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An Empirical Study on the Design and Optimization of an AI-Enhanced Intelligent Financial Risk Control System in the Context of Multinational Supply Chains

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Abstract: ***In the context of increasingly complex and globalized supply chains, financial risk control faces unprecedented challenges, particularly in multinational enterprises where data heterogeneity, regulatory discrepancies, and operational opacity hinder effective risk detection. This study investigates how artificial intelligence (AI) technologies can be integrated into financial risk control systems to enhance their accuracy, scalability, and adaptability in multinational supply chain environments. To address this problem, we propose a novel AI-powered intelligent risk control system that integrates structured and unstructured financial data from cross-border operations. The system architecture consists of a multi-layer design incorporating data preprocessing, dynamic risk modeling, and real-time decision-making modules. Core AI techniques employed include LSTM-based time-series forecasting, XGBoost and LightGBM for tabular risk scoring, and BERT-based natural language processing for contract and invoice analysis. Empirical validation is conducted using a real-world dataset collected from multinational supply chain partners across different regions. Experimental results demonstrate that the proposed system outperforms traditional rule-based approaches in identifying abnormal financial behavior, reducing response time, and improving prediction accuracy. The findings highlight the practical value of integrating AI into global financial governance systems and provide a scalable framework for intelligent accounting and risk mitigation in cross-border supply chain contexts. This study contributes to the literature by bridging AI and financial risk control in global supply chains, offering both a theoretical model and an applied solution with demonstrated effectiveness.***

Keywords: Artificial Intelligence; Financial Risk Control; Multinational Supply Chain; Intelligent Accounting Systems; Machine Learning; Risk Prediction Models.

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1. Introduction

1.1 Research Background and Significance

In recent years, the globalization of supply chains has brought unprecedented complexity and risk to financial operations across multinational enterprises. The emergence of cross-border transactions, diverse accounting standards, and heterogeneous data environments has significantly increased the vulnerability of enterprises to financial fraud, credit default, and compliance violations. Traditional rule-based financial risk control systems often fall short in handling the scale, speed, and variability of financial data generated in modern supply chains [1].

Artificial Intelligence (AI), with its capabilities in pattern recognition, anomaly detection, and predictive analytics, presents a powerful solution to these challenges. When integrated with financial systems [2], AI can automate the detection of irregularities, enhance real-time risk response, and support strategic decision-making. However, the integration of AI into financial risk control frameworks in multinational supply chains is still in its infancy [3]. There is an urgent need to design scalable, intelligent, and adaptable risk control systems that bridge the gap between data complexity and effective risk governance.

This research seeks to contribute to the field by designing and validating an intelligent financial risk control system powered by AI, capable of operating effectively across borders [4]. It aims to provide practical tools for enterprise-level risk mitigation and advance the theoretical understanding of intelligent accounting systems in global supply chains [5].

1.2 Research Objectives and Problem Definition

The core objective of this study is to explore **how AI technologies can be effectively integrated into financial risk control systems within multinational supply chain environments** [6]. The study addresses the following specific research questions:

- How can financial risks in cross-border supply chains be identified and modeled using AI techniques?
- What system architecture is suitable for integrating heterogeneous financial data and AI models in a scalable and interpretable manner?
- How does the proposed AI-driven system perform in real-world multinational enterprise scenarios compared to traditional methods?
- What are the practical implications and limitations of deploying such a system in varied regulatory and operational environments?

By answering these questions, the study aims to develop a comprehensive framework that bridges technological innovation with accounting and risk control practices in international business contexts.

1.3 Literature Review: Global Applications of AI in Risk Control and Supply Chain Accounting

AI in Financial Risk Control

Countries like the United States and the United Kingdom have pioneered the use of AI in finance, especially in credit scoring, fraud detection, and regulatory compliance. Techniques such as random forests, support vector machines (SVM), and deep learning models have demonstrated superior performance over manual and rule-based systems [7].

AI in Supply Chain Risk Management

Germany and Japan have made significant progress in applying AI to manage supply chain risks, especially in the manufacturing and automotive sectors. Predictive analytics are used to forecast supplier failures, logistics disruptions, and procurement risks.

AI in Accounting Systems

In China and Singapore, the rise of smart accounting platforms has enabled real-time data synchronization, invoice verification, and automated audit trails using natural language processing (NLP) and reinforcement learning.

