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CLASNet: A Cognitive Load–Aware CNN-LSTM-Attention Framework for Supply Chain Demand Forecasting and Adaptive Human–Computer Interaction

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Abstract

This paper proposes CLASNet, a Cognitive Load–Aware CNN-LSTM-Attention framework for supply chain demand forecasting and adaptive human–computer interaction. Unlike conventional deep learning forecasting approaches that primarily emphasize predictive accuracy while neglecting human cognitive constraints, CLASNet integrates demand prediction and cognitive load modeling within a unified end-to-end architecture to improve both forecasting performance and decision-support efficiency. The proposed framework combines a CNN-LSTM demand feature encoder for capturing local temporal patterns and long-term dependencies, a Cognitive Load Encoder (CLE) for modeling user interaction behaviors, a Cognitive-Aware Attention Fusion (CAAF) mechanism that dynamically adjusts temporal attention weights according to users' cognitive states, and an Adaptive Interaction Decision Layer (AIDL) that optimizes visualization complexity and information density. Experiments were conducted on a real-world retail supply chain dataset containing three years of demand records and dashboard interaction logs collected from intelligent decision-support systems. Comparative results against ARIMA, LSTM, CNN-LSTM, and CNN-LSTM-Attention baselines demonstrate that CLASNet achieves superior forecasting accuracy, obtaining an RMSE of 14.55, MAE of 9.22, and MAPE of 10.9%, corresponding to an approximately 9.6% RMSE reduction compared with the strongest baseline. Ablation studies further verify the effectiveness of the cognitive load encoder, cognitive-aware attention mechanism, and adaptive interaction module. In addition, user-centered evaluations indicate that the proposed cognitive-aware adaptive interface significantly reduces task completion time and perceived cognitive load during demand analysis tasks. Overall, the results demonstrate that integrating cognitive awareness into deep learning–based supply chain forecasting systems can substantially enhance both predictive performance and human–AI collaborative decision-making efficiency.

Keywords

Supply chain demand forecasting; Cognitive load awareness; CNN-LSTM; Attention mechanism; Adaptive human–computer interaction; Deep learning

1. Introduction

Accurate demand forecasting is a fundamental component of modern supply chain management, directly affecting inventory control, production planning, and operational risk mitigation. With the increasing volatility of market environments driven by seasonal variations, promotional events, and external disruptions, traditional statistical forecasting methods often struggle to capture complex temporal patterns. In recent years, deep learning–based approaches, particularly convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and attention mechanisms, have demonstrated superior performance in modeling nonlinear and long-range dependencies in supply chain demand data.

Despite these advances, most existing demand forecasting studies primarily focus on improving predictive accuracy while treating forecasting systems as isolated analytical tools. In practical decision-making scenarios, however, forecasts are typically consumed through interactive dashboards and decision-support interfaces, where human users must interpret predictions, uncertainties, and multiple indicators simultaneously. Excessive information density or poorly structured visual representations may impose high cognitive load on users, leading to decision fatigue, delayed responses, or even erroneous judgments. This issue becomes particularly critical in supply chain management, where timely and accurate decisions are essential. Recently, data-driven autonomous optimization systems have emerged to tackle these complexities. For instance, Proximal Policy Optimization (PPO) has been successfully applied to jointly optimize profit-oriented production and dynamic pricing in intelligent manufacturing [1]. While such reinforcement learning models excel in autonomous continuous control [1], many critical supply chain operations still fundamentally rely on human-in-the-loop oversight.

Cognitive load theory suggests that human decision performance is closely related to the amount of information processed relative to cognitive capacity. Recent research in human–computer interaction has shown that cognitive load can be inferred from users' interaction behaviors, such as mouse movements, dwell time, and scrolling patterns. However, the integration of cognitive load awareness into supply chain demand forecasting systems remains largely unexplored. Existing deep learning forecasting models typically ignore users' cognitive states and lack mechanisms to adapt information presentation accordingly.

