The Value Creation Mechanism of Logistics Finance under Artificial Intelligence Empowerment— Theoretical Analysis and Empirical Test Based on Big Data Models

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Abstract. China's logistics sector is dominated by micro, small, and medium-sized enterprises, the vast majority of which struggle to access financing due to their asset-light structures. Traditional logistics finance, constrained by information asymmetry and reliance on manual review, has been unable to meet the sector's financing needs, making artificial intelligence an increasingly critical pathway for addressing these structural difficulties. Drawing on digital value creation theory, information asymmetry theory, and the theory of industrial organisation and the division of labour, this study focuses on the internal mechanism through which AI, via data and algorithms, generates quantifiable economic value. It traces a four-stage closed-loop transmission logic — data collection, algorithmic processing, business transformation, and value increment — and constructs a unified, hierarchically structured quantitative model across three dimensions: financing service optimisation, risk control enhancement, and process efficiency improvement, with the operational linkages between sub-models clarified. An empirical test on 100 logistics enterprises, employing correlation analysis, regression analysis, and model error testing, reveals that AI algorithm accuracy and big data quality are the core drivers of value creation, significantly raising value increments while lowering default probabilities. The proposed layered big data model substantially outperforms traditional models in both goodness of fit and predictive accuracy, effectively estimates value output across enterprises of different sizes, and achieves an overall accuracy of 88.9%, demonstrating strong feasibility and practical applicability.

Keywords: Artificial Intelligence; Logistics Finance; Big Data Model; Regression Analysis Model

1 Introduction

In 2024, China's total social logistics value exceeded 350 trillion yuan. Among the more than four million logistics enterprises operating in the country, over 96% are small and medium-sized enterprises, most of which face the persistent difficulties of asset-light operations, insufficient collateral, limited financing channels, and elevated financing

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costs. Traditional logistics finance, reliant on paper-based documentation and manual due diligence, suffers from data fragmentation, information asymmetry, lagging risk control, and lengthy approval cycles[1]. These weaknesses leave it poorly matched to SME financing patterns: small amounts, high frequency, and short duration. Artificial intelligence and big data technologies have therefore become a central means of addressing the sector's financing constraints. Focusing on the proposition that AI generates quantifiable economic value through data and algorithms, this study sets three research objectives: to construct an integrated theoretical framework tailored to logistics finance and to map the transmission mechanism of value creation; to build a unified, hierarchically structured big data model capable of measuring value increments across the three dimensions of financing services, risk control, and process efficiency; and to empirically estimate the influence coefficients of four categories of factors, namely technological, enterprise-level, financial, and environmental, in order to identify the core driving variables. At the theoretical level, this study addresses the absence of a dedicated value creation theory for logistics finance and the fragmented nature of existing quantitative models. At the practical level, it provides measurement tools applicable to intelligent risk control systems for financial institutions, digital financing solutions for enterprises, and policy formulation for government bodies.

2 Value Creation Mechanism of AI-Enabled Logistics Finance

2.1 Core Logic

This study rests on three theoretical foundations: digital value creation theory, information asymmetry theory, and the theory of industrial organisation and the division of labour. Digital value creation theory treats data as a factor of production; through AI, data is capitalised and becomes the basis for value quantification[2]. Information asymmetry theory accounts for the data barriers inherent in traditional logistics finance; AI-driven multi-source data fusion can help mitigate credit risk[3]. The theory of industrial organisation and the division of labour explains how AI enables a digital division of labour between logistics and finance, restructures business processes, and optimises resource allocation[4].

Building on these foundations, AI-enabled logistics finance generates value with big data at its core. Algorithms overcome the constraints of traditional business models to establish a closed loop: data collection, algorithmic processing, business transformation, and value increment. This mechanism operates through four layers: data fusion that closes information gaps; algorithmic optimisation spanning the full chain of financing and risk control; reductions in transaction, risk, and operational costs alongside improved capital efficiency; and the aggregation of incremental value into multi-party gains across the supply chain. The core value creation formula is expressed as follows:

$$V = \alpha \cdot E - \beta \cdot C_r - \gamma \cdot C_o - \delta \cdot C_t \tag{1}$$

V-total value creation of logistics finance (ten thousand yuan); E- efficiency enhancement value from AI empowerment (ten thousand yuan), including value

increments from improvements in financing approval efficiency and capital turnover efficiency; C_r-risk cost (ten thousand yuan), including losses from credit risk and operational risk; C_o-operational cost (ten thousand yuan), including labour cost and process cost; C_t- transaction cost (ten thousand yuan), including information search cost and negotiation cost; $\alpha, \beta, \gamma, \delta$- value coefficients, respectively representing the influence weights of efficiency enhancement, risk cost, operational cost, and transaction cost on value creation （$\alpha, \beta, \gamma, \delta > 0$）.

