

Original Article

# Systematic Approach to Enhance Explainable Memory-Augmented Hybrid Graph Attention Framework for Intelligent Banking Risk Prediction

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**Abstract** - Intelligent prediction of banking risk has drawn more attention with the emergence of the digitization of financial systems due to increasing threats from financial fraud. Standard machine learning and deep learning frameworks have struggled to identify hidden relational dependencies and behavioral patterns in customer datasets in the banking domain. To address the limitations of existing frameworks, an Explainable Memory-Augmented Hybrid Graph Attention Intelligent Framework is designed for intelligent banking risk prediction. In this framework, the following components are included for effective risk prediction: dense feature learning for banking data, semantic graph attention for identifying relational dependencies in banking data, memory augmentation for recalling historical representations of banking risks, and explainable attention-based fusion. A comparative study of the proposed framework with the latest approaches, like Artificial Neural Network, Random Forests, Support Vector Machines, Graph Convolutional Networks, and Graph Attention Networks, reveals the superiority of the proposed model, with 90.81% classification performance and an ROC-AUC of 0.940.

**Keywords** - Banking Risk Prediction, Graph Attention Networks, Adaptive Memory Learning, Hybrid Deep Learning, Financial Intelligence.

## 1. Introduction

Given the rapid advancement of transaction platforms, financial services, and online banking, there is a critical need to develop efficient risk prediction systems for banks. This necessitates analysing large, voluminous datasets, including demographic information, property ownership, and socio-economic indicators. Accurately identifying high-risk customers is essential for minimizing losses, ensuring stable bank operations, and supporting sound financial decision-making.

The banking risk prediction systems use several ensemble methods to categorize hazards based on financial data. These approaches show decent performance on banking datasets, but they are limited in their ability to capture hidden customer relationships and interactions. Also, standard machine learning approaches do not model banking intelligence or consider client relations in relational finance. The modelling of nonlinear customer intelligence and financial habits has yielded impressive results with deep learning. These algorithms can learn complex financial behaviours and client dangers. However, they are not capable of capturing the customer relationships and neighbourhood linkages in banking databases.

Recently, Graph Neural Networks (GNNs) have demonstrated strong performance in intelligent financial learning by capturing latent consumer associations. For example, the CDGAT model, which is based on a graph attention network, was used to predict credit card default, and relational financial intelligence was improved through neighbourhood aggregation.

One of the major problems in creating intelligent finance systems is the lack of clarity and transparency in decision-making procedures. Not only should the model make accurate predictions, but it should also explain why certain risks were considered and why certain financial decisions were taken. However, most models, whether machine learning algorithms or graph-based approaches, are black boxes.

Despite the advancements in intelligent banking risk prediction frameworks, several challenges persist. Most machine learning and deep learning approaches are unable to capture hidden customer relationships and neighborhood dependency. Additionally, most graph learning approaches do not provide historical reasoning about banking risk or offer explainable financial intelligence. Few studies have addressed the integration of semantic graph intelligence, adaptive



memory fetching, attention fusion, and hybrid banking representation learning into intelligent financial systems.

Accordingly, this paper discusses the implementation of an Explainable Memory-Augmented Hybrid Graph Attention Framework for Intelligent Banking Risk Prediction. The proposed system incorporates statistical intelligence learning, dense neural learning, semantic graph attention learning, adaptive memory retrieval, and explainable attention fusion.

Intelligent learning based on statistics enhances clients' financial understanding and risk classification. Deep learning is useful in detecting the nonlinear interrelations in the banking industry. However, semantic graph learning aids in discovering the hidden connections in the banking industry and its clients. The graph attention network model facilitates neighborhood intelligence in banks, whereas adaptive memory recall enhances risk-based banking reasoning.

The main contributions of this paper are described below:

- An Explainable Memory-Augmented Hybrid Graph Attention Framework is proposed for intelligent banking-risk prediction.
- Semantic customer graph learning is proposed for intelligent financial learning with relational banking intelligence and neighborhood customer interaction.
- Adaptive memory retrieval is developed to increase historical banking risk reasoning capability.
- Explainable attention fusion is proposed to provide transparent banking-risk prediction.
- The Superior performance of the proposed method for intelligent banking risk prediction is demonstrated in comprehensive experiments in comparison with traditional machine learning, deep learning, and GNN baselines.

The novelty of this study to propose the Explainable Memory-Augmented Hybrid Graph Attention Framework (EM-HGAF) for intelligent banking-risk prediction. Different from traditional machine learning, deep learning and existing graph neural network methods, EM-HGAF incorporates semantic customer graph learning, adaptive memory retrieval, and explainable attention fusion into a unified architecture, where feature learning, relation modelling and risk interpretation are not separated.

The framework aims at learning meaningful customer relations with semantic graph representations, exploiting historical risk patterns through memory augmentation and generating transparent and interpretable banking-risk predictions through an explainable attention mechanism. This design restructures banking-risk prediction from independent feature-based analysis to a holistic and deployable intelligent financial framework with relational learning, historical

reasoning and explainable decision support. In this way, the proposed EM-HGAF model provides a practical and context-aware way for trustworthy banking-risk assessment in the real-world heterogeneous and imbalanced financial settings.

## 2. Related Work

Generally, banking risk prediction systems apply various machine learning methods and ensemble learning for intelligent financial classification. Although such machine learning models can achieve adequate predictive performance when handling structured banking datasets, they may struggle to learn hidden customer relationships and complex, nonlinear, and intelligent financial interactions. Wu et al. [1] proposed a credit card default prediction model, CDGAT, that used a graph attention model to learn relational finance. Owusu et al. [2] developed a deep learning framework that learned from imbalanced datasets for intelligent financial risk prediction.

Runchi et al. [3] developed a novel ensemble learning framework for Logistic Regression using heterogeneous balancing and weighting techniques in the intelligent financial classification task. Another framework developed by Rao et al. [4], based on hybrid ensemble learning and a self-attention mechanism, showed promising results for improving banking risk prediction performance.

Graph-based financial intelligence learning models have received considerable attention in recent years due to their ability to learn from hidden relational structures. To address this problem, Shiam et al. [5] proposed applying explainable artificial intelligence to improve credit risk prediction and increase transparency within financial intelligence learning. Furthermore, Talaat et al. [6] demonstrated improved banking risk reasoning using deep learning and explainable artificial intelligence for credit card default prediction.

Xia et al. [7] have developed the XGBoost-B-GHM model for credit scoring using the XGBoost algorithm, feature selection, and a gradient-harmonizing loss function. It proved accurate and efficiently handled imbalanced data in financial datasets. Liu et al. [8] introduced a framework, LG-GNN, that learns local and global customer relationships using graph neural networks to detect defaults.

Furthermore, Shi et al. [9] developed an efficient graph representation learning framework to predict intelligent credit risk. This paper demonstrates the capability of graph-based financial intelligence learning models to uncover hidden customer relationships.

Additionally, explainable artificial intelligence systems have gained popularity in recent years due to the need for transparency in this area. Furthermore, graph neural network models also demonstrated efficiency in recent intelligent

banking applications. Wang et al. [10] discussed the advantages and disadvantages of applying generative models in tabular financial data. Various models are used for tabular generation (Kim et al.). [11] identified some of them, including the Autoencoder, Generative Adversarial Networks (GANs), and Diffusion Models.

The authors highlighted the ability of these models to generate artificial data, perform data augmentation, and handle imbalanced data in the finance and healthcare sectors. Pathak et al. [12] suggested using an XAI model for assessing credit risk, which uses ML algorithms such as XGBoost, LightGBM, and Random Forest. The authors applied SHAP and LIME to make the interpretation of results more transparent. According to the experiment's findings, the model's accuracy in predicting credit risk is quite high.

