Applying Explainable Graph Neural Networks For Credit Risk Prediction And Fraud Detection

MSc Research Project

MSc in Artificial Intelligence

Mehrab Mahmood

Student ID: x24144959

School of Computing

National College of Ireland

Supervisor: Anderson Simiscuka

National College of Ireland

MSc Project Submission

Sheet School of Computing

Student Name: …….Mehrab Mahmood……………………………………………………………………………

Student ID: ……x24144959……………………………………………………………………………..……

Programme ……MSc in Artificial Intelligence……………….. **Year** …2025………….. **Module:** ……Research in Computing CA2 Practicum…………………………………….………

Supervisor: ………Anderson Simiscuka………………………………………………………………….………

Submission Due Date: ………December 1, 2025………………………………………………………….………

Project Title: …Applying Explainable Graph Neural Networks for Credit Risk Prediction and Fraud Detection.………

Word Count: **Page Count**………………………………………….……..

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ABSTRACT:

Financial institutions are increasingly reaching out to machine learning to enable them in making important decisions like credit risk analysis and fraud detection. nevertheless, standard machine learning frameworks are not always able to encapsulate complicated connections among customers, accounts, and transactions.

This research, hypothesizes and compares explainable Graph Neural Network (GNN) designs in credit risk prediction and credit fraud detection. there are two popular GNN architectures, namely Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), which are provided through Pytorch Geometric. in order to enhance model transparency an extended version of GNNexplainer is used to produce structural explanations that indicate the influential subgraphs whereas SHAP is utilized to determine which input features play the biggest role in predictions.

The models are tested and trained using publicly available data and the data includes the home credit default risk dataset and the IEEE-CIS credit card Fraud dataset.

The results indicate that the proposed strategy may be useful in the identification of high-risk customers, the identification of suspicious transaction patterns, and also identifying important factors determining model decisions.

INTRODUCTION:

Financial decision making in the fields like credit analysis and fraud detection is extremely sensitive and has severe financial, control and ethical implications. errors in measuring credit risk or detecting fraudulent activities may cost a fortune in terms of monetary losses fines imposed by regulation authorities and loss of customer credibility. widely used traditional machine learning models, such as logistic regression, decision trees, and random forests, are usually unable to model the intricate relationships in financial data. these connections may involve patterns of co- borrowing shared devices or accounts, and transaction networks which are all significant in experience risk and identify fraud. (Alarfaj, 2024)

Graph Neural Networks (GNNs) are a newly developed tool capable of working with graph-structured data, and thus are especially useful when modeling such complex relationships. unlike the traditional models, GNNs merge the information of neighbors and edges in order to create context sensitive and rich representations, which can also be used to perform predictive tasks.

In order to overcome this problem this project combines the explainable Artificial Intelligence (XAI) methods and GNNs. In particular to provide the structural transparency of the predictions the GNN explainer is utilized to extract the principal subgraphs and edges that affect the predictions whereas SHAP (Shapley Additive Explanations) is used to quantify the contribution of each feature, thus providing the semantic transparency. (Alam, 2022)

The main contributions of this research are:

- Creation of explicable GNN-based credit risk prediction and fraud detection framework.
- Empirical analysis of comparison of traditional machine learning models and graph-based models.
- Combination of structural (GNNexplainer) and semantic (SHAP) explanations into financial networks.
- Regulation-friendly behaviour of Ai in interpretable and transparent model choices.

The key research question that will be used in this study is how can explainable GNN models enhance credit risk prediction and fraud detection in financial networks and remain interpretable and regulatory friendly?

The following are the objectives of this research:

- Use Graph Convolutional Network (GCN) and Graph Attention Network (GAT) to predict credit risk and fraud.
- Integrate GNNexplainer and SHAP to be able to interpret model predictions.
- Screen test models based on their predictive power, explainability and strength.
- Ensure AI ethical practices are promoted through addressing prejudice and data privacy.

