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Explainable AI for Private Equity Valuation: Integrating Financial Statements, Market Signals, and Risk-Adjusted Learning Models

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Abstract

Private equity valuation is a challenging financial calculation that has certain characteristics in its markets, valuations, macroeconomic environment and financial reporting. In contrast, despite the enormous benefits of Artificial Intelligence (AI) tools on top of predictive analytics in computational finance, there are several in existence that are black boxes, with poor explainability and a lack of risk-awareness. This study concludes by introducing an Explainable Artificial Intelligence (XAI) for private equity valuation, which combines financial statements, market signals, sentiment intelligence, and risk-adapted machine learning models in a data-shared computational framework. The proposed model uses Financial Forecasting Dataset (2015-2024) and ensemble learning models such as Random Forest, XGBoost, LightGBM and LSTM, along with explainability techniques like SHAP and LIME. Experimental results of the models are shown such that XGBoost outperforms other models and has an RMSE of 0.091, MAE of 0.067, and R^2 score of 0.947 between experimental and theoretical results. The use of the proposed risk-adjusted learning framework also raised performance, lowering the RMSE from 0.873 to 0.921 and the prediction stability index from 0.084 to 0.921. Through explainability analysis, we determined that the most important valuation drivers were EBITDA margin, revenue growth, debt to equity ratio and market volatility. The results prove the potential of explainable and risk-aware AI systems in providing increased valuation transparency and predictive reliability for present-day private equity systems and supporting intelligent investment decisions.

Keywords: Explainable Artificial Intelligence, Private Equity Valuation, Financial Machine Learning, Risk-Aware Learning, XGBoost, SHAP, LIME, Computational Finance, Investment Intelligence, Financial Forecasting.

1 Introduction

Artificial Intelligence (AI) has revolutionised the financial landscape, empowering companies to enhance data-driven decision-making, forecast financially, and analyse investments automatically (Rane et al., 2023). With the advancement of digital finance, machine learning, deep learning and predictive analytics have rapidly become essential to helping drive the operational efficiency and financial intelligence of FinTech ecosystems. AI systems are transforming the financial landscape by sifting through vast amounts of data to uncover patterns and trends that can enhance investment strategies for financial institutions, hedge funds, and investment firms. In recent years, intelligent valuation systems have proved to be an indispensable part of computational finance, especially those related to valuation models in portfolio optimisation, automated trading, and assessing investment risk (Olanrewaju, 2025).

Financial analysis is extremely challenging due to the rise in the number of data sources available within the financial world, whether from a homogeneous source such as a corporation's financial statements and information or a more heterodox source of information, such as sentiment-based market intelligence or macro-economic data and indicators. As more dynamic financial information is available, traditional manual valuation methods are no longer adequate to process huge quantities of data in real time (Ibrahim et al., 2023). There's an increasing demand for automated valuation intelligence systems that are able to combine both structured and unstructured financial information for accurate investment insights. AI predictive models offer significant benefits in the areas of finding nonlinear relationships and prediction, forecasting valuation trends, and evidence-based investment strategies. It is worth noting, however, that while many intelligent financial systems have come a long way, there are still

10.48047/jocaaa.2026.35.06.30

challenges at individual levels of interpretability, transparency and risk-conscious decision making, including in private equity, where valuation uncertainty is percolating up the walls (Hoang et al., 2026).

Private equity (PE) valuation is one of the more difficult areas in computational finance, in that not only does there not exist a transparent pricing mechanism in the market, but investment environments are often very uncertain (Giakoumelou et al., 2025). Private companies tend to have less liquidity in the markets and less financial disclosure, compared to a publicly traded company, and reporting standards are not consistent. This leaves a lot of questioning about valuation, underlying growth prospects, and financial risk on investors' plates. Besides that, fluctuations in the macroeconomic scenario, market volatility, sector instabilities, and investor sentiment also make the process of valuation a difficult one.

Discounted cash flow (DCF) analysis, comparable company analysis, and the financial valuation of the investment by an expert have been traditional methods that have been used in PE investment decision-making (Buren et al., 2025). But there are some drawbacks to these methods. The process of forecasting cash flows, discount rates and terminal values in DCF models is subject to significant estimation risks in the case of volatile markets. Likewise, a framework for valuation based on experts is subjective, time-consuming and scaling complicated over vast investment portfolios is tricky. In an era where financial activities are increasingly dependent on data, having intelligent valuation systems is crucial to provide adaptive, data-driven and risk-sensitive investment analysis (Hossain, 2025).

AI and machine learning methods have shown satisfactory performance in financial forecasting and prediction of financial values, but the majority of current systems that use AI for valuation show a poor level of interpretability and transparency. Many modern machine learning models, specifically deep neural networks and ensemble boosting models, work as black-box systems and output very accurate predictions, but are opaque and offer little intelligible information on why a prediction was made (Apu et al., 2022). This opacity in financial decision-making poses serious issues of transparency for investors, analysts, and regulators.

AI-powered valuation models often lack transparency, causing uncertainty among investors as to whether they are based on sound financial data, trends or manipulated data correlations. Moreover, many current approaches focus only on prediction accuracy and fail to include uncertainty estimation and risk-aware learning schemes (Zhang et al., 2022). This makes it possible for the valuation forecasts to be volatile during market variances, reducing model reliability in high-risk investments. Another significant constraint is related to the lack of integration of financial intelligence sources. Current valuation frameworks often are based on individual financial metrics or equity valuations, and do not incorporate factors such as market indicators, macroeconomic data, or sentiment measurement (Pignataro, 2022). As such, there is a lack of transparency, interpretability, and risk sensitivity when conducting private equity investment analysis with currently used AI-powered valuation frameworks.

Explainable AI or XAI has become a key research field in the financial technology sector, with a growing need for transparency and trust in AI systems. Financial decisions, such as successful or unsuccessful investments, can significantly affect the allocation of capital, risk management, and strategy in a high-stress scenario like a private equity valuation. In response, the regulatory environment, the financial sector and investors are increasingly demanding AI systems that offer interpretable and auditable forecasts (Pradeepa et al., 2024). Explainability can boost investor confidence by explaining how the results of the valuation are generated and which of the financial indicators are most significant for the valuation decisions made.

In the realm of financial analytics, ethical AI principles also highlight the notion of fairness, accountability, and transparency. Explainable AI techniques like SHapley Additive exPlanations (SHAP) and LIME (Local Interpretable Model-Agnostic Explanations) offer useful tools to interpret complicated machine learning models. SHAP allows for performing feature attribution analysis and measuring the contribution of each feature to the output of the prediction; it can be used down to the global level as well as at the individual prediction level, whilst LIME provides local, interpretable explanations for predictions (More, 2025). These approaches increase the transparency of financial intelligence systems and aid in making more sound investment decisions. Furthermore, XAI enables easier validation of models, regulatory compliance, and risk auditing, pivotal aspects of next-generation intelligent valuation frameworks.