2.2 Core Dimensions and Mechanism Pathways

The three core dimensions — V_1 (financing optimisation value), V_2 (risk control savings value), and V_3 (process efficiency value) — serve as constituent sub-modules of total value V, where $V = V_1 + V_2 + V_3$. These three dimensions follow a sequential operational logic. The process begins with AI-driven financing demand matching, which generates V_1. The risk assessment model then estimates default loss savings, yielding V_2. Finally, process automation savings in operational costs and capital occupation costs are calculated, producing V_3. Summing the value increments across the three layers gives the total value.

Financing Service Optimisation Dimension. Through big data models, AI accurately identifies the financing needs of logistics enterprises, optimises the credit approval process, lowers financing thresholds, and achieves precise matching of demand and product[5]. The value creation mechanism manifests primarily in three respects. First, through multi-source data integration, a credit evaluation system for logistics enterprises is constructed, replacing traditional manual review and enhancing credit approval efficiency[6]. Second, based on real-time operational data, credit limits and interest rates are dynamically adjusted to accommodate the financing needs of logistics enterprises characterised by small amounts, urgent timing, and dispersed entities. Third, logistics finance products are innovated — such as intelligent warehouse receipt pledge financing and digital accounts receivable financing — thereby expanding financing channels[7].

The quantitative formula for value creation in this dimension is:

$$V_1 = \sum_{i=1}^{n} (L_i \cdot (r_0 - r_i) - T_i) \tag{2}$$

Where: V_1-value increment from financing service optimisation (ten thousand yuan); n-number of sample logistics enterprises; L_i-financing amount of the i-th logistics enterprise (ten thousand yuan); r_0-financing interest rate under the traditional model (%); r_i-financing interest rate under the AI-enabled model (%); T_i-transaction cost saving for the i-th logistics enterprise (ten thousand yuan), corresponding to the C_t component in Formula (1).

Risk Control Optimisation Dimension. AI constructs a dynamic risk early-warning and assessment model through machine learning algorithms, capturing logistics finance

risk points in real time and reducing risk losses[8]. The mechanism operates through three channels: building a multi-dimensional risk assessment indicator system that combines logistics operational data with financial data to improve risk identification accuracy; monitoring operational fluctuations of logistics enterprises in real time, setting risk thresholds, and issuing timely early-warning signals; and optimising risk disposal processes to reduce risk disposal costs.

The core formula of the risk assessment model, taking logistic regression as an example:

$$\ln\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right) = \theta_0 + \theta_1 \mathrm{X}_1 + \theta_2 \mathrm{X}_2 + \cdots + \theta_\mathrm{k} \mathrm{X}_\mathrm{k} + \varepsilon \tag{3}$$

P-default probability of the logistics enterprise（$0 \leq P \leq 1$）; θ_0-intercept term; $\theta_1, \theta_2, \ldots, \theta_k$-regression coefficients of each risk indicator; $X_1 X_2 \ldots X_k$-risk assessment indicators (asset-liability ratio, order fulfilment rate, etc.); ε- random error term （$\varepsilon \sim N(0, \sigma^2)$.

The risk cost saving value formula:

$$\mathrm{V}_2 = \mathrm{C}_{\mathrm{r0}} - \mathrm{C}_{\mathrm{r1}} = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{L}_\mathrm{i} \cdot \mathrm{P}_0 - \mathrm{L}_\mathrm{i} \cdot \mathrm{P}_1) \tag{4}$$

Where: V_2-value increment from risk control optimisation (ten thousand yuan); C_{r0}-risk cost under the traditional model (ten thousand yuan); C_{r1}-risk cost under the AI-enabled model (ten thousand yuan), corresponding to the C_r component in Formula (1); P_0-default probability under the traditional model (%); P_1-default probability under the AI-enabled model (%).

