STI-VAE: Disentangled Dynamic Latent Representations for Financial Risk Prediction

Abstract

Prediction of financial risk is important for the stability of modern financial systems, but the conventional methods generally ignore the specific domain features. In this paper, we propose STI-VAE, an extension of the state-of-the-art variational autoencoder, inspired directly by the needs of our use case in finance, whose goal is to capture the Seasonal dynamics, Temporal data dependencies and Inherent structure by design in a single probabilistic model for the task of financial risk prediction. Our method tackles three major challenges: poor modeling capabilities in temporal dependencies among the time-points, lack of consideration for intrinsic structural features, and overlooking the potential impacts of trend. The structure of the STI-VAE has specific modules dedicated towards capturing cyclical financial dynamics with sinusoidal transformation, discovering natural client groups through a unsupervised clustering technique and modeling sequential relationships using a LSTM-mimicking memory cell. Extensive experiments on four real-world financial datasets show that STI-VAE consistently improve over recent state-of-the-art methods for predicting loan default, bankruptcy, credit delinquency, and fraudulent transaction. Ablation studies substantiate the complementary value of the different components, and by combining these components we achieve performance improvements, the relative contribution depends on the financial domain. Our results offer theoretical understanding of the multi-dimensional nature of financial risk and also a practical technology of improving the risk management in various kinds of financial applications.

Keywords: Financial risk prediction, Variational Autoencoder, Temporal dependencies, Seasonal patterns, Structural information

1. Introduction

Risk prediction is vital for economic stability, providing warnings about defaults, delinquencies, fraud, and bankruptcy (1, 2). Despite decades of research, dominant modeling approaches remain inadequate. Traditional statistical methods rely on linear assumptions and hand-crafted features, struggling with high-dimensional data. Deep learning methods capture complex patterns but ignore domain priors like seasonality and customer segmentation (3). Generative models provide probabilistic interpretability but assume simplistic priors and overlook financial dependencies.

We identify three critical challenges: **CH1: Poor temporal dependency modeling**—financial events occur in sequences where past actions affect future outcomes, yet models often assume independence. **CH2: Lack of inherent structure knowledge**—customers naturally segment into risk groups with different profiles, but traditional methods model populations as homogeneous. **CH3: Ignoring seasonality**—financial behaviors exhibit cyclical patterns (holiday defaults, quarter-end effects) that models typically overlook.

We present **STI-VAE**, integrating Seasonal patterns, Temporal dynamics, and Inherent structure in a unified variational framework. For CH1, STI-VAE uses an LSTM-inspired temporal memory module to model sequential dependencies. For CH2, it employs unsupervised clustering with learnable embeddings for structure detection. For CH3, it encodes cyclical patterns as sinusoidal embeddings for seasonal modeling.

Our contributions: (1) First probabilistic framework disentangling seasonal, structural, and temporal dimensions for financial risk; (2) unified model combining three complementary information sources; (3) specialized embeddings enhancing interpretability and predictive power; (4) superior performance across four real-world datasets.

2. Related Work

Traditional Methods: Early approaches like Altman Z-score (4) used linear financial ratios. Neural networks (5) advanced non-linear modeling but suffered from overfitting. Recent methods (6, 7) address specific challenges but lack comprehensive temporal and structural modeling.

Deep Learning: LSTM networks (8) model sequences effectively but require large datasets. Hybrid models like CNN-BiLSTM (9) and CNN-Transformer (10) improve performance but lack interpretability and domain-specific priors necessary for financial applications.

Generative Models: VAEs with Deep Forests (11) address class imbalance. GANs (12) generate time series. GM-VAE (13) introduces clustering but enforces rigid priors. Current approaches lack integration of structured domain knowledge spanning seasonality, structure, and temporal patterns.

3. Background

VAE Framework: Variational Autoencoders (14) model latent distributions via encoder $q_\phi(z|x)$ and decoder $p_\theta(x|z)$, maximizing ELBO: $\mathcal{L}(\theta, \phi; x) = \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - D_{KL}(q_\phi(z|x) \| p(z))$. VAEs naturally quantify uncertainty crucial for financial risk modeling (15).