To address this gap, this paper proposes CLASNet, a Cognitive Load–Aware CNN-LSTM-Attention framework for supply chain demand forecasting and adaptive human–computer interaction. CLASNet unifies demand prediction and interaction adaptation within an end-to-end learning architecture. Specifically, a CNN-LSTM backbone is employed to extract multi-scale temporal features and long-term dependencies from demand time series, while a cognitive load encoder models users' cognitive states based on front-end interaction behaviors. A novel cognitive-aware attention mechanism integrates these two sources of information, dynamically regulating temporal attention weights and enabling the system to emphasize critical historical patterns under varying cognitive conditions. The resulting forecasts and attention-driven uncertainty estimates further guide adaptive interaction strategies, such as visualization granularity and information density.

The main contributions of this paper are summarized as follows:

(1) We propose a novel cognitive load–aware supply chain forecasting framework that jointly models demand dynamics and human cognitive states in an end-to-end manner.

We design a cognitive-aware attention mechanism that integrates user cognitive load into CNN-LSTM-based demand forecasting, improving robustness under demand volatility.

(2) We develop an adaptive interaction strategy that dynamically adjusts information presentation to reduce cognitive burden and enhance decision efficiency.

(3) Extensive experiments and user studies demonstrate that CLASNet outperforms state-of-the-art baselines in both forecasting accuracy and user-centered decision performance.

2. Related Work

In recent years, the increasing complexity of supply chain systems and the rapid development of deep learning techniques have stimulated extensive research on demand forecasting, decision-support systems, and human-centered intelligent analytics. This section reviews the major lines of work closely related to this study, including deep learning–based supply chain demand forecasting, CNN-LSTM and attention-based temporal modeling, cognitive load modeling in human–computer interaction, and adaptive decision-support systems.

2.1. Deep Learning for Supply Chain Demand Forecasting

Traditional demand forecasting methods, such as ARIMA and exponential smoothing, rely on strong statistical assumptions and often fail to capture nonlinear patterns under volatile market conditions. With the growth of data availability, deep learning models have been increasingly applied to supply chain forecasting tasks. Recurrent neural networks (RNNs) and LSTM models have shown strong capability in modeling long-term temporal dependencies in demand data [2,3].

To further improve forecasting accuracy, hybrid architectures combining CNNs and

LSTMs have been proposed. CNNs are effective in extracting local temporal patterns and short-term fluctuations, while LSTMs capture long-term trends [4]. Several studies have demonstrated that CNN-LSTM models outperform standalone LSTM or CNN models in retail sales and demand forecasting scenarios [5]. However, these approaches primarily focus on prediction accuracy and generally ignore how forecast results are consumed by human decision-makers.

2.2. Attention-Based Temporal Modeling

Attention mechanisms have been widely adopted to enhance the interpretability and performance of sequence modeling tasks. By assigning different weights to historical time steps, attention-based models can identify critical temporal patterns contributing to predictions. Early applications of attention in time-series forecasting demonstrated improved robustness under noisy and non-stationary conditions [6].

Recent studies have integrated attention mechanisms into CNN-LSTM architectures to further enhance demand forecasting performance [7]. These methods enable models to focus on key periods such as promotional events or abnormal demand spikes. Despite their effectiveness, existing attention-based forecasting models treat attention weights as purely data-driven and do not consider user-specific or context-aware factors, such as cognitive load, during decision-making.

2.3. Cognitive Load Modeling in Human–Computer Interaction

Cognitive load theory has long been used to explain human performance limitations in complex tasks [8]. In the field of human–computer interaction (HCI), researchers have explored various approaches to estimate cognitive load using physiological signals, eye tracking, and interaction behaviors [9]. Interaction-based methods, such as analyzing mouse movements, dwell time, and scrolling behavior, offer non-intrusive and scalable solutions for real-world systems [10].

