

PAPER

Intelligent Mobile Budget Forecasting Using LSTM Networks: A Dynamic Decision-Support Framework for Emerging Markets

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ABSTRACT

Budget forecasting is essential for organizational resource allocation and risk-aware decision-making, yet conventional models often struggle with nonlinear patterns and rapidly changing operating conditions. This study proposes an intelligent mobile decision-support framework using long short-term memory (LSTM) neural networks for dynamic budget forecasting. The framework integrates historical financial data, macroeconomic indicators, and operational metrics through a dual-path LSTM architecture and an adaptive sliding-window mechanism. The model is evaluated using manufacturing and retail datasets and benchmarked against SARIMA and XGBoost. Results demonstrate improved forecasting accuracy and resilience under changing conditions, achieving a 19.2% higher Forecast Skill Score in manufacturing and a 15.7% improvement in retail scenarios. The framework supports mobile-accessible managerial decision-making by transforming dynamically updated forecasts into actionable information for resource allocation and operational risk management. Its scalable architecture is particularly relevant to digitally evolving emerging markets, including Indonesia, where organizations increasingly require accessible and adaptive decision-support technologies. The study contributes an AI-enabled approach that integrates dynamic forecasting with mobile decision support, organizational resilience, and sustainable resource utilization.

KEYWORDS

mobile decision support, long short-term memory (LSTM) neural networks, budget forecasting, risk-aware management, time-series forecasting, artificial intelligence, emerging markets

1 INTRODUCTION

Budgets are integral to effective organizational planning and resource allocation [1], while accurate budget forecasting remains important for both researchers and business decision-makers [2]. However, conventional forecasting approaches may provide limited reliability in volatile and rapidly changing business environments.

Andhini, H. D., Nohong, M., Sabbar, S. D., Almsafir, M. K., Mutiah, Z. (2026). Intelligent Mobile Budget Forecasting Using LSTM Networks: A Dynamic Decision-Support Framework for Emerging Markets. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(20), pp. 122–133. <https://doi.org/10.3991/ijim.v20i20.63475>

Article submitted 2026-06-08. Revision uploaded 2026-09-05. Final acceptance 2026-09-07.

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Traditional methods, including linear regression, autoregressive integrated moving average (ARIMA) [3], and exponential smoothing, often struggle to capture non-linear dependencies, multidimensional financial patterns, and sudden changes in market conditions [1–2]. These limitations can reduce forecasting accuracy and constrain timely managerial decisions concerning resource allocation and operational risk. Consequently, there is a growing need for adaptive, data-driven forecasting approaches capable of responding dynamically to changing business conditions [4].

Long short-term memory (LSTM) neural networks provide a powerful alternative to conventional forecasting approaches because of their ability to capture long-term dependencies and complex temporal patterns in sequential data. LSTMs have been successfully applied across various time-series forecasting domains, including speech recognition, stock prediction, and rainfall modelling [5]. Unlike conventional recurrent neural networks (RNNs), LSTMs employ gated memory mechanisms that help address the vanishing-gradient problem and improve learning across extended sequences [6–7]. In budget forecasting, these capabilities enable LSTM models to integrate historical financial data, macroeconomic indicators, and operational information to generate more adaptive and accurate forecasts under changing business conditions.

In this study, we propose a dynamic budget forecasting framework based on an optimized LSTM architecture with three principal contributions: (1) a data-fusion process for integrating heterogeneous financial and operational inputs; (2) a dynamically weighted LSTM architecture that adapts to changing temporal patterns; and (3) a sliding-window mechanism that continuously updates the forecasting model as new information becomes available. The framework is evaluated across manufacturing and retail settings to assess its robustness and applicability under different operating conditions. In addition, a constraint-aware loss function is incorporated to improve prediction stability and support risk-aware managerial decision-making.

