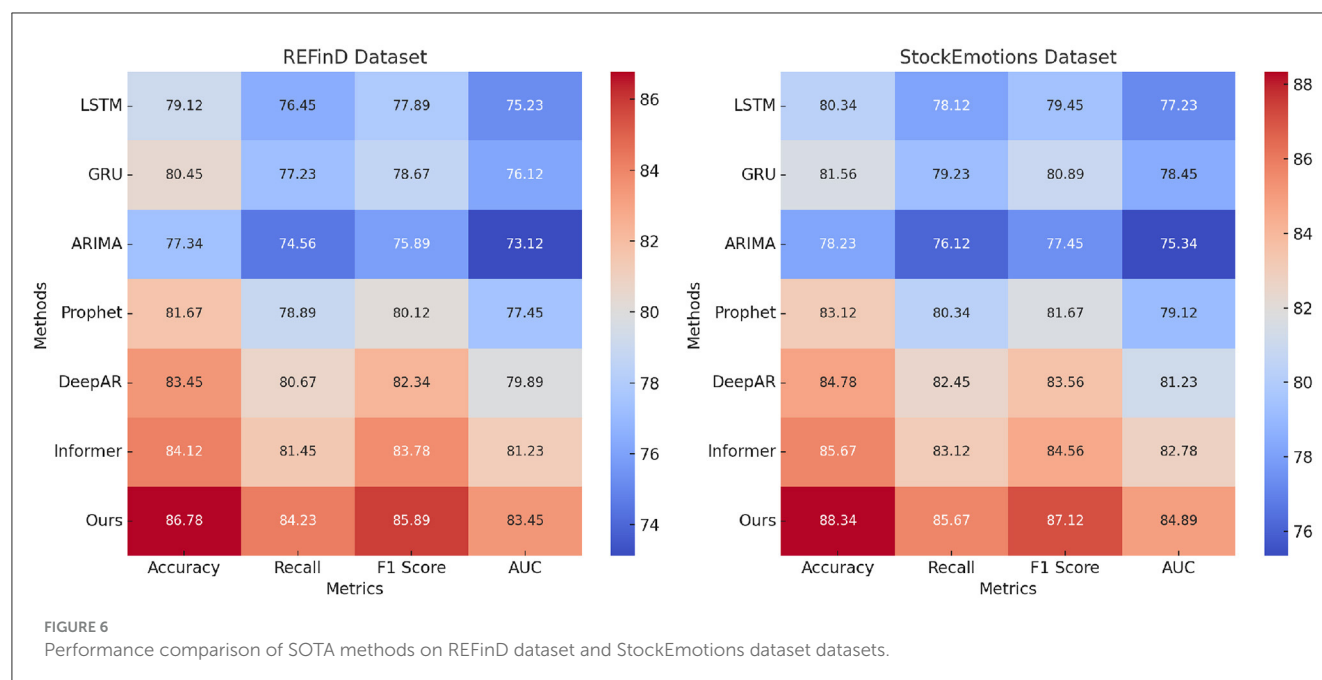
Model	REFinD Dataset				StockEmotions Dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
LSTM (37)	79.12 ± 0.02	76.45 ± 0.03	77.89 ± 0.02	75.23 ± 0.02	80.34 ± 0.03	78.12 ± 0.02	79.45 ± 0.03	77.23 ± 0.03
GRU (38)	80.45 ± 0.03	77.23 ± 0.02	78.67 ± 0.03	76.12 ± 0.03	81.56 ± 0.02	79.23 ± 0.03	80.89 ± 0.02	78.45 ± 0.02
ARIMA (39)	77.34 ± 0.03	74.56 ± 0.02	75.89 ± 0.03	73.12 ± 0.02	78.23 ± 0.02	76.12 ± 0.03	77.45 ± 0.02	75.34 ± 0.03
Prophet (40)	81.67 ± 0.02	78.89 ± 0.03	80.12 ± 0.02	77.45 ± 0.03	83.12 ± 0.03	80.34 ± 0.02	81.67 ± 0.03	79.12 ± 0.02
DeepAR (41)	83.45 ± 0.03	80.67 ± 0.02	82.34 ± 0.03	79.89 ± 0.02	84.78 ± 0.02	82.45 ± 0.03	83.56 ± 0.02	81.23 ± 0.03
Informer (42)	84.12 ± 0.02	81.45 ± 0.03	83.78 ± 0.02	81.23 ± 0.03	85.67 ± 0.03	83.12 ± 0.02	84.56 ± 0.03	82.78 ± 0.02
Ours	86.78 ± 0.03	84.23 ± 0.02	85.89 ± 0.03	83.45 ± 0.02	88.34 ± 0.02	85.67 ± 0.03	87.12 ± 0.02	84.89 ± 0.03