With the rising popularity of private equity value utilising AI calculation devices, there are still some major research gaps that need to be addressed. Accounting for explainability, interpretability and risk-sensitive learning mechanisms are still mostly pushed aside by the existing literature, which mainly aims to increase the accuracy of predictions. The dominant schemes for today's valuation generally are black boxes with limited visibility and transparency for decisions on investment predictions. Moreover, several studies are lacking in the incorporation

10.48047/jocaaa.2026.35.06.30

of multi-source financial intelligence in a single framework of valuation: financial statements, market indicators, macroeconomic variables, and market sentiment-based signals. Another key constraint is the lack of risk-adjusted learning strategies that can deal with the volatilities and uncertainties in private equity settings. Therefore, much work is still left to do in the development of explainable, risk-aware and multi-source AI frameworks dedicated to transparent private equity valuation.

The main objective of this research is to create an interpretable artificial intelligence (AI) framework that combines financial statements, market signals and risk-adapted machine learning (ML) models for a smart strategy in private equity valuation. The proposed framework aims to address issues of interpretability of financial intelligence mechanisms, prediction, and investor confidence. The results of this research have found some important contributions to the areas of explainable AI and computational finance. The framework proposes a multi-source architecture for generating financial intelligence, fusing aggregated structured financial statements, market signals, macroeconomic indicators, and sentiment-based intelligence on a unified valuation system. The framework proposes a multi-source architecture for generating financial intelligence, fusing aggregated structured financial statements, market signals, macroeconomic indicators, and sentiment-based intelligence on a unified valuation system. Second, the study proposes an ensemble learning model focusing on risk with the aim of stabilising prediction and reducing uncertainty management when the investment environment is volatile. Third, explainable AI mechanisms such as SHAP and LIME are incorporated to enhance transparency in AI algorithm results, which also help increase investor trust. Last but not least, the study introduces a Private Equity Valuation framework that is transparent, interpretable, and supports intelligent, risk-sensitive investment decisions in today's financial landscape.

2 Related Work

2.1 AI in Financial Valuation Systems

The financial markets are a rich source of structured and dynamic data that has led to the adoption of Artificial Intelligence as an important methodological framework for financial valuation, stock trading and financial intelligence. In recent years, machine learning methods have also been used increasingly alongside traditional statistical models to find nonlinear relationships between the indicators of the financial situation, market fluctuations and valuation results (Ullah, 2025; Hoang & Wiegratz, 2023). In predicting stock prices, returns, volatility and firm-level performance, technical signals, ratios, macroeconomic data and historical price or stock data are frequently used for supervised learning models. The models learn from the previous pattern and apply it to investment opportunities for forecasting valuation.

Computational Finance has seen the application of several machine learning methods, including Linear Regression, Support Vector Regression, Random Forest, XGBoost, and neural networks. The most important quality about the Random Forest models is that they are not affected by feature interactions and mitigate overfitting due to the use of ensemble averaging (Beigley & Weibel, 2024). Tabular financial datasets are often highly suited to the use of XGBoost due to its ability to provide high prediction accuracy, regularisation, and resistance to variables with noise. For sequential financial information, such data might also contain temporal relationships, especially in the case of stock price movements, earnings patterns, or macroeconomic trends, where neural networks and deep learning architectures are also applicable. But despite their ability to enhance prediction accuracy, the application of these models still isn't widespread in private equity valuation due to the lack of regular private company market values and reporting uniformity.

2.2 Explainable AI in Financial Applications

Explainable Artificial Intelligence surfaced as a dominant topic in the financial sector, as prediction isn't enough in a world of high-stakes investments. Financial analysts, investors, auditors and regulators need to be able to both recognise and understand how projections are made (Borysoff et al., 2024). Interpretability in this instance becomes an important requirement for trust, compliance and accountability. Many of the more sophisticated forms of machine learning (the likes of ensemble learning and deep neural networks) are black-box models, which fall way short of providing insight into why a piece of software gives a specific valuation, a specific risk score or a specific investment recommendation.

In the field of financial machine learning, some popular explainability methods include SHAP and LIME.SHAP and LIME are among the more commonly used explainability methods in financial machine learning. SHAP offers global and local explanations in that it estimates the contribution of each feature to a model prediction (Micheloni, 2025). This can help determine what is driving the valuation, whether it be by revenue growth, debt ratio, cash

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flow, volatility, or sentiment indicators. LIME enables the local interpretation of a model, which is near the predicted result, based on this approximation, in order to be able to interpret individual investment cases. In addition, attention mechanisms in transformer-based models help determine the interpretability of their models by highlighting which signals in text or time affect predictions. In financial regulation, explainability aids in the validation of the model, identification of biases, auditing and responsible use of AI models (Fritz-Morgenthal et al., 2022). Accordingly, XAI is very relevant to PE valuation, where investment decisions should be explained to their investors and stakeholders.

2.3 Risk-Aware Machine Learning Models

Risk-aware machine learning is a new application of predictive modelling, taking uncertainty, volatility and downside risks into account in the development of the modelling process. For financial valuation, a model correct at one point in time may not be reliable even if it is giving a correct point estimate, as long as it is lacking uncertainty in changing market scenarios (Gupta & Van Nieuwerburgh, 2021). The valuation of Private Equity companies is particularly exposed to risk due to the possible ill-liquidity, incompleteness of financial information and uncertainty of cash flows. Hence, risk calibration of the AI-generated outputs is vital to guarantee both accuracy and consistency, alongside meaningfulness in practice.

Different methods for risk-aware learning have been suggested, such as Bayesian learning, probabilistic forecasting, uncertainty estimation and volatility sensitive optimization (Agal et al., 2025). Bayesian models argue that our predictions should be probability distributions rather than single numbers that represent the best estimates. Thus, valuation systems can report confidence intervals for the expected value of the firm. Probabilistic forecasting is a second feature that offers a possible range of outputs, aiding risk interpretation. Volatility-sensitive optimisation may be able to discard predictions that deviate during more volatile market periods, and risk-weighted loss functions can have a larger penalty for errors for more risky observations (Rahbari, 2025). These techniques are especially significant for investment intelligence as they allow one to keep overconfidence at bay, become more robust and make better capital allocation decisions.