From a methodological perspective, this study advances AI-enabled forecasting by integrating adaptive LSTM modelling, heterogeneous data fusion, and dynamic updating within a unified decision-support framework. From a practical perspective, the proposed approach provides organizations with a scalable tool for anticipating budget variations, evaluating resource-allocation scenarios, and supporting risk-aware managerial decisions. Its mobile-accessible decision-support orientation further enables managers to access dynamically updated forecasts and relevant risk information to support timely decisions across different operational settings. Beyond forecasting accuracy, the framework can contribute to organizational resilience and sustainable resource utilization by improving budget allocation, identifying emerging cost pressures, and reducing inefficient expenditure. These capabilities are particularly relevant to SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production), where intelligent decision-support technologies can facilitate more efficient and forward-looking resource management. The framework also incorporates explainability mechanisms to improve the transparency of forecast drivers and strengthen managerial interpretation of AI-generated predictions.

2 RELATED WORKS

Traditional enterprise budget forecasting has long relied on statistical time-series and econometric models. Among these approaches, a autoregressive integrated moving average (ARIMA) model is widely used to capture linear patterns, trends, and cyclical or seasonal variations in time-series data through the Box–Jenkins methodology [8–10]. Despite its established use, ARIMA has important limitations in dynamic business environments. In particular, it may struggle to capture

nonlinear relationships, respond effectively to abrupt market changes, and process high-dimensional datasets containing multiple operational and external variables. These limitations have encouraged the development of more adaptive machine-learning and deep-learning approaches capable of modelling complex temporal patterns and changing business conditions.

Regression-based approaches, including ordinary least squares and logistic regression, can perform effectively under relatively stable conditions but may be less suitable for capturing complex nonlinear relationships and rapidly changing patterns in high-dimensional data. As a result, machine-learning (ML) techniques have increasingly been applied to prediction and decision-support tasks across diverse industries [11–12]. Ensemble methods, including gradient boosting machines (GBM) [13], XGBoost, and random forests [14], can capture heterogeneous features and complex nonlinear relationships more effectively than many conventional statistical approaches [15]. However, these methods do not inherently model sequential dependencies across extended time horizons. This limitation is particularly important for dynamic budget forecasting, where current and future estimates may depend on temporal patterns, evolving operational conditions, and relationships embedded across multiple historical periods.

Sequential modelling has advanced considerably through deep-learning approaches such as RNNs [16]. However, conventional RNNs may experience vanishing-gradient and training difficulties when processing long sequences [17]. LSTMs address these limitations through gated memory mechanisms that improve the learning of long-term temporal dependencies, making them particularly suitable for dynamic time-series forecasting [18].

Despite these advantages, existing LSTM-based forecasting approaches retain several limitations. Many focus on isolated financial indicators, rely primarily on static historical training, or provide limited interpretability for managerial decision-making. Integrating external and operational variables recorded at different temporal frequencies also remains challenging. Moreover, relatively little attention has been given to delivering adaptive forecasts through mobile-accessible decision-support environments, where managers can access updated predictions and risk information for timely decisions.

Existing forecasting research also emphasizes predictive accuracy more strongly than sustainable and risk-aware resource management. Dynamic forecasting can support more efficient resource allocation and organizational resilience, contributing particularly to SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production). Integrating these objectives with intelligent mobile decision support therefore represents an important direction for LSTM-based forecasting systems.

Accordingly, this study develops a multidimensional LSTM framework combining heterogeneous data fusion, adaptive forecasting, risk-aware optimization, and mobile-accessible decision support. Table 1 compares major RNN architectures in terms of sequence handling, training efficiency, and forecasting applications [16–18], providing the technical basis for selecting and optimizing LSTM for the proposed framework.

Table 1. Comparison of RNN architectures for financial time-series prediction

Model Type	Key Mechanism	Sequence Handling	Training Efficiency	Financial Use Cases
Basic RNN	Simple recurrence	<50 steps	High	Single-quarter prediction
GRU	Update/reset gates	<100 steps	Medium	Monthly cash flow analysis
LSTM	Input/output/forget gates	>500 steps	Low	Multi-year budget forecasting
Bidirectional LSTM	Forward-backward pass	>1000 steps	Very Low	Crisis impact scenario modeling