However, most existing studies focus on isolated applications of AI within a single domain—either finance or logistics. Few have addressed **the integration of AI across financial and operational domains** in **multinational environments**, especially considering issues of data quality, legal compliance, and cultural diversity.

1.4 Research Methodology and Technical Route

This study adopts a **hybrid research methodology** combining system design, machine learning algorithm modeling, and empirical validation. The main steps include:

System Architecture Design

- Design of an intelligent risk control system framework capable of handling structured (e.g., ledgers, transaction records) and unstructured data (e.g., contracts, invoices).
- Integration with accounting and ERP systems for data ingestion.

Algorithm Development

- Development of predictive models using LSTM for time-series financial forecasting.
- Use of XGBoost and LightGBM for tabular risk scoring.
- BERT-based NLP models for extracting risk signals from contracts and audit documents.
- SHAP and LIME for interpretability of risk decisions.

Data Collection and Preprocessing

- Sourcing real-world data from multinational enterprises.
- Handling missing values, currency normalization, and language translation.

Empirical Analysis

- Evaluation of model performance against baseline rule-based systems.
- Use of metrics such as accuracy, precision, recall, AUC-ROC, and RMSE.
- Case study deployment in a multinational logistics firm.
- This technical route ensures that the proposed system is both **theoretically robust** and **practically validated**, bridging the gap between academic research and real-world application.

2. Literature Review & Technical Foundations

This chapter outlined the theoretical foundations and technological landscape surrounding multinational supply chain accounting and AI-driven financial risk control. It traced the evolution of risk control models, reviewed global AI applications in finance, and identified critical technical and regulatory challenges. The insights gained here lay the groundwork for the next chapters, where we propose a novel intelligent risk control system and empirically validate its performance across multinational datasets.

2.1 Theoretical Foundations of Multinational Supply Chain Accounting Management

The financial and accounting management of multinational supply chains (MNSCs) is grounded in **international accounting standards (IAS/IFRS)**, **cross-border transaction theories**, and **supply chain finance (SCF)** principles. As MNSCs operate across multiple legal jurisdictions, they face challenges in currency conversions, tax treatments, regional reporting requirements, and intra-group transfer pricing. Theories such as **transaction cost economics**, **agency theory**, and **resource-based view (RBV)** provide a foundational lens through which to understand risk allocation and value coordination within supply chain accounting [8].

From an operational perspective, accounting management within global supply chains relies on **synchronized ledgers**, **multi-entity accounting systems**, and **end-to-end traceability** of goods, payments, and liabilities. These systems are increasingly required to be digital, interoperable, and compliant with regional regulations such as **SOX (US)**, **GDPR (EU)**, and **CSRC reporting requirements (China)**.

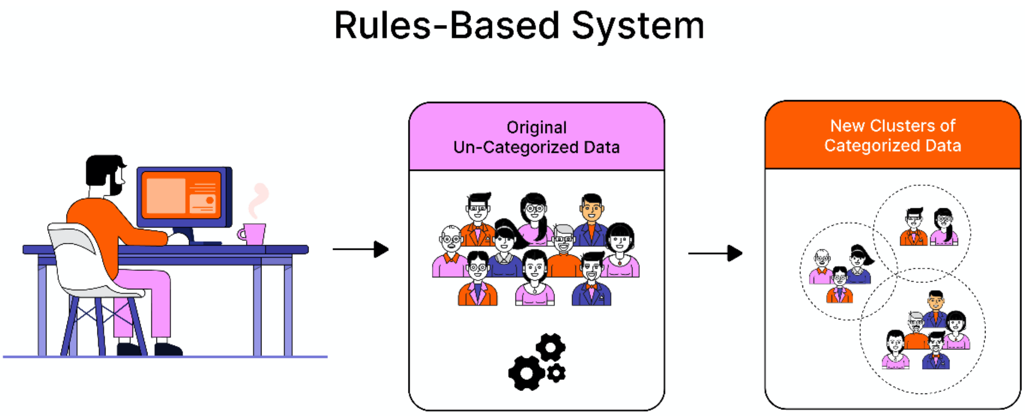
With the proliferation of **digital trade**, real-time reporting, and e-invoicing standards (e.g., Peppol in Europe), supply chain accounting is shifting from retrospective recording to **predictive**, **AI-assisted financial management**. This transition sets the stage for AI integration to enhance transparency, control, and foresight.