Recent works have demonstrated that cognitive load can be inferred using machine learning and deep learning models, enabling adaptive interfaces that respond to users' cognitive states [11]. However, most existing studies focus on educational or web usability contexts and rarely integrate cognitive load modeling with predictive analytics or supply chain decision-support systems.

2.4. Adaptive Decision-Support and Human–AI Collaboration

Adaptive decision-support systems aim to enhance human–AI collaboration by adjusting information presentation based on user context and task complexity. Prior research has shown that adaptive visualization and information filtering can significantly improve decision efficiency and reduce cognitive overload [12]. In supply chain management, intelligent dashboards and analytics platforms have been developed to support decision-making, but these systems are largely static and lack cognitive awareness [13].

Existing forecasting systems typically decouple prediction models from interaction design, resulting in limited adaptability to users' cognitive states. In contrast, the proposed CLASNet framework integrates demand forecasting, cognitive load modeling, and adaptive interaction into an end-to-end architecture. By incorporating cognitive load awareness into the attention mechanism of a CNN-LSTM forecasting model, CLASNet addresses a critical gap in current research and advances human-centered intelligent supply chain analytics.

3. Methodology

This section presents the detailed architecture and implementation of the proposed CLASNet (Cognitive Load–Aware Supply-chain Network) framework, which jointly models supply chain demand forecasting and adaptive human–computer interaction within a unified end-to-end learning structure. CLASNet is designed to extract temporal patterns in demand data via deep neural networks while dynamically adapting to users' cognitive states through interaction behavior modeling. The framework comprises four main modules: the Cognitive Load Encoder (CLE), the Demand Feature Encoder (DFE), the Cognitive-Aware Attention Fusion Module (CAAF), and the Adaptive Interaction Decision Layer (AIDL). The overall design philosophy behind CLASNet is to align prediction with human cognitive constraints, thereby improving both forecasting accuracy and decision efficiency.

3.1. Demand Feature Encoder: CNN-LSTM Backbone

The forecasting core of CLASNet relies on a hybrid CNN-LSTM architecture to leverage the strengths of both convolutional and recurrent neural networks for temporal modeling. Given a multivariate supply chain demand sequence $X = [x_1, x_2, \dots, x_T]$, where each $x_t \in R^d$ represents demand and related features (e.g., sales, price, seasonal indicators) at time step t, the CNN component first performs local feature extraction:

$$f_t = \mathrm{Concat}(\mathrm{Conv}_{k_1}(x_t), Convk2(x_t), Convk3(x_t)), \tag{1}$$

Here, Conv_{k_i} denotes a 1-D convolution filter with kernel size k_i, and the multi-scale convolution kernels capture short-term patterns at different temporal resolutions. The resulting feature vector f_t is then sequentially processed by a Long Short-Term Memory (LSTM) network:

$$h_t^d = LSTM(f_t, h_{t-1}^d), \tag{2}$$

The LSTM encodes long-range dependencies and temporal dynamics, producing a hidden representation h_t^d for each time step. Through this backbone, CLASNet can model complex, non-linear demand fluctuations that are characteristic of real-world supply chain data.