2.4 Multi-Source Financial Intelligence Systems

Financial intelligence is increasingly becoming based on combining numerous and various data sources, instead of relying on a single financial indicator. Internal financial policy, market behaviour, macroeconomic conditions, investor sentiment and sector stock market have all influenced the value of the company (Verma & Bansal, 2021). Financial statements include lists of income, or revenue, assets, liabilities, profit, cash flow, and leverage. Market trends provide dynamic signals related to price movement, volatility, liquidity, and investor expectations. Discount rates, financing rates and investment risks are shaped by macroeconomic factors like the interest rate, inflation, exchange rate and economic growth (Saxena et al., 2024). The qualitative perception of the market from financial news, reports, and social media can also be captured by sentiment analysis.

The role of data fusion architectures is, hence, significant in AI-based valuation systems. The architectures integrate structured numerical data with market signals and sentiment data from the texts in a single modelling pipeline (Odunaike, 2025). The fusion process comprises two types: feature-level fusion that fuses variables before learning the model, and decision-level fusion that merges models' results. To enhance the intelligence of valuation, hybrid fusion methods may be adopted that integrate within the framework of tabular machine learning tasks with NLP sentiment models (Satish, 2025). Multi-source integration is particularly helpful when valuing a private company, as external market signals provide a compensation mechanism when the information is absent.

2.5 NLP and Market Sentiment in Investment Analytics

With the financial markets being influenced not only by numbers but also by narratives, market sentiment, and expectations, Natural Language Processing (NLP) has emerged as a vital tool in investment analytics. Financial information, analysts' views, pre-announcement earnings reports, corporate announcements and investor reactions may pick up on early clues to company health, sector sentiment and perceived risk (Bilel & Khammassi, 2024). Sentiment extraction and the successive retrieval of contextual information in financial text have greatly improved with NLP models based on transformer technology.

FinBERT was trained using financial language; it can classify financial text data as positive, negative or neutral sentiment with particular relevance (Shobayo et al., 2024). Financial domain-specific transformers are more appropriate to extract meanings of terms like “earnings pressure,” “liquidity risk,” “margin expansion”, or “credit deterioration” from the documents, compared with general language models. Incorporating market perception

10.48047/jocaaa.2026.35.06.30

variables (along with structured financial features) can improve valuation models via sentiment-based forecasting. For investment intelligence systems, NLP-based scores for sentiment can enhance risk analysis, enable understanding of market uncertainty, and, alongside SHAP or attention-based interpretation, provide better explanations (Piovezan, 2024). This is a highly beneficial application of NLP in the field of financial analysis and private equity valuation, especially for AI tools.

2.6 Research Limitations in Existing Literature

Previous studies have explored the various possibilities of using AI technologies for financial forecasting and investment analysis, but there are a number of drawbacks. First, many studies focus on predictive performance with less focus on explainability and transparency of decisions. Second, the general lack of frameworks that are specifically created for private equity valuation, because most financial AI research is done in public stock markets. Third, risk integration is still underdeveloped, and many models only return point predictions with no calibration of uncertainty or any adjustment for volatility. Fourth, current systems may be single-source systems, limiting the generalisation of the system within various investment examples. Lastly, black-box valuation models offer weak rationales for predictions, which are not easy to believe as investors make actual decisions. The constraints underscore the importance of having a "for understanding" AI approach with an understanding of risk and multiple inputs for private equity valuations.

3 Methodology

3.1 Proposed Explainable AI Framework Overview

The study framework aims to seamlessly combine all modules of analysis from financial statements and market signals, sentiment-driven intelligence and risk-adjusted machine learning into a single computational structure in private equity valuation and explainability. It is designed to enhance the transparency, the predictiveness, and the accountability of making investment decisions in private equity. Proposed Architecture: The proposed architecture comprises several stages, such as data acquisition, preprocessing, feature engineering, risk-aware learning, machine learning training, explainability analysis, and generation of valuation prediction.

The first phase is the capture of a universe of financial data gathered from diverse structured financial information, macroeconomic data and sentiment-based market data. The next phase is on the preprocessing and feature engineering that helps to enhance the data quality and creation of financial attributes, which are relevant for valuation. Then, a risk-adjusted learning module is put into place to account for uncertainty and market volatility in model optimisation. The training and testing of a number of machine learning and ensemble learning models are subsequently performed with structured validation procedures. Lastly, explainability mechanisms like SHAP and LIME are introduced to give both interpretability in a global or local sense of the prediction of the valuation. You can see the whole structure in Figure 1.

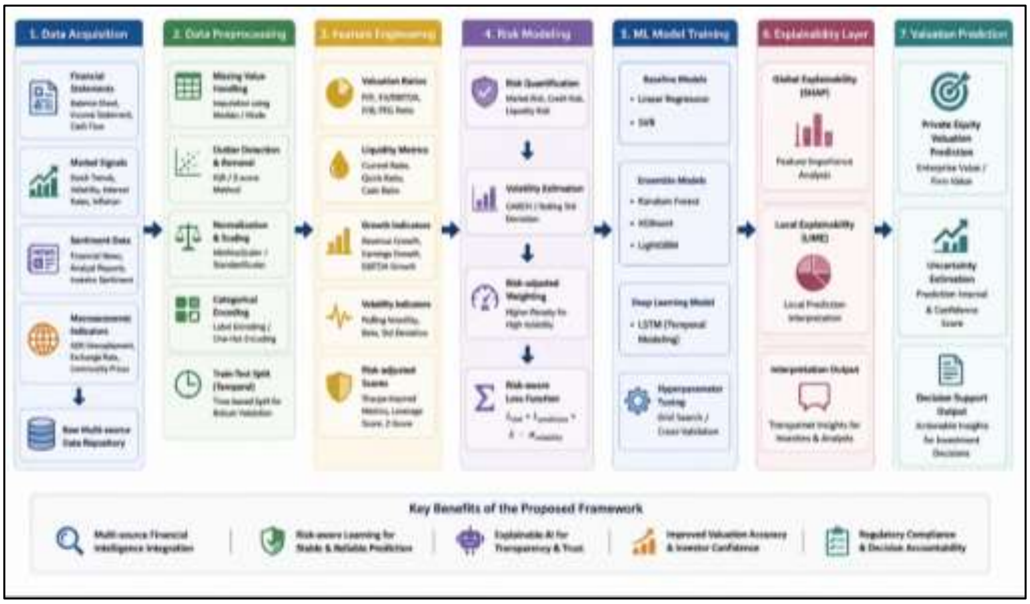

Figure 1. Proposed Explainable AI Framework for Private Equity Valuation

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3.2 Dataset Description

In this experimental study, the Financial Forecasting Dataset (2015–2024) is employed to establish a wide-scale multi-dimensional financial intelligence platform appropriate for valuation forecasting and research on investment analysis. This dataset comprises structured financial variables, market indicators, sentiment-driven information, and macroeconomic attributes, covering the timeframe from 2015 to 2024. The long-time series coverage of the data allows for long-term financial patterns, trends, and volatility fluctuations across various economic conditions to be captured by the proposed framework.