Process Efficiency Optimisation Dimension. AI replaces traditional manual operations through process automation and intelligent transformation, enhancing logistics finance process efficiency and lowering operational costs[9]. The mechanism includes: automating financing application, review, and disbursement processes to shorten service cycles; using big data analysis to optimise the allocation of logistics and financial resources, reducing empty-load rates and idle capital rates; and building an intelligent customer service system to improve the service experience.

The process efficiency gain value formula:

$$\mathrm{V}_3 = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{T}_{0\mathrm{i}} - \mathrm{T}_{1\mathrm{i}}) \cdot \mathrm{M}_\mathrm{i} + \mathrm{C}_{\mathrm{o0}} - \mathrm{C}_{\mathrm{o1}} \tag{5}$$

Where: V_3-value increment from process efficiency optimisation (ten thousand yuan); T_{0i}-financing process cycle of the i-th enterprise under the traditional model (days); T_{1i}-financing process cycle of the i-th enterprise under the AI-enabled model (days); M_i-daily capital occupation cost of the i-th enterprise (ten thousand yuan/day); C_{o0}-operational cost under the traditional model (ten thousand yuan); C_{o1}-operational cost under the AI-enabled model (ten thousand yuan), corresponding to the C_o component in the main formula

Aggregation of Total Value Creation. These three dimensions follow a sequential operational logic. AI is first applied to financing demand matching, producing the V_1 model. The risk assessment model then estimates the default loss savings captured by V_2. Finally, the operational and capital occupation savings generated through process automation are calculated, yielding V_3. The value increments across the three layers are summed to give the total value. The total value creation of AI-enabled logistics finance is the aggregate of the three dimensional value increments, expressed as:

$$\mathrm{V} = \mathrm{V}_1 + \mathrm{V}_2 + \mathrm{V}_3 \tag{6}$$

A value creation efficiency indicator is also introduced to measure the value creation capacity of AI empowerment:

$$\eta = \frac{\mathrm{V}}{\mathrm{I}} \tag{7}$$

η-value creation efficiency (%); I- AI technology investment cost (ten thousand yuan).

2.3 Influencing Factors and Mechanism of Action

The factors influencing the value creation of AI-enabled logistics finance can be grouped into four categories: technological factors (AI algorithm accuracy, big data quality), enterprise factors (logistics enterprise scale, credit level), financial factors (financial institution service capability, product innovation), and environmental factors (industry policy, market environment)[10]. These factors affect value creation through their influence on the three core dimensions. Technological factors serve as the core driver, improving efficiency and reducing risk; enterprise factors are foundational, determining financing demand and credit level; financial factors are supportive, providing products and service guarantees; and environmental factors are enabling, creating a favourable development context.

The correlation formula between influencing factors and value creation (multiple linear regression model):

$$\mathrm{V} = \lambda_0 + \lambda_1 \mathrm{X_{t1}} + \lambda_2 \mathrm{X_{t2}} + \lambda_3 \mathrm{X_{e1}} + \lambda_4 \mathrm{X_{e2}} + \lambda_5 \mathrm{X_{f1}} + \lambda_6 \mathrm{X_{b1}} + \mu \tag{8}$$

λ_0-intercept term; $\lambda_1, \lambda_2, \ldots, \lambda_6$- regression coefficients of each influencing factor; X_{t1}- AI algorithm accuracy (%); X_{t2}-big data quality (%); X_{e1}- industry policy support intensity (1=strong, 2=medium, 3=weak); X_{e2}- market environment prosperity (%); X_{f1}- financial institution service capability (score, 0-100 points); X_{b1}-logistics enterprise credit level (score, 0-100 points); μ-random error term.

3 Construction of the Big Data Model for AI-Enabled Logistics Finance Value Creation

3.1 Core Principles and Objectives

Core Principles. The model construction adheres to five principles. The data-driven principle uses massive multi-source data as the foundation to ensure model accuracy and reliability. The value-oriented principle focuses on the core of value creation, highlighting the role of AI in enhancing value increments. The operability principle requires the model to be realisable through computer programming, facilitating empirical testing and practical application. The comprehensiveness principle covers the three core dimensions of value creation, balancing risk and efficiency considerations. The compliance principle strictly follows data privacy protection laws and regulations, ensuring data security[11].