Chang et al. [13] designed a graph neural network-based framework to perform intelligent online transaction risk assessments through a probabilistic prediction approach. Li [14] introduced graph neural network frameworks for predicting enterprise risks in financial intelligence. Morshed [15] further analyzed the idea of explainable graph intelligence and financial spillover effects within intelligent financial systems.

Recent studies have also addressed graph learning and regulatory intelligence models for banking applications. Nasir [16] specifically developed an explainable graph neural network model for intelligent interbank contagion surveillance and financial soundness monitoring. Additionally, Khanvilkar and Kommuru [17] introduced the idea of regulatory graph intelligence and generative artificial intelligence to monitor transactions and provide explanations in the banking environment. Liu and Kok [18] proposed the use of heterogeneous topological graph neural networks for intelligent credit rating predictions for banks. Hu et al. [19] developed self-explainable graph neural networks for intelligent risk predictions through explainable graph intelligence learning.

In addition, recent research has investigated explainable banking fraud detection and intelligent financial risk management systems. Ononiwu et al. [20] proposed a machine learning-based solution to identify fraud in the mobile banking environment while optimizing the risk analysis process. On the other hand, further studies have been conducted [21, 22] to assess the feasibility of applying explainable artificial intelligence techniques for fraud detection in banks and for efficient financial risk management. Challenges related to explainability requirements within financial artificial intelligence and regulatory banking were also discussed by the BIS Financial Stability Institute [23]. Longo [24] explored the challenge regarding explainability within intelligent artificial intelligence models.

Furthermore, recent research efforts also considered the ideas of generative artificial intelligence and tabular foundation models for banking analytics. TabPFN foundation model [25] also demonstrated effectiveness for tabular learning and intelligent feature representation learning.

However, the existing approaches for banking risk prediction have some limitations despite achieving remarkable success in the field. Firstly, the existing techniques cannot efficiently capture hidden relational customers and neighborhood intelligent financial interactions. Secondly, existing graph learning models are less efficient due to their limited adaptability to historical banking risk reasoning and to explainable learning for intelligent financial predictions. Lastly, very few researchers have considered the combination of semantic graph intelligence, adaptive memory retrieval, explainable attention fusion, and hybrid representation learning.

Machine learning and graph neural network methods have shown promising performance in banking fraud detection, but existing techniques are still limited in their ability to properly interpret and capture heterogeneous transaction relationships and aggregate multi-level structural information. These limitations may limit the approach's ability to identify complex fraud patterns in real-world banking environments.

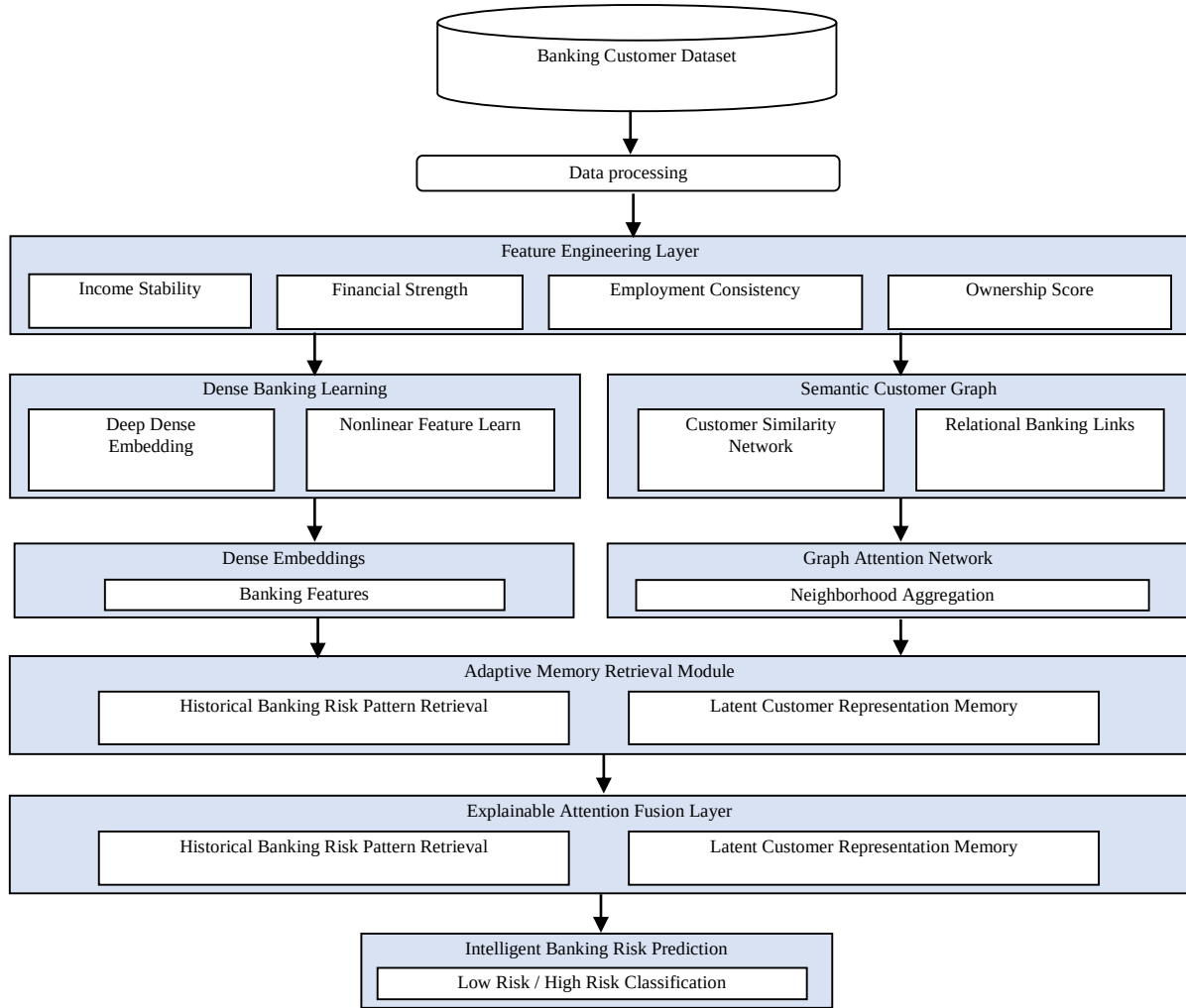
To address this gap, the present study proposes an Explainable Memory-Augmented Hybrid Graph Attention Framework (EM-HGAF) for intelligent bank risk prediction. They propose a unified framework that integrates statistical banking intelligence, semantic graph learning, adaptive memory retrieval and explainable attention fusion for learning better relational representations and improving transparent and interpretable banking-risk prediction.

### 3. Methodology

The Explainable Memory-Augmented Hybrid Graph Attention Model introduced in this study is designed to improve intelligent banking risk prediction by combining the statistical banking intelligence, dense neural representation learning, semantic graph attention learning, adaptive memory access, and explainable attention learning

#### 3.1. Description of the Proposed Framework

The current research proposes an Explainable Memory-Augmented Hybrid Graph Attention Framework for Intelligent Banking Risk Prediction. The proposed framework exploits statistical knowledge in banking intelligence, dense neural feature learning, semantic graph attention, memory-adaptive retrieval of financial information, and attention-based explanation fusion. However, prior research in banking risk prediction has overlooked the role of underlying customer relationships, the nonlinear behaviour of customers' finances, and past bank risks.



**Fig. 1 Proposed hybrid graph attention model for explainable memory-augmented risk prediction**

The proposed hybrid Graph Attention Model for Explainable Memory-Augmented Risk. The prediction is illustrated in Figure 1. Firstly, the customer data of the banking business is collected, and statistical attributes are derived from it. The customer's bank behavior's non-linear relationship will lead to the learning of dense banking knowledge. Secondly, on the basis of similarity in relations of clients in the professional, ownership, financial, and regional aspects, a semantic graph of the client is to be built. Graph attention networks will learn neighborhood banking information, and adaptive memory networks will perform memory retrieval.

