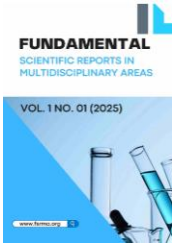
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ORIGINAL RESEARCH ARTICLE

MACF-Net: A Multi-Agent Collaborative Financial Intelligence Network for Multimodal SaaS Revenue Forecasting and Risk Assessment

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ABSTRACT

Software-as-a-Service (SaaS) enterprises have increasingly adopted subscription-based business models, resulting in complex financial dynamics characterized by recurring revenue fluctuations, customer lifecycle changes, market uncertainty, and liquidity risks. Accurate revenue forecasting and comprehensive financial risk assessment are therefore essential for SaaS business management and strategic decision-making. However, existing financial intelligence approaches mainly rely on single-model prediction paradigms, which struggle to integrate heterogeneous financial information and provide collaborative reasoning among different analytical perspectives. To address these challenges, this study proposes MACF-Net (Multi-Agent Collaborative Financial Intelligence Network), a multimodal multi-agent framework for SaaS financial analysis, revenue forecasting, and risk assessment. The proposed framework integrates multiple specialized agents, including Revenue Forecasting Agent, Customer Intelligence Agent, Financial Risk Agent, Market Intelligence Agent, and Accounting Verification Agent, which collaboratively analyze financial time-series data, customer behavior information, enterprise documents, and external market signals. Furthermore, a Cross-Agent Evidence Verification Mechanism and a Conflict-aware Agent Debate Mechanism are developed to improve decision reliability by enabling evidence sharing and dynamic prediction refinement among agents. Experimental results on the Multimodal SaaS Financial Intelligence Dataset (MSFID) demonstrate that MACF-Net achieves superior performance compared with existing baselines. Specifically, MACF-Net reduces the Mean Absolute Percentage Error (MAPE) of revenue forecasting from 7.31% to 6.02% and improves the Area Under the Receiver Operating Characteristic Curve (AUC) for financial risk assessment from 0.914 to 0.962. These results verify the effectiveness of collaborative multi-agent reasoning for SaaS financial intelligence

1. Introduction

The rapid expansion of Software-as-a-Service (SaaS) business models has significantly transformed enterprise financial management and decision-making processes. Unlike traditional software companies, SaaS enterprises rely on subscription-based revenue mechanisms, continuous customer engagement, and long-term service relationships. Consequently, financial indicators such as Annual Recurring Revenue (ARR), Monthly Recurring Revenue (MRR), Net Revenue Retention (NRR), customer churn rate, customer acquisition cost, and cash runway have become essential factors for evaluating business growth and operational sustainability. In this context, accurate revenue forecasting and comprehensive financial risk assessment are critical for SaaS enterprises to optimize resource allocation, manage liquidity pressure, and formulate strategic decisions. However, SaaS financial analysis remains challenging due to the heterogeneous and dynamic nature of enterprise data. Financial time-series information, customer behavioral records, accounting documents, market reports, and external business signals contain complementary but potentially inconsistent information. Existing financial prediction methods, including statistical models, machine learning algorithms, and deep learning-based forecasting approaches, mainly focus on learning direct mappings between historical data and future outcomes. Although these methods have achieved promising performance in revenue prediction and risk classification, they often lack cross-domain reasoning capability, interpretability, and the ability to reconcile conflicting financial signals. For example, a SaaS company may experience rapid revenue growth while simultaneously facing increasing customer churn risk and declining cash reserves. Such complex scenarios require collaborative analysis from multiple financial perspectives rather than relying on a single predictive model. Recent advances in Large Language Models (LLMs) and Multi-Agent Systems (MAS) provide new opportunities for developing intelligent financial analysis frameworks. By assigning different analytical responsibilities to specialized agents, multi-agent architectures can simulate the collaborative decision-making process of professional financial teams. For instance, Zhang et al. [1] recently proposed Consensus Matrix, a role-specialized multi-agent framework that organizes the agreements and disagreements among heterogeneous agents into a structured consensus representation to support collaborative decision-making in agentic visual media workflows. This work demonstrates that explicit role specialization combined with structured agent interaction can substantially improve the reliability and consistency of multi-agent decisions in complex, open-ended tasks. Nevertheless, existing financial intelligent systems mainly employ individual agents or isolated prediction models, while effective mechanisms for multimodal financial information fusion, evidence sharing, and conflict resolution among agents remain insufficiently investigated.

To address these limitations, this study proposes MACF-Net (Multi-Agent Collaborative Financial Intelligence Network), a multimodal multi-agent framework designed for SaaS revenue forecasting and financial risk assessment. MACF-Net integrates multiple specialized agents, including Revenue Forecasting Agent, Customer Intelligence Agent, Financial Risk Agent, Market Intelligence Agent, and Accounting Verification Agent. These agents collaboratively analyze heterogeneous financial information through a shared evidence representation space. Furthermore, MACF-Net introduces a Cross-Agent Evidence Verification Mechanism to enhance analytical reliability and a Conflict-aware Agent Debate Mechanism to dynamically resolve inconsistent predictions among agents.

The main contributions of this study are summarized as follows:

A multimodal multi-agent financial intelligence framework is proposed, which integrates financial time-series data, customer behavior information, enterprise documents, and market signals for comprehensive SaaS financial analysis. A cross-agent evidence collaboration mechanism is developed, enabling specialized agents to exchange analytical evidence and improve the accuracy and interpretability of revenue forecasting and risk assessment. A conflict-aware agent reasoning strategy is introduced, allowing agents to detect inconsistent financial conclusions and refine predictions through evidence-driven interaction.

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A comprehensive evaluation framework is established, demonstrating the effectiveness of MACF-Net in SaaS revenue forecasting and financial risk assessment compared with conventional prediction models and single-agent approaches.