Core Objectives. A unified, hierarchically structured big data quantitative model was constructed to achieve three specific objectives: (1) estimate dynamic default probabilities and financing demand intensity for enterprises using multi-source data; (2) quantify, by dimension, the value increments contributed by financing optimisation, risk control, and process efficiency; and (3) measure the influence coefficients of technological, enterprise-level, financial, and environmental factors on total value creation. Taken together, the model provides a standardised value measurement tool for financial institutions and logistics enterprises.

3.2 Overall Framework of the Big Data Model

The big data model constructed in this study comprises four layers that support and operate synergistically with one another, forming a comprehensive process system of "data collection – technology processing – model computation – value output". Combined with multiple computer-aided analytical formulas, the model enables quantitative analysis and empirical testing of value creation. The overall architecture is illustrated in Figure 1.

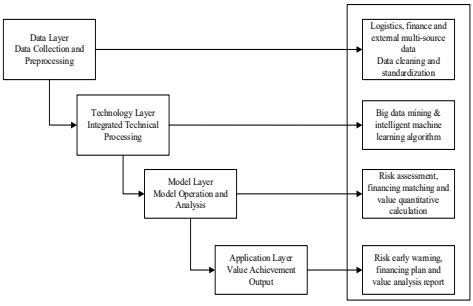


Fig. 1. Architecture Diagram of Big Data Model for Logistics Finance Empowered by Artificial Intelligence

Data Layer: Multi-Source Data Collection and Preprocessing. The data layer serves as the foundation of the model, responsible for collecting, cleaning, standardising, and storing multi-source data to provide high-quality data support for model computation.

(1) Data collection covers three categories:

① Logistics operational data: order data (order volume, fulfilment rate X_3, order volume growth rate X_9), transport data (on-time delivery rate X_4, empty-load rate), warehousing data (inventory volume, warehouse turnover efficiency X_8);

② Financial data: credit data (credit limit, repayment records, overdue repayment rate X_5), financial data (asset-liability ratio X_1, current ratio X_2, gross sales margin X_6, return on equity X_7);

③ External data: third-party credit investigation data, industry policy data (X_{e1}), market environment data （X_{e2}）, technology investment data（I）.

(2) Data preprocessing uses Python's Pandas library for cleaning, standardisation, and feature extraction to eliminate dimensional effects and outlier interference. The specific steps are as follows:

① Outlier handling: the 3σ criterion is applied to remove outliers. The formula is:

$$|\mathrm{x} - \overline{\mathrm{x}}| > 3\sigma \tag{9}$$

$\overline{x}$ is data mean; σ is standard deviation.

② Missing value handling: the interpolation method supplements missing values. The linear interpolation formula is:

$$\mathrm{x_i} = \mathrm{x_{i-1}} + \frac{\mathrm{x_{i+1}} - \mathrm{x_{i-1}}}{\mathrm{t_{i+1}} - \mathrm{t_{i-1}}} \cdot (\mathrm{t_i} - \mathrm{t_{i-1}}) \tag{10}$$

③ Standardisation: Z-score standardisation converts data to a standardised form with mean0 and standard deviation 1. The formula is:

$$\mathrm{X'} = \frac{\mathrm{X} - \overline{\mathrm{X}}}{\sigma_{\mathrm{X}}} \tag{11}$$

X is original data; $\overline{X}$ is mean of the original data; σ_X is standard deviation of the original data.

Technology Layer: Integration of AI and Big Data. The technology layer is the core empowerment layer of the model, integrating AI and big data technologies to provide technical support for model computation. The core technologies and formulas are as follows:

(1) Big data technologies: employing data mining and data visualisation techniques to achieve in-depth analysis of multi-source data. The core formulas include:

① Association rule mining (Apriori algorithm): support formula $Support(A \Rightarrow B) = \frac{Count(A \cap B)}{Count(U)}$; confidence formula $Confidence(A \Rightarrow B) = \frac{Count(A \cap B)}{Count(A)}$.