### 3.2. Banking Customer Dataset

Data preprocessing, Feature Engineering Layer, Income Stability, Financial Strength, Employment Consistency, Ownership Score, Dense Banking Learning Deep Dense Embeddings, Nonlinear Feature Learn, Semantic Customer Graph, Customer Similarity Network, Relational Banking Links, Dense Embeddings, Banking Features, Graph Attention Network, Neighborhood Aggregation, Adaptive

Memory Retrieval Module, Historical Banking-Risk Pattern Retrieval, Latent Customer Representation Memory, Explainable Attention Fusion Layer, Dense Features + Graph Features + Memory Features, Adaptive Importance Weighting, Intelligent Banking-Risk Prediction, Low Risk / High Risk Classification.

The banking customer dataset consists of demographic, financial, employment, ownership, and regional attributes collected from banking customers for intelligent banking risk prediction [26].

Let the banking dataset be represented as follows:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

Where  $D$  denotes the banking customer dataset,  $x_i$  represents the customer feature vector,  $y_i$  denotes the banking-risk label, and indicates the total number of banking customers.

Each banking customer feature vector is expressed as:

$$x_i = [income_i, age_i, experience_i, profession_i, ownership_i, employment_i] \quad (2)$$

where the feature vector includes customer income, age, banking experience, professional category, ownership information, and employment status, the banking-risk binary target label is represented as:

$$y_i \in \{0,1\} \quad (3)$$

where the binary label  $y_i = 0$  represents a low-risk banking customer and  $y_i = 1$  represents a high-risk banking customer. The banking dataset representation stage organizes customer financial information for intelligent banking-risk analysis and relational banking intelligence learning.

### 3.3. Statistical Feature Extraction

Statistical feature extraction is performed to enhance banking risk prediction to deepen the understanding of customer financial behavior. Multiple statistical measures are extracted from the banking dataset to improve the feature separability and hidden banking pattern analysis. The extracted statistical features include mean, standard deviation, variance, kurtosis, skewness, and correlation coefficients.

Initially, the mean value is computed to determine the average distribution of banking customer observations:

$$Mean = \frac{1}{m} \sum_{i=1}^m y_i \quad (4)$$

Where  $m$  denotes the total number of observations and  $y_i$  represents banking feature values. The mean feature improves the normalization of banking features and the estimation of central tendency. Next, the standard deviation is computed to measure the dispersion of banking customer observations around the mean value:

$$std = \sqrt{\frac{1}{m} \sum_{i=1}^m (y_i - Mean)^2} \quad (5)$$

Standard deviation is a measure of the financial variability of the customers. It improves the analysis of the spread of banking risk. The variance feature is also the mean square deviation of the banking observations from the mean value.

$$Variance = \frac{1}{m} \sum_{i=1}^m (y_i - Mean)^2 \quad (6)$$

Variance analysis improves the learning of hidden banking risk patterns and the estimation of customer financial variability. The kurtosis feature is computed to measure the tailedness of banking feature distributions:

$$Kurtosis = \frac{1}{m} \sum_{i=1}^m \left( \frac{y_i - Mean}{std} \right)^4 \quad (7)$$

Kurtosis helps identify abnormal banking behavior and extreme financial patterns among customers.

The skewness feature is calculated to estimate asymmetry in banking feature distributions:

$$Skewness = \frac{\sum_{i=1}^m (y_i - Mean)^3}{(m-1) \times std^3} \quad (8)$$

Skewness improves asymmetric banking risk analysis and understanding of financial imbalance.

Finally, the correlation coefficient is computed to estimate the relationship strength among banking customer features:

$$CC = \frac{\sum (y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum (y_i - \bar{y})^2 \sum (x_i - \bar{x})^2}} \quad (9)$$

The correlation coefficient improves the learning of hidden financial dependencies and the analysis of banking feature relationships. The extracted statistical banking features are combined to form enhanced representations of banking intelligence for intelligent banking risk prediction analysis.

### 3.4. Dense Banking Intelligence Learning

The engineered banking features are processed using dense neural learning to capture nonlinear banking intelligence and hidden financial interactions among banking customers. Dense banking intelligence learning improves customer representation learning and latent financial behavior analysis.

The dense banking transformation is represented as:

$$h_i = \sigma(Wx_i + b) \quad (10)$$

Where  $W$  denotes the trainable weight matrix, represents the bias vector,  $\sigma(\cdot)$  denotes the nonlinear activation function, and  $h_i$  represents the dense banking embedding.

The dense learning stage accurately captures nonlinear financial relationships, hidden customer behaviors, latent banking intelligence patterns, and financial interaction dependencies. Consequently, the dense banking intelligence layer significantly improves the ability for financial representation learning and the performance of banking-risk feature extraction.

### 3.5. Semantic Customer Graph Construction

In this connection, a semantic customer graph is developed to identify any hidden relationships among banking customers. Graph learning helps model the relationship between neighboring customers and provides banking intelligence based on the mined data.

The semantic customer graph is represented as:

$$G = (V, E) \quad (11)$$

where  $V$  denotes customer nodes and  $E$  represents semantic customer relationships.

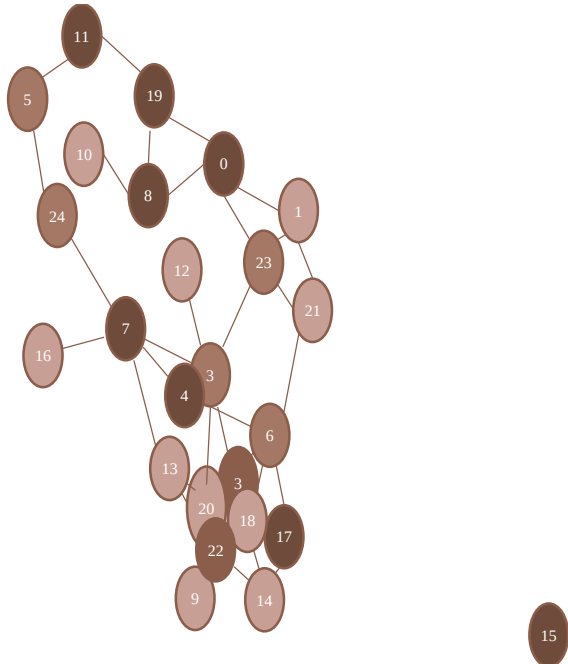
The adjacency relationship between banking customers is defined as:

$$A_{ij} = \begin{cases} 1, & \text{if } \text{similarity}(x_i, x_j) > T \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

where  $A_{ij}$  denotes semantic customer connectivity and  $T$  represents the similarity threshold.

The connection among customers stems from their shared professional backgrounds, ownership, financial characteristics, and place of origin.

This method enhances the learning capability of relational banking intelligence due to the dependencies among bank customers.



Total Nodes: 442008

Total Edges: 40092

Fig. 2 Semantic customer graph

Figure 2 illustrates how to create the semantic customer graph. Customers within the banks are connected based on their similarity in career profiles, behavior, property information, and location. Using a semantic graph representation, the model presented herein can uncover underlying connections among customers and generate neighborhood-based banking insights.

### 3.6. Graph Attention Learning

The Graph Attention Network (GAT) is used in this approach for learning the adaptive aggregation of neighborhood-aware intelligence of the banks, as well as detecting any hidden relations between the bank customers. The graph attention algorithm assigns dynamic weights to the most influential neighbors. This flexible aggregation process greatly improves the learning of hidden customer dependencies and the analysis of banking risk propagation.

The graph attention mechanism assigns higher importance weights to highly influential neighboring customers during the propagation of relational information. The flexible aggregation process substantially enhances the learning of hidden customer dependencies and the analysis of banking risk propagation.

