# Deep Hybrid Learning for Sustainable Industrial Forecasting: Integrating CNN–LSTM Models to Enhance Economic Efficiency and Carbon Performance

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*Abstract*—This paper explores the contribution of neural network-based safeguarding models to enhancing the environmental resilience and economic efficiency of industrial supply chains. The methodology includes a review of existing literature for a quasi-experimental study conducted from the perspective of a manufacturer. Using this approach, the study analyzes the transition from traditional statistical safeguarding practices to modern neural predictive frameworks, the amount of data available, and assesses their impact on decision-making and overall chain performance. The results from a Tunisian organization indicate that deep hybrid training architectures, particularly CNN-LSTM models, significantly improve the accuracy of demand forecasting, resulting in concurrent gains in operational efficiency and environmental performance. The organization also achieved a reduction in its annual costs of 2.25 million Tunisian dinars, leading to a decrease in carbon emissions. The study also identifies key obstacles, such as the fragmentation of data infrastructure, the lack of digital skills, and global development costs, which necessitate the effective adoption of deep training. Based on these findings, the paper proposes a dual-performance neural network framework to help managers and policymakers align technological innovation with the realities of emerging economies.

*Keywords*—*Neural networks; deep learning; CNN-LSTM; AI-enabled demand forecasting; sustainable supply chain; economic performance; digital transformation; data quality; emerging economies*

## I. INTRODUCTION

Global supply chains have undergone significant structural changes over the past decade, driven by market volatility, geopolitical disruptions, expanding e-commerce ecosystems, and increasing sustainability pressures. In this context, demand forecasting plays a critical role in coordinating production, inventory, and logistics decisions. Recent advances in deep learning, particularly neural network (NN) models, have demonstrated superior predictive performance compared to traditional statistical approaches in complex and nonlinear time-series environments [1].

Despite these technical advances, several important gaps remain in the supply chain forecasting literature.

First, the majority of existing studies emphasize improvements in forecasting accuracy, typically measured using error-based metrics such as MAPE or RMSE, without empirically examining how accuracy improvements translate into broader economic and environmental performance outcomes. While it is often assumed that better forecasts improve operational efficiency, the mechanisms linking predictive accuracy to cost reduction and carbon performance remain underexplored in empirical industrial settings [2].

Second, much of the current literature is based on data-rich environments in developed economies. There is limited empirical evidence on the implementation and impact of hybrid deep learning models in emerging industrial contexts characterized by fragmented data infrastructures, limited AI expertise, and constrained digital maturity. As a result, the practical feasibility and performance implications of NN-based forecasting in such environments remain insufficiently documented [3].

Third, organizational readiness factors such as data infrastructure quality and workforce AI literacy are frequently discussed conceptually but are rarely integrated into empirical analyses linking readiness conditions to forecasting effectiveness and downstream supply chain outcomes. This disconnect limits understanding of how technical capability interacts with organizational capacity to generate measurable performance gains [4].

Addressing these gaps is particularly relevant for emerging economies such as Tunisia, where industrial firms face increasing pressure to improve both competitiveness and sustainability performance under resource constraints. Understanding not only whether hybrid NN architectures improve forecasting accuracy, but also how such improvements translate into dual economic and environmental outcomes under real-world organizational conditions, represents a critical research need.

Accordingly, this study investigates the deployment of a hybrid CNN–LSTM forecasting model within a Tunisian manufacturing firm using a mixed-methods quasi-experimental design. Rather than proposing architectural innovation, the study examines how organizational and technical readiness conditions influence forecasting effectiveness, and how improvements in

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demand forecast accuracy (DFA) are associated with operational cost reductions and carbon emission performance.

The study makes three contributions. First, it provides empirical evidence linking forecasting accuracy to dual economic and environmental performance outcomes. Second, it documents the implementation of hybrid deep learning forecasting in a data-constrained emerging industrial setting. Third, it proposes an integrative Neural Network-Driven Dual Performance Framework that connects readiness factors, forecasting effectiveness, and performance translation.

The rest of the paper is organized as follows. Section II reviews the relevant literature and formulates the research hypotheses. Section III outlines the mixed-methods approach and describes the design of the NN models. Section IV presents the empirical findings. Finally, Section V concludes the study by highlighting its limitations and suggesting avenues for future research.