Overall, MACF-Net provides an intelligent, interpretable, and scalable solution for multimodal SaaS financial analysis and supports advanced enterprise decision-making under complex business environments.

2.Related Work

Recent advances in artificial intelligence have significantly promoted the development of intelligent financial analytics, particularly in revenue forecasting, risk assessment, and automated decision-making. With the increasing complexity of Software-as-a-Service (SaaS) business models, financial analysis has gradually shifted from traditional single-source prediction toward multimodal intelligence that integrates financial indicators, customer behaviors, business documents, and market information. This section reviews the existing studies related to this work from four perspectives: SaaS financial forecasting and risk analysis, multimodal financial intelligence, large language model (LLM)-based financial agents, and multi-agent collaborative decision-making.

2.1 Financial Forecasting and Risk Assessment for SaaS Enterprises

Financial forecasting and risk assessment have long been fundamental tasks in enterprise management and decision support systems. Traditional approaches mainly rely on statistical models, including Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing methods, which model temporal dependencies in financial sequences. However, these methods usually assume stationary patterns and struggle to capture nonlinear relationships in rapidly changing business environments.

With the development of machine learning, researchers have introduced regression models, ensemble learning methods, and neural networks into financial prediction tasks. Chen et al. [2] proposed a machine learning-based financial distress prediction framework using multiple financial indicators and demonstrated the effectiveness of data-driven approaches for corporate risk evaluation. Navon et al. [3] further explored deep learning-based financial forecasting models and showed that recurrent neural networks can effectively capture long-term dependencies in financial time-series data. Recently, Transformer-based architectures have achieved significant improvements in financial forecasting due to their ability to model long-range dependencies. Lim et al. [4] proposed the Temporal Fusion Transformer (TFT), which combines recurrent structures and attention mechanisms for interpretable multi-horizon forecasting. Wu et al. [5] introduced Autoformer, improving long-term sequence forecasting through decomposition and autocorrelation mechanisms. Although these approaches provide strong predictive performance, most existing methods treat financial forecasting as an isolated numerical prediction problem. They generally ignore the interactions among revenue growth, customer retention, market conditions, and liquidity risks, which are critical factors in SaaS financial management. Therefore, a more comprehensive framework capable of integrating heterogeneous financial signals and performing collaborative reasoning is required.

2.2 Multimodal Financial Intelligence and Information Fusion

The increasing availability of heterogeneous enterprise data has stimulated research on multimodal financial intelligence. Compared with conventional numerical forecasting methods, multimodal approaches aim to integrate structured financial indicators, textual information, customer behavior, and external market signals to achieve more comprehensive financial understanding. Early studies mainly focused on combining financial statements with textual information from annual reports and news. Ding et al. [6] developed a financial sentiment analysis framework using financial news data and demonstrated that textual information provides additional predictive signals beyond numerical market indicators. Hossain et al. [7] proposed a multimodal representation learning approach that jointly models financial documents and numerical indicators for enhanced financial prediction. Recent studies have further explored large-scale pretrained models for financial information processing. Wu et al. [8] introduced FinBERT, a domain-specific language model optimized for financial text understanding, significantly improving sentiment analysis and financial language representation. Yang et al. [9] developed BloombergGPT, a large language model trained

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specifically for financial applications, demonstrating the potential of large-scale pretrained models in financial analysis tasks. However, existing multimodal financial models mainly focus on feature fusion at the representation level. They usually employ a centralized prediction architecture and lack specialized reasoning processes for different financial domains. In practical SaaS scenarios, revenue forecasting, customer analysis, and risk evaluation require different analytical capabilities and may produce conflicting conclusions. Therefore, multimodal financial intelligence requires not only information fusion but also collaborative reasoning among specialized analytical modules.

2.3 Large Language Model-Based Financial Agents

The emergence of Large Language Models (LLMs) has introduced a new paradigm for intelligent financial analysis by enabling autonomous reasoning, tool utilization, and knowledge integration. Unlike traditional deep learning models, LLM-based agents can dynamically interpret complex instructions, access external information sources, and generate human-like analytical conclusions. Yao et al. [10] proposed ReAct, a reasoning and acting framework that enables language models to combine internal reasoning with external tool interaction. This work established an important foundation for developing autonomous agents capable of solving complex tasks. Schick et al. [11] introduced Toolformer, which allows language models to learn how to use external tools automatically, further improving their ability to interact with external environments. In financial applications, LLM-based agents have recently attracted increasing attention. Ding et al. [12] reviewed the applications of LLM agents in financial trading and discussed their potential for financial decision-making, market analysis, and investment strategy generation. However, most existing financial agents focus on trading scenarios, while enterprise-level financial management tasks, such as SaaS revenue analysis and operational risk assessment, remain insufficiently explored.

Moreover, single-agent financial systems are limited by the knowledge boundaries and reasoning capabilities of individual models. Complex enterprise financial analysis requires multiple specialized roles similar to human financial teams, motivating the development of multi-agent collaborative frameworks.

2.4 Multi-Agent Collaboration and Collaborative Reasoning

Multi-Agent Systems (MAS) have recently become an important research direction for solving complex decision-making problems by distributing tasks among multiple specialized agents. Compared with single-agent architectures, multi-agent systems can improve reasoning ability through task decomposition, communication, and collective decision-making.