The graph attention coefficient is represented as:

$$\alpha_{ij} = \text{softmax}(\text{LeakyReLU}(a^T [Wh_i \parallel Wh_j])) \quad (13)$$

Where  $V$  denotes the graph attention importance coefficient,  $\parallel$  represents feature concatenation,  $W$  denotes trainable attention parameters, and  $h$  denotes transformed customer embeddings.

The graph attention coefficient gives more weight to the closeness of other customers for collecting information in the banking industry. The network emphasizes customers with high transactional correlation relative to their peers, enabling it to identify interconnections among customers.

The updated graph embedding is represented as:

$$z_i = \sum_{j \in N(i)} \alpha_{ij} Wh_j \quad (14)$$

where  $A_{ij}$  denotes the relational banking embedding, and  $T$  represents neighboring customer nodes.

The updated graph embedding integrates neighborhood banking intelligence using attention-guided aggregation. This process improves relational customer representation learning and hidden banking-risk propagation analysis.

The graph attention learning stage effectively captures relational banking intelligence, neighborhood customer influence, hidden financial dependency patterns, and banking-risk propagation behavior. The graph attention workflow is illustrated in Figure 3.



Fig. 3 Graph attention learning

### 3.7. Adaptive Memory Retrieval

An adaptive memory retrieval module is proposed to store and recall historical banking-risk information and financial reasoning for intelligent decision-making. The memory mechanism supports the framework in learning hidden financial patterns and in improving its ability to forecast and analyze banking risk behavior more effectively. The memory mechanism enables the framework to learn hidden financial patterns and also to improve its ability to forecast and analyze banking risk behavior more efficiently.

The banking memory matrix is represented as:

$$M = [m_1, m_2, m_3, \dots, m_k] \quad (15)$$

The memory similarity score is computed as:

$$s_i = \text{softmax}(z_i M^T) \quad (16)$$

The retrieved banking memory representation is expressed as:

$$r_i = \sum s_i m_i \quad (17)$$

where  $r_i$  denotes the retrieved banking intelligence representation.

The adaptive memory retrieval stage improves historical banking-risk reasoning, latent customer intelligence learning, adaptive financial representation analysis, and memory-guided banking prediction capability. The memory retrieval mechanism enables the framework to reuse previously learned banking-risk representations and enhances intelligent financial reasoning capability. The adaptive memory retrieval workflow is illustrated in



Fig. 4 Adaptive memory retrieval

### 3.8. Explainable Attention Fusion

Dense, graph, and memory embeddings are fused using an explainable attention mechanism to improve transparent integration of banking intelligence. The explainable attention mechanism dynamically prioritizes highly influential banking risk features during the final aggregation of financial intelligence.

The fusion representation is expressed as:

$$f_i = [h_i \parallel z_i \parallel r_i] \quad (18)$$

The fusion representation combines nonlinear banking

intelligence, relational customer intelligence, and historical banking-risk reasoning.

The explainable attention mechanism is represented as:

$$\beta_i = \text{softmax}(W_f f_i) \quad (19)$$

Where  $\beta_i$  denotes the explainable attention weight.

The final explainable banking representation is represented as:

$$F_i = \beta_i f_i \quad (20)$$

The proposed attention fusion mechanism depicted in Figure 5 uses several aspects of the banking sector to generate a meaningful banking representation. In this context, the

model places greater emphasis on relevant banking risk attributes, such as income stability, job stability, financial stability, and ownership traits. Such an approach enhances the interpretability of the attention fusion framework while facilitating better learning of significant banking risk attributes.

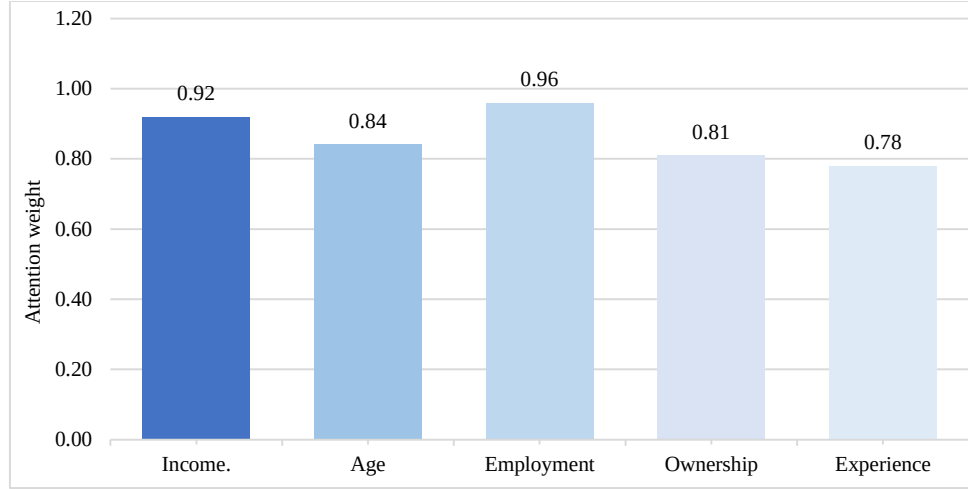


Fig. 5 The explainable attention fusion process

### 3.9. Banking-Risk Prediction

The final banking-risk prediction layer classifies banking customers into low-risk and high-risk categories using the learned banking intelligence representations. The final banking-risk prediction function is represented as:

$$\hat{y}_i = \text{softmax}(W_o F_i + b_o) \quad (21)$$

where denotes the predicted banking-risk probability.

The classification loss function is defined as:

$$L = -\sum y_i \log(\hat{y}_i) \quad (22)$$

The suggested method uses AdamW as the optimizer

during training. The financial intelligence vectors generated by this method enable the banking risk predictor to categorize customers into low- and high-risk groups.

## 4. Results and Discussion

The section conducted a large-scale banking customer risk prediction dataset containing demographic, financial, ownership, employment, and regional customer attributes. The dataset includes customer financial behavior data required for intelligent banking risk analysis and prediction. The experiments have been carried out using the Python programming language, which used the PyTorch, PyTorch Geometric, and Scikit-Learn packages. The proposed EM-HGAF network was optimized, and it took us 100 epochs to successfully train the model.

