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Hybrid Artificial Intelligence Framework for Financial, HR, and Operational Management

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Abstract. *The use of AI to help organizational decision-making has become popular; yet, the financial, HR, and operational tools are designed separately. The current work presents a Hybrid Artificial Intelligence Framework for Financial, HR and Operational Management which combines predictive models tailored for each field with risk fusion and cross-domain rule-based decision support. The HR module uses Logistic Regression, Random Forest and XGBoost to analyze employee attrition. At the same time, the financial module predicts financial distress of a company using similar classification methods. The operational module utilizes machine learning to predict demand based on historical retail transaction data. According to the experimental findings, Logistic Regression reached the ROC-AUC of 0.8273 in HR attrition analysis, whereas XGBoost obtained ROC-AUC of 0.9540 in financial distress prediction. The best performance in terms of R^2 was demonstrated by Random Forest in operational predictions, reaching 0.4439. The results from the three modules are normalized and combined using a weighted risk fusion model. After that, the rule-based decision support system evaluates the risk of cross-domain combinations and offers coordinated managerial solutions.*

Keywords: *Hybrid Artificial Intelligence, Machine Learning, Financial Distress Prediction, Employee Attrition, Demand Forecasting, Risk Fusion, Decision Support Systems.*

1 Introduction

There has been a growing trend in the direction of the use of Artificial Intelligence (AI) tools to help decision-making in organizations by pattern recognition in complex business data. In the four main sectors of organizational management, namely finance, human resources (HR), and operations, directly affect organizational stability and perfor-mance. HR managers need information about employee attrition risk, and machine learning algorithms have proven useful in predicting which employees are likely to leave the firm [1]. Financial managers need early predictions of financial distress and machine learning based prediction models have been extensively explored for this purpose [2]. Likewise, operations managers need information about future demands, and machine learning based demand forecasting has been effective in improving supply chain and operational performance [3].

However, current management solutions based on AI technology tend to be designed separately for each function within the organization. The financial prediction solution might estimate financial stress without regard for the state of the workforce, whereas the HR solution would estimate the level of employee attrition without considering the financial and operational stresses within the organization. These factors are interlinked. Financial strain could lead to cost cutting; however, such cutting in times of high attrition levels and rising operational demands could have negative effects on organizational performance.

To solve this problem, a Hybrid Artificial Intelligence Framework for Finan-cial, HR, and Operational Management is introduced in this study. The framework includes three management problem-specific AI solutions. One deals with employee attrition risk prediction; one predicts corporate financial distress probability; and another one deals with demand forecast based on the history of transactions. Machine learning approaches are compared to choose the right model for each problem of management.

Results obtained through each separate management problem-specific solution are transformed into normalized risk indicators, which are then fused through the cross-domain fusion approach. Overall organization risk score, which describes the risk of management in general, results. Moreover, rules-based reasoning helps to interpret combinations of financial, HR, and operational risks and to make management decisions. Predictive machine learning combined with rules-based reasoning represents the hybrid aspect of the proposed framework.

The main contributions of the research are:

- **Domain specific AI modelling:** predictive models are built for employee attrition, financial distress and operational demand forecast-ing.
- **Cross-domain risk fusion:** HR, financial and operational results are represented through normalized risk scores and used to com-pose an organizational risk score.
- **Hybrid decision-making:** predictions made by machine learning algorithms and rules are used to produce consistent manage-ment recommendations.
- **Interpretability of the model:** feature importance analysis is performed in order to make prediction process more transparent and understandable.
- **Experimental verification:** individual components are tested using public datasets on HR, corporate bankruptcy and on-line retail with relevant classification and forecasting measures.

This framework can be considered as an attempt to go beyond separate uses of AI in organization and offer a unified approach to managerial decision-making.

2 Literature Review

Artificial intelligence is being used more for a variety of organizational management applications. The literature suggests that machine learning algorithms can detect relationships between various financial, personnel, and other management-related data. Nevertheless, most methods used to date consider only one management area.