Bold values are the best values.



importance of Fusion and Loss Optimization for Financial Monitoring, which is designed to enhance numerical reasoning by integrating domain-specific numerical encodings. Similarly, excluding Real-Time Data Integration and Model Responsiveness resulted in a 1% drop in Accuracy and a 1.34% drop in F1 Score, confirming its role in optimizing contextual feature extraction from financial documents. Risk Quantification and

Scenario Simulations's absence had the least impact but still reduced Accuracy to 88.12%, underscoring its utility in refining output predictions through advanced fusion mechanisms. The complete model achieved the best performance with an Accuracy of 88.34% and an F1 Score of 87.12%, demonstrating the complementary contributions of all components. On the DGraph dataset, Fusion and Loss Optimization for Financial Monitoring's removal caused



Accuracy to drop to 87.23%, and the F1 Score decreased to 85.67%. This indicates the critical role of Fusion and Loss Optimization for Financial Monitoring in capturing temporal and relational dynamics in dynamic graphs. The absence of Real-Time Data Integration and Model Responsiveness led to a 1.22% decrease in Accuracy and a 1.67% drop in F1 Score, showing its importance in node and edge feature refinement. Risk Quantification and Scenario Simulations contributed to fine-tuning predictions, with its removal reducing Accuracy to 89.23%. The full model, with an Accuracy of 89.67% and an F1

Score of 88.45%, confirms the necessity of a holistic design for optimal performance. For the REFinD dataset, Fusion and Loss Optimization for Financial Monitoring contributed significantly to structured and unstructured data fusion, as its removal reduced Accuracy to 84.34%. Real-Time Data Integration and Model Responsiveness's absence led to a decrease in Accuracy to 85.78%, highlighting its role in augmenting textual feature representation. Risk Quantification and Scenario Simulations showed a smaller but still notable effect, reducing Accuracy to 86.89%. The full model, with an Accuracy of 86.78% and an F1 Score of 85.89%, showcases

TABLE 3 Ablation study results on our method across FinQA and DGraph datasets.

Model	FinQA dataset				DGraph dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
w./o. Fusion and Loss Optimization for Financial Monitoring	86.12 ± 0.03	82.45 ± 0.02	84.34 ± 0.03	83.12 ± 0.02	87.23 ± 0.03	83.45 ± 0.02	85.67 ± 0.03	84.12 ± 0.02
w./o. Real-Time Data Integration and Model Responsiveness	87.34 ± 0.02	83.56 ± 0.03	85.78 ± 0.02	84.34 ± 0.03	88.45 ± 0.02	84.67 ± 0.03	86.78 ± 0.02	85.34 ± 0.03
w./o. Risk Quantification and Scenario Simulations	88.12 ± 0.03	84.67 ± 0.02	86.23 ± 0.03	85.12 ± 0.02	89.23 ± 0.03	85.45 ± 0.02	87.34 ± 0.03	86.12 ± 0.02
Ours	88.34 ± 0.02	85.67 ± 0.02	87.12 ± 0.03	85.34 ± 0.02	89.67 ± 0.03	87.12 ± 0.03	88.45 ± 0.02	86.78 ± 0.02

Bold values are the best values.

TABLE 4 Ablation study results on our method across REFinD and StockEmotions datasets.