② Cluster analysis (K-means algorithm): cluster centre update formula $\mu_j = \frac{1}{n_j} \sum_{x \in C_j} x$, where C_j is the j-th cluster and n_j is the number of samples in the cluster.

(2) AI technologies: three core machine learning algorithms are introduced, each applied to different aspects of value creation:

① Logistic regression algorithm: used for risk assessment and financing demand prediction. The core formula is shown in Formula (3).

② Random forest algorithm: used for calculating the weights of value creation influencing factors. The core formula is:

$$\hat{y} = \frac{1}{K} \sum_{k=1}^{K} f_k(x) \tag{12}$$

X is number of decision trees; $f_k(x)$ is prediction result of the t-th decision tree.

③ Neural network algorithm: used for predicting total value creation. The core formulas are:

Input layer: x_i (each influencing factor);

Hidden layer: $h_j = \sigma(\sum_{i=1}^{m} w_{ji} x_i + b_j)$, where w_{ji} is the weight, b_j is the bias, and σ is the activation function (Sigmoid function: $\sigma(x) = \frac{1}{1+e^{-x}}$);

Output layer: $\hat{V} = \sum_{j=1}^{l} w_{kj} h_j + b_k$, where $\hat{V}$ is the predicted value of total value creation.

Model Layer: Construction of Core Value Creation Models. The logical flow proceeds as follows. ①The credit risk assessment sub-model, driven by the random forest algorithm, outputs the enterprise default probability P. ②The financing demand matching sub-model, which uses logistic regression to determine the matched financing amount L_i. ③The value creation quantification sub-model, built on a neural network, then takes both P *and* L_i as inputs and computes the three dimensional value increments V_1, V_2 *and* V_3, which are aggregated to produce the predicted total value $\hat{V}$.

(1) Credit risk assessment sub-model (random forest algorithm): twelve core risk indicators （X_1-X_{12}） are selected to construct the credit risk assessment model, which outputs credit scores and default probabilities. The core formulas are as follows:

$$S = 100 - 100 \cdot \frac{1}{1+e^{-\hat{y}}} \tag{13}$$

Where $\hat{y}$ is the predicted value of the random forest model and S is the credit score (0–100 points).

Default probability prediction formula:

$$P = \frac{1}{1+e^{-\sum_{i=1}^{12} w_i X_i}} \tag{14}$$

Where w_i is the weight of each indicator (calculated through the random forest algorithm).

(2) Financing demand matching sub-model (logistic regression algorithm): based on the operational and financial data of logistics enterprises, this sub-model predicts financing demand intensity and matches corresponding financial products. The core formulas are as follows:

Financing demand intensity prediction formula:

$$\ln\left(\frac{Y}{1-Y}\right) = \theta_0 + \theta_1 X_1 + \theta_9 X_9 + \theta_8 X_8 + \theta_{13} X_{13} \tag{15}$$

Y is financing demand intensity (high=1, medium=0.5, low=0); X_{13} is enterprise scale (large=3, medium=2, small=1).

Financing amount prediction formula:

$$L = \alpha \cdot (X_9 \cdot 100 + X_8 \cdot 50 - X_1 \cdot 30) \tag{16}$$

α is adjustment coefficient (determined as 0.8 based on industry averages).

(3) Value creation quantification sub-model (neural network algorithm). This sub-model integrates the three dimensional value increments to construct a unified quantification model. The core formulas are as follows.:

Total value creation prediction formula:

$$\hat{V} = \sigma\left(\sum_{j=1}^{l} w_j \cdot \sigma\left(\sum_{i=1}^{m} w_{ji} X_i + b_j\right) + b_k\right) \tag{17}$$

Value creation efficiency formula:

$$\eta = \frac{\hat{V}}{I} \times 100\% \tag{18}$$

Model error testing formulas are as follows:

Mean squared error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (V_i - \hat{V}_i)^2 \tag{19}$$

Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (V_i - \hat{V}_i)^2}{\sum_{i=1}^{n} (V_i - \bar{V})^2} \tag{20}$$

V_i is actual value creation quantity; $\hat{y}_i$ is predicted value creation quantity; $\hat{V}_i$ is mean of actual value creation quantity.