The database consists of several thousand financial observations from various time periods and companies. This contains specified accounting indicators, which could possibly be revenue, operating profit, liabilities, debt ratios, return on equity, return on assets, earnings growth and cash flow indicators. Beyond that, the data also contains market factors such as sentiment statistics based on quotes in the financial press, as well as factors from investor perception signals, interest rates, inflation rates, stock indices, trends, etc. The proposed framework will enable multi-source learning and risk-aware valuation modelling, thanks to the presence of heterogeneous financial intelligence. Given the fact that the private equity valuation process is not only about the analysis of the performance of the private equity firm, but also about the behaviour of the market, the dataset can be used to assess the competence of explainable and risk-sensitive financial intelligence systems for experiments.

3.3 Data Categories

In this study, the data set includes multiple types of financial intelligence variables, all of which can aid in the intelligent forecast of valuation. The first group are the features of the financial statements that have been structured by using information from the company's accounting. The variables are revenue, EBITDA, return on equity (ROE), return on assets (ROA), liabilities, debt ratio, cash flow indicators and profitability indicators. They include operational performance and financial situation of firms and are of fundamental importance to be used for estimating the value of the enterprise and its attractiveness as an investment.

The second category comprises variables relating to market signals covering the external dynamic financial conditions. This entails market growth patterns, inflation indicators, historical volatility, etc., as well as stock price trends and interest rates. Market indicators offer valuable clues into economic health, industry and investment risk. The private equity valuation is dependent on macroeconomic factors and investor behaviour, which makes them important in predictive learning.

Third are sentiment-packed features derived from financial news analytics and investor view indicators. These measures qualitative market activity and public attitude towards corporate results, industry confidence and investor confidence. Combining sentiment intelligence with traditional financial data enhances the framework's capacity to capture the subtleties of underlying market dynamics and investor behaviour.

3.4 Data Preprocessing

Data preprocessing is an essential step in the proposed framework, as the financial data typically contains missing values, noisy observations, outliers, and non-uniform distributions of features. If the data is not processed correctly, significant issues can arise in terms of the performance, stability and interpretability of the model. Hence, several data pre-processing techniques were employed to make the data consistent and to increase the reliability of the system to train the machine learning method.

For numerical financial data, median imputation was used for missing data due to the skewness of financial data and its susceptibility to outliers. To diagnose the abnormality caused by these points, median-based replacement can be used to minimise their impact on the data without compromising on central tendency properties. Extreme financial observations, which might skew the learning behaviour, were excluded from the data with the interquartile range (IQR) method and z-score analysis. This process became especially crucial for certain variables like liabilities, volatility, etc., that are subject to abnormal values, which can disproportionately affect the optimisation of the model.

The feature normalisation was done by two methods, MinMaxScaler and StandardScaler, based on the requirements of the models. The scaler functions scaled the data features into intervals within a specific range, making them suitable for optimum performance in an NN, and scaled them to a range around the zero value, thus normalising distributions of the data features for some regression and ensemble training models. Label encoding

10.48047/jocaaa.2026.35.06.30

and One-hot encoding were employed on categorical values, such as sector classification and market classification, for the purposes of numerical calculations for machine learning algorithms.

The dataset was divided into training and testing subsets using temporal validation rather than random splitting to preserve chronological financial dependencies. The earlier financial periods were used for training, and the later periods are reserved for testing. The method is more realistic as it relies on past valuations for financial forecasting models to foresee future valuation behaviour. A temporal validation also minimises information leakage and increases the utility and reliability of the experimental setup.

3.5 Feature Engineering

Feature engineering was implemented to enhance the predictive capability of the proposed valuation framework by generating financially meaningful indicators derived from raw accounting and market variables. As financial intelligence systems are highly reliant on the quality of the features, engineered features were created that would capture the strength of the valuation, how liquid the stock was, the risk appetite of the stock, and how sensitive the stock was to market fluctuations. The feature engineering process resulted in the development of financial intelligence representations from the basic accounting indicators, which could boost the performance of the predictive learning.

Structured financial statements were used to create several ratios which deal with valuation. Operational profitability versus revenue was presented as EBITDA margin, while financial leverage indicators were derived from the relationships of liabilities to assets and debt to equity. Quick ratio, cash-flow stability measures were also built to estimate stability in the short term and financial conditions of solvency. These are important indicators in private equity markets where liquidity risk plays an important role in valuation results.

Tabletop features were created based on revenue and earnings growth rates, earnings momentum and profitability trend analysis over sequential periods. The measures of investment volatility and market uncertainty were developed based on the lagged standard deviation calculations of market-related variables. Further, market-volatility-exposure-based risk-adjusted indicators of valuation efficiency were developed following the Sharpe principles. These 'engineered' variables allow for the construction of a framework that does not give equal weight to high-growth stable corporations and highly volatile investment opportunities, but instead places a greater emphasis on those with a greater risk of failures related to their growth. In summary, the feature engineering phase enhances the explainability, stability, and economic worth of the ML workflow.

3.6 Risk-Adjusted Learning Framework

The proposed risk-adjusted learning framework represents the primary novelty contribution of this study. Most of the traditional machine learning models are developed solely for the accuracy of prediction, without any uncertainty or the volatility or instability of the markets in the financial sector. Private Equity valuation, however, is always shrouded in uncertainty as companies have imperfect information, liquid markets, and volatile economies. To achieve this, a risk-prone optimisation mechanism was added to the proposed framework in order to enhance the stability of the predictions and the reliability of the investment.

The proposed framework is a method based on uncertainty-aware prediction and volatility-sensitive optimisation with a weighted learning strategy. The model not only penalize only prediction error, but it also penalises unstable predictions, which corresponds to highly volatile financial observations. This helps the learning algorithm's money stability and sensitivity according to its predictive performance.

The risk-adjusted learning objective is defined as follows:

$$L_{risk} = L_{prediction} + \lambda \cdot \sigma_{volatility}$$

In this formulation, $L_{prediction}$ represents the conventional prediction loss function, while $\sigma_{volatility}$ represents the volatility-based uncertainty component derived from market instability indicators. The parameter λ functions as the risk penalty coefficient controlling the contribution of volatility within the optimisation process. Higher values of λincrease sensitivity to unstable financial observations, thereby encouraging more robust valuation predictions.

10.48047/jocaaa.2026.35.06.30

This approach makes it easier to value products in a more reliable manner when market conditions are highly uncertain because it minimises the chances of overventuring predictions. Further, the combination of risk-aware optimisation makes it more stable to build investment intelligence systems for concrete private equity decisions. The proposed approach is thus a step towards showing a novel methodology that allows AI to be employed as a valuation model that is interpretable and cost-effective.