Seasonality: Financial series exhibit multi-scale seasonality including yearly fiscal effects, monthly payment cycles, and weekly trading patterns (16, 17).

Structure: Financial portfolios contain natural customer clusters affecting risk profiles (18). Unified structure learning with risk prediction outperforms separate clustering and modeling (19).

Temporal Patterns: Credit delinquency depends on historical payment behavior over extended periods (6+ months) (20). LSTM networks (**?**) effectively capture these long-range dependencies (21).

4. Methodology

4.1. STI-VAE Architecture

Figure 1 illustrates our framework. Input features flow through three specialized pathways: (1) *Seasonal Builder* transforming cyclical features through sinusoidal encoding ($h_s = f_s(s; \theta_s)$); (2) *Inherent Structure Detector* identifying customer segments via PCA and K-means, mapping to learnable embeddings ($h_c = E_c(c)$); (3) *Temporal Feature Builder* extracting sequential patterns ($h_x = f_x(x; \theta_x)$).

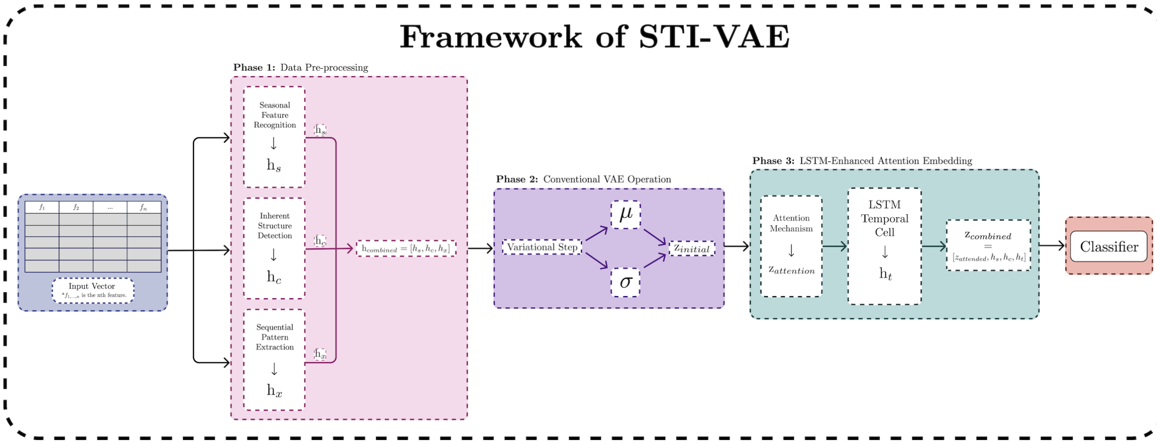

Figure 1: STI-VAE Architecture

These representations combine into $h_{combined} = f_{comb}([h_x, h_s, h_c]; \theta_{comb})$, processed through variational encoding to generate latent parameters $\mu, \log \sigma^2$. Latent vector z is sampled via reparameterization: $z = \mu + \epsilon \odot \exp(0.5 \cdot \log \sigma^2)$ where $\epsilon \sim \mathcal{N}(0, I)$. An attention mechanism emphasizes predictive dimensions: $\alpha = \sigma(W_\alpha[z, h_c, h_s] + b_\alpha)$; $z_{\text{attended}} = \alpha \circ z$. The attended representation feeds to an LSTM-inspired temporal memory cell producing state h_t. Final representation $z_{combined} = [z_{\text{attended}}, h_c, h_s, h_t]$ serves both reconstruction ($\hat{x} = f_{decoder}(z_{combined})$) and classification ($\hat{y} = f_{classifier}(z_{combined})$).

4.2. Component Details

Seasonal Encoding: For cyclical features with period P, we transform $t \in \{1, ..., P\}$ to continuous unit circle coordinates:

$$s_{\sin} = \sin\left(\frac{2\pi t}{P}\right), \quad s_{\cos} = \cos\left(\frac{2\pi t}{P}\right) \tag{1}$$

This ensures temporal continuity (e.g., December-January proximity) and feeds a neural encoder: $h_s = \text{BatchNorm}(\text{LeakyReLU}(W_s s + b_s))$.