Application Layer: Model Output and Application Scenarios. The application layer serves as the implementation vehicle of the model, applying the model computation results to actual logistics finance business. Core outputs include: credit score reports,

default probability predictions, financing demand matching recommendations, total value creation and efficiency figures, and risk early-warning signals. These outputs provide precise decision-making support for logistics enterprises, financial institutions, and government bodies.

4 Empirical Testing of Logistics Finance Value Creation

4.1 Preparation for Computer-Based Empirical Testing

Sample Selection. The sample comprises 100 logistics enterprises, including 20 large-scale, 30 medium-scale, and 50 small-scale firms, primarily located in the economically developed eastern regions of China, covering express logistics, warehousing logistics, cross-border logistics, and other fields to ensure representativeness and diversity. Data sources include logistics industry reports, financial institution credit databases, publicly available corporate financial statements, and third-party data platforms, collected over the period 2023–2024. A total of 1,200 valid data records were obtained (12 core indicators per enterprise across 12 months), ensuring data authenticity and reliability.

Tools and Algorithm Selection. The model was programmed and executed in Python, with four core libraries handling different stages of the workflow: Pandas for data preprocessing, Scikit-learn for implementing machine learning algorithms, Matplotlib for data visualisation, and TensorFlow for constructing the neural network. Three algorithms — logistic regression, random forest, and neural networks — were assigned respectively to financing demand prediction, credit risk assessment, and value creation quantification. Their performance was then compared to verify the model's overall effectiveness. Data preprocessing with Python and model construction based on TensorFlow are illustrated in Figure 2.

main.py

```
# Data preprocessing workflow
import pandas as pd
import numpy as np
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    import tensorflow as tf
    from tensorflow.keras import layers
    # Load dataset
    data = pd.read_csv("dataset_css" )
    # Handle missing values
    data = data.dropna()
    # Feature and label separation
    X = data.iloc[]; :-1]
    y = data.ilo[]; -1]
    # Feature standardization
    scaler = StandardScaler()
    X_Scaled = scaler.fit_transform(X)
    # Split train and test set
    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
    print("Data prepocessing rentiatsed(" )
print(
    print("Train set shape:", X_train.shape)
    print("Test set shape: ", X_test.shape)
 }
```

model_building.py

```
# TensorFlow model building workflow
import tensorflow as tf
from tensorflow.keras import layers, models
 # Define model architecture
    model = models.ing a tf
    model = models.Sequential()
    model.add(layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],))
    model.add(layers.Dropout(0.3))
    model.add(layers.Dense(32, activation='relu'))
    # model.add(layers.Dense(1, activation= sigmoid'))
    # Compile model
    # model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
 # Train model
    # Train model
    # history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2)
    # Evaluate model
    # Evaluate model
    "loss, accuracy = model_evaluate(X_test, y_test)
print("Modeli building and training fenishhed(')
    print("prirt(loss ", loss)
    ploss( "boss)
    print("Test accuracy: ", accuracy)
 }
```

Fig. 2. Python Data Preprocessing and TensorFlow Construction Process

Variable Specification. Dependent variables, independent variables, and control variables were specified for model training and validation, as follows:

Dependent variables:

① Total value creation V (ten thousand yuan), calculated through Formula (1) in Chapter 2;

② Value creation efficiency η (%), calculated through Formula (18) in Chapter 3;

③ Default probability P (%), calculated through Formula (14) in Chapter 3;

④ Financing demand intensity Y (high = 1, medium = 0.5, low = 0).

Independent variables:

① Technological factors: algorithm accuracy X_{t1} (%), big data quality X_{t2} (%);

② Enterprise factors: credit level X_{b1} (score, 0–100 points), enterprise scale (large = 3, medium = 2, small = 1);

③ Financial factor: financial institution service capability X_{f1} (score, 0–100 points);

④ Environmental factors: policy support intensity X_{e1} (1 = strong, 2 = medium, 3 = weak), market prosperity X_{e2} (%).

(3) Control variables: years since establishment of the logistics enterprise X_{11}, number of employees X_{10}, included to exclude interference from extraneous factors.