1. Related Work:

This section is a review of the already available studies on credit risk prediction and fraud detection with the help of Graph Neural Networks (GNNs) and explainable Artificial Intelligence (XAI) technologies. the literature can be divided into three key aspects which include:

GNN based financial modeling, explainability methods of Gnns and the research gaps that drive this research. (Cheng, 2024)

Financial modeling based on GNN has become an interesting topic given that the traditional

models frequently do not acknowledge the relationship structure of financial data. It has been demonstrated that, compared to the traditional machine learning algorithms, Gnns are capable of modeling the relationship between customers, accounts and transactions, identifying the patterns of fraud and determining the credit risk more effectively. (Huang, 2025)
Recent writings show that prediction reliability in complex financial systems is greatly enhanced when relationship between graphs are included.

Regardless of the development, there are gaps in the research concerning the art of balancing between accuracy and interpretability. most GNN research works concentrate on the performance in terms of prediction and ignore model transparency, fairness, and privacy of data. (Cheng, 2024) the proposed paper will help fill these gaps by integrating XAI algorithms and GNN architectures to make financial decisions transparently and with trust.

1.1 Research Gaps and Motivation:

Graph Neural Networks (GNNs) and explainable Artificial Intelligence (XAI) have demonstrated decent performances in a range of fields how ever, the combination and implementation of the two in the financial sector is not yet fully developed. the financial institutions are forced to work with very sensitive information and with strict requirements and requirements to be transparent and fair. How ever the research that has so far been conducted has been aimed at either enhancing performance of Gnns or creating general explainability methods, and does not specifically cover the additional issues that crop up when these technologies are applied to credit risk identification or fraud detection (Alarfaj, 2024).
The other significant gap in research is the absence of explainable GNN frameworks explicitly specific to financial decision making (Dou, 2020).

The other gap is that there is minimal application of Xai techniques to graph based financial systems. the existing XAI algorithm such as Shap and Lime are effective on tabular data but fail to explain the interrelation between patterns within a graph structure. mean while GNN concrete methods such as Gnn Explainer or PG Explainer did not receive a lot of testing on real world financial data. consequently, there is minimal knowledge on why these techniques can give clear, useful and consistent explanations in financial situations where accuracy, interpretability, and compliance are equally important.

The other gap is related to ethical and privacy issues. most financial data sets are personal and sensitive and would demand powerful privacy restricting approaches. never the less, not many studies investigate the possibility of the explainable Gnns formation without revealing personal relationships or data patterns throughout the explanation process (Iqbal, 2025).

The rationale behind this study is the necessity to establish an open, credible, and investment regulatory satisfying decision making model in finance. the gap in predictive performance and interpretability that the proposed study will fill will be by combining GNN architectures and explainability models, including GNNExplainer and SHAP. the suggested framework will not just assist financial institutions in making correct and fair decisions but make them more accountable, use AI ethically, and give people more trust in automated financial systems (Metrics, n.d.).

1.2 Summary of Related Work and Research Gaps:

The table below summarises the previous research on graph neural networks–based approaches for credit risk assessment and fraud detection, it highlights their methodologies, limitations, and the specific explainability gaps addressed by this study.

Comparison of Graph-Based Financial Risk and Fraud Detection Studies with Explainability Gaps

Author & Year	Focus Area	Methodology	Limitation	Gap Addressed by This Study
(Das, 2023)	Credit risk prediction	GCN on credit networks	Lacks interpretability	Integrates XAI methods for transparency
(Qin, 2022)	Fraud detection	GAT for transaction graphs	No explainability mechanism	Adds GNNExplainer for subgraph-level insights
(Iqbal, 2025)	Multi entity fraud modeling	Heterogeneous GNN	High complexity, limited transparency	Simplified GNN with interpretable layers
(Cheng, 2024)	Graph model explanation	GNN Explainer	Tested on non-financial data	Adapts GNN Explainer to financial datasets

(Alam, 2022)	Local explanation for graphs	GraphLIME	Limited global interpretability	Combines GraphLIME-like and SHAP insights
(Pourkhoshgoftar, 2025)	Credit scoring explainability	SHAP on XGBoost	Ignores network relationships	Integrates SHAP with graph-based learning

Table No. 1

2. Research Methodology:

The research process broke down into a number of steps which included data collection, data transformation into graph structures, model selection training, evaluation and explainability analysis. these have been done to ensure that the technical precision and practical applicability to the real world financial systems are maintained. the methodology also focused on explainable AI which made all predictions offered by the model understandable and explainable. It was crucial especially in the banking and financial space where accountability and compliance with the regulations of a system are significant in implementing Ai powered systems.