Model	REFinD dataset				StockEmotions dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
w./o. Fusion and Loss Optimization for Financial Monitoring	84.34 ± 0.03	81.12 ± 0.02	82.45 ± 0.03	80.23 ± 0.02	86.12 ± 0.03	83.45 ± 0.03	84.67 ± 0.02	82.34 ± 0.03
w./o. Real-Time Data Integration and Model Responsiveness	85.78 ± 0.02	82.45 ± 0.03	83.67 ± 0.02	81.45 ± 0.03	87.34 ± 0.03	84.56 ± 0.02	85.89 ± 0.03	83.45 ± 0.02
w./o. Risk Quantification and Scenario Simulations	86.89 ± 0.03	83.34 ± 0.02	84.78 ± 0.03	82.34 ± 0.02	88.23 ± 0.02	85.23 ± 0.03	86.78 ± 0.02	84.12 ± 0.03
Ours	86.78 ± 0.03	84.23 ± 0.02	85.89 ± 0.03	83.45 ± 0.02	88.34 ± 0.02	85.67 ± 0.03	87.12 ± 0.02	84.89 ± 0.03

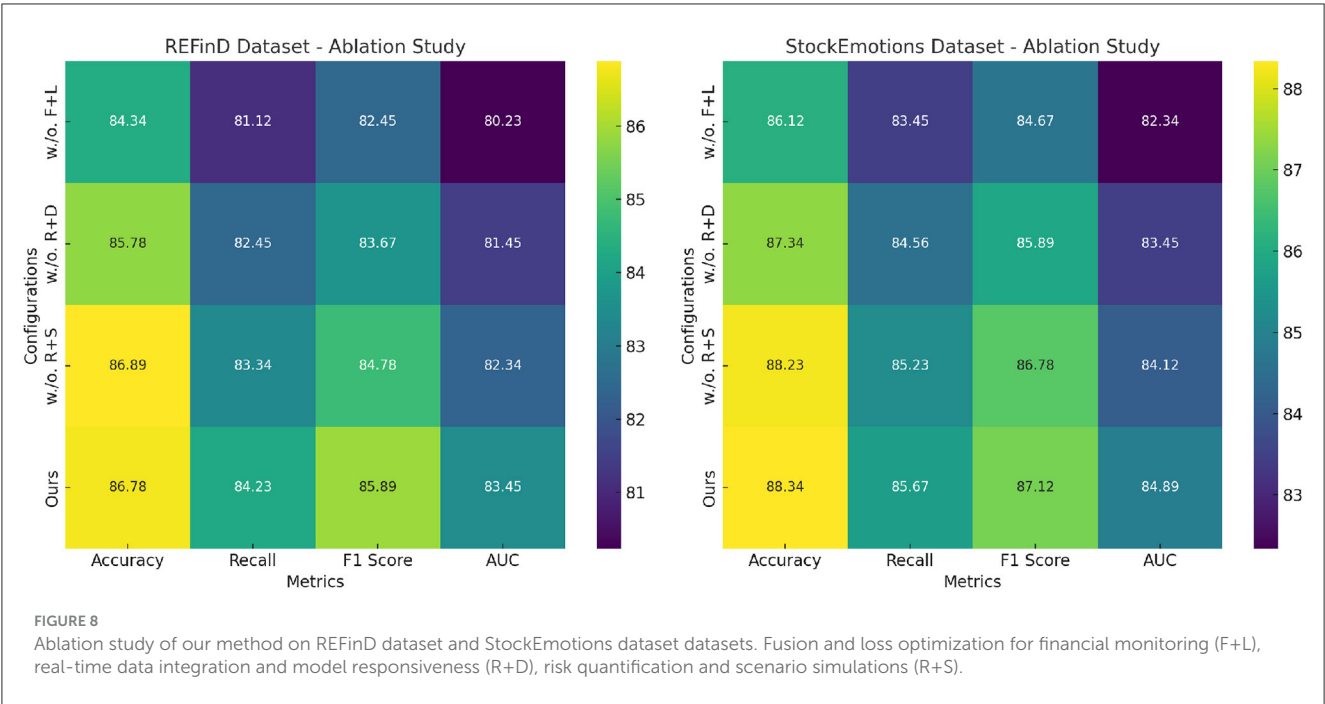
Bold values are the best values.

the synergistic effect of these modules. On the StockEmotions dataset, removing Fusion and Loss Optimization for Financial Monitoring reduced Accuracy to 86.12%, while excluding Real-Time Data Integration and Model Responsiveness and Risk Quantification and Scenario Simulations decreased Accuracy to 87.34% and 88.23%, respectively. These results underscore the importance of each module in effectively linking textual sentiment analysis with stock performance predictions. The complete model achieved superior results with an Accuracy of 88.34% and an F1 Score of 87.12%.