## II. Literature Review and Hypothesis Development

Over the past decade, AI-powered forecasting has emerged as a key focus of supply chain research, with experts agreeing that improved forecast accuracy can significantly enhance operational efficiency, economic performance, and environmental outcomes. Based on this premise, the conceptual model developed in this study, as illustrated in Fig. 1, links an organization's readiness to the effectiveness of NN-based forecasting, thereby connecting it to supply chain outcomes related to operations and sustainability [5].
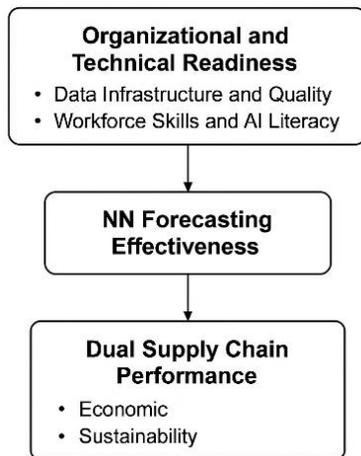


Fig. 1. Conceptual model.

### A. Organizational and Technical Readiness

The successful implementation of advanced NN models relies on a firm's organizational and technical readiness, which is closely linked to its absorptive capacity, defined as the capability to acquire, assimilate, and apply new knowledge effectively.

*1) Data infrastructure and quality:* Research on AI adoption underscores the importance of a strong data infrastructure for realizing the full potential of NN models. The accuracy and reliability of NN forecasting critically depend on large, high-quality, and well-integrated datasets. Common

obstacles, including poor data quality, fragmented legacy systems, and isolated data silos, have been widely recognized as major barriers to NN deployment in Tunisia and elsewhere. Therefore, establishing a robust data infrastructure is a fundamental requirement for the successful development and operationalization of NN-based forecasting systems [6].

In this study, data readiness is operationalized through 1) the level of infrastructure integration (ERP interoperability and reduction of spreadsheet silos) and 2) historical data completeness across multi-year time-series records.

H1a: Higher levels of data readiness positively impact demand forecast accuracy in NN forecasting implementation.

*2) Workforce skills and AI literacy:* The Role of Workforce Expertise and AI Literacy in Enhancing NN Effectiveness: Human capital plays an equally critical role. AI systems require skilled personnel who understand data workflows, interpret model outputs, and integrate predictions into decision-making processes. The lack of data science expertise represents one of the most persistent barriers to Industry 4.0 implementation in Tunisia. Firms with higher AI literacy are better positioned to harness NN capabilities and embed forecasting tools into operational routines [7].

AI literacy in this study is assessed through structured qualitative coding of workforce expertise levels, focusing on analytical capability, familiarity with predictive tools, and ability to interpret NN outputs.

H1b: Higher levels of workforce AI literacy positively affect demand forecast accuracy in NN forecasting implementation.

### B. NN Forecasting, Technological Capability, and Dual Performance

Advanced NN architectures, such as hybrid CNN–LSTM models, provide enhanced forecasting performance by integrating spatial feature extraction with long-term temporal learning. These models are particularly effective at capturing nonlinear relationships in complex time-series data, resulting in substantially improved prediction accuracy [8].

Improved DFA has direct economic implications: lower inventory holding costs, reduced stockouts, fewer production disruptions, and lower reliance on costly emergency logistics. Most importantly, these improvements also translate into gains in sustainability through reduced waste, energy use, and high-carbon transport activities. This mechanism is consistent with existing findings that establish an important link between lean practices and energy-efficient operations and the improvement of the economic and environmental performance of Tunisian industries [9].

In this study, dual performance outcomes are measured using observable KPIs, including annual operational cost reduction, inventory holding cost percentage, and Scope 2 and 3 carbon emissions.

H2: Improvements in DFA positively influence both economic performance and sustainability performance in supply chain operations.

### III. METHODOLOGY

This research uses a mixed approach that combines quantitative assessment of forecasting performance with qualitative insights gathered from key stakeholders in the organization. This approach is particularly suited to examining the dual technical-organizational transformation required for NN adoption in data-constrained industrial environments. Prior empirical evidence from the Tunisian context confirms that machine learning and deep learning architectures significantly outperform traditional statistical models in predictive tasks, particularly under structural and data limitations [10]. The methodological framework consists of three elements: 1) a quasi-experimental design implemented within an industrial case organization, 2) a structured qualitative inquiry to capture readiness and change-management dynamics and, 3) the development, training, and validation of a Hybrid CNN-LSTM forecasting model.