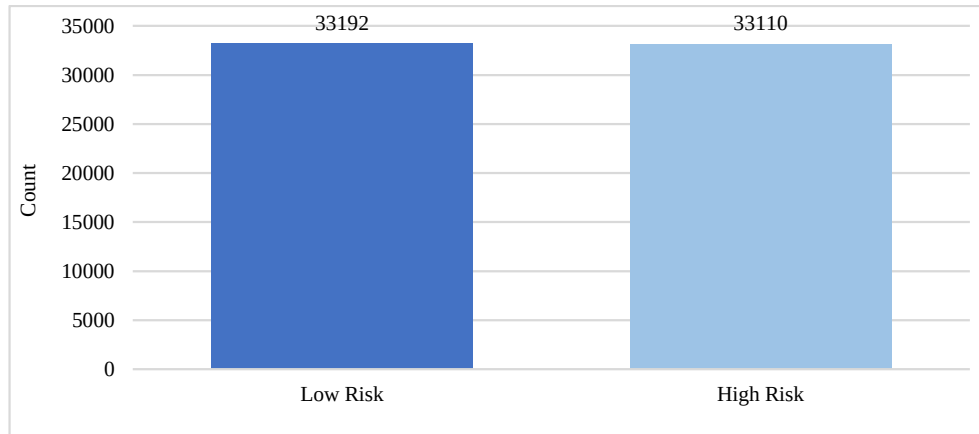


Fig. 6 Banking-Risk class distribution



Fig. 7 Feature correlation analysis

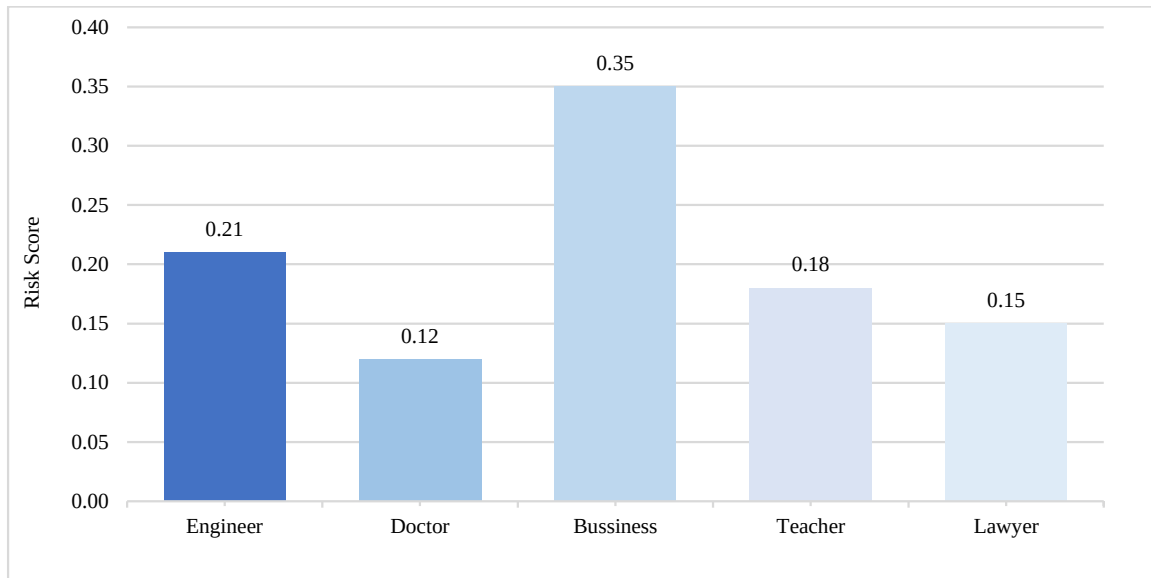


Fig. 8 Professional banking-risk distribution

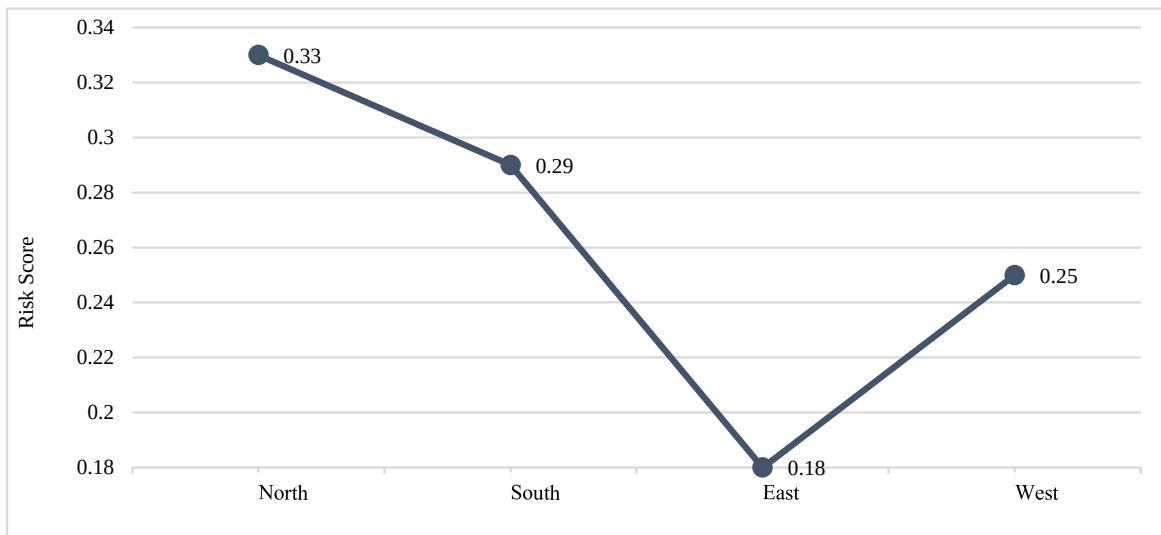


Fig. 9 Regional banking-risk analysis

Banking-Risk class distribution for banking risk classes is illustrated in Figure 6. To improve model stability and the learning process, data preprocessing and normalization were performed before training. The correlation analysis of banking clients' features is illustrated in Figure 7. Financial stability, employment consistency, ownership, and income are analysed. Such an analysis could help identify any dependencies related to banking risks.

The banking risks across professional categories are shown in Figure 8. It was found that certain professional categories exhibited greater financial instability and banking risks than others. Thus, the constructed graph, with the same attributes for each professional category, demonstrates the importance of this step.

Furthermore, an analysis of the regional banking risks was done to examine the impact of geographical and socio-economic factors on banking risks. As illustrated in Figure 9, the region and socio-economic conditions significantly affect customer financial behavior.

#### 4.1. Performance Evaluation Metrics

The effectiveness of the Performance Evaluation Metrics of the proposed EM-HGAF framework was analyzed by exploring many performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

The classification accuracy is represented as :

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

The accuracy metric measures the overall banking-risk prediction performance of the framework.

The precision metric is represented as:

$$Precision = \frac{TP}{TP+FP} \quad (24)$$

The recall metric is expressed as

$$Recall = \frac{TP}{TP+FN} \quad (25)$$

Recall measures the framework's ability to identify high-risk banking customers.

The metric of F1-score is expressed as:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (26)$$

The capacity of the proposed EMHGAF model was evaluated by the use of Receiver Operating to classify the two banking risk classes at different levels of categorization.

#### 4.2. Comparative Banking-Risk Prediction Analysis

The Explainable Memory-Augmented Hybrid Graph Attention Model was evaluated against several benchmark models, including some from classical machine learning, deep learning, and graph neural network frameworks. Some of the models used for benchmarking include Random Forest, SVM, ANN, GCN, and GAT.

The EM-HGAF outperforms because of the semantic customer graph learning, adaptive memory retrieval, and explainable attention fusion. These components improve relational representation learning and improve the accuracy of banking-risk prediction.

The experimental results show that EM-HGAF is effective for heterogeneous and imbalanced banking data; the proposed EMHGAF model can effectively deal with the heterogeneous and imbalanced nature of the banking dataset.

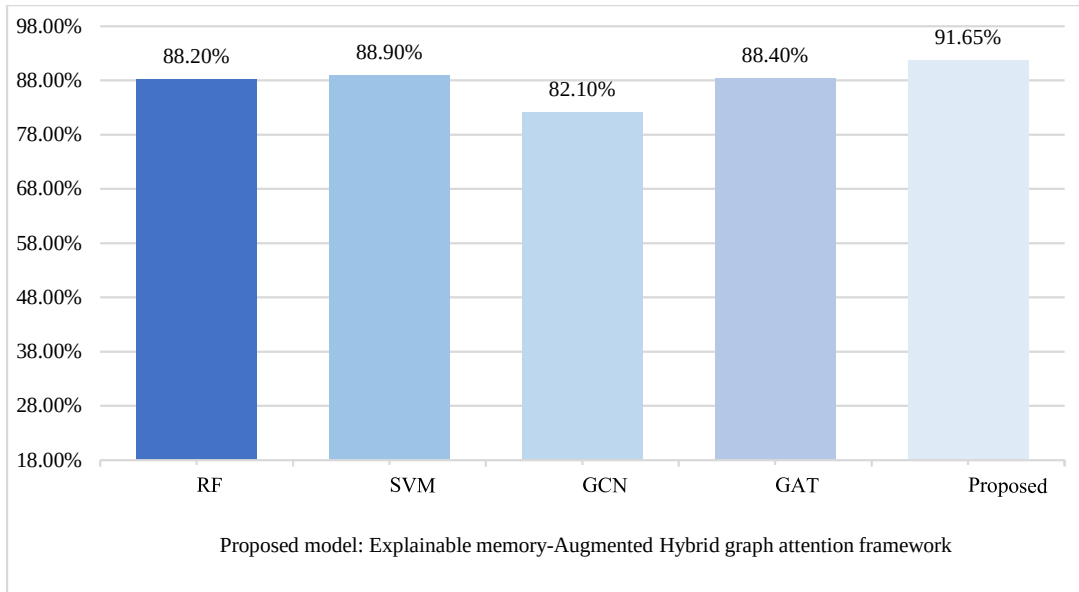
The results were similar across all parameters and revealed that the model accurately discriminated between the two banking risk classes.

