

Construction of Information Health Assessment System for Small and Medium-Sized Enterprises Based on AI Diagnosis Model

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Abstract

Empirical validation across 3 representative SMEs (manufacturing, logistics, software) shows that the system identifies 83% of hidden informatization issues, and targeted optimization plans improve overall health scores by 38.2% (from 52.6 to 72.7/100) within 6 months. Specifically: (1) Lanhui Machinery's ERP integration rate increased from 42% to 89%, reducing production cycle by 23% ($p < 0.01$); (2) Green Star Logistics' data transmission latency decreased by 42%, boosting delivery efficiency by 32% ($p < 0.05$); (3) Zhichuang Software's data leakage risk dropped by 82%, with project success rate rising by 22% ($p < 0.01$). (China SME Development Index, 2024) This study fills the gap in AI-driven dynamic assessment for SME informatization, providing a replicable framework for digital transformation. The model's interpretability (SHAP value analysis identifies top 5 influential metrics) and scalability (adaptable to 8 industries via parameter fine-tuning) enhance its practical value for policymakers and enterprises.

Keywords: small and medium-sized enterprises (SMEs), informatization health assessment, AI diagnostic model, machine learning, Delphi method, digital transformation, SHAP value, performance optimization

1. Introduction

1.1 Research Background

SMEs account for 99.8% of Chinese enterprises and create 82% of urban employment, yet their informatization level lags significantly—only 35% have completed core business system deployment, and 62% lack systematic health monitoring (China SME Development Index, 2024). Key bottlenecks include: (IDC, 2023)

- **Infrastructure Gaps:** 58% of SMEs use outdated servers (average service life >5 years), leading to 2.3x higher system failure rates than industry benchmarks (IDC, 2023).
- **Evaluation Limitations:** Traditional assessment methods (e.g., static checklists) miss 41% of dynamic risks (e.g., real-time network bandwidth saturation), resulting in 27% of digital investments being ineffective (McKinsey, 2023).
- **AI Application Barriers:** 76% of SMEs lack access to high-quality labeled data, restricting the adoption of advanced diagnostic models (IEEE Transactions on Engineering Management, 2024).

The “Shuzhi Zhen” system, developed by Beijing Mint Information Consulting Co., Ltd., addresses these issues by integrating AI with multidimensional assessment, but its theoretical mechanism and quantitative effectiveness remain understudied—this research aims to fill this gap.

1.2 Research Significance

1.2.1 Theoretical Significance

- Propose a “Risk-Diagnosis-Optimization” (RDO) theoretical framework, quantifying the causal

relationship between 128 metrics and informatization health ($\beta = 0.73$, $R^2 = 0.68$, $p < 0.001$).

- Enhance model interpretability via SHAP (SHapley Additive exPlanations) analysis, identifying that “server response time” (SHAP mean = 0.18) and “IT training coverage” (SHAP mean = 0.15) are the top 2 influential indicators.

1.2.2 Practical Significance

- The assessment system reduces diagnostic time by 75% (from 14 to 3.5 days) compared to manual audits, with a cost reduction of 42% (average ¥86,000 vs. ¥148,000 per enterprise).
- The AI model’s online update function (retraining with new data every 3 months) maintains accuracy above 90% across 12 months, outperforming static models (accuracy drops to 78% after 6 months).

1.3 Research Methods and Data Sources

Table 1.

Method	Details
Delphi Method	30 experts (15 academia, 10 enterprise CIOs, 5 policymakers) across 3 rounds; consensus threshold: CV < 0.15.
Machine Learning	Ensemble model (RF + LightGBM) with 5-fold cross-validation; hyperparameter optimization via Bayesian search.
Case Study	3 SMEs selected via stratified sampling (manufacturing: Lanhui, logistics: Green Star, software: Zhichuang); 6-month follow-up.
Statistical Analysis	SPSS 26.0 for paired t-tests (pre- vs. post-optimization); SHAP 0.41.0 for model interpretability.

Data Sources: (1) Primary data: 187,000+ records from enterprise information systems (2023–2024) and 500+ employee questionnaires; (2) Secondary data: Ministry of Industry and Information Technology’s SME Informatization Report and IDC’s Global IT Infrastructure Survey.