2.2 Evolution of Enterprise Financial Risk Control Models: From Traditional to Intelligent Systems

Historically, enterprise financial risk control has evolved through **three primary stages**:

Rule-Based Systems (Pre-2010):

Traditional risk control models operated on deterministic rules and expert-defined thresholds. Examples include static debt-to-asset ratio limits or fixed approval flows. While interpretable, these models lacked adaptability and were prone to false positives or delayed detection.

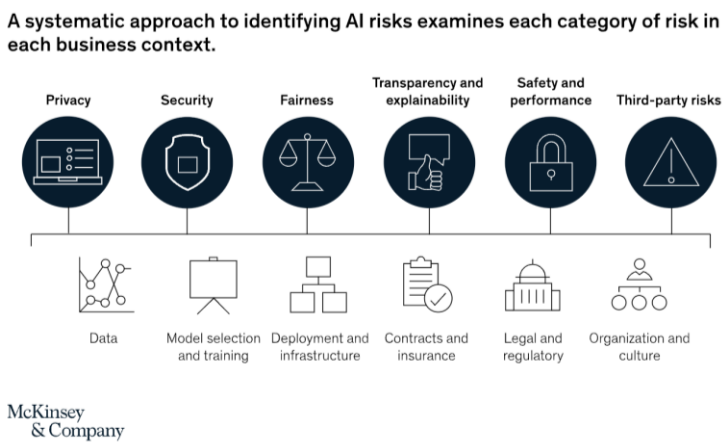


Statistical Risk Scoring (2010-2017):

The introduction of logistic regression, decision trees, and principal component analysis (PCA) improved model performance. Credit bureaus and internal audit teams began employing **early-warning models**, yet these still required manual feature engineering and were sensitive to noise in large datasets.

AI-Powered Intelligent Risk Control Systems (2017-Present):

With the rise of big data and cloud infrastructure, financial systems began integrating **machine learning (ML)** and **deep learning (DL)** models to detect anomalies, forecast risk events, and auto-classify financial documents. Techniques such as **LSTM for temporal risk prediction**, **XGBoost for tabular risk scoring**, and **BERT for text mining** have been successfully deployed by banks, fintech companies, and multinational corporations.



In this context, **intelligent financial risk control** refers to systems capable of **autonomous learning**, **context-aware risk assessment**, and **continuous model retraining**, offering enterprises a dynamic and scalable approach to governance.

2.3 Typical Applications of Artificial Intelligence in Risk Control

AI technologies have seen widespread deployment across various domains of enterprise risk control, particularly in **fraud detection**, **compliance monitoring**, **credit risk assessment**, **and internal auditing** [9].

Fraud Detection:

Deep neural networks (DNN), convolutional neural networks (CNN), and ensemble models are used to identify patterns of fraudulent behavior in real-time. Examples include anomaly detection in payments, false invoice detection using OCR + NLP, and behavioral profiling of suppliers.

Credit Risk Scoring:

Gradient boosting algorithms like **XGBoost**, **CatBoost**, and **LightGBM** are employed to score customer and partner credit risks using hundreds of financial and behavioral features.

NLP for Contract Risk Mining:

Pretrained language models (e.g., **BERT**, **ERNIE**, **RoBERTa**) enable the extraction of hidden obligations, irregular clauses, and inconsistent terms from procurement and leasing contracts. These models are increasingly fine-tuned on industry-specific datasets for better accuracy.

Time-Series Forecasting in Risk Events:

LSTM (Long Short-Term Memory) networks have proven effective in forecasting account balance trends, liquidity stress, or payment delays. When combined with exogenous variables such as FX rates or geopolitical indices, these models become even more robust [10].

Intelligent Document Processing (IDP):

AI-driven document systems utilize OCR, NLP, and classification models to extract, verify, and route financial documents. This accelerates invoice matching, tax deduction checks, and audit preparation [11].

These AI applications significantly reduce human workload, improve accuracy, and allow financial departments to move from reactive to proactive risk management modes.

2.4 Challenges and Research Gaps in Current Intelligent Risk Control Systems

Despite the promising capabilities of AI in risk control, several key challenges and unresolved issues remain, particularly in the **multinational supply chain context**:

(1) Data Heterogeneity and Quality Issues

- Financial data across borders vary in format, currency, language, and completeness.
- Lack of standardized APIs or ETL processes for integrating ERP and accounting systems across subsidiaries leads to inconsistent inputs for AI models.