#### A. Research Design and Contextualization

The research follows a quasi-experimental structure encompassing Pre-Experiment, Experiment, and Post-Experiment phases over 12 months. The firm was selected based on three criteria: 1) persistent forecasting challenges arising from fragmented legacy systems; 2) active engagement in digital transformation initiatives; and 3) representativeness of the Tunisian industrial landscape, which is characterized by constrained data quality, limited AI expertise, and cost-sensitive operations [11].

The research follows a quasi-experimental structure encompassing Pre-Experiment, Experiment, and Post-Experiment phases over 12 months. This structure enables the measurement of performance variations attributable to the implementation of the NN model while preserving the ecological validity of the industrial setting. The design aligns with recent methodological standards in AI-enabled supply chain research, where controlled field experimentation provides robust evidence of performance transformation [12].

*1) Quantitative data collection:* Operational data were extracted from the firm's digital dashboards and ERP modules. Twelve KPIs, covering forecasting, inventory, logistics, and sustainability dimensions, were gathered at daily or weekly intervals depending on the data source. Time-series variables included historical demand, production volumes, lead times, energy use, carbon emissions, and material waste.

*2) Qualitative inquiry:* To complement the quantitative analysis, 35 semi-structured interviews were conducted with personnel across hierarchical levels, including planners, IT specialists, production managers, and senior executives [13]. The interviews examined organizational readiness, technical barriers, workforce skills, and perceptions of AI integration. Thematic analysis was employed to code the transcripts, enabling the identification of patterns related to data quality challenges (H1a) and workforce competencies (H1b).

The integration of qualitative and quantitative data enhances construct validity and offers a nuanced understanding of the ways in which technical interventions align with and influence organizational processes [14].

#### B. Model Development: Hybrid CNN-LSTM Architecture

The central technical contribution of this work is the design of a hybrid CNN–LSTM model for multivariate demand forecasting [15]. This architecture was selected for its capability to simultaneously extract local patterns from time-dependent data (through CNN layers) and model long-term temporal dependencies (via LSTM units). Fig. 2 conceptually illustrates the architecture.
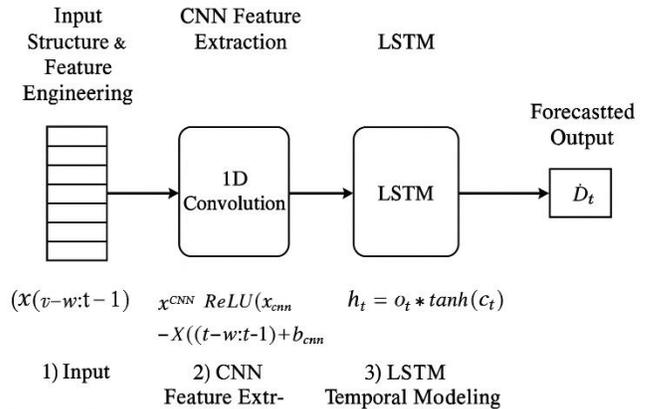


Fig. 2. Model development: Hybrid CNN-LSTM architecture.

*1) Input structure and feature engineering:* The model receives as input a sliding time window of historical observations $X_{(t-w:t-1)}$, comprising sales data, promotional events, production indicators, and external variables relevant to demand fluctuation. Features were normalized using Min–Max scaling to ensure comparable ranges across variables.

*2) CNN feature extraction:* A one-dimensional convolutional layer processes the input window to detect salient localized temporal patterns:

$$x_t^{CNN} = ReLU(W_{cnn} * X_{(t-w:t-1)} + b_{cnn})$$

The CNN layer reduces noise and performs early feature abstraction, producing a compact sequence representation fed into the LSTM component.

*3) LSTM temporal modeling:* The LSTM layer captures long-term dependencies through gated recurrent mechanisms:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t^{CNN}] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t^{CNN}] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t^{CNN}] + b_o)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t^{CNN}] + b_c)$$
$$h_t = o_t \odot \tanh(c_t)$$

The final hidden state $h_t$ is subsequently fed into a fully connected layer to produce the forecasted output $\hat{D}_t$.