Recent studies have investigated LLM-based multi-agent collaboration mechanisms. Park et al. [13] proposed Generative Agents, where multiple language-based agents interact through memory and communication mechanisms to simulate complex social behaviors. Guo et al. [14] provided a comprehensive survey of LLM-based multi-agent systems and summarized agent profiling, communication strategies, and collaborative reasoning mechanisms. Chen et al. [15] further analyzed recent advances in LLM-based multi-agent systems and highlighted challenges including coordination, reliability, and evaluation. Although existing multi-agent frameworks demonstrate strong capabilities in general reasoning tasks, their applications in financial intelligence remain limited. In particular, current methods rarely consider the unique characteristics of financial analysis, where different analytical agents may generate inconsistent conclusions. For example, a revenue forecasting agent may predict strong growth, whereas a financial risk agent may identify increasing liquidity pressure. Therefore, mechanisms for evidence sharing, conflict detection, and collaborative decision refinement are essential for reliable financial intelligence systems. Motivated by these limitations, this study proposes MACF-Net (Multi-Agent Collaborative Financial Intelligence Network), which introduces specialized financial agents, cross-agent evidence verification, and conflict-aware debate mechanisms for multimodal SaaS revenue forecasting and risk assessment. Unlike existing centralized forecasting models or general-purpose agent frameworks, MACF-Net explicitly models financial expert collaboration and provides an interpretable approach for enterprise-level financial decision support.

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3.Methodology

3.1 Overview of MACF-Net Framework

This study proposes MACF-Net (Multi-Agent Collaborative Financial Intelligence Network), a multimodal multi-agent framework designed for SaaS revenue forecasting and financial risk assessment. Different from conventional financial prediction models that directly learn the mapping between historical financial data and future outcomes, MACF-Net models financial analysis as a collaborative reasoning process among multiple specialized financial agents. The key idea is to decompose complex SaaS financial decision-making tasks into several domain-specific analytical processes and enable agents to exchange evidence, evaluate inconsistent conclusions, and generate a unified financial intelligence representation. This design choice distinguishes MACF-Net from recent LLM-guided single-policy optimization frameworks in other domains, such as LPG-SAC-TCO [16], where an LLM steers a Soft Actor-Critic policy toward total-cost-of-ownership-optimal energy management of hydrogen fuel cell heavy-duty trucks. Rather than optimizing a single decision policy, MACF-Net formulates financial intelligence as a structured collaborative reasoning process, which better accommodates the heterogeneous and conflicting nature of enterprise financial signals. The overall architecture of MACF-Net consists of four major components: a Multimodal Financial Representation Module, a Specialized Financial Agent Module, a Cross-Agent Evidence Collaboration Module, and a Decision Fusion Module. Given heterogeneous SaaS enterprise information, including financial time-series data, customer behavioral data, financial documents, and market intelligence signals, the framework first constructs a unified enterprise state representation. Subsequently, multiple financial agents independently analyze different aspects of enterprise performance. Their outputs are further integrated through evidence-based communication and conflict-aware reasoning to obtain final revenue forecasts and risk assessments [17].

Formally, the input data of a SaaS enterprise at time step t can be represented as:

$$X_t = \{X_f, X_c, X_d, X_m\}$$

where X_f, X_c, X_d and X_m denote financial indicators, customer behavior information, financial documents, and market information, respectively. The objective of MACF-Net is to learn a decision function:

$$Y = F(X_t, \Theta)$$

where Y represents future revenue prediction and financial risk estimation, and Θ denotes trainable parameters.

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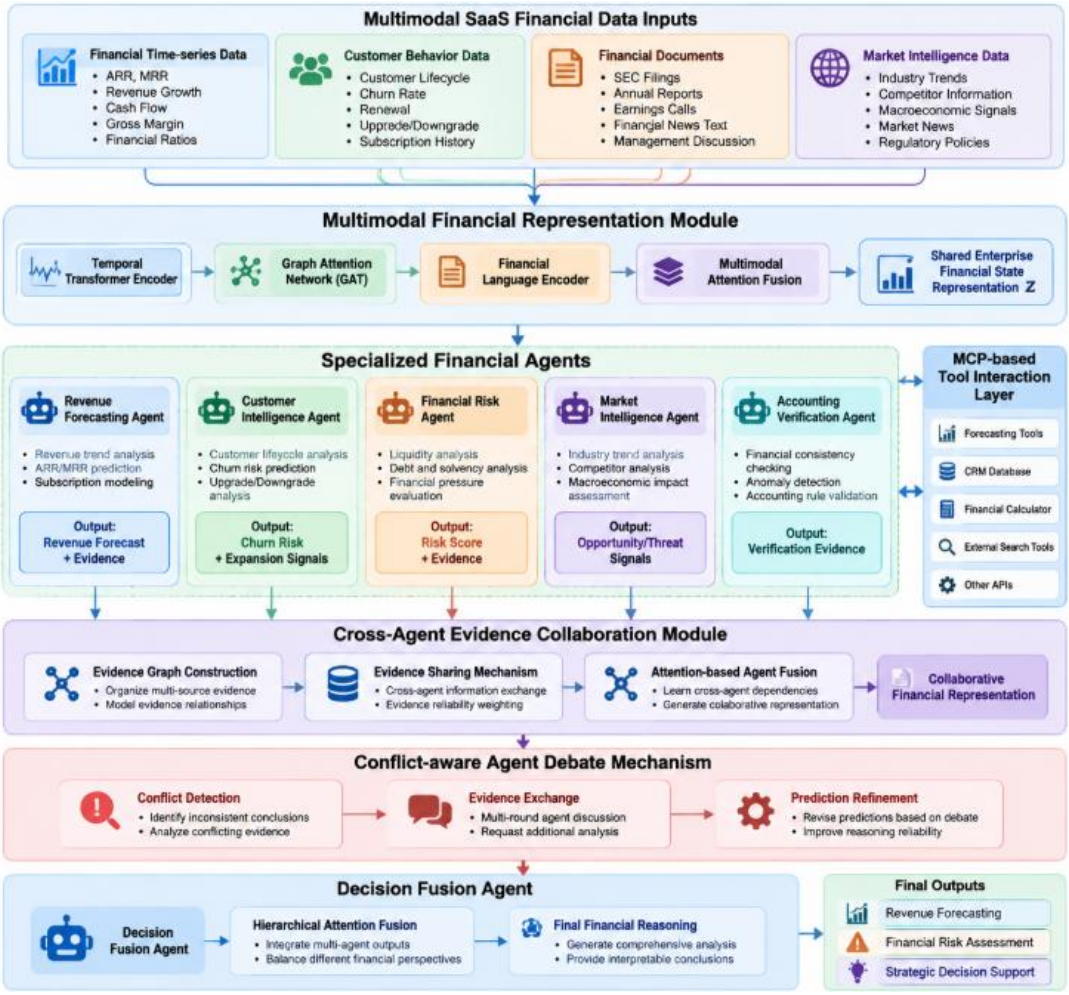