2.1 AI in Financial Management

Risk prediction is another practical application of machine learning algorithms. The methods like Logistic Regression, Random Forest, and XGBoost have been studied for bankruptcy and financial distress prediction using financial features pertaining to profitability, liquidity, and solvency [4]. Ensemble and tree-based learning methods are especially useful as they help model complex and nonlinear relationships between financial features [4].

2.2 AI in Human Resource Management

HR managers utilize predictive modeling in the assessment of attrition rates among employees. Employee-related variables such as satisfaction level with the job, income, overtime, experience, and working environment may be used in predicting the risk of attrition [5]. Through classification models, HR managers can determine which employees are at risk of leaving their jobs [5].

2.3 AI in Operational Management

AI is also used for planning by way of forecasting demand and allocating resources. Data on previous sales and transactions can be used to predict future demand, thus helping organizations plan better and allocate their resources effectively [6]. With the help of machine learning algorithms, one can also find out complex relations between past demand trends and other predictors [6].

2.4 Research Gap

While previous research has already proved the efficiency of AI in specific management areas, predicting financial risks, analyzing employees, and forecasting operations are usually studied separately as predictive tasks. The narrow focus on domains opens up possibilities for researching integrated architectures for decision making that would take into account several organizational risk aspects at once.

This problem is addressed by this paper using the hybrid approach that integrates predictive models, cross-domain risk integration, interpretability, and rules-based reasoning.

3 Methodology

The suggested Hybrid AI Framework for Financial, Human Resources, and Operations Management consists of a multi-phase approach where three independently tested AI modules produce sector specific outputs which are then combined.

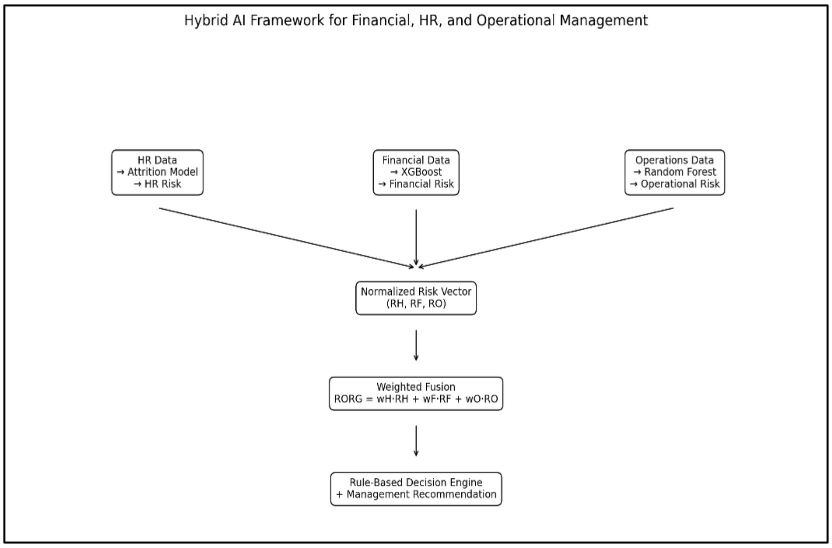

Figure 1. *Architecture of the proposed Hybrid AI Framework.*

3.1 Data and Preprocessing

The following three datasets were utilized for testing the framework: the IBM HR Employee Attrition dataset for HR management [7], the Taiwanese Bankruptcy Prediction dataset for finance management [8], and the Online Retail dataset for operational management [9].

Table 1. Experimental datasets and prediction objectives

Domain	Dataset	Records	Prediction task
HR	IBM HR Employee Attrition	1,470	Attrition classification
Finance	Taiwanese Bankruptcy Prediction	6,819	Financial-distress classification
Operations	Online Retail	541,909 transactions	Demand forecasting

Regarding HR model development, the identifier and constant columns were excluded, the numeric features standardized, and the categorical features one-hot encoded. 80:20 stratified train-test split was used as the data had imbalanced employee attrition.

For the financial dataset, an 80:20 stratified split was made since the data were imbalanced. The im-balance of classes was accounted for during the model training process as only few firms were bankrupt.