#### C. Model Training, Validation, and Metrics

The Hybrid CNN-LSTM model was trained using an 80/20 split between training and testing datasets, with early stopping employed to mitigate overfitting. The Adam optimizer was utilized, with its learning rate calibrated through grid search. In addition, hyperparameters such as the input window size, filter

count, kernel width, and number of LSTM units were tuned using Bayesian optimization [16].

*1) Forecasting accuracy metrics:* Three primary metrics were employed to evaluate the forecasting performance of the model:

$$MAPE = \frac{1}{n}\sum \quad | \frac{D_t - \widehat{D}_t}{D_t} | \times 100\%$$

$$RMSE = \sqrt{\frac{1}{n}\sum(D_t - \widehat{D}_t)^2}$$

$$DFA = (1 - MAPE) \times 100$$

MAPE and RMSE measure prediction error, while DFA serves as the central measure of Neural Network effectiveness. Comparative benchmarking against ARIMA and MLP models provides additional insight into the relative superiority of the hybrid architecture.

### D. Validity and Reliability Considerations

To ensure methodological rigor, the study incorporated multiple safeguards:

- Construct validity: Triangulation of quantitative KPI data and qualitative interview insights.

- Internal validity: Quasi-experimental structure controlling for confounding variables through pre- and post-intervention comparison.

- External validity: Industrial representativeness of IDT within the Tunisian context.

- Reliability: Detailed documentation of model architecture, hyperparameters, and implementation workflow.

## IV. RESULTS AND DISCUSSION

The following section reports the empirical results obtained from deploying the advanced NN forecasting models in the selected Tunisian manufacturing firm. The analysis assesses the predictive accuracy of the proposed architectures and examines their implications for operational efficiency and environmental performance across the supply chain.

### A. Predictive Performance of Neural Network Models

In this paper, the experimental study compared traditional forecasting methods (ARIMA, Holt-Winters, and standard MLP) with advanced hybrid architectures, including the CNN-LSTM and LSTM-GRU models [17]. The CNN-LSTM model consistently achieved the lowest root mean square errors (RMSE) and mean percentage absolute errors (MAPE), with a DFA of 88%, compared to 65% for ARIMA and 77.9% for MLP.

The superior performance of the CNN–LSTM model can be attributed to its dual capability of capturing local temporal patterns through convolutional layers and modeling long-term dependencies via LSTM units. The improvement was especially pronounced during periods of high market volatility, such as sudden demand spikes or promotional campaigns, where classical statistical models struggled to adapt. This confirms H2, indicating that hybrid deep learning architectures provide a robust mechanism to handle nonlinear and complex demand series characteristic of emerging industrial markets.

### B. Operational Efficiency and Cost Reduction

The increase in DFA translated into significant operational gains. Post-implementation, production planning errors, inventory misalignments, and safety stock overstocking decreased substantially [18]. Consequently, the enterprise realized an annual cost reduction of approximately TND 2.25 million, primarily from optimized procurement scheduling, fewer emergency orders, and lower stockholding costs.

The correlation between improved forecast accuracy and cost savings demonstrates the tangible economic impact of NN adoption. Inventory holding costs decreased by 30%, and order fulfillment rates improved by 9.1%, indicating that higher DFA directly enhances operational efficiency. These findings align with prior studies emphasizing that accurate predictive analytics enable firms to reduce inefficiencies and improve resource allocation, particularly in emerging markets where operational margins are often constrained

### C. Environmental Impact and Sustainability Gains

NN-based forecasting also contributed to measurable environmental improvements. Optimized production planning reduced unnecessary machine operation hours, transportation activities, and material waste. Carbon emissions decreased by 15%, while energy consumption per unit declined by 12%, underscoring the potential of AI-driven forecasting as an indirect decarbonization mechanism [19].

The environmental benefits are closely linked to operational improvements; by reducing overproduction and inventory excess, energy usage and waste were minimized. This dual advantage of cost savings and emissions reduction demonstrates how predictive accuracy translates into sustainability performance. The results highlight that in data-constrained settings, NN adoption can simultaneously support economic and environmental objectives.

### D. Organizational and Technical Challenges

Despite these positive results, several barriers emerged during implementation. The enterprise encountered fragmented data architectures, limited digitization of operational processes, and insufficient technical expertise in advanced analytics. High initial investment costs also constrained scalability [20].