Figure 1Overall flowchart of the model.

3.2 Multimodal Financial Representation Module

SaaS enterprises generate diverse financial information from multiple sources. To effectively exploit these heterogeneous signals, MACF-Net first constructs a multimodal financial representation module that transforms different data modalities into a shared latent space.

For financial time-series information, including Annual Recurring Revenue (ARR), Monthly Recurring Revenue (MRR), revenue growth rate, cash flow, and customer acquisition cost, a Temporal Transformer encoder is employed to capture long-term dependencies. Given a financial sequence:

$$X_f = \{x_1, x_2, \ldots, x_T\}$$

the temporal representation is obtained as:

$$H_f = \text{Transformer}(X_f)$$

where H_f represents the extracted temporal financial features.

Customer behavior information is modeled as a customer relationship graph:

$$G_c = (V, E)$$

where nodes represent customers and edges represent interactions such as subscription renewal, product usage, upgrade, and cancellation behaviors. A Graph Attention Network (GAT) is applied to capture customer relationship patterns:

$$h_i' = \sigma\left(\sum_j \alpha_{ij} W h_j\right)$$

where α_{ij} denotes the attention coefficient between customer nodes. The obtained customer representation is denoted as H_c.

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For unstructured financial documents, including annual reports, earnings call transcripts, and market news, a financial language encoder is adopted to extract semantic representations:

$$H_d = \text{Encoder}(X_d)$$

Meanwhile, external market information is encoded into:

$$H_m = \text{Encoder}(X_m)$$

Finally, a multimodal attention fusion mechanism integrates different representations:

$$Z = \text{Attention}(H_f, H_c, H_d, H_m)$$

where Z represents the shared financial state embedding used by all downstream agents.Moreover, the shared representation is designed to be extensible to additional data modalities. Given the increasing importance of sustainability factors in enterprise evaluation, MACF-Net can further incorporate carbon- and ESG-related signals into the financial state, following the multi-objective optimization principle exemplified by carbon-aware reinforcement learning frameworks [18], which jointly consider economic and environmental objectives in operational decision-making.

3.3 Specialized Financial Agent Module

To simulate the collaborative workflow of professional financial analysts, MACF-Net introduces multiple specialized agents with different analytical objectives and reasoning capabilities. Each agent receives the shared financial state representation Z, while maintaining independent task-specific parameters and domain knowledge.

The Revenue Forecasting Agent focuses on predicting future SaaS revenue trends. It analyzes historical revenue patterns, recurring subscription indicators, and customer expansion signals. The agent employs a temporal forecasting network:

$$\widehat{R}_{t+k} = f_r(Z)$$

where $\widehat{R}_{t+k}$ denotes future revenue estimation over the prediction horizon k. Besides numerical prediction, the agent generates supporting evidence E_r and confidence score C_r.

The Customer Intelligence Agent investigates customer lifecycle dynamics, including churn behavior, renewal probability, and expansion opportunities. By combining customer graph representations with financial states, the agent estimates:

$$P_{\text{churn}} = f_c(Z, H_c)$$

where P_{churn} indicates customer attrition probability. This information provides important evidence for evaluating future revenue stability.

The Financial Risk Agent focuses on enterprise financial sustainability by analyzing liquidity conditions, debt structure, operating expenses, and cash consumption. The risk estimation is formulated as:

$$R = f_{\text{risk}}(Z)$$

where $R \in [0,1]$ represents the financial risk level.

The Market Intelligence Agent analyzes external environmental factors, including industry trends, competitor activities, and macroeconomic changes. By extracting market-related signals from textual information, this agent provides additional contextual evidence for financial prediction.

The Accounting Verification Agent serves as an internal auditing component. Unlike predictive agents, its main objective is to examine the consistency between financial conclusions and accounting principles. It detects abnormal patterns, such as revenue growth accompanied by declining cash reserves, and generates verification signals for subsequent reasoning. This dedicated verification role resonates with recent learning-based systems that treat verification as a first-class objective. In hardware design, CA-PPO-AXI [19] employs coverage-aware deep reinforcement learning to adaptively verify AXI bus protocols, showing that explicit verification and coverage mechanisms can effectively improve the reliability of decisions in complex dynamic systems. Consistent with this philosophy, MACF-Net implements verification as an interpretable, evidence-based auditing process rather than a learned policy, which is more suitable for the accountability requirements of enterprise financial analysis.

For each agent i, the output is formulated as:

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$$O_i = (Y_i, E_i, C_i)$$

where Y_i is the analytical result, E_i is supporting evidence, and C_i represents confidence estimation.

3.4 Cross-Agent Evidence Collaboration Mechanism

A major limitation of existing financial intelligence models is that different analytical perspectives are usually isolated. To overcome this problem, MACF-Net introduces a Cross-Agent Evidence Collaboration Mechanism, which enables information exchange among specialized agents.