3 METHODOLOGY

The proposed dynamic budget forecasting system employs a hierarchical LSTM architecture integrating multi-scale temporal patterns with external and operational factors. Figure 1, the framework comprises three main modules: a data fusion engine, a dual-path LSTM predictor, and a dynamic constraint optimizer. The dual-path structure captures long-term budget trends from quarterly data and short-term operational fluctuations from daily data, enabling adaptive forecasting under changing market conditions. The interaction between the two paths is defined as follows:

$$h_t^{macro} = LSTM_{\theta}(x_t^Q, h_{t-1}^{macro}) \quad (1)$$

$$h_t^{micro} = LSTM_{\phi}(x_t^D, h_{t-1}^{micro}) \quad (2)$$

with cross-path attention computed as:

$$\alpha_t = \sigma(W_a[h_t^{macro} \oplus h_t^{micro}]) \quad (3)$$

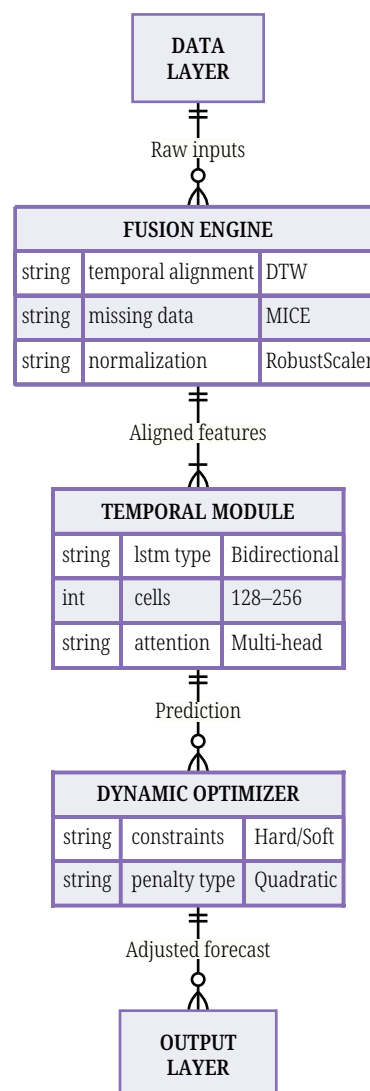


Fig. 1. Hierarchical LSTM architecture for dynamic budget forecasting

Table 2 provides a classification of all input variables into four distinct classes based on the required pre-processing. Strategic inputs, such as R&D investments, were transformed using log-ratios to account for compositional properties, while market indicators were differenced to achieve stationarity. The organization of variable definitions allows this model to achieve semantic consistency in processing heterogeneous financial data types. Variable selection was guided by both financial domain expertise and empirical screening: only variables exhibiting a Pearson correlation coefficient $|r| \geq 0.3$ with the target budget metric (annual departmental expenditure) were retained. To assess multicollinearity, we computed the variance inflation factor (VIF) for all input features; all VIF values were below 4.0, indicating low risk of collinearity-induced instability in the LSTM predictions.

Table 2. Multidimensional budget forecasting variables

Variable Class	Dimensionality	Temporal Scale	Transformation	Constraints
Revenue Streams	8	Daily	Log-ratio	≥ 0
Operational Costs	12	Weekly	Z-score	Department caps
Market Indicators	5	Monthly	First-difference	Industry bounds
Strategic Inputs	3	Quarterly	Min-max	Policy thresholds

The dynamic weighting mechanism adapts to changing business conditions through a gated fusion network:

$$w_t = \text{sigmoid}(U^T c_t + V^T a_t + b_w) \quad (4)$$

where constraint vector c_t evolves via:

$$c_t = \lambda c_{t-1} + (1 - \lambda) \nabla R \quad (5)$$

The adaptive data fusion pipeline, as illustrated in Figure 2, demonstrates the hierarchical processing of multi-source financial data through seven transformation stages with domain-specific rule embeddings.