These challenges had a measurable impact on early forecasting accuracy, particularly due to workforce re-skilling requirements and limited trust in algorithmic outputs. However, explicit discussions of broader unintended consequences, such as workforce displacement or cybersecurity risks, remain largely absent. The findings underscore the critical importance of organizational readiness and capacity building to ensure the sustained effectiveness of AI-enabled forecasting systems, especially in emerging economies characterized by uneven levels of digital maturity.

### E. Strategic and Policy Insights

The results highlight that the effective deployment of NN forecasting models requires both technical integration and organizational adaptation. The presented *Neural Network-Driven Dual Performance Framework* provides practical guidance for managers seeking to align the adoption of deep learning with available resources. For policymakers, the findings underscore the crucial need to invest in digital infrastructure, enhance workforce AI competencies, and implement targeted financial incentives to promote AI readiness across the Tunisian industrial sector [14].

### F. Experimental Study with IDT: Technical and Operational Transformation

*1) Pre-experiment phase:* Before NN implementation, the supply chain department at IDT relied primarily on historical averages and planner judgment, resulting in low forecasting accuracy (65%) and frequent operational disruptions, including stockouts and high expedited freight costs. Data resided in disconnected spreadsheets and paper records, creating a significant barrier to data-driven forecasting.

*2) Experiment phase:* The initial phase involved integrating fragmented data sources, reconciling inconsistent part numbers, and digitizing years of paper-based records. Planners initially expressed skepticism toward the CNN–LSTM "black box," particularly when outputs did not reflect tacit operational knowledge, such as nuanced supplier scheduling. Change management focused on workforce re-skilling, positioning the NN system as a decision-support tool. Workshops demonstrated how the NN model could manage complex multivariate forecasting, freeing planners to focus on strategic decisions informed by validated algorithmic outputs.

### G. Results

The superior predictive capability of the hybrid CNN–LSTM architecture was confirmed through internal benchmarking (Table I), which showed significant reductions in error metrics (MAPE, RMSE) relative to legacy and standard NN models, as shown in Fig. 3 and Fig. 4.

Most importantly, the improved forecasting resulted in measurable and sustainable operational gains (Table II). The increase in demand forecast accuracy (PFD) was 35.4% and was associated with a 15% reduction in operating costs and a parallel 15% reduction in carbon emissions. Storage costs decreased by 30%, while stockout rates plummeted by 73.3%, reflecting

better inventory synchronization and reduced distortions related to safety stock. Furthermore, the on-time and complete (OTIF) delivery rate increased from 88% to 96%, demonstrating enhanced service reliability.

The results highlight that the integration of advanced architectures and human-centered change management is critical for translating technical capability into measurable dual performance.
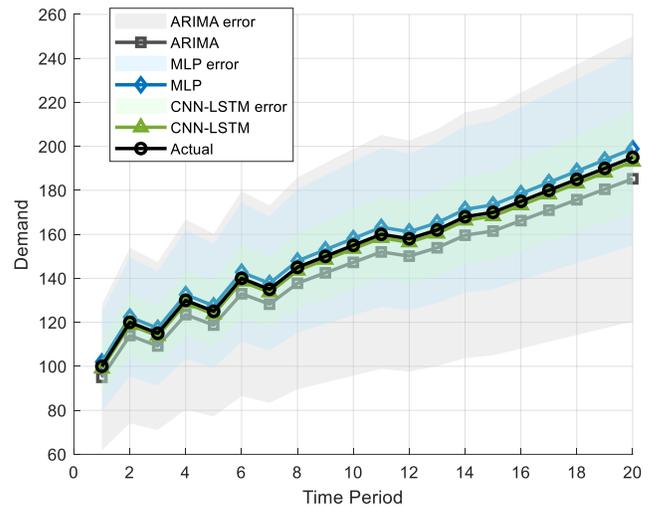


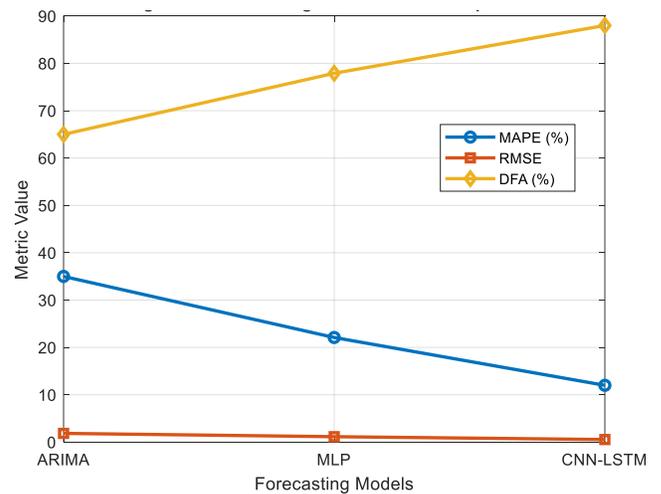Fig. 3. Actual vs. Predicted Demand with Model Performance



Fig. 4. Forecasting performance comparison.