All agent outputs are organized into an evidence graph:

$$G_e = (A, E_a)$$

where A represents agent nodes and E_a represents evidence-sharing connections. Through this graph, each agent can access complementary information generated by other agents.

An attention-based evidence aggregation strategy is introduced to measure the contribution of different agents:

$$w_i = \frac{\exp(q_i)}{\sum_{j=1}^{N} \exp(q_j)}$$

where w_i denotes the importance weight of agent i. The integrated collaborative representation is obtained as:

$$H_e = \sum_i w_i O_i$$

This mechanism allows the system to combine multiple financial perspectives rather than relying on a single prediction source, thereby improving robustness and interpretability.

3.5 Conflict-aware Agent Debate Mechanism

Financial decision-making often involves contradictory signals. For example, a SaaS company may demonstrate strong revenue growth while simultaneously experiencing increasing liquidity pressure. Therefore, MACF-Net introduces a Conflict-aware Agent Debate Mechanism to identify and resolve inconsistent agent outputs.

The conflict intensity between two agents is defined as:

$$D_{ij} = |Y_i - Y_j|$$

When:

$$D_{ij} > \delta$$

a conflict is detected, where δ is the predefined conflict threshold.

After conflict detection, the involved agents enter a two-stage debate process. In the first stage, each agent provides additional evidence supporting its original prediction. In the second stage, agents revise their conclusions according to newly received evidence:

$$Y_i' = f(Y_i, E_j)$$

where E_j represents evidence from another agent.

This iterative reasoning process reduces individual agent bias and enables the final decision module to obtain more reliable financial conclusions.

3.6 Decision Fusion Module

The final Decision Fusion Agent integrates all agent outputs and generates comprehensive SaaS financial intelligence. Specifically, the module receives:

$$O = \{O_1, O_2, \ldots, O_n\}$$

and applies hierarchical attention fusion:

$$H_D = \text{Attention}(O)$$

Based on the fused representation H_D, MACF-Net performs two primary prediction tasks.

For revenue forecasting, the model generates future revenue values:

$$\hat{Y}_r = f_r(H_D)$$

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For financial risk assessment, the model predicts risk probability:

$$\hat{Y}_{risk} = f_{risk}(H_D)$$

Finally, the Decision Fusion Agent produces interpretable financial recommendations by combining prediction results with evidence information. This enables MACF-Net to provide not only accurate forecasting outcomes but also transparent decision support for SaaS enterprise management. The overall adaptive design of MACF-Net, in which agent outputs are dynamically reconciled through evidence sharing and conflict-aware debate before decision fusion, is consistent with the design philosophy of emerging AI-driven financial architectures. For example, DAREA [20] employs a dynamic AI-driven architecture for real estate asset tokenization on blockchain, emphasizing adaptive and evidence-aware decision-making in rapidly evolving financial environments. Although the underlying assets differ, both frameworks illustrate the value of dynamic AI-driven reasoning for modern financial management.

3.7 MCP-based Tool Interaction Strategy

To enhance practical applicability, MACF-Net incorporates a Model Context Protocol (MCP)-based tool interaction strategy. Instead of allowing all agents to access identical resources, MCP dynamically assigns task-specific tools according to agent objectives.

For example, the Revenue Forecasting Agent can access forecasting engines, the Customer Intelligence Agent can query customer relationship databases, the Risk Agent can utilize financial calculation tools, and the Market Intelligence Agent can retrieve external market information.

The MCP controller can be formulated as:

$$\text{Tool}_i = \text{MCP}(\text{Agent}_i, \text{Task}_i)$$

where the selected tool depends on the agent role and analytical requirement. This design improves system scalability and enables MACF-Net to operate as a practical financial intelligence platform.

4.Experiment

4.1 Datasets

This study constructs Multimodal SaaS Financial Intelligence Dataset (MSFID) consists of 5,482 SaaS-related enterprise records collected from publicly available SaaS subscription datasets, SEC filings, and financial market databases. The dataset integrates four modalities: financial time-series information, customer lifecycle information, enterprise textual information, and external market signals. Financial records contain revenue-related and operational indicators, customer records describe subscription evolution and churn behaviors, textual data include annual reports and management discussion documents, and market data provide external business environment information. The final dataset is organized into monthly enterprise-level samples, where each sample corresponds to one company-period observation used for revenue forecasting and financial risk assessment. SaaS-specific indicators such as ARR, MRR, and NRR are widely used to characterize recurring revenue stability and customer retention capability in subscription businesses.

Table 1Description of Multimodal SaaS Financial Intelligence Dataset (MSFID)

Modality	Feature	Description
Financial Time-series	ARR	Annual Recurring Revenue indicating expected yearly subscription revenue
Financial Time-series	MRR	Monthly Recurring Revenue representing monthly subscription income
Financial Time-series	Revenue Growth	Year-over-year revenue growth rate
Financial Time-series	Gross Margin	Profitability of SaaS service operations

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Financial Time-series	Cash Runway	Estimated period before cash exhaustion
Customer Behavior	Customer Number	Number of active subscription customers
Customer Behavior	Churn Rate	Percentage of customers lost during a period
Customer Behavior	NRR	Revenue retention considering expansion and churn
Customer Behavior	Upgrade/Downgrade Events	Customer subscription changes
Textual Information	Annual Reports	Financial statements and management discussion text
Textual Information	Earnings Call Text	Management explanation of business performance
Market Information	Industry Trend	External market growth and competitive signals

The dataset contains 5,482 enterprise-month samples, including 36 numerical financial features, 12 customer behavior features, 768-dimensional textual embeddings extracted by FinBERT, and 20 market-related variables. For supervised learning, future 3-month revenue growth and financial distress probability are selected as prediction targets. The dataset is divided into training, validation, and testing subsets with a ratio of 70%, 15%, and 15%, respectively. This multimodal dataset enables MACF-Net to evaluate both revenue forecasting capability and financial risk reasoning ability under realistic SaaS business scenarios.