The following data cleaning procedures were conducted for operations: cancellation of transactions and removal of non-positive quantities/ prices. The transactions were aggregated daily into demand. Features such as lags with values of 1, 2, 3, 7, 14, and 28 days, averages and calendar variables were constructed. A chronological 80:20 split was performed.

3.2 Domain-Specific AI Models

The following models for HR and finance classifications: Logistic Regression, Random Forest, and XGBoost were derived using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

The prediction of operational forecasting was measured using both baseline methods and machine learning approaches, and the criterion for evaluation includes MAE, RMSE, and R^2.

3.3 Hybrid Risk Fusion and Decision Layer

The three modules generate normalized domain risks R_H, R_F, and R_O. These are integrated as:

$$R_{ORG} = w_H R_H + w_F R_F + w_O R_O$$

where $w_H + w_F + w_O = 1$. Equal weights are adopted for the neutral state, whereas different weighting values are analyzed using sensitivity analysis.

At last, a decision rule layer analyzes the risk combination and converts the organizational risk index into Low, Medium, or High risk along with a managerial suggestion.

4. Results And Discussion

The framework under consideration was tested in two steps. First, each module in HR, finance, and operations was separately tested against criteria appropriate for each type of prediction. The second step involved fusing the predictions in the three domains into one system, which was done based on the risk fusion and decision rule approach. This is critical as it prevents mixing the results of classification in HR and finance and forecasting in operations.

4.1 HR Management: Employee Attrition Prediction

The HR module was developed to find out the employees that could leave the company. Due to the imbalance in the dataset, Recall, F1-score, ROC-AUC, along with Accuracy were used to evaluate the performance of the model. Five-fold Stratified Cross-validation was performed to have a better evaluation of the model.

Table 2. The Five-Fold Cross-Validation Results for Employee Attrition Prediction

Model	Accuracy	Recall	F1-Score	ROC-AUC
Logistic Regression	0.7534	**0.7368**	0.4925	**0.8273**
Random Forest	**0.8614**	0.1737	0.2835	0.8077
XGBoost	0.8452	0.5737	**0.5442**	0.8151

Several observations can be derived from Table 2:

- Logistic Regression had the highest recall of 0.7368 which means that this method has detected quite a significant portion of the employees at risk.
- Also, it had the highest ROC-AUC equal to 0.8273 which shows the ability to differentiate between employees who stay in the company and those who leave.
- XGBoost had the highest F1-score of 0.5442, and it allows to balance precision and recall.
- Random Forest had the highest accuracy of 0.8614; however, its recall was 0.1737 which means that the high accuracy of the model was affected by the majority class.

These observations reveal the reason why accuracy is not to be considered independently for the imbalanced HR dataset. From the management standpoint, missing the employees at risk might be much more costly than generating extra retention notifications. Hence, Logistic Regression showed the highest sensitivity and discrimination, while XGBoost – the best precision-recall trade-off.

4.2 Financial Management: Financial Distress Prediction

The financial model was assessed as a binary classification task whose goal was to differentiate between financially stable firms and firms that were at risk of bankruptcy. Since the instances of bankruptcies were only a small percentage of the entire data, recall, F1 score, and AUC-ROC became significant metrics for assessment.

Table 3. Test-Set Performance for Financial Distress Prediction

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.8783	0.1856	**0.8182**	0.3025	0.9171
Random Forest	**0.9714**	**0.6923**	0.2045	0.3158	0.9506
XGBoost	0.9399	0.3208	0.7727	**0.4533**	**0.9540**

Financial results depict the trade-off between accuracy and the detection of financially distressed firms. The Random Forest approach had a very high level of accuracy at 97.14% but recall of 0.2045 suggests that many cases of bankruptcies remained undetected by it.

Simultaneously, Logistic Regression has delivered the best recall of 0.8182 but have lower levels of precision. But XGBoost showed the best ROC-AUC value at 0.9540 and F1-Score of 0.4533 and recall of 0.7727. Therefore, XGBoost was selected as the primary estimator of financial-risk because it gave the strongest overall balance for the problem of imbalanced financial-distress.

