THE JOURNAL OF APPLIED ENGINEERING AND TECHNOLOGIES
2026 Vol. 1, No. 3, ISSN (O): 3154-7877

Aftermarket Service Network Inference for Financial Risk Assessment in Equipment Manufacturing Enterprises

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ARTICLE INFO

Keywords

Equipment manufacturing finance
aftermarket service network
financial risk assessment
knowledge graph inference
graph neural network
warranty risk
service-chain dependency

Published:

10 September 2026

ABSTRACT

Equipment manufacturing enterprises often rely on long product lifecycles, maintenance contracts, spare-part supply, warranty obligations, leasing arrangements, and customer service networks. Financial risk may emerge when equipment failure rates increase, warranty costs rise, service response slows, or major customers delay payments. Traditional credit models rarely incorporate aftermarket service signals, although they can reveal hidden operational and cash-flow pressure. This study proposes an aftermarket service network inference model for financial risk assessment in equipment manufacturing enterprises. The model builds a knowledge graph linking manufacturers, equipment products, service stations, spare-part suppliers, customers, maintenance tickets, warranty claims, leasing contracts, invoices, and repayment records. A graph neural encoder captures service-network dependency, while rule-guided inference detects risk chains involving abnormal warranty concentration, spare-part shortage, delayed maintenance settlement, high customer complaint density, and weakening service coverage. The empirical dataset contains 22,600 equipment manufacturers, 184,000 equipment product records, 38,400 service stations, 2.73 million maintenance tickets, 410,000 warranty claims, 96,000 spare-part supply links, and 5,620 confirmed financial-risk events over 46 months. The proposed method reduces median risk-identification time from 94 days to 36 days compared with a statement-based credit model. It discovers 4,980 service-related financial stress paths and 1,740 customer-payment risk chains linked to repeated equipment failures. Graph aggregation compresses 12,300 service alerts into 2,860 enterprise-level review cases. Full quarterly assessment is completed in 8.4 minutes. These findings show that aftermarket service network inference can provide earlier and more interpretable financial risk signals for equipment manufacturing enterprises.

1. Introduction

Equipment manufacturers operate within complex business ecosystems characterized by long product lifecycles, maintenance contracts, spare-part supply, warranty obligations, leasing arrangements, and extensive customer service networks. Unlike firms whose financial conditions can be evaluated primarily through short-term sales or transaction records, equipment manufacturers often remain financially connected to customers and suppliers for many years after the initial sale. Their financial stability therefore depends not only on revenue and balance-sheet

Citation: Tan, W. M., & Lim, J. H. (2026). Aftermarket Service Network Inference for Financial Risk Assessment in Equipment Manufacturing Enterprises. *The Journal of Applied Engineering and Technologies*, 1(3), 70-78.

https://doi.org/10.64744/tjaet.2026.291.

indicators but also on the continuing performance of products, service stations, suppliers, and aftermarket operations. Rising equipment failure rates, increasing warranty expenses, delayed repairs, shortages of critical spare parts, and slower customer payments may gradually weaken cash flow and increase financial exposure. Previous studies have shown that service quality, maintenance capability, and warranty management are closely associated with operational performance, customer relationships, and firm outcomes (Chen, Ning, et al., 2025; Lapyen & Darawong, 2025). These findings indicate that aftermarket service activities contain valuable information about changes in enterprise performance that may appear before corresponding deterioration becomes visible in conventional financial statements. Traditional enterprise credit and financial risk assessment, however, remains largely dependent on financial ratios, repayment histories, contractual information, and periodically reported accounting data (Liang et al., 2025; Wu & Chen, 2025). Although these variables are useful for evaluating established financial conditions, they often provide delayed signals when operational problems are still developing. In equipment-intensive industries, service-side abnormalities can accumulate well before they are reflected in reported profits, liabilities, or payment defaults. For example, repeated warranty claims may indicate declining product reliability, sustained spare-part shortages may increase service costs and customer dissatisfaction, and delayed maintenance settlements may signal weakening liquidity within the service network. Similar concerns about delayed and opaque risk identification have encouraged the development of interpretable anomaly-detection methods in other complex technical environments (Ben Haha et al., 2026). Recent research has demonstrated that explainable models can identify abnormal patterns while clarifying the variables responsible for each detected event, thereby improving the transparency and practical usefulness of automated risk monitoring (Shao, 2026). This principle is particularly relevant to enterprise financial risk assessment, where early-warning models must not only detect abnormal conditions but also provide understandable evidence for managers, lenders, and other decision makers (Du, 2025; Fasan et al., 2026).