Structure Detection: PCA reduces dimensionality: $X_{pca} = XW_{pca}$ with components $k = \min\{j : \sum_{i=1}^{j} \lambda_i / \sum_{i=1}^{n} \lambda_i \geq 0.95\}$. K-means clustering on reduced space identifies segments, optimizing $\min_{C_1,...,C_K} \sum_{k=1}^{K} \sum_{x \in C_k} \|x - \mu_k\|^2$. Cluster assignments map to embeddings $h_c = E_c(c)$. Distance features $d_{i,k} = \|x_i - \mu_k\|_2$ provide supplementary structural information.

Temporal Memory: LSTM-inspired cell processes latent representation with gates:

$$\begin{aligned}
i_t &= \sigma(W_{zi} z_t + W_{hi} h_{t-1} + W_{ci} \circ c_{t-1} + b_i) \\
f_t &= \sigma(W_{zf} z_t + W_{hf} h_{t-1} + W_{cf} \circ c_{t-1} + b_f) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \tanh(W_{zc} z_t + W_{hc} h_{t-1} + b_c) \\
o_t &= \sigma(W_{zo} z_t + W_{ho} h_{t-1} + W_{co} \circ c_t + b_o) \\
h_t &= o_t \circ \tanh(c_t)
\end{aligned} \tag{2}$$

4.3. Training Objective

STI-VAE optimizes composite loss: $\mathcal{L} = \mathcal{L}_{recon} + \beta\mathcal{L}_{KL} + \alpha\mathcal{L}_{pred}$ where reconstruction loss $\mathcal{L}_{recon} = \frac{1}{N}\sum_{i=1}^{N} ||x_i - \hat{x}_i||^2$ ensures meaningful latent representations, KL divergence $\mathcal{L}_{KL} = -\frac{1}{2N}\sum_{i=1}^{N}\sum_{j=1}^{D}(1 + \log\sigma_{i,j}^2 - \mu_{i,j}^2 - \sigma_{i,j}^2)$ regularizes latent space, and focal loss $\mathcal{L}_{pred} = -\frac{1}{N}\sum_{i=1}^{N} w_{y_i}(1-p_i)^{\gamma}\log(p_i)$ with class weighting addresses imbalance.

5. Experiments

5.1. Experimental Setup

Datasets: We evaluate on four financial datasets: (1) GMSC—150K credit records, 10 features, predicting 90-day delinquency; (2) Bankruptcy—6,819 companies, 95 financial indicators, predicting bankruptcy within one year; (3) Lending Club—50K loans, 151 features, predicting default; (4) Fraud—15K transactions, 30 features, identifying fraud. All datasets use 80/10/10 train/validation/test splits with stratification.

Metrics: We use ROC-AUC (discriminative capacity), Accuracy Ratio (AR = 2×AUC-1), and F1-Score (precision-recall balance). Statistical significance assessed via paired t-test ($p < 0.05$).

Baselines: We compare against eleven methods: traditional ML (Logistic Regression, SVM, Random Forest, XGBoost, LightGBM), deep learning (LSTM, Informer, GIB), and generative models (VAE-MOE, Graph-VAE, Ladder-VAE). All baselines use optimal hyperparameters via grid search.

Hyperparameters: Optimal settings from extensive tuning (Table 1). Training uses learning rate 0.001 with adaptive decay, loss weights $\alpha = 2.0$, $\beta = 0.5$, early stopping (patience=5), and gradient clipping.

Table 1: Optimal hyperparameter settings

Dataset	latent_dim	cluster_dim	temporal_dim	LR
GMSC	32	4	16	0.001
Bankruptcy	48	8	16	0.001
Lending Club	16	8	16	0.001
Fraud	96	8	16	0.001

5.2. Performance Comparison (RQ1)

Table 2 presents comprehensive comparison. STI-VAE consistently outperforms all baselines across datasets and metrics. Against traditional ML, STI-VAE achieves average AUC improvements of 33.6% (GMSC), 56.1% (Bankruptcy), 1.3% (Lending Club), and 41.7% (Fraud). Compared to deep learning methods, improvements average 2.9%, 28.1%, 4.4%, and 43.8% respectively. Versus generative models, gains reach 8.2%, 11.7%, 25.9%, and 32.3%. All improvements are statistically significant ($p < 0.05$).