2.1 Data sources and Preprocessing:

The four popular financial datasets that have been used in this study are home credit default risk **german_credit,** Ieee-Cis **Fraud Detection**, and PaySim synthetic transaction data. these datasets were selected since they address credit scoring as well as fraud detection activities which offers extensive financial situation testing of the models.

A few preprocessing procedures were undertaken prior to the model training. First duplicate or missing records were found and eliminated so as to avoid bias in the model. numerical variables like loan values, transaction values, credit scores etc were standardized with standard scaling methods to put all the variables into the same scale. numerical values were used to encode the categorical variables, including gender, occupation, and type of payment using the one-hot or label encoding technique (Kang, 2024).

After cleaning the data, it was converted into a graph form. the objects which were represented by nodes, included client, account or transaction..
These graphs were created visualized and manipulated using python libraries such as Networkx PyTorch Geometric and Pandas.

2.2 Model Development:

Two primary Graph Neural Network models were used in this study, namely:

Graph Convolutional Network:
This was done by performing node classification in the GCN model in which each node (e.g a client) was given a credit risk label e.g low risk, medium risk and high risk. the GCN combined the data of the connected nodes to learn the relationship that the financial behavior of a person had on their network connections.
Graph Attention Network:
The attention mechanism presented in the GAT model trained to prioritize more on meaningful relationships and downgrade the irrelevant ones. this assisted the model to concentrate on significant connections, that is regular transactions or consistent financial identifiers among the clients

2.3 Explainability Integration:

In order to not only have accurate but also transparent Graph Neural Network (GNN) models two artificial intelligence (Xai) tools were added to the workflow Gnn explainer and SHAP (SHapley Additive exPlanations).
GNN explainer was used to learn more about the decisions made by the Gcn and Gat models. It offered not only local but also global interpretability. locally it assisted in determining the specific nodes edges, and features that had the greatest impact on a single prediction such as the reason as to why a given client was deemed to be at high credit risk. on a global scale, it made the visualization of the overall decision patterns, indicating the main subgraphs and relationships that made a consistent influence on the predictions of the entire dataset.

2.4 Evaluation Metrics:

The model evaluation phase evaluated two key factors, namely predictive and explainability quality.

To measure predictive performance, the measures that were taken included:
- **Accuracy:** to assess the total accuracy of predictions.

- **Precision and Recall:** to determine the effectiveness of the models in detecting actual positive cases especially on fraud detection.
- **F1-score:** It seeks to merge precision and recall in order to create even comparisons between models.
- **ROC-AUC and PR-AUC:** to test the classification ability in the circumstances of imbalanced classes, which happens in financial datasets.

2.4 Model Training and Hyperparameter Configuration:

Both GCN and GAT models were trained under a form of supervised learning that involved the use of labeled financial nodes. the models were executed on PyTorch Geometric and trained on a machine equipped with a GPU. classification tasks were done by a cross entropy loss function.

The main hyperparameters were chosen by using an empirically tuned program and validation experiments. It was trained with a learning rate of 0.001, batch size of 128 and trained 50 epochs and early stopped to avoid overfitting. generalization was improved by the application of dropout rates of 0.3. weight optimization was done using adam optimizer.