2. Literature Review

2.1 SME Informatization Research

Existing studies confirm that informatization improves SME productivity by 18–25% (Petropoulou et al., 2024), but challenges persist: (Gouveia, S., et al., 2025)

- **Resource Constraints:** SMEs allocate only 3.2% of revenue to IT (vs. 8.5% for large enterprises), limiting infrastructure upgrades (Gouveia et al., 2025).
- **System Fragmentation:** 67% of SMEs have data silos between ERP and SCM systems, leading to 35% higher operational errors.

However, few studies focus on dynamic risk assessment—only 12% of frameworks include real-time metrics (e.g., network latency), failing to capture time-varying issues.

2.2 Informatization Evaluation Index Systems

Traditional index systems (e.g., EU Digital Economy and Society Index) have limitations:

- **Overlooking SMEs:** 78% of indicators are designed for large enterprises (e.g., “cross-border data integration”), with 43% of metrics unavailable for SMEs (OECD, 2021).
- **Lack of AI Integration:** Only 9% of studies use machine learning for automated diagnosis, resulting in 5–7 days of assessment cycle.

2.3 AI Applications in Evaluation

AI models (e.g., neural networks) improve assessment accuracy by 15–20%, but SME-specific challenges remain:

- **Data Scarcity:** 68% of SMEs have <10,000 labeled data points, leading to overfitting (training accuracy: 92%, test accuracy: 76%) (Kergroach, 2021).
- **Interpretability:** Black-box models (e.g., deep learning) fail to explain 63% of diagnostic results, reducing enterprise trust.

2.4 Research Gaps

Table 2.

Gap Category	Description
Theoretical	Lack of causal link between metrics and informatization health; no dynamic assessment framework.
Methodological	Single-algorithm models underperform in multi-industry scenarios; low interpretability.
Practical	High assessment cost (>¥100,000/enterprise) and long cycle (>10 days) limit scalability.

3. Construction of SME Informatization Health Assessment Index System

3.1 Construction Principles and Theoretical Basis

3.1.1 Core Principles

- **Scientific Rigor:** All indicators align with ISO/IEC 29110 (SME IT management standards) and pass KMO (0.83) and Bartlett's test ($\chi^2 = 1267.3$, $p < 0.001$). (Kergroach, S., 2021)
- **Dynamic Adaptability:** 32% of metrics (e.g., real-time server CPU utilization) are updated hourly, capturing transient risks.
- **Data Accessibility:** 91% of indicators use data from existing systems (e.g., ERP logs, network monitors), avoiding additional data collection costs.

3.1.2 Theoretical Framework

Integrate Resource-Based View (RBV) and Dynamic Capability Theory:

- **RBV:** IT infrastructure (e.g., server performance) and human capital (e.g., IT skill level) are core resources ($\beta = 0.62$, $p < 0.001$).
- **Dynamic Capability:** Application system flexibility (e.g., ERP module scalability) enables rapid adaptation to market changes (correlation with health score: $r = 0.71$, $p < 0.001$).

3.2 Index System Structure

Table 3.

First-Tier Indicator	Weight (%)	Second-Tier Indicators (Key Examples)
IT Infrastructure	28	Server performance (uptime rate, response time), network bandwidth (utilization rate, latency), hardware update cycle.
Application Systems	32	ERP integration rate, system failure rate, response time, functional coverage.
Data Management	22	Data accuracy, integrity, encryption rate, backup frequency.
Personnel & Training	18	IT training coverage, skill proficiency, certification rate, digital awareness.

Weight Determination: Analytic Hierarchy Process (AHP) with consistency ratio $CR = 0.08 < 0.1$, ensuring rationality.

3.3 Delphi Method Validation

3.3.1 Expert Panel Composition

Table 4.

Expert Type	Number	Affiliation	Expertise Field
Academia	15	Top 10 Chinese universities (e.g., Tsinghua)	IT management, operations research
Enterprise CIOs	10	SMEs across manufacturing/logistics/software	Practical informatization implementation
Policymakers	5	Ministry of Industry and Information Technology	SME digital policy formulation

3.3.2 Validation Results

Consensus Level: After 3 rounds, 128 indicators achieve a consensus coefficient of 0.89 (initial: 0.67), with 96% of indicators rated “highly necessary” (score $\geq 4.2/5$). (McKinsey & Company, 2023)

Indicator Optimization: 12 indicators (e.g., “cloud adoption rate”) were added, and 8 (e.g., “paper document ratio”) were removed due to low data accessibility (score $< 3.0/5$).

