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Regular Research Article

Strategic Planning in Maritime Logistics for Less Than Container Load (LCL) Forecasting of Pharmaceutical Packaging

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Abstract: Fluctuating volumes of Less Than Container Load (LCL) shipments in pharmaceutical packaging create risks of underutilization and overbooking that complicate maritime logistics planning and operational efficiency. This study aims to analyze LCL shipment patterns at PT ABC and to compare the forecasting performance of the Holt–Winters Additive method and a Long Short-Term Memory (LSTM) model in supporting adaptive maritime logistics planning. A mixed-methods approach was applied by combining quantitative time series analysis of monthly operational data from August 2023 to July 2025 with semi-structured interviews with logistics personnel to contextualize the quantitative findings. Forecast accuracy was evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Square Error (RMSE). The results indicate that the Holt–Winters model has limitations in handling irregular and highly volatile shipment patterns, producing operationally unrealistic zero-volume forecasts during certain periods. In contrast, the LSTM model generated more stable forecasts, achieving a MAPE of 14.56% and a MAD of 10.38 m^3. These findings suggest that LSTM provides greater operational reliability for forecasting LCL shipments under fluctuating conditions. From a practical perspective, more stable forecasts can support a transition from spot-based shipments to contract-based space booking strategies and facilitate consolidation postponement during low-utilization periods to improve freight cost efficiency. Although regulatory compliance is not directly measured, forecasting-informed planning can support logistics practices aligned with Good Distribution Practice (GDP) principles by improving shipment coordination and reducing operational uncertainty.

Keywords: less than container load, distribution forecasting, pharmaceutical packaging distribution

1. Introduction

In the global logistics system, ocean freight using the Less than Container Load (LCL) scheme plays a vital role in supporting distribution efficiency, particularly within the pharmaceutical industry, which is characterized by fluctuating and time-sensitive demand. Pharmaceutical packaging, often shipped in partial volumes, requires precise planning to prevent distribution delays, inventory accumulation, or material shortages that could disrupt the continuity of the pharmaceutical supply chain [1].

PT ABC, a manufacturer of sterile pharmaceutical packaging marketed internationally, faces these challenges by adopting the LCL scheme to accommodate small-volume shipments that do not meet full container capacity. While this scheme offers flexibility, it demands high accuracy in logistics planning to ensure supply chain continuity. The company has established a measured shipping strategy with an optimal threshold of 7–13 LCL shipments per month, as stated by PT ABC's logistics representative during an internal interview. Fluctuations beyond this threshold pose risks of underutilization or overbooking, which adversely affect cost efficiency and compliance with international pharmaceutical distribution standards such as Good Distribution Practice (GDP) and ISO 15378.

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The LCL shipment data of PT ABC from August 2023 to July 2025 reveals a significant fluctuation in monthly shipment volumes. Based on the company's operational threshold of 7–13 shipments per month, the data indicates periods of underutilization and overbooking that require strategic anticipation. Underutilization occurred in January 2024 with only 3 shipments, April 2024 with 5 shipments, and January 2025 with 3 shipments. These conditions reflect suboptimal container usage, leading to increased fixed costs and reduced operational efficiency. Conversely, overbooking was observed in February 2024 with 20 shipments, September 2024 with 16 shipments, December 2025 with 18 shipments, February 2025 with 15 shipments, and June 2025 with 16 shipments. These surges suggest seasonal demand exceeding normal capacity, posing risks of distribution delays and additional costs.