**Table 1. Comparative performance analysis of the proposed banking-risk prediction framework**

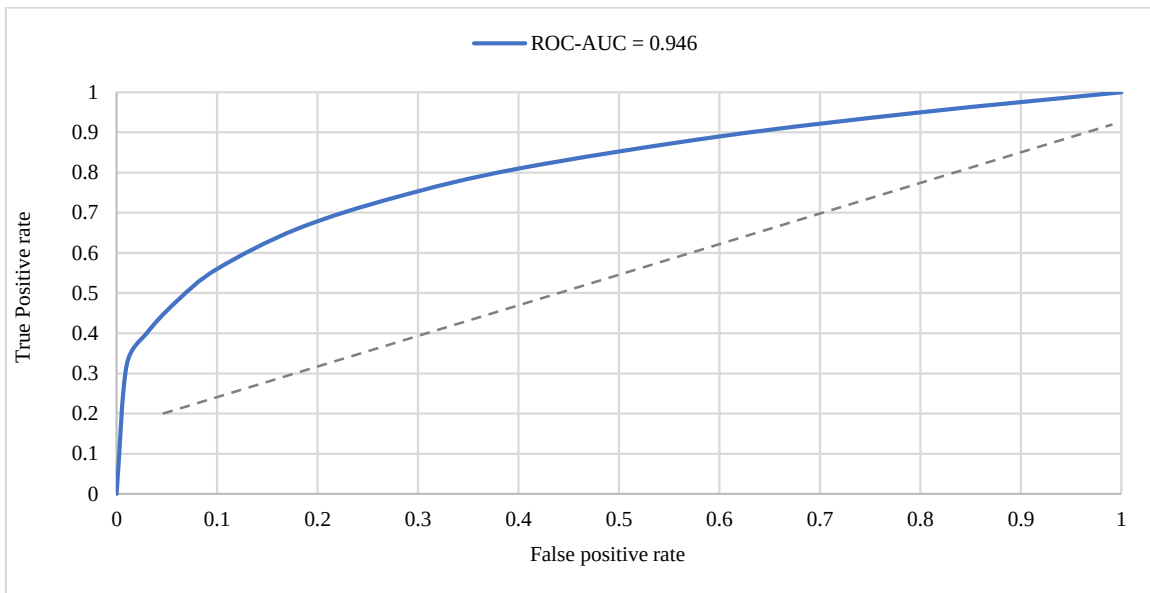
| Model         | Accuracy | Precision | Recall | F1-score | ROC-AUC |
|---------------|----------|-----------|--------|----------|---------|
| Random Forest | 88.20    | 87.90     | 88.10  | 87.50    | 0.910   |
| SVM           | 84.50    | 83.80     | 84.00  | 83.80    | 0.870   |
| ANN           | 88.90    | 89.10     | 88.00  | 88.10    | 0.920   |
| GCN           | 82.10    | 81.40     | 82.00  | 81.30    | 0.850   |
| GAT           | 88.40    | 88.90     | 88.00  | 88.00    | 0.930   |
| EM-HGAF       | 90.81    | 91.00     | 91.00  | 91.00    | 0.940   |

Table 1: Comparative Performance Analysis of the proposed EMHGAF framework achieved an accuracy of 90.81% and ROC-AUC of 0.940, indicating high discriminate capacity between the two classes of banking risk. The classification performance of the model was attributed to the

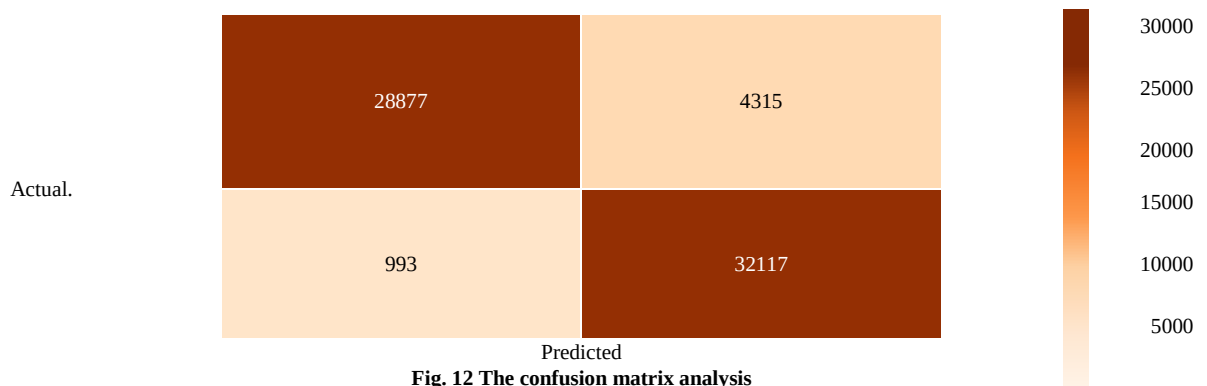
fusion of Semantic Graph Intelligence, Adaptive Memory Retrieval and Explainable Attention Fusion. The ROC curve and confusion matrix further confirmed its capability to categorize the risk classes with very low false-positive and false-negative rates.



**Fig. 10 Performance comparison of proposed explainable memory-augmented hybrid graph attention framework with baseline models**



**Fig. 11 ROC curve analysis**



**Fig. 12 The confusion matrix analysis**

Figure 10 depicts the comparative experimental analysis. From the above analysis, it is clear that the designed model outperforms existing baseline models for bank risk prediction. Firstly, the semantic customer graph proved helpful in detecting latent relationships among customers in the banking industry. Secondly, the adaptive memory retrieval helped the model learn about the history of banking risks. In addition, the explainable attention method enabled dynamic emphasis of significant banking risk factors. The ROC analysis of the suggested EMHGAF model is shown in Figure 11. The ROC-AUC of 0.940 was obtained using the model, indicating its discriminative power for banking risk. The ROC analysis indicates that the proposed model is sensitive in predicting banking risk with a minimum false-positive rate. Figure 12 shows the confusion matrix analysis of the proposed model. The results shown above indicate that the designed model can detect high-risk banking customers.