4. Development of “Shuzhi Zhen” AI Diagnostic Model

4.1 Data Collection and Preprocessing

4.1.1 Data Scope and Characteristics

Sample Size: 18,000+ data points from 50 SMEs (8 industries), split into training (70%), validation (15%), and test (15%) sets.

Data Types: (1) Structured data (e.g., server CPU utilization: 20–100%); (2) Unstructured data (e.g., system error logs: text format, parsed via NLP).

4.1.2 Preprocessing Pipeline

Table 5.

Step	Method	Effectiveness
Missing Value Handling	KNN imputation ($k=5$) for numerical data; mode imputation for categorical data.	Reduced missing rate from 12% to 0.3%.
Outlier Detection	IQR rule ($\pm 1.5 \times \text{IQR}$) + DBSCAN clustering ($\epsilon=0.5$, $\text{min_samples}=5$).	Removed 2.8% outliers, improving model stability by 11%.
Feature Scaling	Standardization (Z-score) for numerical features; one-hot encoding for categorical features.	Reduced training time by 35%.
Class Imbalance	SMOTE (Synthetic Minority Oversampling Technique) for high-risk samples (1:1.2 ratio).	Recall rate for high-risk cases increased from 76% to 91%.

4.2 Algorithm Selection and Optimization

4.2.1 Algorithm Comparison

Table 6. Performance Comparison of Different Algorithms (Test Set)

Algorithm	Accuracy (%)	Recall (%)	F1-Score (%)	Training Time (min)
Logistic Regression	82.3	79.5	80.9	2.1
Random Forest (RF)	87.6	86.8	87.2	15.3
SVM	85.2	83.1	84.1	22.7
LightGBM	89.4	88.7	89.0	8.6
RF + LightGBM Ensemble	92.3	91.7	92.0	12.8

4.2.2 Hyperparameter Optimization

Using Bayesian search with 5-fold cross-validation, optimal parameters for the ensemble model:

- **RF:** $n_estimators=200$, $max_depth=12$, $min_samples_split=5$.
- **LightGBM:** $learning_rate=0.05$, $num_leaves=31$, $subsample=0.8$.

4.3 Model Validation and Interpretability

4.3.1 Performance Metrics

Table 7. “Shuzhi Zhen” Model Performance Across Datasets

Metric	Training Set	Validation Set	Test Set
Accuracy (%)	95.1	93.4	92.3

Precision (%)	94.8	92.9	91.5
Recall (%)	94.5	92.2	91.7
F1-Score (%)	94.6	92.5	92.0
AUC-ROC	0.97	0.95	0.94

4.3.2 Interpretability Analysis (SHAP Value)

- **Top 5 Influential Indicators:** (1) Server response time (SHAP mean = 0.18); (2) IT training coverage (0.15); (3) ERP integration rate (0.14); (4) Data encryption rate (0.12); (5) Network bandwidth utilization (0.10). (Ministry of Industry and Information Technology, 2024)
- **Case Interpretation:** For Lanhui Machinery, SHAP values show that “ERP integration rate” (-0.23) is the primary factor lowering its health score, consistent with on-site audits.

5. Case Analysis of SME Informatization Health Assessment

5.1 Case Enterprise Profiles and Pre-Assessment Status

Table 8.

Enterprise	Industry	Annual Revenue (¥M)	Key Informatization Issues (Pre-Assessment)	Health Score (Pre)
Lanhui Machinery	Manufacturing	320	ERP integration rate = 42%, outdated servers (failure rate = 18%), IT training coverage = 35%.	52.6/100
Green Star Logistics	Logistics	200	Network bandwidth saturation (utilization = 92%), no data analytics tools, employee digital skill score = 4.1/10.	48.3/100
Zhichuang Software	Software	190	Data encryption rate = 58%, no unified IT strategy, training frequency = 2 times/year.	56.8/100

5.2 Diagnostic Process and Key Findings

5.2.1 Data Collection and Analysis

- **Automated Data Acquisition:** 85% of data (e.g., server logs, ERP transaction records) is extracted via API, with 15% supplemented by employee questionnaires (Cronbach’s $\alpha = 0.89$).
- **AI Diagnosis Output:** Each enterprise receives a 3-tier report: (1) Overall health score; (2) Dimension-specific scores (e.g., IT Infrastructure: 45.2/100 for Lanhui); (3) Risk heatmap (red = high risk, yellow = medium, green = low).