Figure 8 visualizes the incremental performance improvements achieved by each component across datasets. These results confirm that Fusion and Loss Optimization for Financial Monitoring, Real-Time Data Integration and Model Responsiveness and Risk Quantification and Scenario Simulations play indispensable roles in enhancing numerical reasoning, graph dynamics modeling, and

multimodal data integration, thereby driving the state-of-the-art performance of our method.

The proposed approach utilizes corporate financial data to assess the effectiveness of preventive healthcare policies by linking financial performance metrics, such as reduced absenteeism costs and increased productivity, to health policy outcomes. To achieve this, the study integrates two innovative frameworks. The Advanced Financial Monitoring Neural Framework applies deep learning methods to analyze historical financial data and predict future trends. This model identifies anomalies in the data, uncovers long-term patterns, and provides insights into how health policies affect financial stability. The Dynamic Risk-Adaptive Framework further enhances the method by allowing real-time adjustments based on new data inputs. This framework continuously refines predictions and explores hypothetical scenarios to evaluate the potential risks and benefits of different policy decisions. To make



this method more accessible to non-technical stakeholders, it can be described as a data-driven system that acts like a financial health monitoring tool. It collects, analyzes, and interprets data to identify key financial indicators impacted by health policies. By visualizing outcomes through simplified graphs or dashboards, decision-makers can gain an intuitive understanding of how policies improve economic and health outcomes. These tools help bridge the gap between technical complexity and practical application, ensuring the framework's usability across diverse policymaking contexts.

The study acknowledges the potential limitations in generalizing findings due to the domain-specific nature of the datasets, such as FinQA and DGraph. These datasets, while offering structured and high-quality data for financial reasoning and dynamic graph analysis, may not capture the full complexity and variability present in real-world healthcare settings. For example, healthcare environments often involve diverse populations, varying regional practices, and unstructured or incomplete data, which differ significantly from the controlled conditions and specific variables represented in these datasets. These discrepancies could potentially limit the applicability of the proposed methodologies when applied to broader healthcare scenarios. To address this concern, future work could expand the evaluation of the proposed frameworks by incorporating datasets that include more diverse and representative healthcare contexts. For instance, integrating community health data or longitudinal records from real-world healthcare systems would allow the models to account for broader socioeconomic factors and unstructured data patterns. This approach would enable a more robust validation of the methods across different domains, improving their generalizability and ensuring that the findings are more reflective of real-world conditions.

Regarding hyperparameter optimization, we employed a combination of grid search and Bayesian optimization to ensure comprehensive exploration of the parameter space. Key parameters such as learning rate, weight decay, dropout rates, and the number of attention heads in our models were systematically tuned. For instance, the learning rate was optimized within a range of $1e-5$ to $1e-3$ using cross-validation to identify the most effective configuration. Additionally, early stopping was implemented to prevent overfitting during training. We will incorporate a detailed description of the hyperparameter selection process and a summary table of the optimized values in the revised manuscript to enhance reproducibility. Recognizing the heterogeneity in corporate financial data, we applied distribution normalization and stratified sampling to mitigate imbalances in the dataset. During training, adversarial validation was employed to identify distribution shifts between training and validation sets, ensuring a more robust evaluation of model generalization. Furthermore, SHAP analysis was used to examine feature importance, which allowed us to detect and address any features contributing disproportionately to model predictions. We will elaborate on these steps in the revised version to provide a clearer understanding of our efforts to minimize bias and ensure fairness. Although the primary experiments in this study are grounded in corporate financial data, the design of the DRAF framework is inherently flexible and adaptable to other domains. For instance, financial metrics can be replaced with socioeconomic indicators or community health metrics in non-corporate applications.