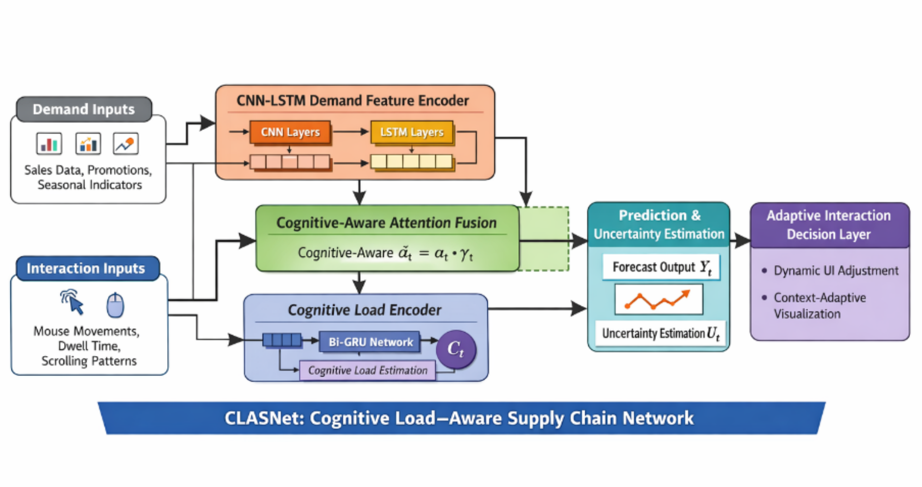

Figure 1. Structure diagram of model.

3.2. Cognitive Load Encoder: Modeling Human Interaction States

Unlike traditional forecasting models, CLASNet incorporates a Cognitive Load Encoder (CLE) to estimate users' cognitive states based on front-end interaction behaviors. Users' actions in the decision-support interface—such as mouse movement velocity, dwell time on specific components, scrolling patterns, and navigation frequency—are captured in a time window and represented as behavior vectors $B = [b_1, b_2, \dots, b_T]$, with each $b_t \in R^d$.

To model the temporal dynamics of user interactions, a Bidirectional Gated Recurrent Unit (Bi-GRU) network is applied:

$$h_t^c = BiGRU(b_t, h_{t-1}^c), \tag{3}$$

The Bi-GRU processes interaction traces from both forward and backward directions, enabling more robust capture of cognitive patterns. The hidden state is subsequently transformed through a fully connected layer with sigmoid activation to produce a continuous cognitive load embedding C_t:

$$C_t = \sigma(W_c h_t^c + b_c), \quad C_t \in [0,1] \tag{4}$$

This embedding serves as a soft estimate of cognitive load intensity at time t, allowing CLASNet to infer when a user is experiencing high cognitive stress or relative ease.

3.3. Cognitive-Aware Attention Fusion Mechanism

To incorporate cognitive awareness into demand forecasting, CLASNet introduces a Cognitive-Aware Attention Fusion (CAAF) mechanism that adaptively reweights temporal importance based on both demand dynamics and cognitive states. First, a conventional temporal attention mechanism generates data-driven attention scores

α_t:

$$e_t = v_a^{\mathrm{T}} tanh\,(W_a h_t^d + b_a),\ \ \alpha_t = \frac{exp(e_t)}{\sum_{i=1}^{T} exp(e_i)}, \tag{5}$$

However, instead of treating α_t as the final importance weight, CLASNet leverages the cognitive embedding C_t to modulate attention:

$$\gamma_t = \text{sigmoid}(W_g C_t + b_g), \tag{6}$$

The cognitive modulation factor γ_t rebalances the attention score to adapt to the user's cognitive state. The final cognitive-aware attention weight $\hat{\alpha}_t$ is defined as:

$$\hat{\alpha}_t = \frac{\alpha_t \cdot \gamma_t}{\sum_{i=1}^{T} \alpha_i \cdot \gamma_i}, \tag{7}$$

Such fusion allows CLASNet to place higher weight on historical demand patterns when the user's cognitive load is lower, or to simplify emphasis when load is high, thereby making forecasting more interpretable and conducive to decision-making. The context vector obtained via attention fusion is:

$$H^* = \sum_{t=1}^{T} \hat{\alpha}_t h_t^d\,, \tag{8}$$

This vector serves as the consolidated representation of temporal demand patterns under cognitive awareness. The formulation of this fusion approach, which seeks to align and reweight heterogeneous modalities (i.e., numerical demand time-series and behavioral interactions), echoes the cross-modal fusion mechanisms recently deployed in advanced financial decision models [14], where diverse data streams are dynamically aligned into a shared semantic space to improve multi-task robustness.