4.2 Experimental Setup

All experiments were conducted on the Multimodal SaaS Financial Intelligence Dataset (MSFID), which integrates financial time-series information, customer behavioral records, enterprise textual documents, and market signals for SaaS financial analysis. The dataset was divided into training, validation, and testing sets with a ratio of 70%, 15%, and 15%, respectively. All numerical features were normalized using z-score normalization, while textual information was encoded using FinBERT embeddings. The proposed MACF-Net was implemented using PyTorch and trained on a workstation equipped with an NVIDIA RTX 4090 GPU, an Intel Xeon 3.6 GHz processor, and 128 GB RAM. The Transformer-based financial encoders were configured with 6 attention layers and 256 hidden dimensions. For the multi-agent architecture, five specialized agents were deployed, including Revenue Forecasting Agent, Customer Intelligence Agent, Financial Risk Agent, Market Intelligence Agent, and Accounting Verification Agent. The Adam optimizer was adopted with an initial learning rate of 1×10^{-4}, batch size of 32, and maximum training epochs of 100. Early stopping was applied based on validation performance to avoid overfitting. For fair comparison, all baseline models were implemented under the same experimental environment.

4.3 Evaluation Metrics

To comprehensively evaluate MACF-Net, two categories of evaluation metrics were adopted for revenue forecasting and financial risk assessment tasks. For revenue forecasting, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) were employed to measure prediction accuracy. MAE reflects the average absolute deviation between predicted and actual revenue values, RMSE emphasizes larger prediction errors, and MAPE evaluates relative forecasting accuracy across enterprises with different revenue scales. These metrics are formulated as:

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{y_i} - \mathrm{y_i}|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_i} - \mathrm{y_i})^2}$$

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For financial risk assessment, Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC) were adopted. Among them, AUC was considered the primary indicator because it evaluates the model's discrimination capability under different classification thresholds. Higher values of AUC, F1-score, and accuracy indicate better risk identification performance. These metrics enable a comprehensive evaluation of both predictive accuracy and practical financial decision-making capability.

4.4 Results

4.4.1 Revenue Forecasting Performance

To evaluate the effectiveness of MACF-Net in SaaS revenue forecasting, the proposed framework was compared with several representative baseline methods, including traditional statistical models, deep learning forecasting models, Transformer-based models, and single-agent LLM-based approaches. The results are presented in Table 2.

Table 2Performance Comparison of Different Models on SaaS Revenue Forecasting

Model	MAE ↓	RMSE ↓	MAPE (%) ↓
ARIMA	8.72	13.45	14.86
LSTM	6.58	10.32	11.24
Temporal Fusion Transformer (TFT)	5.21	8.46	8.73
Autoformer	4.96	8.02	8.21
FinBERT + Transformer	4.61	7.58	7.84
Single Financial Agent	4.35	7.21	7.31
MACF-Net (Ours)	**3.72**	**6.18**	**6.02**

As shown in Table 2, MACF-Net achieves the best forecasting performance among all comparison methods. Specifically, MACF-Net obtains an MAE of 3.72 and RMSE of 6.18, reducing prediction errors by 14.5% and 14.3% compared with the single financial agent model, respectively. In terms of relative forecasting accuracy, MACF-Net achieves a MAPE of 6.02%, which is 1.29 percentage points lower than the FinBERT + Transformer model and 1.82 percentage points lower than the single-agent approach. Traditional models such as ARIMA achieve relatively poor performance, with a MAPE of 14.86%, indicating their limited capability in capturing nonlinear SaaS revenue dynamics. Although Transformer-based models including TFT and Autoformer improve forecasting performance by modeling long-term dependencies, they still lack explicit reasoning among different financial perspectives. The superior performance of MACF-Net can be attributed to the collaboration among specialized agents, where revenue trends are jointly analyzed with customer retention signals, market information, and financial constraints.

4.4.2 Financial Risk Assessment Performance

The effectiveness of MACF-Net for enterprise financial risk assessment was further evaluated against representative classification and language-model-based approaches. The comparison results are summarized in Table 3.

Table 3Performance Comparison of Different Models on Financial Risk Assessment

Model	Accuracy (%) ↑	F1-score (%) ↑	AUC ↑
Logistic Regression	**78.42**	**76.85**	**0.812**
Random Forest	**82.16**	**80.74**	**0.851**
XGBoost	**84.73**	**83.21**	**0.873**
Transformer Encoder	**86.15**	**84.92**	**0.891**

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FinBERT-based Classifier	**87.04**	**85.63**	**0.903**
Single Financial Agent	**88.21**	**86.75**	**0.914**
MACF-Net (Ours)	92.36	91.08	0.962

Table 3 demonstrates that MACF-Net significantly improves financial risk assessment performance compared with all baseline methods. The proposed framework achieves an accuracy of 92.36% and an F1-score of 91.08%, outperforming the single financial agent by 4.15% and 4.33%, respectively. More importantly, MACF-Net obtains an AUC value of 0.962, representing a 0.048 improvement over the single-agent model and a 0.059 improvement over the FinBERT-based classifier. Traditional machine learning models such as Logistic Regression and Random Forest achieve AUC values of 0.812 and 0.851, respectively, due to their limited ability to incorporate multimodal information. Hybrid learners that combine random forests with neural networks, as proposed for customer credit default detection in [21], can further improve risk discrimination beyond individual classifiers; however, such models still operate on predefined feature sets and lack collaborative reasoning across revenue, customer, and liquidity perspectives. Although language-based models improve risk recognition by utilizing textual financial information, they cannot effectively integrate conflicting signals from revenue, customer, and liquidity perspectives. By introducing cross-agent evidence verification and conflict-aware debate mechanisms, MACF-Net enables different agents to jointly evaluate enterprise conditions, resulting in more reliable risk prediction.