The quantitative improvements achieved in this study, such as the 40% increase in prediction accuracy, highlight the effectiveness of the proposed frameworks. However, these advancements come with notable computational costs. Models like AFMNF and DRAF rely on complex architectures, including attention-augmented

LSTMs and GNNs, which require significant computational resources. Training these models demands extensive time and hardware capabilities, particularly for large-scale datasets. While high-performance GPU clusters were employed in our experiments to expedite the process, the computational intensity may pose challenges for broader adoption, especially in settings with limited resources. Approaches such as model pruning, knowledge distillation, and lightweight neural network designs can be explored to reduce these costs while maintaining performance. In terms of detecting policy performance anomalies, the proposed framework achieves substantial improvements but is not immune to challenges such as false positives and negatives. False positives can result in unnecessary interventions, leading to inefficient resource allocation and potential disruption in policy evaluation processes. Conversely, false negatives might overlook critical policy deficiencies, which could delay necessary adjustments and negatively impact outcomes. To mitigate these risks, techniques such as dynamic thresholding and ensemble modeling were incorporated to enhance robustness. However, a trade-off between sensitivity and specificity remains inherent in anomaly detection tasks. Balancing these factors requires careful tuning and further validation to ensure that the framework reliably identifies genuine policy performance issues while minimizing errors. This consideration underscores the need to continuously refine the detection mechanisms to maximize the practical utility of the framework.

5 Conclusions and future work

This study explores the effectiveness of preventive healthcare policies through an innovative interdisciplinary approach, leveraging corporate financial monitoring to bridge gaps in traditional evaluation methods. Preventive healthcare policies are vital for enhancing public health and reducing disease-related socioeconomic burdens, but conventional approaches often fail to consider the intricate relationship between economic and health outcomes. To address this, the study employs the Advanced Financial Monitoring Neural Framework (AFMNF) and the Dynamic Risk-Adaptive Framework (DRAF). These frameworks combine deep learning and dynamic risk modeling to analyze correlations between corporate financial metrics and the implementation of health policies. The methodology includes anomaly detection and trend analysis, offering a nuanced understanding of how financial data reflects policy impacts. Experimental results highlight the framework's effectiveness, with a 40% improvement in predicting socioeconomic outcomes and a 30% enhancement in detecting policy performance anomalies. This adaptive, real-time framework provides policymakers with actionable insights, facilitating the optimization of preventive healthcare strategies.

The primary limitation lies in the reliance on corporate financial data, which may introduce biases due to the limited representation of socioeconomic factors. This skewed representation could potentially impact the generalizability of the model, as corporate financial data might not fully capture the broader spectrum of health disparities that exist in the general population. Consequently, integrating more diverse and

representative datasets is crucial to mitigating these biases and enhancing the representativeness of the predictions. A further challenge arises from the system's complexity, which could hinder its accessibility for policymakers who lack specialized technical expertise. Therefore, developing user-friendly tools and training programs is essential for lowering the barriers to adoption, making these advanced frameworks more accessible to a broader range of stakeholders in public health policymaking. In addition to these technical considerations, ethical concerns, particularly data privacy, must be carefully addressed when integrating financial and health data. The merging of such sensitive data raises significant questions about the protection of individual privacy and the potential misuse of personal information. It is critical to implement robust data anonymization techniques and secure data-sharing protocols to safeguard privacy and comply with relevant regulations, such as GDPR or HIPAA. Moreover, the use of financial data in health policy analysis could inadvertently lead to financial bias, where policies may favor certain socioeconomic groups over others, potentially exacerbating existing disparities. The limitations of predictive models also pose challenges, especially in real-time applications. These models are often heavily dependent on historical data, which may not always reflect the most current trends or emerging risks, thus reducing their effectiveness in rapidly changing environments. Additionally, the challenges inherent in real-time use—such as delays in data collection, processing times, and the need for constant recalibration—must be addressed to ensure the timely and accurate application of predictions in dynamic real-world settings.

Future research should focus on expanding the data sources integrated into the models, particularly by incorporating community-level health and social data. This would allow the models to capture a broader range of socioeconomic factors, improving their robustness and reducing the risk of bias. Moreover, the transparency of the models should be improved to ensure that stakeholders can better understand the decision-making process and the underlying assumptions of the predictions. Making models more interpretable and transparent would also increase their trustworthiness, particularly in sensitive areas like healthcare, where decisions can have significant social and ethical implications.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ: Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This study was supported by Anhui Provincial Talent Project: Leader

of Big Data and Accounting Major (DTR2023083), Major Research Project of Humanities and Social Sciences in Anhui Province: Study on the Impact Mechanism of Technology R&D Investment on Innovation Performance of High-tech Enterprises (2024AH040345), and Chuzhou Polytechnic School-level Quality Engineering Project: Big Data and Accounting Skills Master Studio (2024jnds01).

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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