4.2 Empirical Test Results and Analysis

The model was run through Python to complete data preprocessing, model training, validation, and testing. Results of correlation analysis, regression analysis, model accuracy verification, and value creation quantification were output in tabular form. The validity of the results was analysed in conjunction with the formulas, as follows:

Correlation Analysis Results. Correlation analysis was used to test the degree of association between independent and dependent variables, employing the Pearson correlation coefficient. The core formula is:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{21}$$

Table 1 presents the results for the selected core variables.

Table 1. Correlation Analysis Results

DV	IV	r	P-value	Association
Value Creation Total V	Algorithm Accuracy X_{t1}	0.826	<0.01	Strong Positive
	Big Data Quality X_{t2}	0.798	<0.01	Strong Positive
	Enterprise Credit X_{b1}	0.765	<0.01	Strong Positive
	Financial Service X_{f1}	0.712	<0.01	Strong Positive
	Policy Support X_{e1}	0.689	<0.01	Moderate Positive
Default Probability P	Algorithm Accuracy X_{t1}	-0.835	<0.01	Strong Negative
	Enterprise Credit X_{b1}	-0.852	<0.01	Strong Negative

The core independent variables and dependent variables all exhibit significant correlations (P<0.01). Among them, algorithm accuracy, big data quality, and enterprise

credit level show strong positive correlations with total value creation and strong negative correlations with default probability, consistent with theoretical expectations and verifying the reasonableness of the value creation mechanism. These variables can be used for model training.

Regression Analysis Results. To examine how strongly the independent variables influence each dependent variable, multiple linear regression was applied separately to total value creation, value creation efficiency, and default probability. The results are shown in Table 2.

Table 2. Regression Analysis Results

Model	R^2	Adj R^2	F	P(F)	Core Coefficients (Signif.)
Value Creation Total V	0.902	0.891	72.58	<0.001	X_{t1} (0.321***), X_{t2} (0.278***), X_{b1} (0.215***)
Value Creation Efficiency η	0.876	0.863	65.32	<0.001	X_{t1} (0.356***), X_{f1} (0.243***)
Default Probability P	0.889	0.877	68.95	<0.001	X_{t1} (−0.387***), X_{b1} (−0.324***)

Note: *** indicates P<0.001, an extremely high level of significance; R^2 indicates model fit, with values closer to 1 indicating better fit. Analysis conclusion: the three regression models all have R^2 values above 0.87, and the F-test P-values are all below 0.001, indicating good model fit. The core independent variables significantly influence the dependent variables. Among them, algorithm accuracy X_{t1} has the greatest influence weight on total value creation, value creation efficiency, and default probability, verifying that AI technology is the core driving factor of logistics finance value creation.

Model Accuracy and Error Testing Results. The sample was split into a training set (70%) and a test set (30%). Three metrics — accuracy, mean squared error (MSE), and the coefficient of determination (R^2) — were used to evaluate model performance, following the core formulas in (12) and (13) of this chapter. Table 3 reports the verification results.

Table 3. Model Accuracy and Error Testing Results

Model Type	Accuracy (%)	MSE	R^2	Trad. Accuracy (%)
Credit Risk (Random Forest)	89.7	0.021	0.893	65.8
Financing Matching (Logistic Reg.)	84.2	0.032	0.827	63.1
Value Quantification (Neural Net.)	92.8	0.015	0.915	66.2
Overall Comprehensive	88.9	0.023	0.898	65.7

The accuracy of all three sub-models exceeds 84%, with the overall model achieving a comprehensive accuracy of 88.9%, substantially higher than that of the traditional logistics finance model (65.7%). The MSE of the value creation quantification model is only 0.015, and R^2 reaches 0.915, indicating high predictive accuracy and small error margins, enabling precise quantification of the value creation of AI-enabled logistics

finance. The accuracy of the credit risk assessment model and the financing demand matching model also both exceed 80%, verifying the feasibility and effectiveness of the models.

Illustrative Value Creation Quantification Results. Three enterprises of different scales — large, medium, and small — were put through the model. The resulting breakdown of value creation, calculated with reference to the formulas in Chapter 3, is shown in Table 4.