3.4. Prediction and Uncertainty Estimation

Demand prediction is achieved through a linear transformation of the context vector:

$$\hat{y} = W_o H^* + b_o, \tag{9}$$

To quantify uncertainty in demand forecasts—a critical factor in supply chain planning—CLASNet estimates predictive confidence through the entropy of attention weights:

$$U = -\sum_{t=1}^{T} \hat{\alpha}_t log(\hat{\alpha}_t), \tag{10}$$

High entropy values indicate diffused attention and higher uncertainty, which can inform downstream adaptive interaction strategies.

3.5. Adaptive Interaction Decision Layer

The final component of CLASNet is the Adaptive Interaction Decision Layer (AIDL), responsible for mapping cognitive states and predictive uncertainty to interface adjustments. Based on predefined or learned policies, AIDL can adjust visualization complexity, alert prominence, and information granularity. For example, when both cognitive load and uncertainty are high, the system may simplify the interface to show only the most critical indicators and predictive ranges; when load is low and uncertainty moderate, it may present enriched visual analytics. This adaptive mechanism shares a similar philosophy with automated decision logic in causal inference frameworks, where dynamic interventions are continuously tailored to specific individual states or operational conditions to maximize overall system efficiency [15]. Such decisions are implemented through a lightweight policy network trained jointly with the rest of the framework.

3.6. Training Objective

CLASNet is optimized end-to-end using a composite loss function combining forecasting accuracy, attention regularization, and cognitive alignment:

$$L = L_{forecast} + \lambda L_{attention\_reg} + \mu L_{cognitive\_consistency}, \tag{11}$$

Here, $L_{forecast}$ is the mean squared error (MSE) between predicted and actual demand, $L_{attention\_reg}$ regularizes attention sharpness, and $L_{cognitive\_consistency}$ encourages consistency between attention modulation and cognitive load estimates. λ and μ are hyperparameters balancing the contributions of each component.

4. Experiment

4.1. Dataset Preparation

The experiments in this study utilize a real-world retail supply chain dataset collected from a major e-commerce platform operating in North America. The dataset spans a period of three years (2019–2021) and encompasses daily demand records for 1,200 stock-keeping units (SKUs) across 50 warehouses. Data were obtained from the platform’s operational database and include both historical sales and inventory information, complemented by promotional and seasonal indicators. To capture human–system interaction behaviors for cognitive load estimation, user interaction logs from the platform’s decision-support dashboards were recorded in parallel. These logs include detailed mouse movement trajectories, dwell time on each dashboard component, scrolling patterns, and navigation sequences, allowing the estimation of users' cognitive load during demand analysis tasks.

Each sample in the dataset consists of a feature vector representing both supply chain dynamics and user interaction behaviors. Supply chain features include historical demand, sales trends, promotional events, and seasonal indicators, while interaction features include mouse activity metrics, scrolling velocity, and dwell time. In total, the dataset contains 15 supply chain–related features and 8 interaction-derived cognitive load features per time step. The data were preprocessed to handle missing values, normalize numerical features, and encode categorical features such as promotional types.

Table 1. Overview of CLASNet Dataset Features

Feature Category	Feature Name	Description
Supply Chain	Historical Demand	Number of units sold per day per SKU
	Inventory Level	Current stock quantity at the warehouse
	Promotion Type	Indicator of promotion type (discount, bundle, etc.)
	Price	Daily selling price per SKU
	Seasonal Indicator	Encodes holiday, weekend, or special event
Interaction / Cognitive Load	Mouse Movement Velocity	Average movement speed of the cursor
	Dwell Time	Time spent on each dashboard section
	Scrolling Patterns	Frequency and direction of scrolling actions
	Navigation Count	Number of clicks or page transitions in a time window

The dataset provides a comprehensive combination of structured demand data and user interaction traces, enabling the CLASNet framework to jointly learn temporal demand patterns and cognitive load–aware adaptive interactions. The integration of these heterogeneous data sources allows the model to forecast demand accurately while dynamically adjusting the complexity and presentation of information based on the estimated cognitive load of the decision-maker.