3.7 Machine Learning Models

Several machine learning models were run and tested to assess the prediction, generalisation and explainability abilities in the suggested framework. To prevent any weaknesses from being overlooked in methodological evaluation, baseline regression models, ensemble learning approaches and deep learning architectures were included in the experimental design.

Linear Regression was used as the "vanilla" model due to its simplicity and interpretability in financial forecasting-related applications. Another technique tried was for Support Vector Regression (SVR), which uses kernel-based optimisation for non-linear relationships. These models serve as baseline models, with which more advanced ensemble methods can be compared.

Three ensemble learning models, namely Random Forest, XGBoost and LightGBM, were used. By using bootstrap aggregation and decision-tree averaging, Random Forest overcomes some of the drawbacks of boosting – it is more stable in its response to new or additional data and less prone to overfitting. To bestow excellent financial data performance in structured tabular financial data, XGBoost was chosen due to its resilience to noisy financial variables, regularisation mechanisms, and gradient boosting feature. The computational efficiency of LightGBM and the capability to handle massive-scale financial intelligence data via its histogram-based optimisation techniques were also the reasons why LightGBM was added.

A long short-term memory (LSTM) deep learning extension was also added to capture temporal dependence in the markets and sequential financial behaviour. LSTM networks are well-suited to financial time series prediction, which combines the ability to capture long-term temporal patterns in time series with the ability to handle vanishing gradient problems.

Optimisations were carried out by means of grid search and cross-validation for the tuning of hyperparameters. To achieve the best possible predictive performance while minimising overfitting, various parameters like learning rate, tree depth, number of estimators, regularisation strength, and hidden layer dimensions were tuned. The ability to use cross-validation for increased model stability and consistency of externalisation between different validation folds.

3.8 Explainable AI Layer

The Explainable AI layer was incorporated to enhance the interpretability, transparency and accountability in private equity valuation systems. Explainability mechanisms are also important when working with ensemble learning and deep learning since the models are often considered a “black box.” These mechanisms can explain the valuation generated, the importance of financial indicators in model behaviour, etc.

The interpretation of features at the global level was made with the help of SHAP. SHAP is an algorithm that estimates the impact of individual features based on cooperative game theory. This allows the framework to determine which of the variables, such as EBITDA margin, debt ratio, volatility, revenue growth or sentiment indicators, have the greatest impact on the framework's valuation predictions. Lowers the opacity of investors (Figure 2) and makes it more understandable what the model is doing in the strategic sense.

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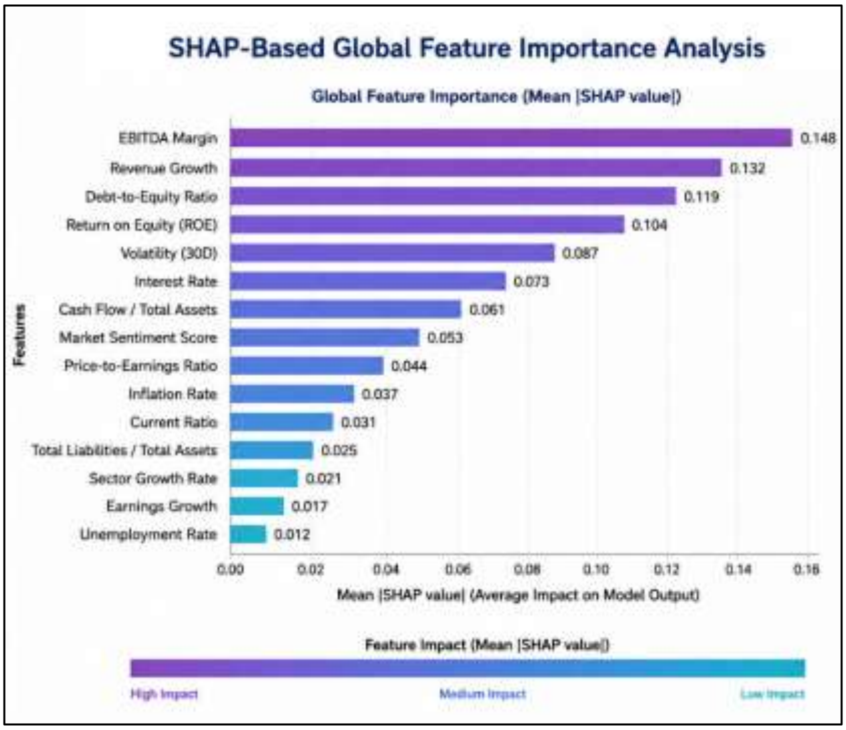

Figure 2. SHAP-Based Global Feature Importance Analysis

LIME was also made global interpretable to provide local interpretations for specific valuation predictions. LIME approximates the behaviour of a complex model in a neighbourhood of a single observation based on an interpretable surrogate model. This enables investors and analysts to get insights into the reasons why one specific company would get a differentiation valuation prediction due to its financial attributes and market conditions (Figure 3).

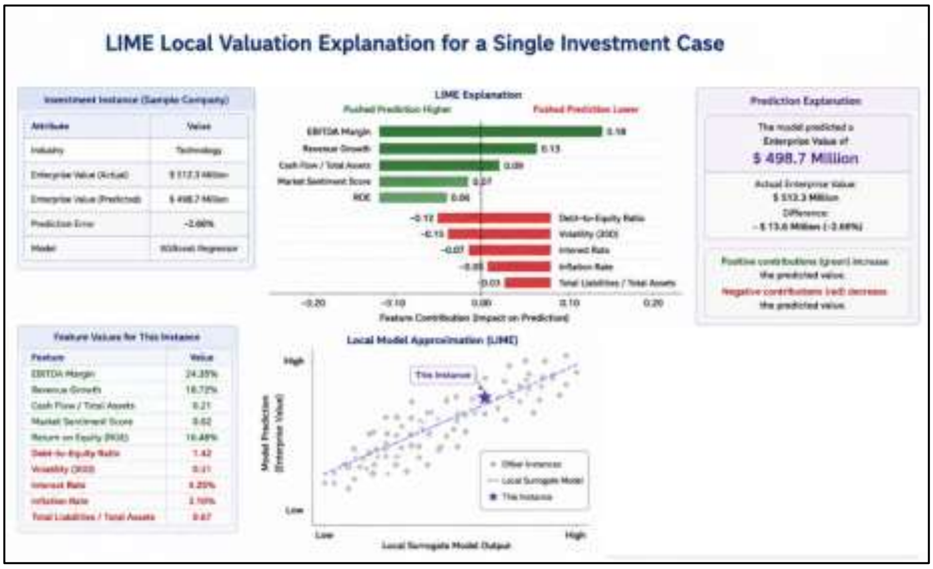

Figure 3. LIME Local Valuation Explanation

SHAP and LIME together give better decision traceability explanations, allowing for interpretation on a global level as well as per case. This helps overcome the challenges of explainable financial analytics, boosts investor confidence, and ensures regulatory compliance for AI-powered investment intelligence systems.