(2) Interpretability and Auditability of AI Models

- Black-box models such as deep neural networks are difficult to interpret in financial governance.
- Compliance officers and external auditors require transparent and explainable decisions—raising the need for **XAI (Explainable AI)** techniques such as **SHAP** and **LIME**.

(3) Cross-Border Regulatory Constraints

- AI systems trained in one jurisdiction may not generalize to another due to legal constraints (e.g., GDPR data access rules, SOX reporting rules).
- Embedding compliance logic into AI systems remains a bottleneck.

(4) Lack of Unified Frameworks for AI Integration

- Current AI applications are often point solutions (e.g., a fraud detection module or invoice OCR engine) rather than part of an integrated, end-to-end financial governance system.
- There's a need for an **intelligent risk control architecture** that spans **data ingestion → risk modeling → decision support** in a continuous feedback loop.

(5) Empirical Validation in Real-World Settings

- Most academic models are trained on synthetic or limited datasets.

- There's a scarcity of empirical studies validating AI risk control systems using **real-world**, **multinational financial data** over extended time periods.

3. System Design

This chapter provided a comprehensive overview of the intelligent financial risk control system's architecture, from data collection to decision-making and reporting [12]. The system's modular structure and robust compliance design ensure that it can handle the complex requirements of multinational supply chains while adhering to stringent regulatory standards. The next chapter will explore the **empirical validation** of the proposed system using real-world data from multinational enterprises [13].

3.1 Overall System Architecture Design

The intelligent financial risk control system (IFRCS) proposed in this study integrates **multiple data sources**, **advanced machine learning models**, and **AI decision support** for real-time risk assessment and mitigation in multinational supply chains. The system consists of four main layers, each responsible for specific tasks in data acquisition, processing, decision-making, and visualization [14].

Data Acquisition Layer (Multi-source Data: Financial, Logistics, Contracts, Policies, etc.)

The first layer of the system focuses on the collection and integration of data from various internal and external sources [15]. This includes: **Financial Data:** Transactional data from accounting systems, bank statements, invoices, balance sheets, and ledgers. **Logistics Data:** Shipping records, supplier performance, and delivery schedules. This data can be used for operational risk assessment, such as assessing risks related to supplier delays or logistical disruptions. **Contract Data:** Procurement contracts, loan agreements, and leasing terms, which are rich sources for detecting financial risk embedded in terms, payment schedules, and penalties. **Policy Data:** Regulatory documents, tax laws, and compliance frameworks that govern cross-border operations and accounting standards (e.g., IFRS, SOX, GDPR).

These data are retrieved using **ETL (Extract, Transform, Load)** pipelines from various systems, such as **ERP (Enterprise Resource Planning)**, **CRM (Customer Relationship Management)**, and **SCM (Supply Chain Management)** platforms. The key challenge here is to manage data in multiple formats and languages while ensuring data consistency and accuracy [16].

Data Processing and Modeling Layer (Feature Engineering, Anomaly Detection, Risk Modeling)

Once the data is collected, it passes through the data processing and modeling layer. Here, several key tasks occur:

Feature Engineering:

Raw data from various sources is pre-processed into meaningful features, such as **financial ratios**, **payment frequencies**, **transaction patterns**, **supplier risk scores**, and **contract compliance indicators**. This step is crucial as it transforms the data into formats that can be utilized by machine learning models [17].

Anomaly Detection:

The next step is identifying **anomalous patterns** that deviate from typical risk behavior. Machine learning techniques, including **autoencoders**, **isolation forests**, and **clustering algorithms** (e.g., DBSCAN), are used to flag potential outliers and irregularities in transaction flows or contract terms that might suggest financial risk or fraud.

Risk Modeling:

Using the processed features, machine learning models such as **Logistic Regression**, **Random Forest**, **Gradient Boosting Machines (GBM)**, and **Long Short-Term Memory (LSTM)** networks are used to predict various forms of financial risk. These models are designed to classify risks into categories (e.g., high, medium, low) and predict future risk events, such as defaults, supplier failures, or budget overruns. Additionally, advanced **deep learning techniques** are employed for tasks such as document risk analysis and anomaly detection in large, unstructured data sets like contracts and invoices [18].