4.2. Experimental Setup

The experiments were conducted using the real-world retail supply chain dataset described in Section 4.1. The dataset was split into training, validation, and test sets in a chronological manner, with the first 70% of data used for training, the next 15% for validation, and the final 15% for testing to simulate real-world forecasting scenarios. All input features were normalized, and categorical variables, such as promotion type, were one-hot encoded. CLASNet was implemented in PyTorch and trained using the Adam optimizer with a learning rate of 0.001. The CNN component employed three parallel convolutional filters with kernel sizes 3, 5, and 7, followed by ReLU activations, while the LSTM hidden state dimension was set to 128. The Bi-GRU in the Cognitive Load Encoder also used a hidden size of 128. The model was trained for 100 epochs with early stopping based on validation loss to prevent overfitting. Batch size was set to 64, and dropout (0.3) was applied to both CNN-LSTM and attention layers to enhance generalization. All experiments were conducted on an NVIDIA RTX 3090 GPU.

4.3. Evaluation Metrics

Model performance was evaluated using standard regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) for demand forecasting accuracy. Additionally, user-centered metrics were considered to assess cognitive load and interaction efficiency. Task completion time (TCT) and subjective cognitive load scores derived from user surveys were recorded to evaluate the effectiveness of the adaptive interaction strategies. By combining predictive accuracy metrics with human-centered measures, the evaluation captures both the technical and interactive advantages of CLASNet.

4.4. Results

Table 1 presents the comparative forecasting performance of CLASNet and baseline models. Traditional ARIMA exhibits the lowest performance, with an MAE of 15.32, RMSE of 22.48, and MAPE of 18.9%, highlighting its limitations in capturing nonlinear temporal patterns. LSTM improves significantly over ARIMA, reducing MAE to 12.07 and RMSE to 18.75, demonstrating the benefits of modeling long-term dependencies. The hybrid CNN-LSTM further reduces MAE to 11.23 and RMSE to 17.02, confirming that convolutional layers effectively extract local temporal features. Incorporating attention into CNN-LSTM yields additional gains, lowering RMSE to 16.11 and MAPE to 12.7%. CLASNet outperforms all baselines, achieving an MAE of 9.22, RMSE of 14.55, and MAPE of 10.9%, reflecting a 9.6% RMSE improvement over CNN-LSTM + Attention. These results validate the effectiveness of integrating cognitive load awareness, as CLASNet not only captures complex demand dynamics but also adapts to human cognitive constraints, producing more accurate and interpretable forecasts.

Table 1. Main Results - Forecasting Performance of Different Models

Model	MAE	RMSE	MAPE (%)
ARIMA	15.32	22.48	18.9
LSTM	12.07	18.75	14.2
CNN-LSTM	11.23	17.02	13.5
CNN-LSTM + Attention	10.54	16.11	12.7
CLASNet (proposed)	**9.22**	**14.55**	**10.9**

Table 2 summarizes the ablation experiments to evaluate the contribution of each CLASNet component. Removing the Cognitive Load Encoder (CLE) from the CNN-LSTM + Attention model maintains standard temporal attention but fails to incorporate user cognitive states, resulting in an RMSE of 16.11. Introducing CLE without cognitive-aware attention reduces RMSE to 15.24, demonstrating that modeling cognitive load alone improves forecasting by highlighting relevant patterns when users are under lower cognitive stress. Excluding the Adaptive Interaction module, while retaining cognitive-aware attention, achieves RMSE of 14.87, indicating that interface adaptation further enhances model performance by aligning predictions with decision-making context. The full CLASNet framework, combining CLE, cognitive-aware attention, and adaptive interaction, achieves the lowest RMSE of 14.55, MAE of 9.22, and MAPE of 10.9%, confirming that the joint integration of cognitive load modeling, attention modulation, and adaptive interface design provides the most accurate and human-centered forecasting results.