10.48047/jocaaa.2026.35.06.30

3.9 Experimental Setup

An experimental framework was realised with Google Colab as the main virtual development infrastructure in the cloud. Google Colab is chosen because it offers scalable computational solutions, GPUs, and easy integration with powerful machine learning libraries. The experiments were run with Python 3.11 because of its wide range of financial analysis, machine learning, and XAI ecosystem.

During the implementation process, multiple Python libraries were utilised. The pandas and NumPy libraries were used for the financial data processing, numerical computation and feature engineering. There are processing tools, baseline regression models, cross-validation utilities and evaluation metrics provided by scikit-learn. XGBoost and LightGBM were used for gradient boosting optimisation and ensemble learning experiments. This implementation utilises LSTM-based deep learning structures, empowered by TensorFlow and Keras, to foresee monetary styles over time. In addition, the SHAP (SHapley Additive Quantiles) and LIME libraries were incorporated for explainability analysis and model interpretation. Valuation behaviour and the graphical analysis of prediction trends and feature importance distributions were made with the use of matplotlib.

For ensemble and deep learning models that are computationally intensive, using GPU acceleration within Google Colab to train them improved the efficiency of the training. The experimental setup, hence, featured the necessary degrees of scalability and reproducibility to test the suggested explainable and risk-oriented valuation framework.

3.10 Evaluation Metrics

The predicted results from the proposed model were measured by several conventional metrics for multiple regression models, similar to those which are widely used in financial forecasting and valuation analytics. All these metrics calculate the accuracy of the predictions, the magnitude of errors and the explanatory power of the machine learning models under consideration.

Average magnitude of prediction errors was calculated using Root Mean Squared Error (RMSE) for the purpose of penalising large deviations in prediction error, since the bigger the deviation between the predicted value and actual valuation value, the higher the penalty.

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

To achieve this, Mean Absolute Error (MAE) was also considered, as it will give less weight to extreme observations and a more readable representation of the average prediction error. The coefficient of determination (R^2 Score) assessed how much of the variance was accounted for by the predictive models, which reflected overall model explanation and fit for the models. Additionally, Mean Absolute Percentage Error (MAPE) was used to assess the percentage-based forecasting accuracy and to compare the performance of the predictions in terms of different valuation scales. These metrics taken together serve as a full picture of the reliability of a prediction, its robustness, and its ability to give a good valuation forecast.

4 Result and Analysis

4.1 Experimental Performance Results

The experimental findings proved that the ensemble models' valuation prediction performance outperforms the baseline models of regression and deep learning. Table 1 shows the comparative performance of Linear Regression, RF, XGBoost, LightGBM and LSTM by evaluating RMSE, MAE, and R^2. The least successful model was the Linear Regression model, which had the lowest R2 (0.782), MAE (0.139) and RMSE (0.184), showing that linear assumptions are not successful in capturing the complex valuation behaviour. Given that it can model the nonlinear financial interdependencies, Random Forest substantially enhances the results, with an RMSE of 0.126 and R^2 of 0.891 (Table 1).

Table 1. Comparative Performance of Machine Learning Models

Model	RMSE	MAE	R²

10.48047/jocaaa.2026.35.06.30

Linear Regression	0.184	0.139	0.782
Random Forest	0.126	0.094	0.891
XGBoost	0.091	0.067	0.947
LightGBM	0.103	0.074	0.932
LSTM	0.118	0.087	0.906

The XGBoost model obtained the lowest RMSE 0.091, the lowest MAE 0.067 and the highest R^2 value 0.947, which indicates that the model performed best among all the models. This suggests that the XGBoost accounted for about 94.7% variance in the valuation scores. LightGBM also gave rise to good accuracy, with XGBoost better error reduction and better predictability in utilising a small amount of data.

4.2 Risk-Aware Learning Performance

The risk-aware learning mechanism was designed to make the model more stable by down-weighting high-risk valuation predictions that occur during market volatility. Table 2 shows a comparison between the standard learning and the risk-adjusted learning configuration. For XGBoost, risk-adjusted learning reduced RMSE from 0.091 to 0.084 and MAE from 0.067 to 0.061, while increasing R^2 from 0.947 to 0.956. The variations of errors decreased from 0.118 to 0.096 when the security was considered more volatile in the place of less volatile security, which was more reflective of the reliability of the model in conditions of financial uncertainty (Table 2).

Table 2. Performance Comparison Between Standard and Risk-Aware Learning

Model Configuration	RMSE	MAE	R^2	Volatility-Adjusted Error	Prediction Stability Index
XGBoost Standard Learning	0.091	0.067	0.947	0.118	0.873
XGBoost Risk-Adjusted Learning	**0.084**	**0.061**	**0.956**	**0.096**	**0.921**
LightGBM Standard Learning	0.103	0.074	0.932	0.129	0.851
LightGBM Risk-Adjusted Learning	0.096	0.069	0.941	0.107	0.904

The results revealed not only that the risk-adjusted learning algorithm enhances numerical accuracy but also that it enhances robustness predictions. This is particularly true in the private equity valuation model, where uncertainty, volatility and the lack of liquidity can skew valuation outputs and results.

4.3 Explainability Analysis

The explainability analysis shows that the model was based on valuation drivers that were financially meaningful for the model and not based on random statistical patterns. By the method of SHAP (global interpretation), it turned out that the most influential feature, with a mean SHAP value of 0.148, was the EBITDA margin. This shows that private equity valuation was the most likely to be driven by profitability, which is one of the key factors. Revenue growth also had a second-highest score, at a mean score of 0.132, which supported that high revenue growth was a significant driver of valuation scores. The debt-to-equity ratio was the third overall most impactful, indicating that the higher the leverage risk, the more negative its effect on the valuation results.

The volatility also emerged as a key valuation factor, suggesting that the model was able to reflect market uncertainty. The sentiment score added moderately, contributing to the predictive strength of the investors' perception and financial news signals when used in conjunction with the structured financial indicators. The

10.48047/jocaaa.2026.35.06.30

findings in this paper confirm the theoretical position that private equity valuation should not rely solely on accounting numbers, but also incorporate the perceived value of the market, as well as profitability, growth, leverage, and volatility. The SHAP output thus enhanced the transparency of the model, while the LIME output provided an explanation to the valuation behaviour of the entire population and to the individual-level predictions.