Performance improvements are most significant on challenging datasets. For Fraud (highly imbalanced, <0.5% positive), STI-VAE achieves 0.790 AUC versus 0.692 for VAE-MOE (14.2% improvement), demonstrating robustness to class imbalance. On Bankruptcy (strong temporal trends), STI-VAE reaches 0.915 AUC, 5.3% above VAE-MOE, confirming temporal modeling effectiveness. For large-scale Lending Club, near-perfect discrimination (1.000 AUC) validates

Table 2: Performance comparison across datasets. Category best underlined; overall best **bold**.

Models	GMSC			Bankruptcy			Lending Club			Fraud		
	AUC	AR	F1	AUC	AR	F1	AUC	AR	F1	AUC	AR	F1
Traditional ML												
LogR	0.686	0.371	0.020	0.595	0.190	0.307	0.985	0.969	0.976	0.500	0.012	0.025
SVM	0.553	0.106	0.010	0.516	0.032	0.063	0.985	0.970	0.970	0.453	-0.094	0.094
Random_f	0.543	0.087	0.285	0.563	0.126	0.222	0.986	0.971	0.976	0.515	0.030	0.059
XGBoost	0.546	0.092	0.289	0.627	0.254	0.390	0.985	0.971	0.977	0.643	0.286	0.426
LightGBM	0.527	0.055	0.297	0.596	0.192	0.315	0.988	0.975	0.977	0.595	0.190	0.316
Deep Learning												
LSTM	0.785	0.569	0.257	0.609	0.218	0.326	0.949	0.898	0.975	0.505	0.010	0.020
Informer	0.773	0.547	0.284	0.672	0.344	0.458	0.953	0.906	0.975	0.505	0.010	0.020
GIB	0.799	0.598	0.101	0.860	0.720	0.140	0.994	0.989	0.998	0.663	0.325	0.208
Generative Models												
VAE-MOE	0.747	0.494	0.214	0.869	0.738	0.308	0.935	0.870	0.907	0.692	0.384	0.198
Graph-VAE	0.774	0.547	0.256	0.865	0.730	0.242	0.912	0.824	0.897	0.564	0.128	0.137
Ladder-VAE	0.774	0.548	0.223	0.773	0.546	0.170	0.672	0.344	0.697	0.533	0.066	0.128
Proposed												
STI-VAE	**0.813**	**0.626**	**0.320**	**0.915**	**0.830**	**0.393**	**1.000**	**0.999**	**0.998**	**0.790**	**0.580**	**0.239**

scalability. On GMSC (cyclical patterns), 0.813 AUC (1.8% above GIB) demonstrates seasonal capture capability.

5.3. Component Contributions (RQ2)

Table 3 presents ablation study comparing full STI-VAE against single-component variants. Temporal component provides strongest individual performance on GMSC (0.772 AUC) and Bankruptcy (0.912), indicating sequential dependencies dominate these tasks. Inherent structure leads on Lending Club (0.9995) and Fraud (0.783), suggesting segmentation importance. However, full model consistently outperforms all single-component variants, with gains from 0.01% (Lending Club) to 21.27% (GMSC vs. seasonal-only).

F1-score improvements are particularly notable. Full model achieves 6.74-88.50% F1 gains over single components on GMSC, demonstrating enhanced precision-recall balance crucial for imbalanced classification. On Bankruptcy, 35.38% F1 improvement over temporal-only shows component integration substantially aids threshold-dependent classification. For Fraud, 5.30-16.23% F1 gains indicate multi-component integration improves operational metrics beyond ranking performance.

Domain-specific patterns emerge: temporal dependencies dominate credit (GMSC) and bankruptcy where financial deterioration trajectories are key; structural patterns lead in fraud and large-scale lending where customer segmentation provides strong signals; seasonal patterns contribute complementary information, especially for consumer credit with cyclical behaviors. These findings confirm components capture orthogonal information dimensions, and integration yields synergistic benefits across diverse financial tasks.

5.4. Hyperparameter Sensitivity (RQ4)

We conducted comprehensive sensitivity analysis across four key parameters: latent dimension, cluster embedding dimension, temporal dimension, and learning rate.