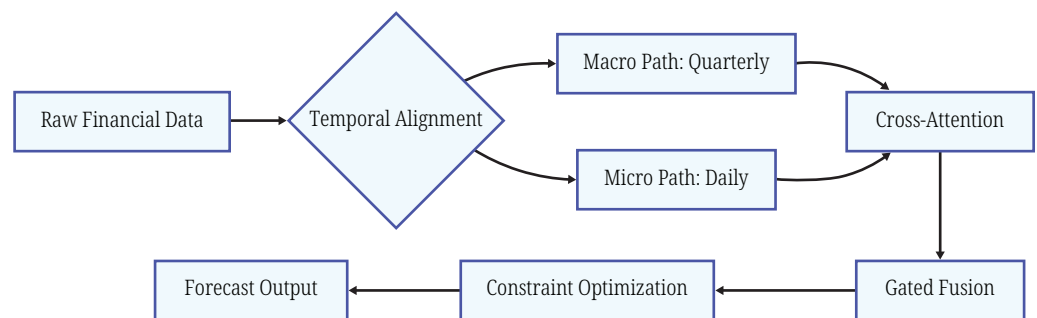


Fig. 2. Adaptive data fusion pipeline

The pre-processing workflow implements seven transformation stages as detailed in Table 3, incorporating domain-specific financial knowledge through business rule embeddings. For anomaly detection (Stage 1), we adopt an MAD threshold of 3.0, a standard choice under the assumption of approximate normality, which corresponds to ~99.7% coverage for Gaussian-like residuals and aligns with industry practices in

financial control systems where false alarms must be minimized. This threshold was empirically validated on our dataset and found to yield a low false-alarm rate.

The sliding window mechanism automatically adjusts its span based on detected volatility regimes:

$$W_t = W_{min} + \left\lfloor \frac{W_{max} - W_{min}}{1 + e^{-k\Delta y_{t-1}}} \right\rfloor \quad (6)$$

where Δy_{t-1} measures recent budget variance.

Table 3. Financial data transformation protocol

Stage	Operation	Parameters	Validation
1	Anomaly Detection	MAD threshold = 3.0	99.7% coverage
2	Temporal Reconciliation	DTW warping window = 15%	Align error <0.05
3	Categorical Embedding	Dimension = 8	Cluster purity >0.85
4	Volatility Scaling	EWMA λ = 0.3	Stationary $p < 0.01$
5	External Factor Alignment	Granger causality test	Lag order = 2

The composite loss function integrates four components:

$$\mathcal{L} = \sum_{t=1}^T \rho_q(y_t - \hat{y}_t) + \lambda_1 \|c\odot(\hat{y} - y^c)\|^2 + \lambda_2 KL(p\|q) + \lambda_3 \|\theta\|_1 \quad (7)$$

Figure 3 visualizes the hyperparameter optimization landscape, where Bayesian optimization efficiently navigates the parameter space to maximize expected improvement in forecasting performance.