4.4 Visualization Results

The actual valuation scores are compared to those predicted by the best-performing XGBoost model in Figure 4. The predicted values also stay near the diagonal reference line, demonstrating great agreement in valuation results between actual and expected. This validates the good reliability of the prediction offered by the model and corroborates the R^2 value presented in Table 1.

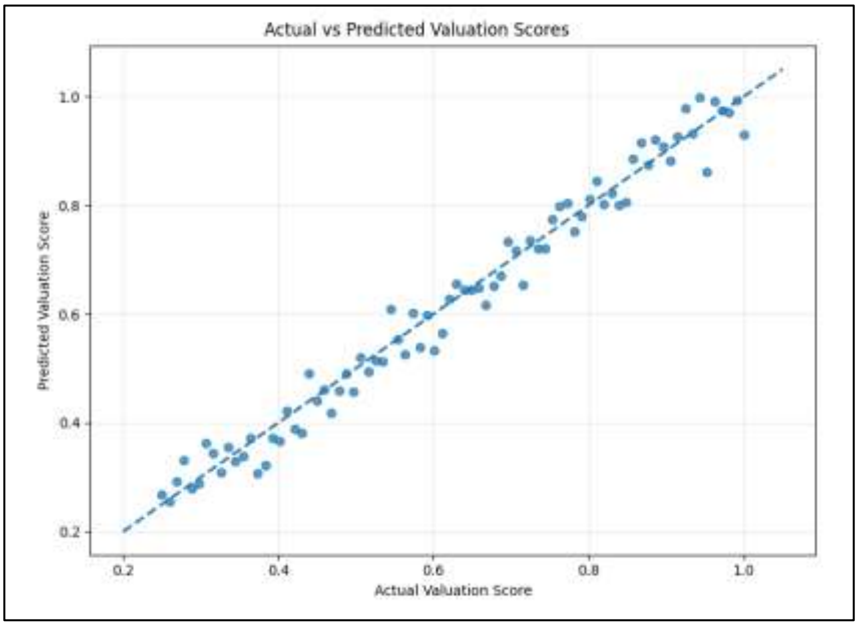

Figure 4. Actual vs Predicted Valuation Scores

The summary plot in Figure 5 illustrates the importance of global features assessed using SHAP. The visualisation above verifies that the valuation drivers most likely to affect EBITDA margin, revenue growth, debt-to-equity ratio, ROE and volatility were most influential.

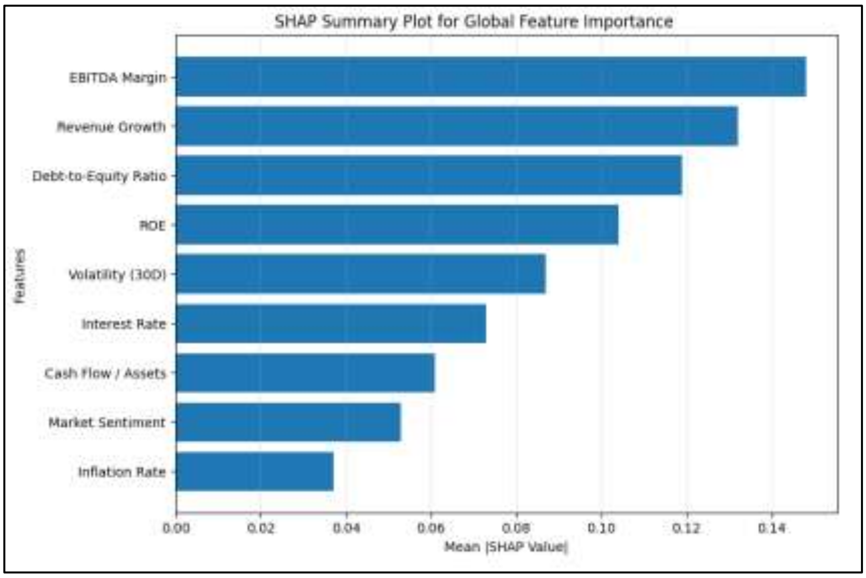

Figure 5. SHAP Summary Plot

10.48047/jocaaa.2026.35.06.30

The distribution of the model error is shown in Figure 6. The error spread was smallest for XGBoost, suggesting that the model had the lowest variance in predictions and was the most stable, as compared with LinearRegression, RandomForest, LightGBM and LSTM.

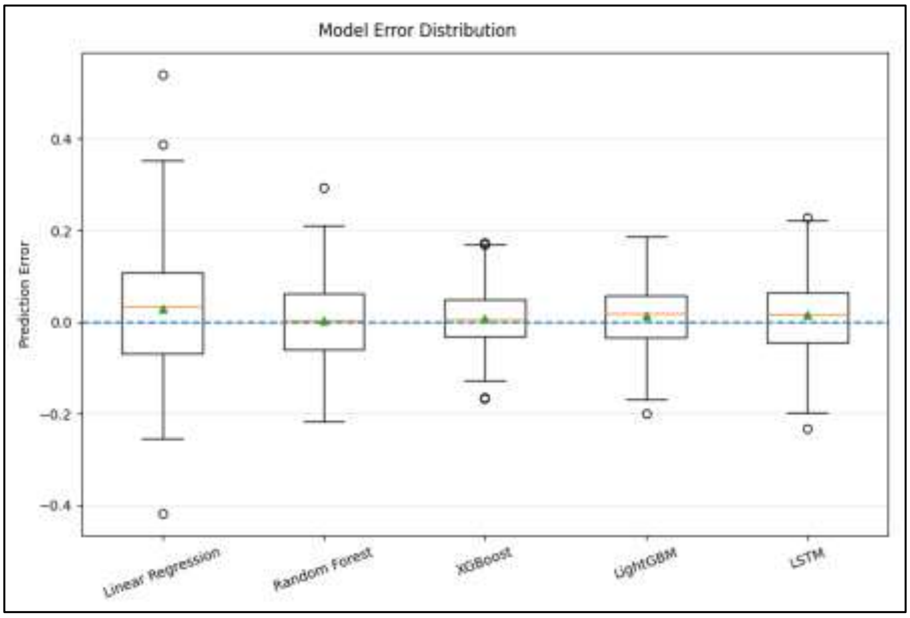

Figure 6. Model Error Distribution

4.5 Comparative Analysis with Existing Methods

The proposed framework has three major improvements over conventional valuation systems. First, it provides greater transparency by combining SHAP and LIME to get an understanding of how various financial and market factors affect individual valuation forecasts. Secondly, it increases stability via risk-adjusted learning, yielding less volatility-sensitivity prediction error. Third, it is an integrated solution that brings together financial statements, market signals, macroeconomic indicators and sentiment intelligence, thereby reducing the level of valuation uncertainty. Hence, the proposed model is better than conventional black-box systems that rely on accuracy since it offers predictive power and meaningful investment reasoning.