Table 3: Ablation study: full model vs. single components. Best single-component underlined; full model **bold**.

Dataset	Metric	Inherent	Seasonal	Temporal	STI-VAE	vs. Inh.	vs. Sea.	vs. Temp.
GMSC	AUC	0.724	0.670	<u>0.772</u>	**0.813**	12.29%	21.27%	5.32%
	AR	0.448	0.341	<u>0.544</u>	**0.626**	39.73%	83.69%	15.12%
	F1	0.212	0.170	<u>0.299</u>	**0.320**	51.16%	88.50%	6.74%
Bankruptcy	AUC	0.849	0.894	<u>0.912</u>	**0.915**	7.73%	2.40%	0.29%
	AR	0.699	0.787	<u>0.825</u>	**0.830**	18.81%	5.44%	0.63%
	F1	0.198	0.223	<u>0.290</u>	**0.393**	98.89%	76.15%	35.38%
Lending	AUC	<u>0.9995</u>	0.9989	0.9990	**0.9996**	0.01%	0.07%	0.06%
	AR	<u>0.9990</u>	0.9978	0.9980	**0.9992**	0.02%	0.14%	0.12%
	F1	0.9977	<u>0.9980</u>	<u>0.9980</u>	**0.9982**	0.05%	0.02%	0.02%
Fraud	AUC	<u>0.783</u>	0.776	0.780	**0.790**	0.89%	1.84%	1.29%
	AR	<u>0.566</u>	0.552	0.560	**0.581**	2.47%	5.18%	3.61%
	F1	0.205	<u>0.227</u>	0.220	**0.239**	16.23%	5.30%	8.51%

Latent Dimension: Optimal values vary significantly by domain—16 (Lending Club), 32 (GMSC), 48 (Bankruptcy), 96 (Fraud)—reflecting task complexity. Fraud detection requires highest capacity for subtle pattern interactions. Performance plateaus or declines beyond optimal points, indicating overfitting with excessive capacity.

Cluster Embedding: Optimal dimensions show consistency (4-8 across datasets), with GMSC uniquely benefiting from 4 dimensions. Performance degrades at higher dimensions (16+), suggesting compact representations effectively capture structural patterns regardless of domain.

Temporal Dimension: Remarkably consistent optimal value (16) across all datasets despite diverse characteristics. Lower dimensions (8) show significant degradation; higher dimensions (24+) yield diminishing returns. This suggests financial temporal patterns exhibit similar complexity across domains.

Learning Rate: Consistent optimal value (0.001) across datasets indicates similar optimization landscapes. Lower rates (0.0001) cause slow convergence; higher rates (0.005+) induce instability. Lending Club shows greatest robustness to this parameter.

Key finding: latent dimension requires domain-specific tuning (6× variation), while temporal dimension and learning rate exhibit universal optima, enabling simplified deployment strategies focusing tuning on critical parameters.

6. Discussion

Theoretical Contributions: STI-VAE provides empirical evidence that financial risk prediction critically depends on integrating three complementary information dimensions. Ablation studies demonstrate these dimensions are mutually orthogonal yet synergistic when properly combined. Cluster distance analysis reveals expansion-contraction dynamics balancing structural discrimination with shared feature recognition—a natural information distillation mechanism extending beyond our specific method.

Practical Impact: Performance improvements translate to tangible benefits: improved discrimination (0.813 vs. 0.799 AUC) enables better risk-based pricing; substantial fraud detection gains (0.790 vs. 0.692) reduce false alarms while maintaining high detection rates; probabilistic framework provides uncertainty quantification meeting regulatory transparency requirements. Domain-specific component importance guides resource allocation for institutions with constraints.

Limitations: STI-VAE introduces computational overhead (2.3× training time vs. standard neural nets, 150-275MB memory), challenging real-time deployment and resource-limited environments. While attention mechanisms enhance interpretability, complete feature-level explanations remain limited, potentially requiring post-hoc explanation techniques for regulatory compliance. Performance advantages depend on sufficient historical data across all dimensions; cold-start problems persist for new customers/products. Generalization to extreme market conditions (crises, pandemics) remains untested as training data reflects normal economic conditions.