#### 4.3. Graph Intelligence and Explainable Financial Analysis

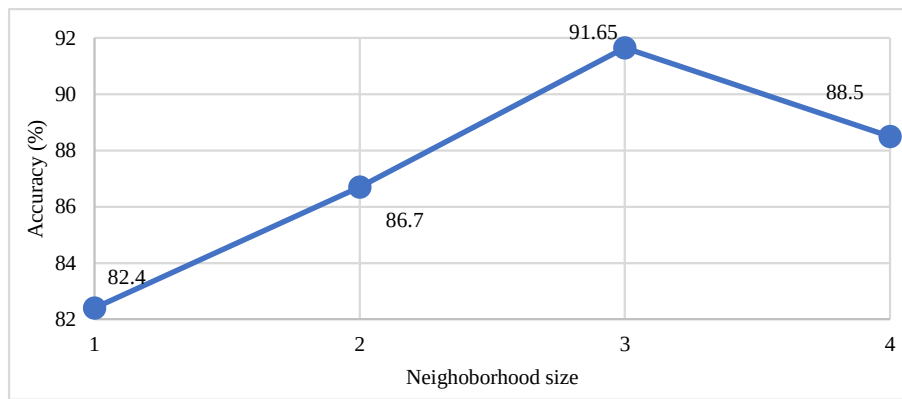
The complexity of the graph analysis is provided in Table 2 to analyze the impact of neighborhood sizes on the learning

process for relational banking intelligence. From the experimental findings, it is clear that moderate-sized neighborhoods perform better than others because small neighborhoods lack information, and large neighborhoods introduce noise into client relations.

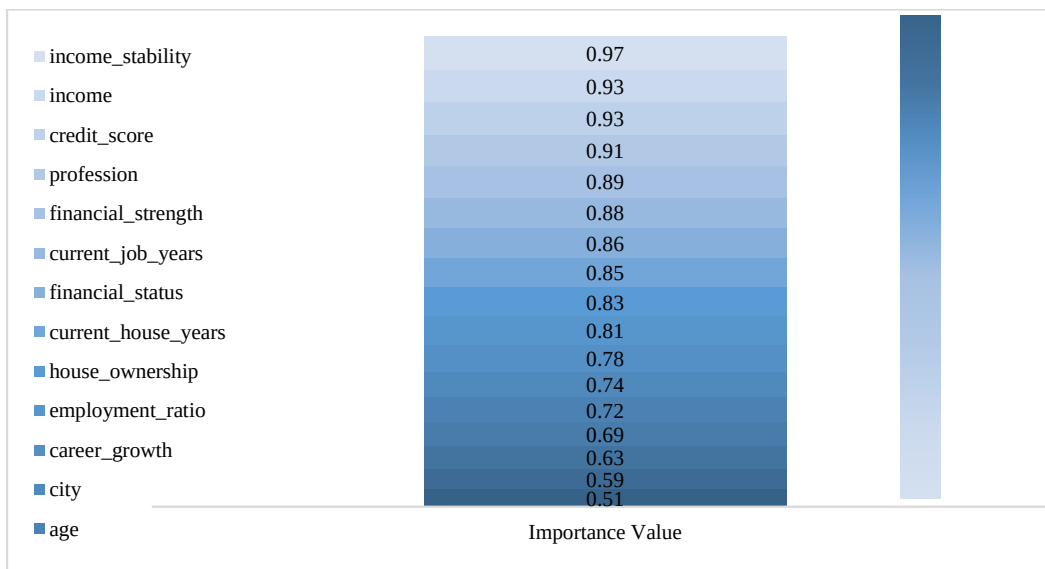
Furthermore, an analysis is performed to explain explainability, considering the parameters that significantly contribute to bank risks. A feature attention saliency visualization technique is used in this regard to analyze how a model based on attention assigns greater weight to income stability, financial strength, job stability, and ownership features.

**Table 2. Graph complexity analysis**

| Graph Neighborhood Size | Accuracy (%) | ROC-AUC |
|-------------------------|--------------|---------|
| 2                       | 82.40        | 0.840   |
| 5                       | 86.70        | 0.890   |
| 10                      | 90.94        | 0.944   |
| 20                      | 88.50        | 0.910   |



**Fig. 13 The graph complexity analysis**



**Fig. 14 Feature attention heatmap**

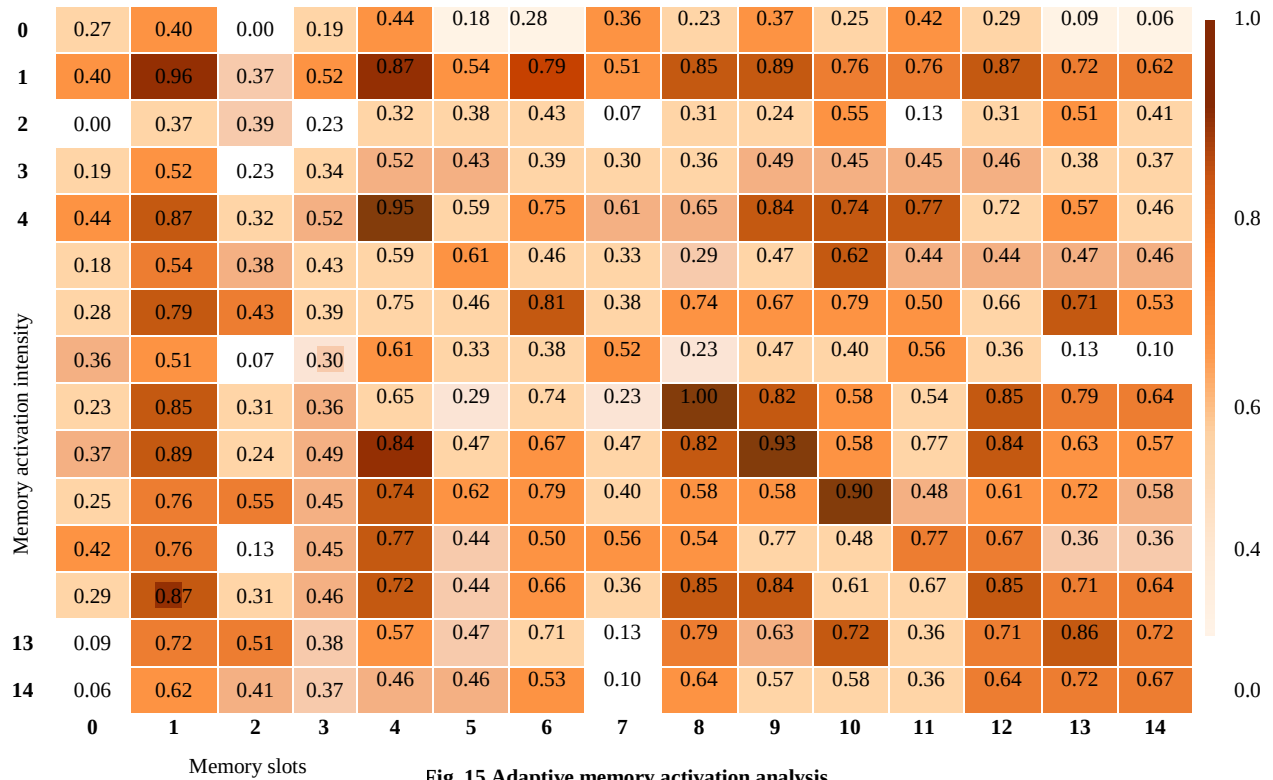


Fig. 15 Adaptive memory activation analysis

The graph complexity analysis is illustrated in Figure 13. The results demonstrated that a graph neighborhood size of 10 achieved the highest classification performance, with 90.94% accuracy and a ROC-AUC score of 0.944. Figure 14: Feature Attention Heatmap. The saliency analysis demonstrates that the proposed framework successfully learns interpretable financial intelligence representations and transparent banking-risk reasoning. The adaptive memory activation analysis is illustrated in Figure 15. It was conducted to evaluate historical banking risk-reasoning capability. Certainly, the suggested memory-guided retrieval approach was able to identify all possible trends in historical banking risks and to employ memory-enabled financial intelligence to forecast future banking risks. The activation of specific regions on the memory map indicates a strong ability to retrieve information on historical banking risks.

#### 4.4. Ablation Study and Stability Testing during Training

An ablation study was conducted to determine the contributions of the major components' framework, including graph attention learning, adaptive memory extraction, and explainable attention integration, as shown in Table 3 below.