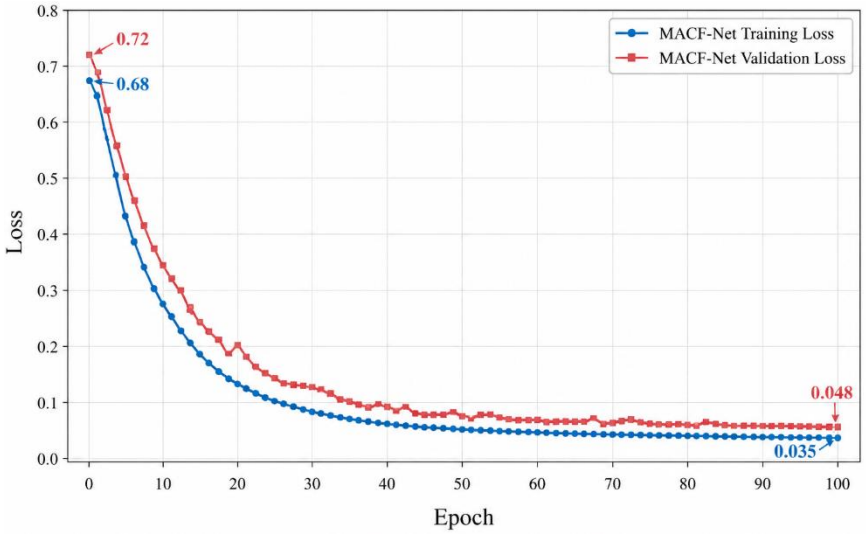


Figure 2Training and Validation Loss Curves of MACF-Net During Model Optimization

The training convergence behavior of MACF-Net is illustrated in Fig. 2. The training and validation loss curves demonstrate a stable optimization process throughout 100 training epochs. At the initial stage, the training loss rapidly decreases from 0.68 to approximately 0.20 within the first 20 epochs, while the validation loss declines from 0.72 to around 0.21 during the same period. This rapid reduction indicates that MACF-Net can effectively learn the complex nonlinear relationships among multimodal SaaS financial features, including revenue trends, customer behaviors, financial indicators, and market signals. After approximately 40 epochs, both curves gradually converge, with only minor fluctuations caused by the interaction among multiple financial agents and evidence-sharing mechanisms. At the end of training, the training loss reaches 0.035, while the validation loss stabilizes at 0.048, indicating strong generalization capability without obvious overfitting. The small gap between training and validation losses further verifies the effectiveness of the Cross-Agent Evidence Collaboration and Conflict-aware Agent Debate mechanisms.

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The stable convergence of MACF-Net provides a reliable foundation for achieving the forecasting performance reported in Table 2, where the model achieves an MAPE of 6.02%, and the risk assessment performance presented in Table 3, where the model obtains an AUC value of 0.962.

4.5 Discussion

The superior performance of MACF-Net demonstrates that collaborative reasoning among specialized financial agents provides significant advantages over conventional single-model financial prediction approaches. The main reason is that SaaS financial analysis is inherently a multi-perspective decision-making problem rather than a simple forecasting task. The Revenue Forecasting Agent captures subscription growth patterns, while the Customer Intelligence Agent identifies retention and churn-related signals. Meanwhile, the Financial Risk Agent and Accounting Verification Agent provide complementary perspectives regarding liquidity constraints and financial consistency. The interaction among these agents enables MACF-Net to construct a more comprehensive representation of enterprise status.

Furthermore, the Cross-Agent Evidence Verification Mechanism improves model reliability by allowing agents to exchange supporting evidence rather than independently generating predictions. The Conflict-aware Agent Debate Mechanism further enhances robustness by identifying inconsistent conclusions and encouraging agents to revise their decisions according to additional evidence. This capability is particularly important in SaaS scenarios where revenue expansion and financial risks may coexist. Therefore, the effectiveness of MACF-Net does not only come from stronger feature extraction but also from the structured collaboration and reasoning process among agents. These findings indicate that multi-agent financial intelligence provides a promising direction for developing interpretable and scalable enterprise decision-support systems.

5.Conclusions

This study proposes MACF-Net, a Multi-Agent Collaborative Financial Intelligence Network for multimodal SaaS financial analysis, revenue forecasting, and financial risk assessment. Motivated by the complex financial dynamics of subscription-based SaaS enterprises, where recurring revenue, customer retention, liquidity conditions, and external market changes are highly interconnected, MACF-Net moves beyond conventional single-model prediction paradigms by formulating financial intelligence as a collaborative reasoning process among specialized agents. The framework integrates financial time-series data, customer behavior information, enterprise documents, and external market signals to construct a comprehensive representation of SaaS business conditions. MACF-Net incorporates five specialized analytical agents, namely the Revenue Forecasting Agent, Customer Intelligence Agent, Financial Risk Agent, Market Intelligence Agent, and Accounting Verification Agent. Through the Cross-Agent Evidence Verification Mechanism, these agents exchange and validate complementary evidence, while the Conflict-aware Agent Debate Mechanism identifies inconsistent conclusions and dynamically refines predictions. Consequently, the framework can jointly capture revenue growth potential, customer churn signals, liquidity pressure, and accounting consistency rather than relying on isolated financial indicators. Experimental results on the Multimodal SaaS Financial Intelligence Dataset (MSFID) demonstrate the effectiveness of the proposed framework. For revenue forecasting, MACF-Net achieves an MAE of 3.72, an RMSE of 6.18, and a MAPE of 6.02%, reducing MAPE from 7.31% achieved by the strongest single-agent baseline. For financial risk assessment, MACF-Net obtains an accuracy of 92.36%, an F1-score of 91.08%, and an AUC of 0.962, compared with an AUC of 0.914 for the single financial agent. These results indicate that multimodal representation learning combined with cross-agent collaboration can improve both predictive accuracy and decision reliability in SaaS financial intelligence. Nevertheless, several limitations remain. The framework may be affected by incomplete enterprise disclosures, noisy market information, and distribution shifts caused by unexpected economic or industry events. Future work will therefore investigate larger and more diverse SaaS datasets, adaptive agent weighting, uncertainty-aware reasoning, and real-time financial data integration. Further research will also explore dynamic agent composition and stronger evidence-grounding mechanisms to improve robustness, scalability, and practical deployment in enterprise