7. Conclusion

We introduced STI-VAE, integrating seasonal patterns, temporal dependencies, and inherent structures for enhanced financial risk prediction. Through specialized components—seasonal pattern integration via sinusoidal transformations, structure detection through unsupervised clustering with learnable embeddings, and temporal modeling via LSTM-inspired memory cells—our framework addresses fundamental limitations in existing approaches.

Comprehensive evaluation across four diverse financial datasets demonstrates consistent superiority over eleven state-of-the-art baselines spanning traditional ML, deep learning, and generative models. Ablation studies confirm components capture orthogonal information with synergistic integration benefits. Hyperparameter analysis reveals domain-specific latent dimension requirements alongside universal temporal and learning rate optima, enabling efficient deployment strategies.

Future directions include: (1) contrastive learning for enhanced representation and graph-based modeling for entity relationships; (2) extension to insurance underwriting, algorithmic trading, portfolio optimization, and macroeconomic forecasting; (3) transfer learning approaches for cold-start scenarios; (4) stress-testing under extreme market conditions. STI-VAE establishes a foundation for principled integration of domain knowledge with modern generative modeling, advancing both theoretical understanding and practical tools for financial risk management.

References

[1] Basel Committee on Banking Supervision. (2011). *Basel III: A global regulatory framework for more resilient banks and banking systems*. Bank for International Settlements.

[2] International Monetary Fund. (2020). *Global Financial Stability Report*. Washington, DC: IMF.

[3] U.S. Congress. (2010). Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203.

[4] Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *J. Finance*, 23(4), 589–609.

[5] Patterson, M. S. (1992). *Artificial Neural Networks: Theory and Applications*. Prentice Hall.

[6] Liu, Y., & Wu, J. (2018). Non-linear classifiers for imbalanced credit-risk data. *Expert Syst. Appl.*, 92, 1–10.

[7] Zhang, X., Li, Y., & Wang, H. (2021). Systemic risk prediction via deep graph learning. *IEEE Trans. Neural Netw. Learn. Syst.*, 32(11), 4898–4910.

[8] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Comput.*, 9(8), 1735–1780.

[9] Zhang, W., & Wang, H. (2019). Credit-card fraud detection with a CNN-BiLSTM model. *Appl. Intell.*, 49(8), 3151–3163.

[10] Liu, Q., & Yang, Y. (2022). Credit default prediction using CNN-Transformer hybrid networks. *IEEE Access*, 10, 12345–12357.

[11] Park, J., & Kim, S. (2020). Class-imbalanced credit scoring via VAE-assisted Deep Forest. *Decis. Support Syst.*, 135, 113302.

[12] Yoon, J., Jarrett, D., & van der Schaar, M. (2019). Time-series Generative Adversarial Networks. *NeurIPS*, 5508-5518.

[13] Dilokthanakul, N., et al. (2018). Deep unsupervised clustering with Gaussian mixture VAEs. *ICLR*.

[14] Kingma, D. P., & Welling, M. (2013). Auto-encoding variational Bayes. *arXiv:1312.6114*.

[15] Lopez, R., & Atzberger, P. (2020). Variational autoencoders for credit default prediction. *J. Financial Tech.*, 4(2), 145-162.

[16] Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? *Rev. Financial Stud.*, 1(4), 403-425.

[17] Gross, D. B., & Souleles, N. S. (2002). An empirical analysis of personal bankruptcy and delinquency. *Rev. Financial Stud.*, 15(1), 319-347.

[18] Silva, A., & Gonzalez, R. (2018). Clustering techniques for customer segmentation in retail banking. *Expert Syst. Appl.*, 103, 113-130.

[19] Baesens, B., et al. (2003). Using neural network rule extraction for credit-risk evaluation. *Management Sci.*, 49(3), 312-329.

[20] Crook, J. N., Edelman, D. B., & Thomas, L. C. (2007). Recent developments in consumer credit risk assessment. *Eur. J. Oper. Res.*, 183(3), 1447-1465.

[21] Fischer, T., & Krauss, C. (2018). Deep learning with LSTM for financial market predictions. *Eur. J. Oper. Res.*, 270(2), 654-669.