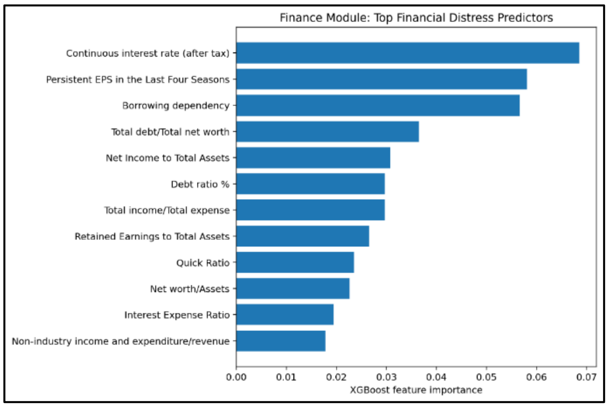

Figure 2. *Feature importance obtained from the XGBoost financial-distress prediction model.*

Figure 2 adds another layer of interpretability by highlighting the financial indi-cators that had the highest contribution towards the XGBoost model. This is especially important in the context of managerial application, where the risk probability becomes even more valuable if decision-makers can analyze the financial indicators as well.

4.3 Operational Management: Demand Forecasting

Differing from the human resources and financials modules, the operations module was designed as a time series regression problem. Data on historical sales was aggregated by days and lagged days, moving average, and calendar features were considered as predictors.

A chronological split of training/test data was preserved in order to avoid using future data in the prediction of past periods.

` **Table 4. Operational Demand Forecasting Performance**

Model	MAE	RMSE	R^2
Random Forest (final model)	**6,800.49**	**11,384.66**	**0.4439**

The random forest model accounted for about 44.39% of variance in daily unseen demand. The MAE of 6,800.49 shows the average of the absolute deviation between the forecasted and observed daily quantities, whereas the higher RMSE of 11,384.66 denotes that there were periods of large deviations in the forecast.

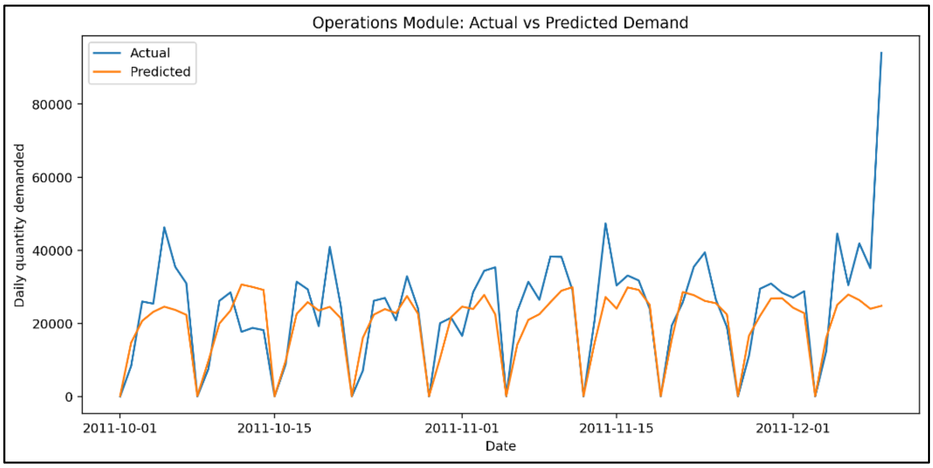

Figure 3*. Comparison between actual and Random Forest-predicted daily operational demand.*

Figure 3 shows that the model captures a large part of the total demand trend despite the unpredictability of some demand spikes. This is understandable as far as retail transactional data are concerned since demand is influenced by various factors such as promotions, seasonality, customer behavior, and so forth, which may not be captured through historical quantity data alone.

It is hence important to regard the operational model as a tool for decision-making in demand forecasting rather than an exact measure of demand.

4.4 Cross-Domain Hybrid Risk Fusion

The key benefit of the proposed framework lies in the combination of the three domain outputs developed separately. The normalized HR, financial, and operational risks are denoted by R_H, R_F, and R_O, respectively.