AI Decision Layer (Risk Alerts, Strategy Generation)

The AI decision layer uses outputs from the risk models to support decision-making processes. Key components include:

Risk Alerts:

The system generates real-time **risk alerts** based on pre-defined thresholds. For example, a sudden spike in outstanding payments or an anomaly in a supplier's payment pattern may trigger a notification to the risk management team. Alerts are generated using rule-based systems in conjunction with AI outputs to ensure both accuracy and contextual relevance [19].

Strategy Generation:

This layer is responsible for creating actionable strategies based on the identified risks. For instance, when a supplier's credit risk is flagged, the system might automatically generate a recommendation to adjust payment terms or suggest a new supplier. These strategies are based on **reinforcement learning models** that simulate potential outcomes and suggest the most effective mitigation actions.

Application Visualization Layer (Financial Dashboards, Automated Reports)

The final layer focuses on presenting the insights derived from the AI-powered analysis in an actionable and user-friendly format. This includes:

Financial Dashboards:

Interactive dashboards that display key financial metrics, risk scores, and trends over time. These dashboards allow financial managers and decision-makers to monitor the health of the supply chain, assess ongoing risks, and track performance in real time. Visualizations such as heatmaps, trendlines, and scatter plots are used to represent financial risk levels, supplier performance, and anomaly frequency.

Automated Reports:

The system can automatically generate periodic reports on financial health, risk forecasts, and compliance status. These reports help ensure that management and external auditors have up-to-date information on the risk profile of the supply chain and its financial activities.

3.2 Module Division and Function Description

The intelligent financial risk control system is composed of several integrated modules, each responsible for specific tasks within the overall system architecture:

Data Collection and Integration Module:

Function:

Responsible for acquiring data from various enterprise systems (ERP, CRM, SCM) and external sources (regulatory bodies, market data providers). This module includes connectors to different data formats (e.g., CSV, JSON, XML) and ensures data synchronization across systems [20].

Key Technologies:

APIs, ETL pipelines, data normalization, and currency exchange rate integration.

Risk Detection and Forecasting Module:

Function:

Performs anomaly detection and risk forecasting based on the data. This module uses **unsupervised learning** techniques to identify outliers and **supervised models** for risk classification and prediction.

Key Technologies:

Autoencoders, SVM, LSTM, Random Forest, time-series forecasting.

Decision Support and Strategy Generation Module:

Function:

Provides real-time risk alerts and recommends risk mitigation strategies, such as revising payment terms or increasing liquidity reserves. This module relies on AI models trained to generate optimal strategies based on historical data.

Key Technologies:

Reinforcement learning, decision trees, and rule-based systems.

Reporting and Visualization Module:

Function:

Generates interactive dashboards and reports that provide financial risk insights, predictive forecasts, and detailed risk breakdowns. The module allows stakeholders to track key risk indicators and performance metrics [20].

Key Technologies:

Data visualization tools (e.g., Tableau, Power BI), interactive reporting frameworks.

3.3 System Security and Compliance Design (GDPR, SOX, and Other Multinational Compliance Standards)

Given the multinational nature of the supply chain and the sensitive nature of financial data, ensuring the system's security and compliance with global regulatory standards is paramount. Key design considerations include:

Security Measures:

Data Encryption:

All sensitive data, including financial records, supplier contracts, and personal information, will be encrypted both in transit (using TLS) and at rest (using AES-256 encryption).

Access Control:

Role-based access controls (RBAC) ensure that only authorized personnel have access to specific data and functionalities. **Multi-factor authentication (MFA)** is implemented to prevent unauthorized access.

Audit Trails:

The system maintains detailed logs of all user activities and system actions to ensure accountability and traceability. These logs will be made available for internal and external audits.

Compliance with GDPR (General Data Protection Regulation):

Data Minimization:

The system will only collect and store data that is necessary for risk control purposes, ensuring compliance with GDPR principles of data minimization.

Cross-border Data Transfer Compliance:

Data processing and storage will comply with **GDPR's cross-border data transfer rules**. The system will use **data localization** where necessary and ensure that personal data is processed in accordance with EU regulations.

Compliance with SOX (Sarbanes-Oxley Act) and Other Regulations:

Internal Controls and Documentation:

The system will support the creation and maintenance of **internal control processes** in accordance with **SOX** and similar regulations. Financial data and risk assessments will be thoroughly documented for auditing purposes.