Table 3. Ablation study

| Model Variant             | Accuracy (%) |
|---------------------------|--------------|
| Without Graph Attention   | 86.20        |
| Without Memory Retrieval  | 87.40        |
| Without Feature Attention | 88.10        |
| Full Proposed Framework   | 90.94        |

The ablation study results are illustrated in Figure 16. The experimental results demonstrated that removing any major component significantly reduced the performance of banking risk prediction. The full proposed framework achieved the highest classification accuracy of 90.94%, validating the effectiveness of semantic graph learning, adaptive memory retrieval, and explainable attention fusion.

Figure 17: Training stability Curve of EM-HGAF was conducted to evaluate optimization convergence behavior of the proposed framework. The training convergence curve shows that the optimization process is smooth, the learning process of banking intelligence is steady, the training instability is reduced, and the banking risk prediction is consistently improved.

The AdamW optimization algorithm was effective in minimizing classification loss in training and improving the ability to learn relational banking intelligence. The AdamW optimization algorithm successfully minimized the training loss and improved the relational banking intelligence learning ability.

Figure 18: t-SNE Representation of EM-HGAF. t-SNE visualization was conducted to evaluate the separability of the learned banking customer embedding. The t-SNE visualization showed that low-risk banking customers formed compact clusters, while high-risk customers formed distinct relational groups. The representation learning analysis

validates the effectiveness of hybrid banking intelligence learning within the proposed framework. The semantic graph

intelligence significantly improved customer embedding separability and relational banking intelligence learning.

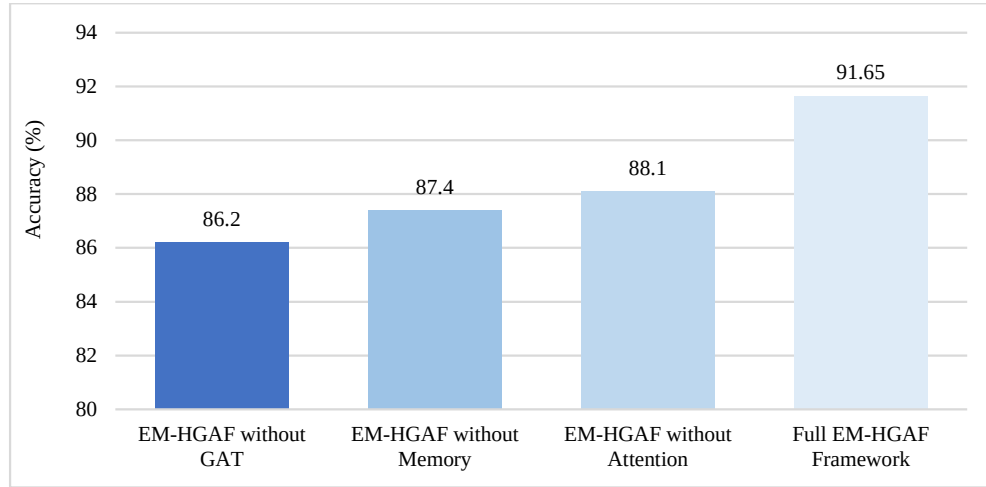


Fig. 16 Ablation study of EM-HGAF framework

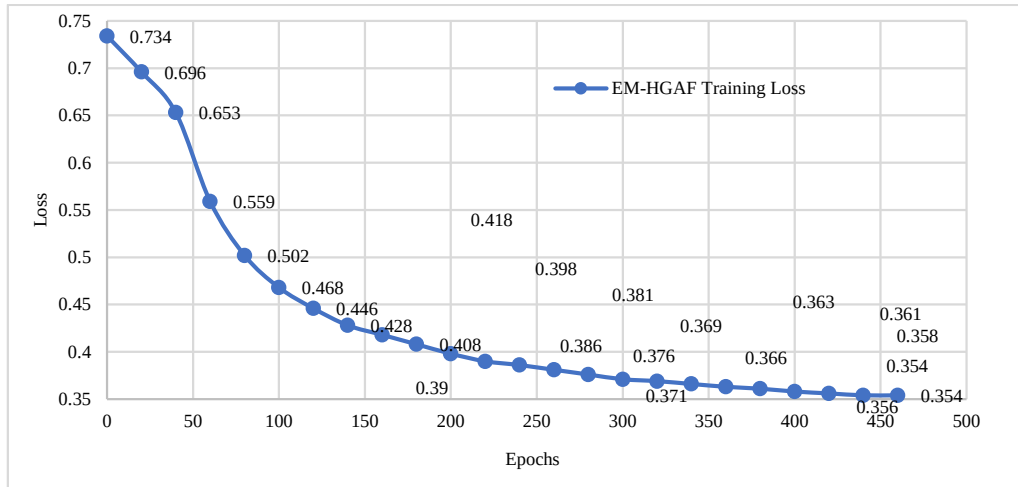


Fig. 17 Training stability curve of EM-HGA

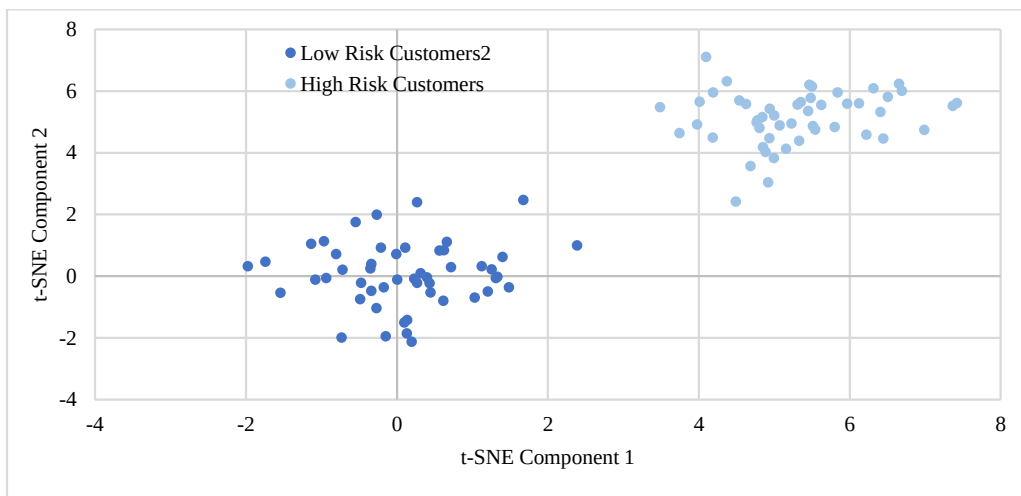


Fig. 18 t-SNE representation of EM-HGAF

## 5. Conclusion and Future Work

The proposed Explainable Memory-Augmented Hybrid Graph Attention Framework for predicting the intelligent banking risks. Statistical feature analysis, dense neural learning, semantic graph attention, adaptive memory retrieval, and explainable attention fusion were used to enable this novel framework to conduct improved banking risk analysis and financial intelligence learning. Semantic customer graphs were built from similarities in profession, finance, ownership, and region among customers, enabling the framework to explore hidden customer relationships and relational banking risks.

The proposed model achieved 90.81% classification accuracy and 0.940 ROC-AUC value, validating its potential for intelligent banking risk prediction. Additional evaluations, including the explainability analysis, graph complexity analysis, memory activation analysis, and ablation experiments, further validated the reliability and robustness of the approach. The experimental results also indicated that semantic graph learning and memory retrieval will be helpful

for improving relational financial reasoning and banking risk prediction.

Potential future work may focus on evolving into the temporal graph learning framework, federated financial intelligence system, multimodal banking risk prediction model, and transformer dynamic graph architecture.

## Data Availability Statement

The fraud detection bank dataset is used in this research from <https://www.kaggle.com/datasets/dhaundiyalokesh/comp1-data/code>, accessed in May 2024.

## Conflicts of Interest

Not applicable.

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