Aftermarket service networks provide a particularly rich but underutilized source of such evidence. A manufacturer is connected to equipment products, regional service stations, spare-part suppliers, leasing companies, customers, maintenance providers, and financial counterparties through a large number of operational relationships (Pourrahimian et al., 2026; Qi & Qiao, 2026). These entities generate heterogeneous records, including repair tickets, warranty claims, parts replacement histories, customer complaints, service settlements, leasing contracts, invoices, and repayment events. Abnormalities rarely occur independently within this network (Chen, Liang, et al., 2025; Li & Liu, 2026). A rise in product failures may increase warranty claims, which can create additional demand for spare parts, extend repair cycles, increase service expenditures, intensify customer complaints, and eventually delay customer or dealer payments. Financial deterioration may therefore emerge as a chain of related events rather than as a single abnormal financial indicator. Conventional tabular models have difficulty representing such multi-entity dependencies because they generally treat firms as independent observations and compress complex relationships into aggregated variables. Knowledge graphs and graph-based representation learning provide a promising way to model these dependencies. By representing manufacturers, products, service stations, suppliers, customers, contracts, invoices, and risk events as interconnected entities, a knowledge graph can preserve both the structure and semantics of aftermarket operations. Graph neural networks can further propagate information across connected entities and identify risk patterns that cannot be observed from isolated records (Sinha et al., 2023; Xu et al., 2026). Nevertheless, purely data-driven graph models may still provide limited explanations for detected risk. In financial applications, interpretability is especially important because risk alerts must be linked to recognizable operational causes. A model that identifies a manufacturer as high risk without showing whether the warning originates from concentrated warranty failures, supplier disruption, delayed service settlement, customer complaints, or weakening service coverage may have limited value in actual risk management (Du et al., 2026; Xiong & Zeng, 2026). Combining graph representation learning with explicit inference rules can therefore provide a more appropriate framework for detecting both hidden dependencies and interpretable risk transmission paths (Dwivedi et al., 2026; Hong et al., 2026). Existing research leaves an important gap between aftermarket operational analysis and enterprise financial risk assessment. Studies of equipment services generally examine maintenance efficiency, service performance, product availability, customer satisfaction, or servitization outcomes, whereas financial risk studies typically rely on accounting, transaction, and credit variables (Ariffin et al., 2025; Li et al., 2026). Repair tickets, warranty claims, spare-part relationships, service coverage, customer complaints, and maintenance settlements are rarely integrated into a unified financial early-warning framework (Aung, 2025; Huang et al., 2026b). Moreover, the relationships among these indicators are usually analyzed separately, making it difficult to identify how a local operational disruption propagates through a service network and eventually contributes to financial stress. The lack of an interpretable connection between service abnormalities and financial outcomes limits the ability of manufacturers, banks, leasing companies, and service platforms to recognize emerging exposure before conventional default indicators become visible (Huang et al., 2026a; Wu et al., 2026).