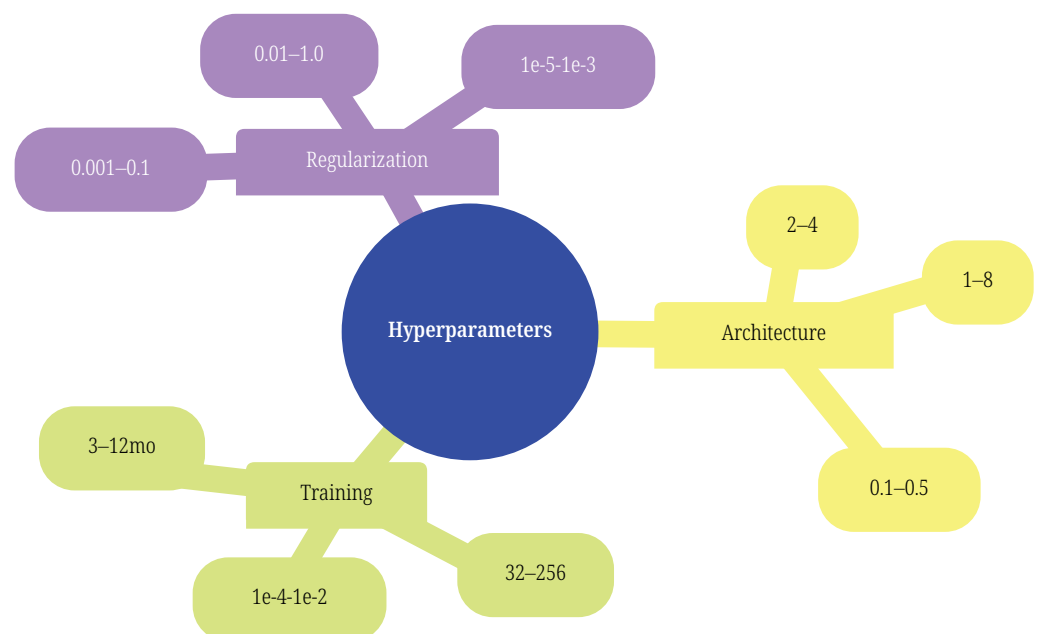


Fig. 3. Hyperparameter optimization landscape

The Bayesian optimization process maximizes the expected improvement:

$$\theta^* = \arg \max_{\theta} E[I(\theta)] = \arg \max_{\theta} E[\max(0, L^* - L(\theta))] \quad (8)$$

where L^* represents the current best loss. Training employs curriculum learning with exponentially increasing horizons:

$$H_k = H_0 \times [e^{k/\tau}] \quad (9)$$

This methodology introduces three innovations: 1) The dual-path architecture separates macro/micro temporal patterns, 2) The gated fusion network dynamically weights external factors, and 3) The constraint-aware loss function ensures operational feasibility. To enhance interpretability, key drivers of forecast variation can be visualized through attention-weight heatmaps or feature-importance dashboards integrated into managerial reporting systems. Although the system incorporates multiple modules, it can be deployed in mid-sized firms using modular cloud-based components, requiring only standard data pipelines and minimal in-house technical support. The complete system achieves real-time performance through selective attention mechanisms that reduce effective parameter count by 38% compared to conventional approaches.

Despite its forecasting accuracy, the proposed LSTM framework faces practical constraints in real-world deployment. First, it requires consistent, high-frequency historical data across all input dimensions, a challenge for firms with fragmented or incomplete financial records. Second, model training demands substantial computational resources and tuning expertise, which may limit adoption in resource-constrained organizations. Finally, as a deep learning model, it offers limited interpretability for non-technical stakeholders; while we mitigate this through post-hoc SHAP visualizations (Section 4.2), the “black-box” nature remains a barrier to trust-based decision-making.