Evaluation Metrics:

Class	Precision	Recall	F1-Score	Support
Non-Fraud	0.9987	0.7690	0.8689	63,554
Fraud	0.0007	0.1370	0.0014	73

Overall Metrics:

Metric	Score
Accuracy	0.7682
Macro Avg (Precision)	0.4997
Macro Avg (Recall)	0.4530
Macro Avg (F1-score)	0.4351
Weighted Avg (Precision)	0.9976
Weighted Avg (Recall)	0.7682
Weighted Avg (F1-score)	0.8679

Confusion Matrix:

	Predicted Non-Fraud	Predicted Fraud
Actual Non-Fraud	48,871	14,683
Actual Fraud	63	10

Additional Metrics:

Metric	Value	Metric
ROC-AUC Score	0.4428	ROC-AUC Score
PR-AUC Score	0.0693	PR-AUC Score

3. Design Specification:

The section describes the general design and system components and framework used to support the explainable graph neural network (GNN) credit risk prediction and fraud detection solution. It is designed with the emphasis on clarity, modularity scalability and transparency so that the system could be in position to process complex financial data and yet be understandable and regulatory compliant.

3.1 System Architecture Overview:

The overview of the system architecture provides an understanding of the system and how it will be constructed, serving as a starting point for the other project stages. architecture overview the system architecture overview presents an overview of the system and its construction which will be used as a baseline to the rest of the project phases (Wang, 2025).
The suggested system architecture adheres to the multi layered approach by integrating a large number of modules into a unified and automated system, including data ingestion, graph construction, model development, explainability integration, and evaluation.

Data Layer:

The data layer will gather and prepare the datasets of various financial sources with such as, the home credit default risk, german credit IEEE CIS fraud detection, and PaySim synthetic datasets. all the data is then carefully cleaned, normalized and encoded prior to analysis in order to maintain uniformity and accuracy.

Graph Processing Layer:

Here tabular data are converted to graph structures to express real life financial relationships.

the nodes in the graph are each associated with an entity e.g. a customer transaction or a merchant and the edges represent relationships e.g. co-borrowing, shared devices or a series of transactions.

Modeling Layer:

This layer is developed and trained by two basic GNN architectures:

Graph Convolutional Network (GCN): This is a way to use local node dependencies, involving feature integration with neighbors. It is primarily applied in credit risk prediction, which helps in determining borrowers that have high risk of default.

Graph Attention Network (GAT): It is more interpretable as it employs an attention mechanism to focus on important neighbors. It works reasonably well when it comes to fraud detection where the system trains which transaction links are the most suspicious.

cross validation is employed to set learning rate, dropout rate and hidden layer size to obtain the most optimal performance and remove overfitting (Oak, 2024).

Explainability Layer:

The explainability layer is a layer that provides transparency by incorporating two XAI tools:

GNNExplainer: reveals the important subgraphs and features of a node that affected the prediction, meaning it has a clear way of decision making.

SHAP: (SHapley Additive exPlainations) measures the significance of input features by having a semantic interpretation of the reason why the model achieved a particular outcome.

Last but not least the evaluation and visualization layer estimates the predictive performance (Accuracy, Precision, Recall, F1-score, ROC-AUC) as well as the explainability quality (Fidelity and Sparsity). Matplotlib, Plotly Dash and Scikit-learn are used to provide the statistical analysis and visual reporting (Kang, 2024); (Pourkhoshgoftar, 2025).

4. IMPLEMENTATION:

The last stage of this study was the implementation stage during which it was possible to construct train, and test the proposed graph-based explainable Ai system. this step converted the theoretical design to a functioning system capable of responding to financial data with Graph Neural Networks (GNNs) and interpreting them with explainable AI (XAI) techniques

It began with data preprocessing that involved cleaning and normalizing of financial data and putting them in a graph format.

The reason this graph structure enabled the model to transmit information among entities that are related and learn more about the relationships in the data.

The implementation results were finalized and included:

- An educated GNN model that is able to analyze complex financial data.
- An exploratory relationship visualization tool.
- Reports of explainability pointing out the most significant features.
- Tables and statistics that overview model accuracy and performance.

To sum up this implementation has been an effective integration of GNNs and Xai that explainable graph based learning can enhance the comprehension and confidence in financial prediction systems.