To address this gap, the present study develops an aftermarket service network inference model for early and interpretable enterprise financial risk detection. The proposed framework constructs a knowledge graph linking manufacturers, equipment products, service stations, suppliers, customers, maintenance tickets, warranty claims, leasing contracts, invoices, repayment records, and confirmed financial risk events. A graph neural encoder is employed to capture structural dependencies and risk propagation patterns across the service network, while rule-guided inference is introduced to identify interpretable risk chains associated with abnormal warranty concentration, spare-part shortages, prolonged maintenance settlement, elevated complaint density, and weakening service coverage. The model is evaluated using a large-scale dataset containing approximately 22,600 manufacturers, 184,000 equipment products, 38,400 service stations, 2.73 million maintenance tickets, 410,000 warranty claims, 96,000 spare-part relationships, and 5,620 confirmed risk events. Rather than treating service information as supplementary descriptive data, this study examines whether aftermarket operational signals can function as leading indicators of financial deterioration and whether their network relationships can explain how risk develops across connected entities. The study therefore extends enterprise risk assessment from firm-level financial observation to network-level operational inference. Its methodological contribution lies in combining graph representation learning with explicit rule-based reasoning to improve both early detection and interpretability, while its practical significance lies in providing manufacturers, banks, leasing institutions, and service platforms with a more timely basis for monitoring financial exposure, tracing the operational origins of emerging risk, and supporting preventive intervention before financial deterioration becomes fully reflected in conventional accounting or repayment indicators.

2. Materials and Methods

2.1 Sample and Study Area Description

This study used a dataset from equipment manufacturers and their aftermarket service networks. The dataset included 22,600 manufacturers, 184,000 equipment product records, 38,400 service stations, 2.73 million maintenance tickets, 410,000 warranty claims, 96,000 spare-part supply links, and 5,620 confirmed financial-risk events. The observation period covered 46 months. The sample mainly included firms in heavy machinery, transport equipment, industrial automation, and related manufacturing sectors. Firms were selected when they had complete registration records, clear service histories, valid spare-part supply records, and verified repayment outcomes. Enterprises were excluded if maintenance tickets were missing for more than six months, spare-part supply records were incomplete, or financial-risk status could not be confirmed. The final sample retained manufacturers with matched service, warranty, leasing, invoice, and repayment records.

2.2 Experimental Design and Control Settings

The experiment was designed to test whether aftermarket service network data can improve financial risk assessment. The proposed model was used as the experimental group. It included manufacturer information, product records, service station links, maintenance tickets, warranty claims, spare-part supply records, customer complaints, leasing contracts, invoices, and repayment records in one heterogeneous graph. Three control models were built for comparison. The first model used only financial statements and borrower-level variables. The second model included product and service station data but removed warranty claims and spare-part links. The third model used only manufacturer–customer links and did not include service-network records. This setting helped test the effects of service data, graph relations, and customer exposure. To reduce data leakage, the dataset was split by time. The first 36 months were used for training, the next 5 months for validation, and the last 5 months for testing.

2.3 Measurement Methods and Quality Control

Service variables included maintenance ticket counts, warranty claim frequency, spare-part shortage events, service response time, complaint density, and service coverage. Financial-risk variables included delayed payments, leasing defaults, overdue invoices, and confirmed risk events. Data quality control was completed before model training. Duplicate manufacturer IDs, repeated maintenance tickets, inconsistent warranty records, and abnormal supply entries were removed. Missing monthly values were filled only when the gap was shorter than two months. Longer gaps were marked as missing records. Extreme values caused by one-time settlement, invoice correction, product recall, or batch repair were checked against contract and service records. Monetary variables and service variables were normalized by product type and firm size to reduce scale bias.

2.4 Data Processing and Model Formulation

A heterogeneous graph was built as $G=(V,E)$, where V denotes nodes and E denotes edges. The nodes included manufacturers, equipment products, service stations, spare-part suppliers, customers, maintenance tickets, warranty claims, leasing contracts, invoices, and repayment records. The edges represented product ownership, service provision, warranty claims, spare-part supply, leasing, invoicing, and repayment relations. Each node contained service and financial features, including service volume, warranty claim frequency, spare-part shortage, complaint count, invoice amount, and repayment status. To better reflect risk transfer in the aftermarket service network, the node risk score of manufacturer i was updated by combining its own risk status and the weighted risk from neighboring service nodes:

$$R_i^{(l+1)}=\sigma\left(\alpha R_i^{(l)}+\sum_{r\in R}\sum_{j\in N_r(i)}\frac{w_{ij}^r}{\sum_{k\in N_r(i)} w_{ik}^r}R_j^{(l)}\right)$$