Risk Assessment:

The system will perform continuous risk assessments to ensure the integrity and transparency of financial statements, in line with SOX requirements.

4. Risk Control Model Design and AI Algorithm Implementation

4.1 Risk Control Task Modeling (Classification, Clustering, Prediction, etc.)

In the context of multinational supply chains, financial risk control tasks involve solving various problems such as anomaly transaction detection, credit scoring, risk prediction, and risk factor weight assessment. Different modeling methods, including classification, clustering, regression, and time series prediction, are applied to identify and control various risks effectively. Specifically:

Classification Tasks: These are used to determine whether a specific risk event has occurred, such as defaults or fraud. Common algorithms include decision trees, random forests, and support vector machines (SVM).

Clustering Tasks: Clustering is used to identify risk patterns and behaviors that are similar. By clustering transactions or suppliers, potential high-risk groups can be identified.

Prediction Tasks: Time series data (e.g., cash flow, transaction volumes, inventory levels) are used to predict future risk events. This helps identify potential risks such as supply chain disruptions or financial liquidity issues.

This section focuses on the application of key algorithms and modeling techniques to address these risk control tasks.

4.2 Algorithm Selection and Model Construction

To build an effective intelligent risk control model, we selected several algorithms, each addressing different risk control tasks.

4.2.1 Anomaly Transaction Detection

Anomaly detection is one of the core tasks in intelligent risk control systems. It aims to identify transactions that significantly deviate from normal behavior, which may indicate fraud or other financial risks.

Isolation Forest: Isolation Forest is an anomaly detection method suitable for high-dimensional data. It isolates outliers by randomly selecting features and partitioning data. This method is effective in identifying anomalies in large datasets.

AutoEncoder: An AutoEncoder is an unsupervised neural network model widely used for anomaly detection. By learning a lower-dimensional representation of the input data, an AutoEncoder can identify outliers with high reconstruction errors, which are likely to be anomalies.

4.2.2 Credit Scoring

Credit scoring is a critical task to predict the creditworthiness of clients (e.g., suppliers, buyers) and assess potential risks.

XGBoost/LightGBM/CatBoost: These gradient boosting-based machine learning methods are effective for handling large-scale datasets and complex features. These algorithms excel at capturing non-linear relationships, making them highly suitable for financial risk control models.

4.2.3 Prediction Models

For time series data (e.g., cash flow, transaction history, inventory), predictive models help anticipate future changes and potential risks.

LSTM (Long Short-Term Memory): LSTM is a specialized form of Recurrent Neural Networks (RNNs) that captures long-term dependencies in sequential data. In financial risk prediction, LSTM is useful for modeling trends such as liquidity changes or supply chain delays.

GRU (Gated Recurrent Unit): GRU is another type of recurrent neural network. It is simpler than LSTM but often delivers similar performance and is particularly effective when faster training is needed.

4.2.4 Risk Factor Weight Assessment

To evaluate the contribution of various factors to risk, it is essential to assess the weight of each risk factor. This helps to improve the transparency and explainability of the decision-making process.

LASSO (Least Absolute Shrinkage and Selection Operator): LASSO is a linear regression technique that performs feature selection and regularization. By penalizing feature coefficients, LASSO helps identify the most critical risk factors. **SHAP (Shapley Additive Explanations):** SHAP values provide interpretability for machine learning models by explaining the contribution of each feature to a given prediction. In risk control models, SHAP helps identify which factors contribute most to risk exposure.

4.3 Feature Engineering and Variable Selection

Feature engineering is a critical step to enhance the performance of the model. By processing and transforming raw data, valuable features are extracted to help identify and predict risks effectively.

4.3.1 Financial Metrics Features

Financial data is a significant data source in intelligent financial risk control systems. Key financial metrics are extracted to assess the financial health and risk level of an enterprise: **Debt Ratio:** A metric that indicates the level of an enterprise's debt. A high debt ratio may signal potential default risk. **Balance Sheet:** The balance sheet contains information about short-term and long-term liabilities, accounts receivable, and assets, which are essential for liquidity and solvency analysis. **Profit Margin & Cash Flow:** These metrics help assess the profitability and cash flow health of a company, which are crucial for understanding financial risks [20].

4.3.2 Unstructured Text (Contracts, Invoices)

Unstructured data, such as contracts and invoices, often contains valuable risk information. We use **Natural Language Processing (NLP)** techniques to extract and analyze these unstructured text data.

