International Journal of Decision Support System Technology
Volume 18 • Issue 1 • January-December 2026

A Closed-Loop Financial Decision Support System With Explainable AI for Manufacturing

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Received: November 10th, 2025 | **Accepted:** February 18th, 2026

ABSTRACT

Traditional financial forecasting systems often operate as black boxes, lacking the transparency required for regulatory compliance and strategic decisions. To address this, the author proposes a closed-loop decision support system that integrates accurate forecasting with built-in explainability for manufacturing finance. The end-to-end framework, centered on an enhanced temporal fusion transformer plus model, automates data ingestion, feature distillation, predictive inference, and adaptive feedback. The system provides visual explanations through attention heatmaps, enabling managers to understand model decisions, and incorporates a self-correcting mechanism that triggers model hot-swapping upon performance drift. Empirical results from 120 A-share manufacturing firms show the system achieves a mean absolute percentage error of 12.1% and reduces budget review time by 39%. This study demonstrates a template that transforms AI from a passive forecaster into an interpretable and adaptive partner for financial management.

KEYWORDS

Financial Forecasting, Explainable Artificial Intelligence, Temporal Fusion Transformer, Decision Support System, Closed-Loop System

INTRODUCTION

The financial management of the manufacturing industry involves the continuous evaluation of capital allocation, liquidity risk, and operational benefit, which is a complex decision-making process. In the environment of Internet of Things and industrial internet, machine learning (ML) has become the key driving force for intelligently analyzing massive data and promoting the application of automation (Tufail et al., 2023). Especially in the intersection of manufacturing and finance, how to extract valuable insights from multivariate and high-dimensional time series data with the help of ML models to support real-time decision-making has become an important challenge. The traditional decision support system (DSS) relies on manual ledgers and static templates and is increasingly overwhelmed by the quantity and speed of modern financial data. The annual announcements of the Shanghai and Shenzhen stock exchanges have surged from 58,000 in 2015 to 112,000 in 2024. This trend clearly shows that the traditional system has obvious shortcomings in ensuring the timeliness, depth, and traceability of decision-making (Klein & Walther, 2024).

DOI: 10.4018/IJDSST.402902

The increasingly strict regulatory environment has further aggravated the crisis of DSS. According to the European Union's Artificial Intelligence Act, artificial intelligence (AI) systems in the financial sector are classified as "high-risk," which requires them to have complete traceability and transparency (Mazzini & Bagni, 2023). At the same time, the Ministry of Finance of China also proposed that by 2025, the sustainability disclosure will become the focus of audit work.

Therefore, as previous research has emphasized, decision support systems for finance must now resolve the tension between compliance and practicality (Awwad et al., 2025; Bredt, 2019). In this context, the demand for rapid, data-driven decision-making conflicts with the need for rigorous and explainable processes. Most current financial AI applications cannot be used as effective DSS. Because of the dependence on single modal data, they either provide scattered analysis or operate as "black boxes," which cannot provide operational insights for management decisions.

Meanwhile, temporal forecasting models like the temporal fusion transformer (TFT) show great potential in dealing with multimodal data in DSS (Bonaparte, 2024; Chen et al., 2023). Theoretically, their interpretable attention mechanism can provide the transparency needed for regulatory compliance and management trust. However, these technologies have not been applied to the integrated closed-loop DSS covering the whole decision-making cycle from "data access to business feedback" (Ali et al., 2025). The focus is still on isolated algorithm performance, leaving a key system-level gap between model output and decision-making action.

Based on this, although the model based on the transformer has achieved remarkable success in forecasting, there is still a clear gap in deploying it as a sustainable enterprise-level DSS. This study identified three core DSS technical challenges: first, how to implement a standardized data integration workflow and integrate multi-source inputs such as extensible business reporting language (XBRL) reports and news texts without destroying the existing enterprise information technology ecosystem; second, how to embed the built-in interpretable mechanism to meet the regulatory auditability while maintaining the prediction accuracy required for reliable decision support (Arsenault et al., 2025); and third, how to design the real-time feedback loop, realize dynamic model adaptation and provide interactive insights, and turn static forecasting tools into active decision partners.

To address these challenges, this paper proposes a closed-loop DSS deeply integrated within manufacturing financial workflows. Moving beyond a mere algorithmic enhancement, our work presents an end-to-end system architecture that unifies data ingestion, interpretable forecasting, and adaptive optimization. This design aligns with the paradigm of Automated ML (AutoML), which has been recognized as a vital tool in the fourth industrial revolution for streamlining data-driven industrial application development (Addula & Sekhar Sajja, 2024). By automating key stages of the ML pipeline, from hyperparameter optimization to model lifecycle management, this approach develops a forecasting tool that is not only accurate but also capable of sustainable, self-adapting operation. The proposed framework is designed not only to improve forecasting metrics but also to fundamentally enhance the speed, transparency, and efficacy of financial decision-making processes in complex manufacturing environments.

LITERATURE REVIEW

AI in Financial Analysis: Evolution and Manufacturing Challenges

With the deepening of the digital transformation of enterprises, the scale, diversity, and processing speed of financial data have been significantly improved, which has promoted the transformation of the decision-making mode from traditional manual operations to AI. The initial research revealed the influence of AI in customer protection and asset pricing (Y. Cao & Zhai, 2022), and subsequent research indicates that the complexity of operations in the manufacturing sector exacerbates data challenges, with studies increasingly emphasizing the importance of integrating domain expertise with advanced analytics (Yi et al., 2023). However, this development path also highlights a key issue. Although the potential of AI in financial field has been widely recognized, the existing research mostly

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