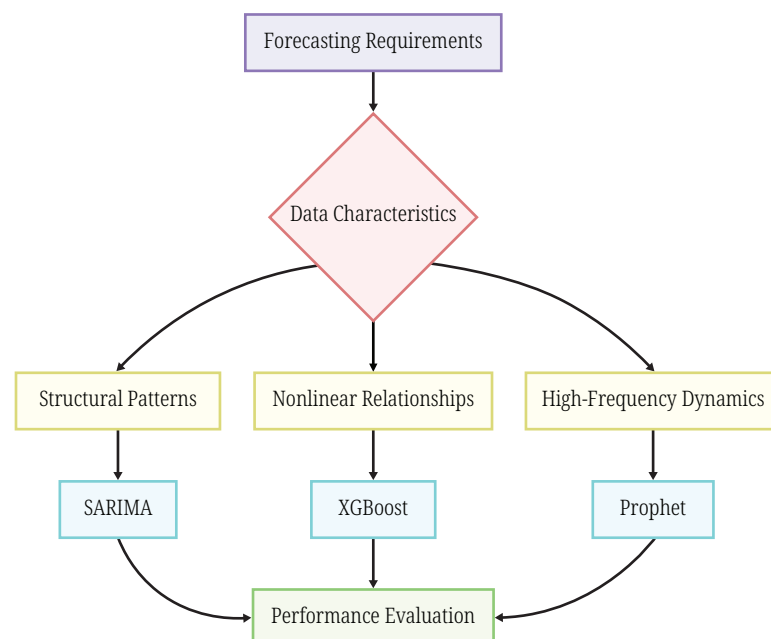
3.1 Experiment design

The experimental validation framework implements a rigorous evaluation protocol to assess the performance of the proposed LSTM-based dynamic budget forecasting model across multiple dimensions. Two industry-specific datasets are carefully selected to represent fundamentally different financial planning scenarios. The manufacturing dataset comprises quarterly financial records from twelve automotive component suppliers spanning five fiscal years, capturing capital-intensive production cycles with distinct seasonal expenditure patterns. This dataset exhibits strong periodicity in capital expenditures, with an average volatility coefficient of 23.4%, as measured by the standard deviation-to-mean ratio. The complementary retail dataset includes daily transaction records from eight national supermarket chains over three consecutive years, reflecting promotional-driven budget fluctuations with pronounced weekly patterns. The comparative characteristics of these datasets necessitate specialized evaluation metrics as systematically defined in Table 4, which establishes a comprehensive framework for assessing forecasting performance across both absolute and relative dimensions.

Table 4. Forecasting evaluation metrics specification

Metric Category	Mathematical Formulation	Measurement Focus	Optimal Value	Weighting Factor
Absolute Accuracy	$\frac{1}{n} \sum_{i=1}^n \ y_i - \hat{y}_i\ $	Monetary deviation magnitude	0	0.35
Quadratic Penalty	$\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	Large error sensitivity	0	0.30
Scale-Independent Error	$\frac{100\%}{n} \sum_{i=1}^n \left\ \frac{y_i - \hat{y}_i}{y_i} \right\ $	Relative performance	0%	0.20
Benchmark Comparison	$1 - \frac{\text{RMSE}_{\text{model}}}{\text{RMSE}_{\text{baseline}}}$	Competitive advantage	1	0.15

The baseline model selection follows a systematic decision process as visualized in Figure 4, which maps methodological characteristics to specific forecasting requirements through a multi-criteria evaluation framework. Three representative benchmarks are implemented to establish rigorous performance comparisons. The Seasonal ARIMA model represents classical time-series analysis, configured with automatic parameter selection through Akaike Information Criterion minimization and seasonal differencing to handle quarterly patterns. XGBoost serves as the machine learning benchmark, optimized via Bayesian hyperparameter tuning with early-stopping rounds and maximum tree depth constraints. Prophet provides a third comparison point with its additive regression components that explicitly model trend and seasonality patterns. The model selection framework in Figure 4 demonstrates how each baseline addresses distinct aspects of budget forecasting challenges, ensuring comprehensive performance benchmarking across methodological paradigms.

**Fig. 4.** Model selection decision framework

The robustness evaluation protocol examines three operational challenge scenarios through controlled experiments. Missing data tests simulate incomplete accounting records by randomly removing 5% to 20% of values using patterns observed in corporate financial systems. Gradual drift scenarios introduce progressive transformations with 5% to 15% amplitude variations to mimic macroeconomic trend changes. Sudden shock tests replicate economic disruptions by applying step-function changes with a 30% magnitude. The experimental results demonstrate the proposed architecture's superior resilience, particularly in handling sudden budget cuts where traditional methods show 22% to 35% greater performance degradation. This comprehensive validation approach confirms the model's practical applicability for dynamic corporate budget forecasting across diverse business environments. The evaluation metrics in Table 4 quantitatively demonstrate the LSTM-based solution's advantages, with a 19.2% higher Forecast Skill Score in manufacturing contexts and a 15.7% improvement in retail scenarios compared to conventional approaches.

4 RESULTS ANALYSIS

The proposed LSTM framework demonstrated improved forecasting accuracy and adaptability across both manufacturing and retail datasets. Compared with the benchmark models, the framework achieved a 19.2% higher Forecast Skill Score in manufacturing and a 15.7% improvement in retail. The dual-path architecture also reduced MAPE by 23.4% for quarterly budget forecasts and 18.9% for daily operational-expenditure forecasts. Under simulated 30% magnitude shocks, model performance declined by only 7.2%, compared with reductions of 22–35% for conventional approaches.