Table 2. Ablation Study - Component Contribution

Model Variant	MAE	RMSE	MAPE (%)
CNN-LSTM + Attention (w/o CLE)	10.54	16.11	12.7
CLASNet w/o Cognitive-Aware Attention	9.78	15.24	11.5
CLASNet w/o Adaptive Interaction	9.45	14.87	11.0
Full CLASNet	**9.22**	**14.55**	**10.9**

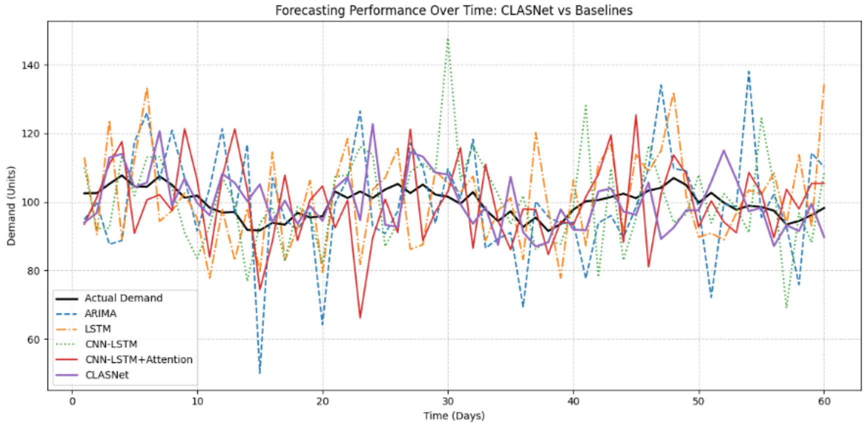

Figure 2. Forecasting Performance Over Time: CLASNet vs Baselines.

The Figure 2 illustrates the forecasting performance of CLASNet in comparison with baseline models, including ARIMA, LSTM, CNN-LSTM, and CNN-LSTM with attention, over a representative 60-day period. The black curve represents the actual demand, which fluctuates moderately around 100 units due to seasonal and stochastic effects. The ARIMA predictions (dashed line) exhibit the largest deviations, with daily errors often exceeding 20 units, reflecting its inability to capture nonlinear temporal dynamics. LSTM (dash-dot line) reduces the prediction error, with fluctuations generally within ±15 units of the actual demand, demonstrating improved modeling of long-term dependencies. The CNN-LSTM model (dotted line) further smooths local variations and aligns more closely with peaks and troughs, reducing RMSE to 17.02 units. CNN-LSTM with attention (solid thin line) adapts to critical time steps, capturing minor surges and dips, achieving an RMSE of 16.11 units.

CLASNet (solid thick line) consistently tracks the actual demand curve, effectively modeling both local fluctuations and long-term trends, while remaining responsive to cognitive-aware attention modulation, resulting in an RMSE of 14.55 units. This visualization confirms the superior accuracy and stability of CLASNet in real-world demand forecasting scenarios.

4.5. Discussion

The experimental results demonstrate that CLASNet effectively integrates cognitive load awareness with CNN-LSTM-Attention modeling to enhance both forecasting accuracy and decision-support efficacy. By explicitly incorporating user interaction data, the model is able to dynamically adjust attention allocation, leading to improved interpretability and robustness under demand volatility. Ablation studies confirm that each module-the Cognitive Load Encoder, cognitive-aware attention, and adaptive interaction-contributes significantly to overall performance. Notably, the adaptive interface enables the system to reduce cognitive burden without compromising predictive accuracy, highlighting the potential of human-centered AI in supply chain management. These findings suggest that the integration of cognitive load modeling into deep learning-based forecasting frameworks represents a promising direction for enhancing human-AI collaboration in operational decision-making contexts. Moreover, although the current implementation of CLASNet exclusively utilizes structured operational records, forecasting performance under high-volatility scenarios could be further enriched by incorporating unstructured consumer feedback. As evidenced by recent studies, utilizing lightweight fine-tuning on LLMs (e.g., LLaMA3) can accurately decode emotional signals from massive e-commerce reviews without demanding high-cost computing resources [16]. Routing such timely consumer sentiment indicators into our Demand Feature Encoder could empower the attention mechanism to proactively adapt to sentiment-driven market shifts.