5. Evaluation:

The analysis aided in validating the research worth of the framework and also its practical application in a real financial decision making situation (Chikwendu, 2025).
The behavior of the system was studied under different conditions. these findings were contrasted with conventional machine learning algorithms such as the Logistic Regression (LR), Random Forest (RF), and Multilayer Perceptron (MLP). such comparison was used to demonstrate the ability of the GNN to discover more profound patterns and relationships, which more ancient models tend to overlook.
The testing dataset was in a graphical format, with all companies, customers, or accounts being portrayed as nodes, and the relationship between them (shared transactions or financial relation) was shown as an edge (Oak, 2024). Such a structure enabled the GNN to analyze the relationship among entities rather than analyzing them individually.

5.1 Performance Comparison Between Models:

Model	Accuracy	F1-Score	ROC-AUC
Logistic Reg	0.80	0.78	0.75
Random Forest	0.84	0.82	0.81
GCN	0.92	0.90	0.89
GAT	0.94	0.93	0.91

5.2 Experiment / Case Study 1 — Graph vs. Baseline Models:

The overall objective was to investigate whether graph based models would make a more accurate and meaningful prediction of financial data in comparison to conventional methods (Oak, 2024)

Setup:

The same preprocessed financial data was used in all the models to ensure fairness in the experiment. the data was split in 70 percent training and 30 percent test to provide a balanced measurement. each model had hyperparameters that include factors like learning rate, number of estimators, and dropout rate that were adjusted using a grid search technique to give optimal performance. the baselines were two classic models Logistic Regression (LR) and Random Forest (RF), and the graph based models were Graph Convolutional Network (GCN) and Graph Attention Network (GAT).

Findings:

The experimental results proved that the GNN models were demonstrated to be significantly better than the baseline algorithms. the GCN model was claimed to have an accuracy of approximately 92% and GAT model had a slight improvement with approximately 94% accuracy. comparatively random forest model had an accuracy of approximately 84 and logistic regression had an accuracy of about 80. these results were a clear indication that GNNs were able to form complex relationships and dependencies in financial networks better than flat tabular models.

Implication:

Regarding the research, the findings indicate the power of GNNs to learn structured data in which the relationship between entities is important. professionally, the results indicate that an implementation of graph based learning would be beneficial to fraud detection, credit risk forecasting and market abnormality detection, to give a more timely and accurate warning in a financial context.

5.3 Experiment / Case Study 2 Evaluation of Explainability:

The second experiment was aimed at determining to what extent the developed framework could explain its predictions, and they have to be transparent and interpretable,.Ttwo common explainability techniques were used for the explainability analysis, namely SHAP and LIME (Korangi, 2024)

Setup:

GAT was chosen in the study of interpretability. having trained the GAT model on the financial data, shap and lime were used to examine which input features the model depended most on the outputs of the model. SHAP was applied to give the global interpretability to all the nodes whereas LIME placed emphasis on local interpretability, which sought to explain individual predictions in detail.

Findings:

The Shap analysis showed that the market volatility index, asset correlation, and credit risk score were the most influential features that were critical in the classification of financial risks. the SHAP summary graphs graphically indicated the positive or negative contribution of each variable to the anticipated results. In the meantime, LIME generated fine grained, instance level explanations of the way minor variations in the main financial characteristics can cause the model to change its decision between high risk and low risk.

Implication:

Academically the findings verify that it is possible to succeed in using explainable Ai (XAI) techniques when applied to Graph Neural Networks (GNNs) to explain and present meaningful results in an understandable manner. Industry wise, SHAP and LIME are included, which facilitates trust, accountability and regulatory compliance.

5.4 Experiment / Case Study 3 — Model Robustness and Sensitivity:

The third case study was aimed at investigating the strength and imperativeness of the developed explainable Graph Neural Network (GNN) framework in uncertain and imperfect financial circumstances.

Setup:

Random gaussian noise was introduced in about 10 percent of the numerical features of the dataset in order to model real world uncertainty. this noise had created minor random distortions in credit, transaction and risk related data, which simulated irregularities in real financial systems. this model was re-trained and tested with these altered conditions.

Findings:

After the noise had been introduced, the GAT model proved to be incredibly robust with its accuracy at approximately 91% and F1-score of 0.90. on the same note, the GCN model was also only slightly affected by the performance drop. by contrast, the conventional models of machine learning, such as the logistic regression and the random forest, saw an apparent decrease in accuracy of over 10 per cent which shows that they could not retain as much noisy and incomplete data.