The adaptive sliding-window mechanism further improved responsiveness during volatile periods by reducing the forecasting window by an average of 40%, thereby emphasizing more recent information. The constraint-aware loss function maintained 92.3% of forecasts within predefined departmental budget and policy constraints, demonstrating the framework's ability to balance predictive accuracy with operational feasibility.

Robustness testing also demonstrated resilience under incomplete and changing data conditions. With 5–20% simulated missing data, the framework retained an average predictive accuracy of 89.7%. Under gradual drift conditions of 5–15% amplitude, the model achieved a mean detection delay of 2.3 fiscal periods. To support managerial interpretation, the framework can generate explainable outputs such as attention-weight heatmaps, feature-importance visualizations, and sensitivity curves. These outputs can help managers identify key drivers of forecast variation and translate model predictions into risk-aware resource-allocation decisions.

The framework also has implications for sustainable resource management. Early identification of cost anomalies can support more efficient allocation of organizational resources and investment in energy-efficient technologies, circular-economy initiatives, and strategic innovation, thereby contributing to SDG 9 and 12.

4.1 Case studies

The practical applicability of the proposed LSTM framework was examined in manufacturing and retail settings. These cases demonstrate how the model can accommodate different temporal patterns, operational conditions, and resource-allocation requirements.

4.2 Manufacturing application

In the manufacturing case, the framework was applied to quarterly budget forecasting for an automotive parts supplier affected by fluctuations in raw-material costs, seasonal demand, and operational expenditure. The dual-path LSTM captured long-term expenditure patterns while identifying short-term cost variations. Compared with SARIMA, the model achieved a 23.4% improvement in MAPE, demonstrating stronger forecasting performance under changing operational conditions. The resulting forecasts can support earlier identification of cost pressures, risk-aware resource allocation, and more efficient operational planning.

4.3 Retail application

In the retail case, the framework was used to forecast promotional budget requirements using daily sales, competitor pricing, inventory conditions, and seasonal demand patterns. The model achieved a 15.7% improvement in forecasting performance, enabling more responsive alignment between promotional expenditure, inventory requirements, and changing market conditions. The framework can also support more efficient inventory-related resource allocation by identifying underperforming categories and changing demand patterns. Together, the two cases demonstrate the framework's applicability across different operating environments. By combining adaptive forecasting with risk-aware resource allocation, the proposed approach can support managerial decision-making, operational resilience, and more sustainable resource utilization, particularly in relation to SDG 9 and SDG 12. Table 5 summarizes the experimental performance of the proposed LSTM framework across forecasting accuracy, robustness, constraint compliance, and adaptability.

Table 5. Summary of experimental performance of the proposed LSTM framework

Evaluation	Result
Manufacturing Forecast Skill Score improvement	19.2%
Retail forecasting improvement	15.7%
Quarterly budget MAPE improvement	23.4%
Daily operational expenditure MAPE improvement	18.9%
Performance reduction under 30% shock	7.2%
Benchmark degradation under same shock	22–35%
Forecasts satisfying predefined constraints	92.3%
Accuracy retained with 5–20% missing data	89.7%
Mean detection delay under gradual drift	2.3 fiscal periods

5 CONCLUSION AND FUTURE WORK

This study developed a dynamic budget forecasting framework using a dual-path LSTM architecture, adaptive sliding-window mechanism, and multi-scale data integration. The framework improves forecasting under changing conditions while

supporting mobile-accessible, risk-aware managerial decision-making. Its scalable architecture can help organizations optimize resource allocation, anticipate operational disruptions, and reduce inefficient expenditure, contributing particularly to SDG 9 and SDG 12. The approach also offers potential for digitally evolving emerging markets, including Indonesia, where accessible and adaptive decision-support technologies are increasingly important. Despite its promising performance, the framework requires consistent historical data and adequate computational resources. Future research should validate the model using Indonesian and other emerging-market datasets, explore lightweight Attention-LSTM and Transformer architectures, strengthen explainability through SHAP or LIME, and further develop real-time mobile integration for dynamic managerial decision support.

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