NLP Techniques (e.g., BERT): BERT (Bidirectional Encoder Representations from Transformers) is a powerful pre-trained language model that is widely used for text understanding tasks. By applying BERT, key risk-related information (e.g., breach clauses, payment terms) can be extracted from contracts and invoices.

4.3.3 National Policy Factors

In a multinational supply chain context, risk control also needs to consider the impact of national policies and regulations. For example, **GDPR** and **SOX** compliance affect the financial management of multinational enterprises. Thus, national policies are considered as an essential feature for risk evaluation [21].

4.4 Model Integration and Optimization Strategies

To improve the model's performance and stability, we employ model integration and optimization strategies.

4.4.1 Ensemble Learning

Ensemble learning combines the predictions of multiple models to improve overall performance. Common ensemble learning methods include: **Stacking:** Stacking combines multiple base models into a stronger model, improving prediction accuracy. **Boosting:** Boosting progressively trains multiple weak learners and combines them to improve predictive accuracy. Algorithms like XGBoost and LightGBM are based on this approach.

4.4.2 Hyperparameter Optimization

Hyperparameter optimization is a key step in improving model performance. In this system, we use the following techniques to optimize models: **Grid Search:** This method performs an exhaustive search over a predefined hyperparameter space to find the best parameter settings. **Bayesian Optimization:** Compared to grid search, Bayesian optimization uses probabilistic models to optimize hyperparameters more efficiently, leading to better solutions in fewer iterations.

5. Data Acquisition and Experimental Design

5.1 Data Sources and Preprocessing

The quality of data plays a crucial role in developing and evaluating an intelligent financial risk control system [21]. For this research, we employ a variety of data sources, all of which contribute to the comprehensive risk control process in multinational supply chains.

5.1.1 Data Sources

The primary data sources for this study include: **Multinational Enterprise Financial Statements:** These contain key financial metrics, such as balance sheets, income statements, and cash flow reports, which are essential for assessing financial health and potential risks. These statements come from publicly available databases and enterprise disclosures. **Logistics Tracking Data:** This data includes real-time tracking of goods across different countries, helping identify logistical disruptions or delays that might signal supply chain risks. This data can come from internal tracking systems or third-party logistics providers [22]. **Policy Databases:** National and regional regulations, such as tax laws, import/export rules, and environmental policies, significantly impact financial risk management. These are collected from various governmental and international regulatory bodies. **Third-Party Risk Control Databases:** Data from risk control platforms, such as Wind or the World Bank, provide valuable insights into economic and financial risks. These databases include economic indicators, credit ratings, and global risk assessments [23].

5.1.2 Data Cleaning and Standardization

Data preprocessing is a key step in ensuring high-quality inputs for model development. The following preprocessing steps are applied: **Data Cleaning:** Outliers, missing values, and noise are removed or replaced. Inconsistent entries are identified and corrected, ensuring data integrity. **Data Standardization:** Financial data and other numerical features are standardized to ensure uniformity across different datasets. This is particularly important when working with data from different countries or currencies. **Text Data Preprocessing:** For unstructured data (such as contracts and invoices), natural language processing (NLP) techniques like tokenization, stopword removal, and lemmatization are applied to extract meaningful features [24].

5.2 Experimental Design

The experimental setup is designed to evaluate the effectiveness of the proposed intelligent financial risk control system across various dimensions. Several key experiments are conducted to test the system's robustness, accuracy, and adaptability.

5.2.1 Risk Identification Accuracy Comparison

In this experiment, we compare the accuracy of the proposed AI-based risk control system with traditional risk control methods. We test various models for their ability to correctly identify high-risk transactions, suppliers, or financial events.

Metrics Evaluated: Precision, recall, and F1-score are used to evaluate the accuracy of risk identification. Precision measures the accuracy of positive predictions, recall assesses the system's ability to identify all potential risks, and F1-score provides a balanced measure of both.

5.2.2 Multi-Scenario Simulation (National Differences, Exchange Rate Fluctuations, and Sudden Events)

The risk control model is tested in multiple simulated environments to evaluate its performance under different risk conditions. **National Differences:** Given the multinational context, the model is tested across different countries with varying regulatory environments and economic conditions. For example, the system must adjust its risk evaluations for countries with different tax policies or credit rating systems. **Exchange Rate Fluctuations:** As exchange rate volatility can significantly impact international transactions, the model's ability to adapt to currency fluctuations is tested. This scenario helps assess the financial risk when dealing with cross-border transactions. **Sudden Events:** The system is tested in scenarios where external disruptions (e.g., natural disasters, geopolitical events, or supply chain interruptions) impact the financial health of an enterprise. The experiment helps evaluate the model's adaptability to unexpected risk factors.