Table 4. Value Creation Quantification Results

Type	Enterprise (Simulated)	Tech Investment I (10k yuan)	Financing Value V_1 (10k yuan)	Risk Value V_2 (10k yuan)	Efficiency Value V_3 (10k yuan)	Total Value V (10k yuan)	Efficiency η (%)
Large	A Logistics Group	800	420	380	350	1150	143.75
Medium	B Logistics Co.	300	150	130	120	400	133.33
Small	C Logistics Office	80	45	38	32	115	143.75

From the quantification results, it can be seen that AI empowerment significantly enhances value creation for logistics enterprises of different scales. Large-scale logistics enterprises, owing to their substantial technology investment and rich business scenarios, achieved the highest total value creation (11.5 million yuan). Small-scale logistics enterprises, although producing a lower total value creation, attained a value creation efficiency (143.75%) on a par with large-scale enterprises, indicating that AI empowerment can effectively narrow the value creation efficiency gap between enterprises of different sizes and, in particular, help small-scale enterprises reduce costs and overcome financing difficulties. The risk value V_2 and efficiency value V_3 were positive across all three enterprise types, verifying the value contributions of the "risk control optimisation" and "process efficiency optimisation" dimensions, consistent with the preceding theoretical analysis.

4.3 Summary of Empirical Testing

Drawing together the correlation analysis, regression analysis, model validation, and value creation quantification results, the empirical testing yields the following core conclusions. First, AI technology — centrally algorithm accuracy and big data quality — is the core driving factor of logistics finance value creation, exhibiting a strong positive correlation with total value creation and a strong negative correlation with default probability, and can significantly enhance value creation efficiency. Second, the constructed big data value creation model — comprising the credit risk assessment, financing demand matching, and value creation quantification sub-models — demonstrates high fit, high predictive accuracy, and a comprehensive accuracy of 88.9%, markedly superior to traditional models, and possesses good feasibility and practical utility. Third, AI-

enabled logistics finance value creation operates through the three dimensions of financing service optimisation, risk control optimisation, and process efficiency optimisation, with all sizes of logistics enterprise standing to benefit; among these, small-scale enterprises exhibit outstanding value creation efficiency, offering an effective means of addressing their financing difficulties and high cost burdens. Fourth, enterprise credit level, financial institution service capability, and industry policy support all exert significant positive influences on value creation, jointly underpinning the realisation of AI-enabled logistics finance value creation.

At the same time, the empirical testing further corroborates the reasonableness of the previously constructed value creation formulas and model framework, providing solid empirical support for the subsequent formulation of optimisation recommendations. It also exposes certain issues: some small-scale logistics enterprises have insufficient technology investment, resulting in low total value creation; the value creation of sample enterprises varies considerably across regions, with enterprises in eastern regions generally showing higher value creation efficiency than those in central and western regions (which were not fully covered by the current sample). Future work can further expand the sample coverage and optimise model algorithms.

5 Conclusion

This study has examined the value creation mechanism of AI-enabled logistics finance through both theoretical analysis and empirical testing. The core findings are as follows. First, AI, by leveraging big data as a factor of production, reconstructs the closed-loop system of data, technology, process, and value in logistics finance; grounded in the three foundational theories, this shifts value creation from experience-driven to data-driven. Second, value creation follows a fixed hierarchical trajectory in which the three dimensional increments — financing optimisation V_1, risk control savings V_2, and process efficiency gains V_3 — aggregate to form total value. Third, AI algorithm accuracy and big data quality serve as the core driving variables, supported by a multi-layered structure of enterprise-level, financial, and environmental factors. Fourth, the hierarchically structured big data model developed in this study is internally consistent in its variable framework, logically coherent, and achieves a comprehensive predictive accuracy of 88.9%, demonstrating strong practical utility. Fifth, AI empowerment can narrow the value creation efficiency gap among large, medium, and small logistics enterprises, offering an effective means of alleviating the financing difficulties faced by SMEs. Based on these findings, optimisation recommendations are proposed for three stakeholder groups. Logistics enterprises should strengthen data management, increase technology investment, and improve their credit standing. Financial institutions should deepen the integration of technology and business, innovate their product offerings, and expand multi-party collaboration. Government bodies should refine the policy environment, improve the regulatory framework, and promote cross-sector coordination within the logistics industry. This study has limitations that point toward future work: expanding sample coverage, optimising model algorithms, investigating dynamic evolutionary mechanisms, and exploring pathways for constructing a logistics finance ecosystem.

Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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