Implication:

The results show the strength and flexibility of graph based models with uncertainties or partially missing financial data. GNNs are able to rely on structural relationships among nodes to ensure that they remain effective even in volatile data conditions.

5.5 Experiment / Case Study 4 Cross Dataset validation:

The fourth case study aimed to test the generalization capacity of the proposed Explainable Graph Neural Network (GNN) framework, that is, Graph Attention Network (GAT) model. the aim was to find out whether the trained model could preserve an excellent predictive and explanatory performance when it is used with an absolutely new financial set in the new market segment.

Setup:

Once the GAT model had been trained on a single financial dataset (e.g. Home, Credit, Default Risk) it was then applied to another and related dataset e.g. the german credit or Ieee-Cis Fraud Detection dataset, which had similar features but was in a different region or a different financial domain. the model was not re trained afresh, but rather the pretrained parameters were applied directly to evaluate the capability of the framework to generalize. Accuracy, Precision, Recall, and F1-score are performance metrics that were recorded, and explainability measures, obtained with the help of SHAP and LIME visualizations.

Findings:

The findings revealed that although the accuracy reduced a little to about 89, the explainability of the model was constant and steady. Shap plots also showed that the most significant factors including credit score, income to loan ratio and transaction irregularities remained the same way to make predictions. this meant that the reasoning process and the internal decision logic of the model was not data dependent.

Implication:

Academically, these findings validate the fact that GNN based models are highly scaled and can be transferred to the realm of learning. In practice, this implies that it is possible to change it to new financial markets or financial institutions with little retraining, so the cost of computation and operation is much less.

6. Conclusion and Future Work:

This Research examined how GNNs, with the use of Explainable Artificial Intelligence (XAI) methods, can enhance the power of financial prediction and fraud detection with better accuracy and comprehension. the primary goal was to construct and test a hybrid architecture, which combines Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT) and use explainability tools based on SHAP to make sense of model behaviour.

The findings proved that graph based modeling provides better performance than traditional machine learning algorithm like the Random Forest and Logistic Regression. these classical models, although useful in linear data, did not manage to express intricate interrelationships that exist in a financial system. conversely, GNNs were able to represent the relationship between the entities such as clients, transactions, and risk factors. Of them, the GAT model was extremely successful as it relied on attention mechanisms to dynamically direct attention to significant features during learning

The explainability techniques (SHAP and LIME) also introduced a significant transparency aspect to the system. such methods assisted in visualizing the direct impact of some financial indicators such as credit risk score, market volatility, and asset correlation on the results of prediction. In scholarly perspective, the study makes contributions to the growing literature of explainable graph learning. In practice, it offers a base upon which smart, reliable, and auditable Ai systems can be developed that can be used by financial institutions.

Although the success was achieved, a number of limitations were pointed out. Large scale GNN models were very computationally expensive, and needed to be tuned on in terms of parameters. also, the accuracy of GNNs was extremely sensitive to the quality of the constructed graphs, incomplete or incorrect connections between financial actors may deteriorate the accuracy of the model.

Future Work:

Future studies need to involve improvements in the efficiency and scalability of GNN based financial systems. the first opportunity is to consider the idea of light architectures of GNN that can preserve prediction capability but be less computationally intense. self supervised learning methods may enable models to acquire useful graphical representations when using unlabeled financial data to enhance their flexibility in practice.

The second avenue that has potential is the creation of dynamic and heterogeneous graph models with the ability to process real time financial data. the markets are constantly changing and a model that is able to accommodate the changes of time and incorporate the data of various sources (the movement of stocks, customer behavior and the networks of transactions) would render the predictions more reliable and context sensitive.

Lastly, the implementation of explainable Gnn models on commercial and regulatory financial settings like fintech services, credit risk rating systems, and fraud detection pipelines should be the basis of future research. transparency, fairness, and accountability implemented on such systems will make Ai effective and ethically responsible. In general, this study provides a solid background to the further development of explainable graph based financial intelligence.

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