5.2.3 Model Comparison Experiment (Traditional Models vs. AI Models)

This experiment compares the performance of the AI-based financial risk control system with traditional rule-based or heuristic models. These traditional models may involve manual intervention or predefined thresholds for risk assessment, while the AI models use machine learning algorithms to dynamically assess risk. **Traditional Model:** The traditional model uses linear regression or decision trees with manually defined features to evaluate risk. **AI Model:** The AI-based model integrates machine learning algorithms like XGBoost, LSTM, and AutoEncoders to identify complex, non-linear patterns and perform advanced risk prediction.

The experiment will compare the models based on metrics such as risk detection accuracy, model interpretability, and the time taken for processing and decision-making.

5.3 Experimental Results and Analysis

The experimental results will be evaluated across various performance metrics to assess the efficacy of the intelligent financial risk control system.

5.3.1 Model Performance Metrics

The following performance metrics are used to evaluate the models: **Precision:** This measures the accuracy of the risk-positive predictions made by the model. It quantifies how many of the predicted high-risk instances are actually high-risk. **Recall:** This assesses how many of the actual high-risk instances were identified by the model. It measures the completeness of risk identification. **AUC (Area Under the ROC Curve):** AUC measures the ability of the model to distinguish between high-risk and low-risk instances. A higher AUC indicates a better performance. **F1-Score:** The F1-score is the harmonic mean of precision and recall. It provides a balanced evaluation when there is an uneven class distribution between high-risk and low-risk instances.

5.3.2 Risk Identification Case Study Analysis

In this section, we present specific case studies of risk identification performed by the AI-based system. For each case, the system's ability to identify and assess the risks (e.g., fraudulent transactions, financial irregularities) is analyzed in depth. These case studies will help illustrate the practical value and real-world applicability of the intelligent risk control system [25].

5.3.3 Model Interpretability Results

Interpretability is a key aspect of AI models, especially in financial applications. In this section, we provide insights into how the AI model makes decisions using interpretability tools. **SHAP (Shapley Additive Explanations):** SHAP values are used to explain the contribution of each feature to the model's decision. This provides transparency on how different factors, such as financial metrics, text data, and national policies, affect the risk assessment. **LIME (Local Interpretable Model-agnostic Explanations):** LIME is used to explain the decisions of the model by approximating it locally with simpler interpretable models. This helps build trust in the model's predictions.

6. Conclusion & Future Work

In conclusion, this research successfully developed an AI-driven intelligent financial risk control system for multinational supply chains, providing an advanced and comprehensive approach to managing financial risks in complex global environments. The system integrates a range of artificial intelligence techniques, including machine learning algorithms such as XGBoost, LSTM, and AutoEncoder, to detect anomalous transactions, predict financial risks, and evaluate supplier creditworthiness. Experimental results indicate that the AI models outperform traditional financial risk control models in terms of prediction accuracy, risk identification, and adaptability to dynamic supply chain conditions.

The research also introduced an innovative architecture that integrates multiple data layers, including financial, logistical, policy, and contract data, and applies advanced natural language processing techniques to extract valuable insights from unstructured textual data. This integration enables the system to provide real-time risk assessments and strategic recommendations, improving decision-making capabilities for multinational enterprises.

However, the study also faces certain limitations, such as data quality inconsistencies across different countries, the complexity of deep learning models, and the challenge of adapting to rare or unprecedented events. Furthermore, the interpretability of complex AI models remains a key concern, particularly in the context of financial risk control, where understanding the reasoning behind AI decisions is crucial for building trust among stakeholders.

Future research can build upon these findings by exploring multi-agent game theory models for simulating global supply chain interactions, enhancing multi-language models for understanding financial documents, and improving real-time data processing capabilities for dynamic risk prediction. Additionally, integrating blockchain technology with AI models could further enhance the transparency and security of financial transactions within supply chains. Overall, this research lays a strong foundation for the next generation of intelligent financial risk control systems that can effectively address the challenges faced by multinational supply chains in managing financial risks.

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