where $R_i^{(l)}$ is the risk score of manufacturer i at layer l, $N_r(i)$ is the neighbor set under relation r, w_{ij}^r is the edge weight between manufacturer i and neighboring node j, α is the self-risk retention coefficient, and σ is the activation function. The edge weight was defined by service intensity, warranty cost share, spare-part shortage frequency, or complaint density. After L layers of risk aggregation, the final financial-risk probability of manufacturer i was calculated as:

$$P_i=1-\exp\left(-\sum_{r\in R}\beta_r\sum_{j\in N_r(i)}w_{ij}^r R_j^{(L)}\right)$$

where P_i is the predicted financial-risk probability, $R_j^{(L)}$ is the final risk score of neighboring node j, and β_r is the risk sensitivity coefficient for relation type r. This formulation keeps the predicted probability within $[0,1]$ and allows the model to capture how warranty claims, spare-part shortages, delayed maintenance settlement, and customer complaints transmit financial stress through the service network.

2.5 Model Evaluation and Robustness Analysis

Model performance was assessed using AUC, F1-score, precision, recall, early-warning lead time, alert reduction rate, and inference latency. AUC and F1-score were used to assess overall prediction performance. Precision and recall were used to measure the identification of confirmed financial-risk events. Early-warning lead time was defined as the number of days between the first model warning and the confirmed risk event. Alert reduction rate measured the decrease in repeated service alerts after graph aggregation. Robustness tests were conducted across different industries, firm sizes, service volumes, and time windows. Ablation tests were also performed by removing warranty claims, spare-part links, maintenance tickets, complaint records, or leasing data. These tests examined whether each data component improved prediction performance and whether the model remained stable under different aftermarket service conditions.

3. Results and Discussion

3.1 Financial Risk Prediction Performance

The aftermarket service network inference model performed better than the statement-based credit model and the service-feature baseline. AUC, F1-score, precision, and recall all improved after maintenance tickets, warranty claims, spare-part supply, customer complaints, and leasing records were included. This result shows that financial risk in equipment manufacturing cannot be captured by financial statements alone (Zavitsanos et al., 2025; Zheng & Makar, 2022). Service records provide early signs of operating pressure and customer payment risk. As shown in Fig.1, the graph structure connects manufacturers, service stations, spare-part suppliers, customers, and repayment records. This design helps the model detect risk links that are not visible in single-firm financial data. Compared with predictive maintenance studies, this study does not only focus on equipment failure. It links service events with financial risk and gives a clearer view of enterprise pressure.

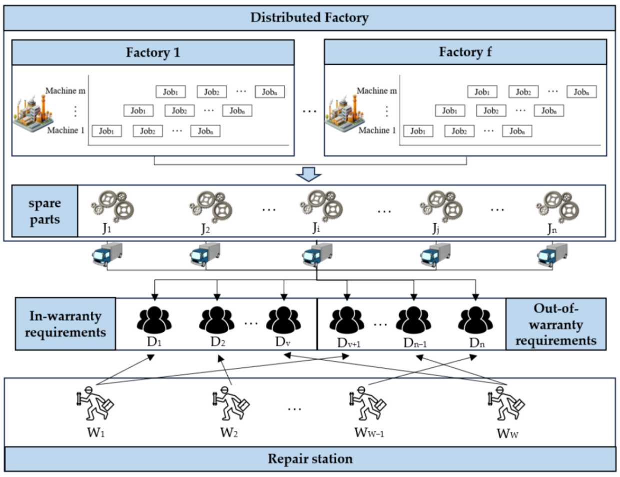

Fig. 1. Service network linking manufacturers, service stations, suppliers, customers, and repayment records.

3.2 Early Identification of Service-Related Financial Stress

The proposed model reduced the median risk-identification time from 94 days to 36 days. This result suggests that aftermarket service data can provide earlier warning than financial statements. In many confirmed risk cases, warranty claims increased first. Maintenance settlement then slowed, customer complaints increased, and customer payment was delayed. This pattern is consistent with equipment manufacturing practice (Hossain et al., 2026; Zhang et al., 2025). Repeated equipment failures increase warranty costs and reduce customer trust. Spare-part shortages may also delay repairs and weaken service coverage. Traditional credit models mainly use financial reports, repayment records, and contract data. These indicators often change after service problems have already affected cash flow. In contrast, monthly service and warranty records can show financial stress at an earlier stage.