The risk assessment for the organization will be:

$$R_{ORG} = w_H R_H + w_F R_F + w_O R_O$$

subject to:

$$w_H + w_F + w_O = 1$$

Equal weights were adopted to provide a neutral prototype configuration. Since the three public data sets come from diverse organizational environments, the fusion experiment is considered a decision problem with control conditions rather than one from an actual organization.

Table 5. Cross-Domain Risk Scenarios

Scenario	HR Risk	Financial Risk	Operational Risk	Organizational Risk	Level
Balanced low risk	0.22	0.18	0.25	**0.2167**	Low
HR pressure	0.78	0.31	0.40	**0.4967**	Medium
Finance + operations pressure	0.38	0.82	0.73	**0.6433**	Medium
Cross-domain high risk	0.72	0.81	0.68	**0.7367**	High

The examples show how the framework reacts to different combinations of organiza-tional pressure. For instance, a high HR risk doesn't mean that the organization will have a high organizational risk. But when all these risks are high, the total score will increase significantly.

In the last scenario:

$$R_H = 0.72,\ R_F = 0.81,\ R_O = 0.68$$

Using equal weights:

$$R_{ORG} = \frac{0.72 + 0.81 + 0.68}{3} = 0.7367$$

The resulting **73.67% organizational risk** is classified as **High**.

4.5 Sensitivity and Rule-Based Decision Analysis

An equal weightage of all the risks cannot always apply to each company. A company that is limited by its finances can put more emphasis on financial risk, while an HR-heavy firm can emphasize HR risk more. Thus, sensitivity analysis was conducted where the weightages were changed.

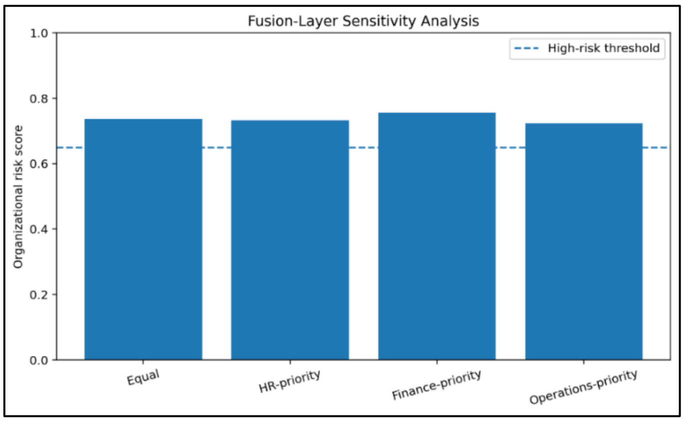

Figure 4. *Sensitivity of the organizational risk score under alternative HR, financial, and operational weighting strategies.*

It was also shown that the interpretation of the high-risk scenario was rela-tively stable when other domain priorities were considered. Thus, the model is not fully dependent on a specific arbitrary weighting configuration.

Finally, the decision-making process of the rule-based decision layer trans-forms these numbers into actionable decisions. For instance:

- **High HR + High Operational Risk:** It prioritizes employee retention and workforce coverage to resist operational disruption.
- **High Financial + High Operational Risk:** It controls discretionary expenditure along with maintaining capacity required to fullfill demand.
- **High Financial + High HR Risk:** It focuses retention resources on critical employees and limits non-essential workforce expenditure.
- **High risk across all three domains:** It prioritizes financial stabilization while protecting essential staffing and operational capacity.

This aspect makes the proposed framework separate from the three independent predictive tools. In place of providing probabilities or predictions independently, the framework evaluates their combined effects and offers a unified management recommandation.

To sum up the results from the experiment show that many AI algorithms are suitable to solve many organizational challenges. Logistic Regression and XGBoost were good in solving attrition problems, XGBoost gave excellent financial distress difference, and Random Forest was able to understand trends in demand operationally. The addition of these algorithms with risk fusion and rule-based reasoning gives predictive ability and cross-functional decision-making support to the hybrid framework.