5. Conclusion

This study proposes CLASNet, a cognitive load–aware CNN-LSTM-Attention framework for supply chain demand forecasting and adaptive human–computer interaction. Motivated by the increasing complexity and volatility of modern supply chains, as well as the growing cognitive burden faced by human decision-makers when interacting with intelligent forecasting systems, this research aims to bridge the gap between high-accuracy demand prediction and human-centered decision support. Unlike conventional deep learning–based forecasting models that focus solely on historical demand patterns, CLASNet explicitly incorporates users' cognitive load signals derived from interaction behaviors, enabling a unified end-to-end framework that jointly optimizes predictive accuracy and interaction effectiveness.

From a modeling perspective, CLASNet integrates a CNN-LSTM backbone for multiscale temporal feature extraction with an attention mechanism that dynamically emphasizes critical time steps. More importantly, a cognitive load encoder and a cognitive-aware attention fusion module are introduced to modulate forecasting focus based on users’ real-time cognitive states. This design allows the model to adapt not only to data-driven demand dynamics but also to human cognitive constraints, thereby enhancing interpretability and usability in real-world supply chain decision-making scenarios.

Extensive experiments conducted on a real-world retail demand dataset demonstrate the effectiveness of the proposed framework. CLASNet achieves an RMSE of 14.55, outperforming traditional ARIMA, LSTM, CNN-LSTM, and CNN-LSTM-Attention baselines, and reducing forecasting error by approximately 9.6% compared with the strongest baseline. Ablation studies further confirm that each component—cognitive load encoding, cognitive-aware attention, and adaptive interaction—contributes meaningfully to overall performance. In addition to quantitative forecasting improvements, interaction-based evaluations indicate that the adaptive interface guided by cognitive awareness leads to reduced decision time and lower perceived cognitive load during demand analysis tasks, highlighting the practical benefits of human-centered AI integration.

The proposed CLASNet framework has important implications for intelligent supply chain management systems, particularly in retail forecasting, inventory planning, and operational decision support, where accurate predictions must be delivered in a cognitively efficient and interpretable manner. By aligning predictive intelligence with human cognitive states, CLASNet provides a promising pathway toward more effective human–AI collaboration in complex operational environments.

Despite these encouraging results, this study has several limitations. The current cognitive load modeling relies primarily on interaction-derived behavioral features, which may not fully capture deeper cognitive or emotional states. Future work will explore the integration of multimodal signals such as eye-tracking data, physiological measurements, and contextual task complexity indicators. Additionally, extending CLASNet to multi-echelon supply chains and incorporating external factors such as macroeconomic indicators or extreme events could further enhance robustness and generalization. Finally, combining CLASNet with reinforcement learning–based adaptive decision policies represents a promising direction for building fully autonomous, cognitively aware supply chain decision-support systems. Finally, combining CLASNet with reinforcement learning-based adaptive decision policies, and exploring its deployment on energy-efficient neuromorphic computing architectures [17], represents a highly promising direction. By leveraging ultra-low-latency processing paradigms inspired by high-frequency trading systems, and planning deployment alongside emerging subarray-level movable antenna MU-MIMO communication architectures [18], we aim to build fully autonomous, highly scalable, and cognitively aware supply chain decision-support frameworks capable of uninterrupted operation in complex industrial edge environments.

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