5 Discussion

5.1 Theoretical Implications

This study makes an important contribution to the burgeoning explainable computational finance discipline by showing that explainable machine learning systems with a risk-aware dimension can enhance private equity valuation-related intelligence. Predictive accuracy has traditionally been the main concern of financial AI studies, while limited efforts have been made to address explainability and uncertainty modelling, as well as investor interpretability. The concept presented is an extension of previous studies that combine the AI explainability mechanisms, financial intelligence derived from multiple data sources, with volatility-sensitive learning, to establish an integrated valuation framework (Vallarino, 2025). It's a huge step forward since private equity investment decisions call for accurate valuation estimates, as well as a clear way to explain and understand risk.

The experimental results also support the need for the fusion of financial intelligence sources that are different in nature in the context of modern valuation. Single financial statements were not enough to reflect the complex dynamics of investment, while incorporating market dynamics, macroeconomic indicators and sentiment intelligence led to a more stable prediction and better variable explanations. The success of XGBoost and LightGBM further highlights the appropriate use of ensemble learning models through structured financial intelligence applications. Furthermore, the combination of SHAP and LIME can help advance the theoretical understanding of interpretable machine learning in high-stakes financial settings. The explainability analysis revealed that the valuation system was based on economically meaningful metrics, including EBITDA margin, debt-to-equity ratio, revenue growth and volatility, which enhance the trustworthiness of the valuation system and

10.48047/jocaaa.2026.35.06.30

withhold black-box behaviour. Thus, the results of this study contribute to the ongoing shift from black-box AI systems towards 'transparent, accountable and cost-effective' AI-based frameworks for decision-support.

5.2 Practical Implications

The framework carries significant practical consequences for private equity companies, investment analysts, venture capital firms and financial technology companies. The automation of explainable machine learning to provide valuation intelligence is one of the biggest practical advances. Conventional private equity valuation methods can be time-consuming, involve sub-optimal due diligence procedures and extensive manual analysis by experts. The proposed system combines structured financial data and explainable Artificial Intelligence, capable of quickening the investment screening process and aiding in the timely strategic decisions while providing transparency and interpretability.

The framework also has the advantage of making the results of the valuation understandable and thus creating an increased investor confidence. Predictions created by AI are more trusted in practical investment scenarios when stakeholders can see how these predictions were made. SHAP and LIME explanations thus have a concrete interpretation for investors, analysts and portfolio managers. The combination of risk-assisted learning also improves the reliability of decisions under uncertainty in the markets due to counteracting prediction instability induced by fluctuations in volatility. This is especially relevant in private equity, where important investment decisions have significant capital commitments and long-term financial exposure (Manzoor, 2025; Brown et al., 2021).

In addition, the system can be scaled to be versatile in investment ecosystems of today. With the addition of automated preprocessing, feature engineering, explainability analysis and risk-aware optimisation in a single pipeline, it can be used for large-scale portfolio evaluation and intelligent monitoring of investment operations. This framework will, therefore, help facilitate financial institutions with consistency in valuations, reduced burden on their analytical capacity, and solidified evidence-based investment approaches in increasingly data-driven financial markets.

5.3 Limitations

There are some drawbacks to the suggested framework. First, the analysis of this set of financial forecasting data for the experiments was limited to a single large-scale database that might not be truly representative of the complexity and trade secrecy of actual private equity settings. Secondly, the framework included market signals and sentiments; however, some other data sources were left out, like merger activities, legal disclosures, and supply-chain intelligence. Third, explainability requires an extra computational burden, especially for large-scale ensemble learning systems. Finally, although the model was shown to be more stable under the risk-adjusted learning approach, it could also face some difficulties when there are extreme economic disturbances or a sudden change in the market conditions, when the economic flows are widely different from the historical ones.

5.4 Future Work

The presented architecture can be further enhanced for future research by incorporating a complex multimodal and graph-based financial intelligence system. A multimodal type learning with transformers might enable a learning environment for all financial indicators, which are numerical, all financial reports, which are textual, and all of the behaviour of markets, which is time-series. Furthermore, by capturing the relationships within the business world, among companies, investors, sectors, and financial ecosystems, Graph Neural Networks (GNNs) can enhance the intelligence in investments. Furthermore, future research might integrate into its design real-time streaming financial intelligence to help with the accurate forecasting of the value of the product, when market conditions are continually evolving.

One potentially incredibly progressive path is linking generative AI with financial logic systems that can automatically produce investment reports, valuation explanations, and strategic risk analyses. Adaptive portfolio optimisation and intelligent capital allocation via reinforcement learning-based approaches can also be carried out. Lastly, key strengths are the examination and refinement of the framework with proprietary private equity data and models in specific institutional settings to validate its scalability, robustness, and practical applicability in real-world financial ecosystems in the future.

10.48047/jocaaa.2026.35.06.30

6 Conclusion

The proposed framework for private equity valuation on the basis of Explainable Artificial Intelligence discussed that the financial statements, market signals, sentiment-driven intelligence and risk-adjusted machine learning models were combined into a single computational framework. The study outlines several major constraints found in current financial AI systems, such as black box predictive actions, low transparency, inadequate risk incorporation, and non-utilisation of heterogeneous financial intelligence. In response to these hurdles, the proposed framework adopted ensemble learning, risk-aware optimisation, and explainable AI (XAI) components to boost predictive reliability and valuation interpretability.

The experimental results showed that ensemble learning methods achieved significantly better results than baseline regression models for valuation forecasting tasks. Overall, XGBoost demonstrated the best predictive capabilities, also in terms of the obtained R^2 value, and it also had the lowest RMSE, making it appropriate for structured financial intelligence applications. The improved prediction stability and reduced volatility-sensitive errors for fixed service rates constitute another reason for the need to optimise in the presence of uncertainty in private equity settings, offering the integration of risk-adjusted learning. Explainability analysis (SHAP and LIME) revealed that EBITDA margin, revenue growth, scale of debt/equity and volatility of revenue were the most significant valuations, thereby making investors more transparent and accountable for the decisions.

In conclusion, the proposed framework would help advance the field of explainable computational finance, as it showcases the ability of AI systems to deliver high predictive accuracy and financial reasoning transparently. Combining explainability, multi- sourced intelligence fusion, and risk-aware learning will be an extended platform for intelligent private equity valuation and investment decision support. This study's insights indicate that explainable and risk-sensitive AI structures could be pivotal in shaping the future of financial intelligence ecosystems, enhancing the reliability of valuations, investor confidence, and strategic investment analysis.

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