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financial decision-support systems. Furthermore, in light of the increasing threats to data integrity posed by incomplete disclosures, noisy signals, and network attacks, we plan to incorporate security-aware data quality monitoring and autonomous repair mechanisms, drawing on frameworks such as CyberDQFormer [22], to further enhance the reliability of MACF-Net under adversarial data conditions.

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References

Zhang, Bingli, et al. "Consensus Matrix: A Role-Specialized Multi-Agent Framework for Structured Collaborative Decision-Making in Agentic Visual Media Workflows." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2026.

Chen, Wen. "Enterprise financial risk prediction and intelligent early warning model based on deep learning." Discover Artificial Intelligence 5.1 (2025): 227.

Navon, Ariel, and Yosi Keller. "Financial time series prediction using deep learning." arXiv preprint arXiv:1711.04174 (2017).

Lim, Bryan, et al. "Temporal fusion transformers for interpretable multi-horizon time series forecasting." International journal of forecasting 37.4 (2021): 1748-1764.

Wu, Haixu, et al. "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting." Advances in neural information processing systems 34 (2021): 22419-22430.

Ding, Xiao, et al. "Deep learning for event-driven stock prediction." Ijcai. Vol. 15. 2015.

Hossain, Md Refat, et al. "Enhancing Credit Scoring with Multimodal Deep Learning: A Hybrid Neural Network Approach Using Structured and Unstructured Financial Data." International Interdisciplinary Business Economics Advancement Journal 6.07 (2025): 09-22.

Araci, Dogu. "Finbert: Financial sentiment analysis with pre-trained language models." arXiv preprint arXiv:1908.10063 (2019).

Wu, Shijie, et al. "Bloomberggpt: A large language model for finance." arXiv preprint arXiv:2303.17564 (2023).

Yao, Shunyu, et al. "React: Synergizing reasoning and acting in language models." arXiv preprint arXiv:2210.03629 (2022).

Schick, Timo, et al. "Toolformer: Language models can teach themselves to use tools." Advances in neural information processing systems 36 (2023): 68539-68551.

Ding, Han, et al. "Large language model agent in financial trading: A survey." Proceedings of the 2026 9th International Conference on Computers in Management and Business. 2026.

Park, Joon Sung, et al. "Generative agents: Interactive simulacra of human behavior." Proceedings of the 36th annual acm symposium on user interface software and technology. 2023.

Guo, Taicheng, et al. "Large language model based multi-agents: A survey of progress and challenges." arXiv preprint arXiv:2402.01680 (2024).

Chen, Shuaihang, et al. "A survey on llm-based multi-agent system: Recent advances and new frontiers in application." arXiv preprint arXiv:2412.17481 (2024).

Hua, Zonghui, Yue Luo, and Yunting Ling. "LPG-SAC-TCO: A Large Language Model--Policy-Guided Soft Actor-Critic Framework for Total Cost of Ownership--Optimal Energy Management of Hydrogen Fuel Cell Heavy-Duty Trucks." European Journal of AI, Computing & Informatics 2.3 (2026): 1-11.

Ling, Yunting, and Wenxuan Liu. "SR-DTMA: A Digital Twin-Driven LLM Multi-Agent Framework for Systemic Risk Simulation and Coordinated Decision-Making in Supply Chains." Journal of Computer, Signal, and System Research 3.1 (2026): 123-132.

Li, Jiawei, Yue Luo, and Yunting Ling. "Carbon-Aware Reinforcement Learning for Cost-Optimal Energy Management of Hydrogen-Electric Heavy-Duty Trucks." Strategic Management Insights 3.2 (2026): 1-10.

Zhang, Jingsi, and Jixiang Ding. "CA-PPO-AXI: Coverage-Aware Deep Reinforcement Learning for Adaptive AXI Bus Protocol Verification." Fundamental Scientific Reports in Multidisciplinary Areas 2.02 (2026): 159-169.

Zhao, Qinhe, and Yuheng Huang. "DAREA: A Dynamic AI-Driven Architecture for Real Estate Asset Tokenization on Blockchain." Fundamental Scientific Reports in Multidisciplinary Areas 2.02 (2026): 182-192.

© 2026 The Author(s). Licensed under CC BY 4.0

Li, Siyu, Rongshuang Sun, and Jinlin Hu. "Adaptive risk control model: A customer credit default detection framework based on random forest and neural network." Journal of Technology Innovation and Engineering 1.3 (2025).

Qiu, Min, Linting Wu, and Shanshan Wang. "CyberDQFormer: A Knowledge Graph-Enhanced Transformer Framework for Security-Aware Data Quality Anomaly Detection and Autonomous Repair Against Network Attacks." Fundamental Scientific Reports in Multidisciplinary Areas 2.3 (2026): 34-52.

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