5.2.2 Key Issues Identified

- **Lanhui Machinery:** (1) Server CPU utilization peaks at 95% (threshold = 80%), causing 1.2-hour weekly downtime; (2) ERP-SCM data silo leads to 32% inventory discrepancy.
- **Green Star Logistics:** (1) Peak-hour network latency = 800ms (benchmark = 300ms), delaying delivery updates; (2) Manual route planning results in 15% higher fuel costs.
- **Zhichuang Software:** (1) Unencrypted customer data accounts for 42%, violating GDPR requirements; (2) Agile development tool adoption rate = 35%, slowing project delivery.

5.3 Optimization Plans and Post-Assessment Results

5.3.1 Lanhui Machinery (Manufacturing)

Table 9.

Optimization Measure	Investment (¥M)	Post-Assessment Outcome	Statistical Significance
Server upgrade (replace 12 old servers)	8.5	Server failure rate = 2.3%, response time reduced by 68%.	$p < 0.01$

ERP-SCM integration	12.3	Inventory discrepancy = 5%, production cycle shortened by 23%.	$p < 0.01$
IT training (120 employees)	3.2	Training coverage = 92%, operational error rate reduced by 62%.	$p < 0.05$
Overall	32.0	Health score = 75.8/100 (+44.1%)	$p < 0.001$

5.3.2 Green Star Logistics

Table 10.

Optimization Measure	Investment (¥M)	Post-Assessment Outcome	Statistical Significance
Network bandwidth expansion	5.8	Latency = 464ms, system efficiency increased by 53%.	$p < 0.05$
Deploy AI route optimization tool	7.2	Transportation cost reduced by 22%, customer satisfaction = 84.5% (+18.3%).	$p < 0.01$
Digital management training	2.5	Employee productivity increased by 32%, complaint rate reduced by 52%.	$p < 0.05$
Overall	20.0	Health score = 69.7/100 (+44.3%)	$p < 0.001$

5.3.3 Zhichuang Software

Table 11.

Optimization Measure	Investment (¥M)	Post-Assessment Outcome	Statistical Significance
AES-256 data encryption	6.7	Data leakage risk = 3.6%, recovery time <1.2 hours.	$p < 0.01$
Formulate IT strategy framework	4.2	Digital transformation speed increased by 32%, project success rate = 89% (+22%).	$p < 0.01$
Agile tool training (80 employees)	2.8	Development efficiency increased by 37%, on-time delivery rate = 92% (+15%).	$p < 0.05$
Overall	19.0	Health score = 73.1/100 (+28.7%)	$p < 0.001$

6. Conclusions and Future Outlook

6.1 Research Conclusions

- **Index System Validity:** The 4-dimensional, 128-metric system captures 92% of SME informatization characteristics, with expert consensus coefficient (0.89) confirming scientific rigor.
- **Model Superiority:** The RF-LightGBM ensemble model outperforms single algorithms by 4.7–7.1% in accuracy, and SHAP analysis enhances interpretability, addressing the “black-box” issue.
- **Practical Effectiveness:** Targeted optimization improves SME health scores by 28.7–44.3%, with significant improvements in operational efficiency ($p < 0.05$) and risk reduction ($p < 0.01$).

6.2 Research Limitations

- **Sample Scope:** Current validation covers 3 industries; adaptability to high-tech or agriculture SMEs needs further testing.
- **Long-Term Effects:** 6-month follow-up is insufficient to evaluate model performance under technological Iteration (e.g. 5G adoption).
- **Data Bias:** 72% of data comes from East China; regional differences (e.g., Western China’s infrastructure

gaps) may affect generalization.

6.3 Future Research Directions

- **Index System Update:** Incorporate emerging technologies (e.g., 5G, blockchain) as new metrics (e.g., “blockchain traceability coverage”) to adapt to Industry 4.0.
- **Model Enhancement:** Integrate transformer-based NLP to analyze unstructured data (e.g., employee feedback) and improve real-time diagnostic speed (target: <10 minutes/enterprise).
- **Cross-Industry Validation:** Expand samples to 10+ industries, develop industry-specific parameter templates (e.g., manufacturing: weight ERP integration higher; logistics: weight network latency higher).
- **Policy Integration:** Collaborate with local governments to embed the system into SME digital subsidy programs, reducing implementation costs by 30% via policy support.

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