5. Conclusion And Future Work

In this research, we have developed a Hybrid Artificial Intelligence Framework for Financial, HR, and Operational Management incorporating domain-based learning models with risk fusion and decision rules. In contrast to independent applications of AI, the suggested framework takes into account multiple organizational areas at once to make more coordinated management decisions.

Key results can be highlighted as follows:

- **HR Management:** Logistic Regression obtained the maximum ROC-AUC and recall of 0.8273 and 0.7368 respectively whereas the model with the maximum F1-score was the XGBoost with 0.5442.
- **Financial Management:** XGBoost showed to have the best performance for predicting financial distress as it obtained the maximum ROC-AUC of 0.9540 in the test data set.
- **Operational Management:** Random Forest was the best model for forecasting the demand as it resulted in an R^2 of 0.4439, MAE of 6,800.49, and RMSE of 11,384.66.

- **Hybrid Decision Support:** Fusion layer performed well in terms of aggregating normalized risks from each domain.

The framework shows that an individual AI algorithm is not always the most suitable solution for the various management functions. The use of appropriate domain models and the subsequent integration of the results is a more flexible way to achieve organizational decision support.

5.1 Limitations and Future Scope

One of the limitations is that the three experimental data sets have been collected from different business environments. This means that cross-domain fusion has been tested based on experiments and not through longitudinal analysis of the same organization. In the future, research could validate the entire framework through financial, human resources, and operational data from one company.

Some of the possible extensions to the framework include dynamic or learned risk weights, real-time ERP integration, improved time series analysis models, SHAP local explanations, and dynamic decision-making criteria. These could make the framework adaptable to changes in business environment and provide managers with actionable AI-driven advice.

References

1. S. Najafi-Zangeneh, N. Shams-Gharneh, A. Arjomandi-Nezhad, and S. Hashemkhani Zolfani, "An Improved Machine Learning-Based Employees Attrition Prediction Framework with Emphasis on Feature Selection," *Mathematics*, vol. 9, no. 11, Art. no. 1226, 2021, https://www.mdpi.com/2227-7390/9/11/1226
2. L. Zhu, D. Yan, Z. Zhang, and G. Chi, "Financial Distress Prediction of Chinese Listed Companies Using the Combination of Optimization Model and Convolutional Neural Network," *Mathematical Problems in Engineering*, vol. 2022, Art. no. 9038992, 2022, https://onlinelibrary.wiley.com/doi/10.1155/2022/9038992
3. J. Feizabadi, "Machine learning demand forecasting and supply chain performance," *International Journal of Logistics Research and Applications*, vol. 25, no. 2, pp. 119–142, 2022, https://www.tandfonline.com/doi/full/10.1080/13675567.2020.1803246
4. S. Shetty, M. Musa, and X. Brédart, "Bankruptcy Prediction Using Machine Learning Techniques," *Journal of Risk and Financial Management*, vol. 15, no. 1, Art. no. 35, 2022, https://www.mdpi.com/1911-8074/15/1/35
5. F. K. Alsheref, I. E. Fattoh, and W. M. Ead, "Automated Prediction of Employee Attrition Using Ensemble Model Based on Machine Learning Algorithms," *Computational Intelligence and Neuroscience*, vol. 2022, Art. no. 7728668, 2022.
   https://onlinelibrary.wiley.com/doi/10.1155/2022/7728668
6. "Demand Forecasting Using Machine Learning to Manage Product Inventory for Multi-channel Retailing Store," in *2023 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*, 2023.
   https://ieeexplore.ieee.org/document/10189241
7. P. Subhash, "IBM HR Analytics Employee Attrition & Performance," *Kaggle*, dataset.
   IBM HR Analytics Employee Attrition Dataset. https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset
8. F. Soriano, "Company Bankruptcy Prediction," *Kaggle*, dataset.
   Company Bankruptcy Prediction Dataset. https://www.kaggle.com/datasets/fedesoriano/company-bankruptcy-prediction
9. S. Kumar, "Online Retail.xlsx," *Kaggle*, dataset.
   Online Retail Dataset https://www.kaggle.com/datasets/sachinkumar27oct/online-retail-xlsx