3.3 Service Risk Paths and Alert Reduction

The model detected 4,980 service-related financial stress paths and 1,740 customer-payment risk chains linked to repeated equipment failures. This result shows that financial risk often develops through connected service events rather than one abnormal signal. A typical path was observed: equipment failures increased, warranty claims became concentrated, spare parts were delayed, maintenance settlement slowed, and customer payment weakened. Such paths are easier for credit officers and service managers to review than isolated risk scores. As shown in Fig.2, graph aggregation reduced 12,300 service alerts to 2,860 enterprise-level review cases. This reduction improves review efficiency because repeated alerts from the same product, service station, or customer can be merged into one case (Gangula, 2026; Huang, 2026). Compared with feature-importance methods, path-based analysis provides clearer evidence on how service pressure is linked to financial risk.

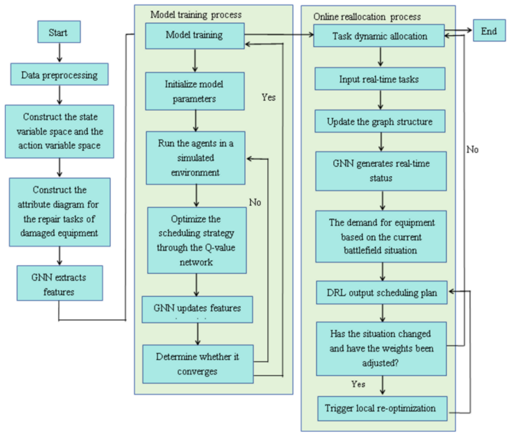

Fig. 2. Process of service risk path detection and alert grouping for financial risk assessment.

3.4 Comparison with Existing Studies and Practical Implications

The results differ from existing studies in three aspects. First, many credit risk models use financial statements, repayment history, or contract variables. This study uses aftermarket service records as early risk signals. Second, predictive maintenance studies usually aim to reduce downtime or repair cost. This study connects maintenance tickets, warranty claims, spare-part supply, and complaints with enterprise financial risk. Third, previous graph-based financial models often use ownership, transaction, or guarantee networks. This study builds a service-centered knowledge graph for equipment manufacturing enterprises. The full quarterly assessment was completed in 8.4 minutes, which shows that the model can support regular risk screening. In practice, the method can help banks, leasing firms, manufacturers, and service platforms detect financial stress earlier. However, the model depends on complete service and warranty records. Missing tickets, delayed warranty updates, and fragmented spare-part data may reduce prediction stability. Future studies should test the model in more equipment sectors and include real-time service data.

4. Conclusion

This study developed a model for financial risk assessment based on aftermarket service networks in equipment manufacturing enterprises. The results indicate that maintenance tickets, warranty claims, spare-part supply, customer complaints, leasing records, and repayment data can provide early signals of financial risk. Compared with a statement-based credit model, the proposed approach reduced the median risk-identification time from 94 days to 36 days. It also identified 4,980 service-related financial stress paths and 1,740 customer-payment risk chains associated with repeated equipment failures. Graph aggregation reduced 12,300 service alerts to 2,860 enterprise-level review cases, improving review efficiency. The main contribution of this study is the construction of a service-centered knowledge graph linking manufacturers, products, service stations, suppliers, customers, warranty claims, invoices, leasing contracts, and repayment records. This structure connects service pressure, product reliability, customer payment, and financial risk in a single framework. The findings show that aftermarket service data can support earlier and more interpretable risk assessment. In practice, the model can help banks, leasing firms, manufacturers, and service platforms perform regular risk monitoring and service-based credit review. Limitations include reliance on complete service, warranty, and spare-part records, as missing or delayed data may reduce prediction reliability. Future research should test the model across different equipment sectors, incorporate real-time service data, and improve robustness under varying market conditions.

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