TABLE I. COMPARATIVE FORECASTING PERFORMANCE (PRE-EXPERIMENT VS. POST-EXPERIMENT)

| Forecasting Model | MAPE (Demand) | RMSE (Demand) | DFA (Accuracy) | Rationale |
|---|---|---|---|---|
| Traditional (ARIMA) | 35.0% | 1.85 | 65.0% | Baseline statistical system |
| Shallow NN (MLP) | 22.1% | 1.15 | 77.9% | Standard ANN |
| Hybrid CNN-LSTM | 12.0% | 0.55 | 88.0% | Deployed model; superior for complex series |

TABLE II.     OPERATIONAL AND SUSTAINABILITY OUTCOMES

| KPI | Dimension | Metric | Pre-Experiment | Post-Experiment | % Change |
|---|---|---|---|---|---|
| Operational Costs | Economic | TND Million/Year | 15.00 | 12.75 | -15.0% |
| Inventory Holding Costs | Economic | % of Total Inventory | 20 | 14 | -30.0% |
| OTIF Rate | Economic | % of Orders | 88 | 96 | +9.1% |
| Carbon Emissions (Scope 2 & 3) | Sustainability | tCO₂e/Year | 1,500 | 1,275 | -15.0% |
| Material Waste Rate | Sustainability | % of Raw Material | 7 | 5.5 | -21.4% |
| Energy Consumption per Unit | Sustainability | kWh/Unit | 12.5 | 11.0 | -12.0% |
| Demand Forecast Accuracy | Forecasting | % Accuracy | 65 | 88 | +35.4% |
| Inventory Stockout Rate | Forecasting | % of SKUs | 15 | 4 | -73.3% |

*H. Neural Network-Driven Dual Performance*

The framework translates NN accuracy into dual outcomes via five dimensions:

- Foundational Data Integration (H1a): Centralize and standardize infrastructure to eliminate fragmentation.

- Hybrid Architecture Selection: Employ CNN–LSTM models for multivariate data.

- Workforce Re-Skilling (H1b): Transition planners from operators to validators of algorithmic outputs.

- Targeted Dual Optimization: Minimize both costs and emissions through NN-informed decision-making.

- Measurable Performance Translation: Directly link DFA improvements to operational and sustainability KPIs.

By addressing organizational and technical barriers, this framework enables firms in emerging economies to achieve substantial dual benefits from NN adoption. It demonstrates that technical accuracy alone is insufficient; complementary organizational change is essential for realizing the full economic and environmental potential of AI-enabled forecasting.

## V.     CONCLUSION

This study investigated the relationship between neural network–based demand forecasting and dual performance outcomes in a Tunisian industrial supply chain context. Using a mixed-methods quasi-experimental design, the findings demonstrate that hybrid CNN–LSTM architectures significantly outperform traditional statistical models in forecasting accuracy.

The empirical results indicate that improved DFA is associated with measurable reductions in operational costs and carbon emissions. However, these gains are contingent upon organizational readiness, including data infrastructure quality and workforce analytical capability.

While the single-case design limits external generalizability, the study provides evidence that hybrid deep learning models can generate economically and environmentally meaningful outcomes when supported by appropriate organizational conditions.

Future research should incorporate multi-firm datasets, formal mediation modeling, statistical significance testing, and comparisons with transformer-based architectures to strengthen causal inference and scalability assessment

Future research can extend this work in several directions. First, applying the proposed framework across different industrial sectors would provide broader validation and support cross-sectoral generalization. Second, integrating reinforcement learning or transformer-based architectures may further enhance predictive capabilities in dynamic environments. Finally, expanding the analysis to include socio-economic dimensions, such as workforce transformation and digital upskilling, would offer a more holistic understanding of AI-driven supply chain advancement in emerging markets.

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