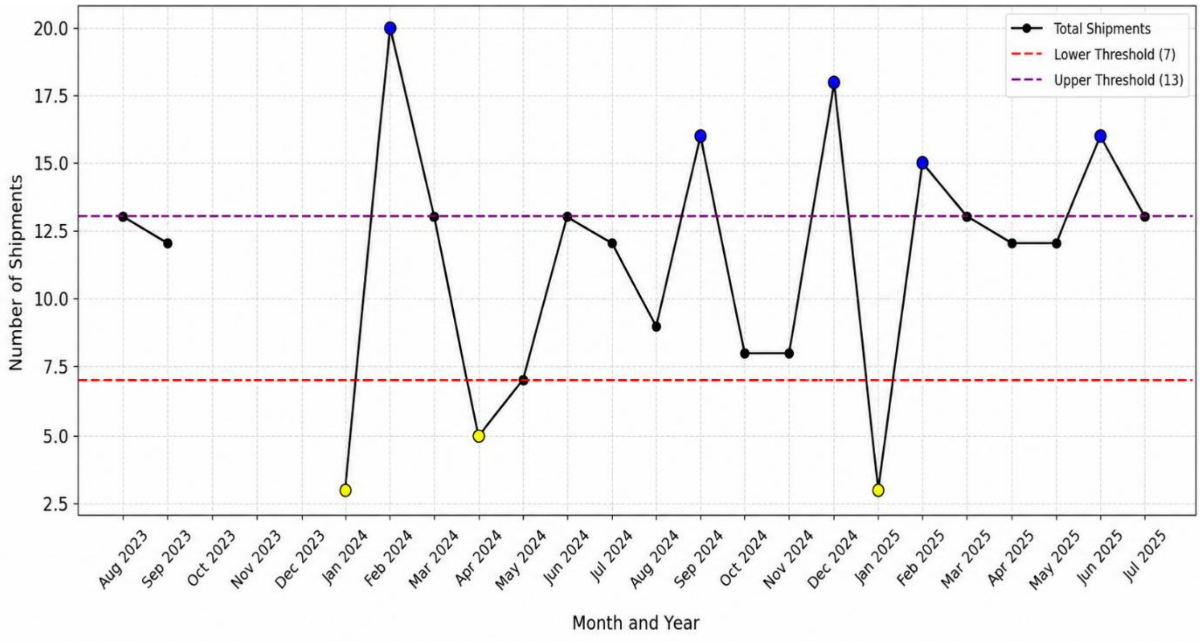

Figure 1. LCL Shipment Graph August 2023 – July 2025

Meanwhile, other months fall within the optimal range, maintaining relatively stable operational efficiency. This pattern indicates the presence of seasonal cycles in pharmaceutical distribution, which necessitates the application of data-driven forecasting methods such as Holt-Winters (HW) and Long Short-Term Memory (LSTM). These models are essential to mitigate capacity imbalance risks and support compliance with international pharmaceutical distribution standards.

This study is driven by three interrelated research problems arising from the operational dynamics of pharmaceutical packaging logistics at PT ABC. First, it seeks to examine how fluctuations in Less than Container Load (LCL) shipments affect the efficiency of maritime logistics, particularly in terms of container utilization and scheduling consistency. Second, the study aims to evaluate the forecasting accuracy of two time series methods Holt-Winters and Long Short-Term Memory (LSTM) in predicting monthly shipment volumes. Third, it investigates which of these forecasting models is more suitable to support a data-driven, adaptive, and efficient maritime logistics strategy that aligns with the operational thresholds and regulatory standards of pharmaceutical distribution.

Previous studies have explored forecasting methods based on statistical and artificial intelligence approaches within the logistics context. [2]demonstrated that the Holt-Winters method is effective in capturing seasonal patterns and long-term trends, but it has limitations when dealing with non-linear and dynamic data. In contrast, [3] and [4] confirmed that the Long Short-Term Memory (LSTM) model can process complex time series data with high accuracy, particularly in pharmaceutical logistics, where precise forecasting of demand and capacity is critical.

However, a research gap remains in the integration of these two approaches within the

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context of LCL pharmaceutical shipments in Indonesia, especially in comparing their effectiveness using actual operational data from companies. Most prior studies have focused on forecasting end-product demand rather than shipment volumes of pharmaceutical packaging as part of the upstream supply chain. Furthermore, no existing research has explicitly linked forecasting outcomes to operational thresholds and their implications for compliance with Good Distribution Practice (GDP) standards.

The novelty of this research lies in its empirical approach, which utilizes actual Less than Container Load (LCL) shipment data from the pharmaceutical packaging industry in Indonesia, specifically from PT ABC a context that has received limited attention in existing pharmaceutical logistics literature. Unlike previous studies that primarily focus on forecasting end-product demand, this research specifically compares two time series forecasting methods Holt-Winters and Long Short-Term Memory (LSTM) in the context of shipment volumes for pharmaceutical packaging as part of the upstream supply chain.

This comparison is conducted directly using the company's operational data, resulting in a more relevant and applicable analysis for logistics decision-making. Furthermore, the research integrates forecasting outcomes into maritime logistics planning strategies that consider not only container capacity efficiency but also compliance with international standards such as Good Distribution Practice (GDP) and ISO 15378. Accordingly, this study offers a novel contribution in the form of an adaptive and accurate forecasting model, along with a strategic logistics framework that supports the reliability of pharmaceutical distribution.

The objective of this study is to analyze and compare the effectiveness of the Holt-Winters and Long Short-Term Memory (LSTM) methods in forecasting the shipment patterns of Less than Container Load (LCL) at PT ABC. Specifically, the research aims to identify fluctuations in shipment volumes, including periods of underutilization and overbooking, based on the company's operational thresholds, and to evaluate the predictive accuracy of each method. The Holt-Winters method is expected to capture trends and seasonal patterns in shipment data, while LSTM is employed to process complex and non-linear time series data.

By comparing the strengths and limitations of both approaches, this study seeks to formulate a more adaptive and efficient maritime logistics planning strategy for PT ABC. The findings are expected to support pharmaceutical distribution efficiency, reduce the risk of capacity imbalance, and ensure compliance with international standards such as Good Distribution Practice (GDP) and ISO 15378.

This study is guided by the following hypotheses. The null hypothesis (H_0) posits that there is no significant difference in forecasting accuracy between the Holt-Winters method and the Long Short-Term Memory (LSTM) model when applied to the LCL shipment data of PT ABC. In contrast, the alternative hypothesis (H_1) asserts that a significant difference does exist, with LSTM providing more accurate and stable predictions compared to Holt-Winters. These hypotheses are formulated to empirically test the comparative effectiveness of statistical and artificial intelligence-based forecasting approaches in the context of pharmaceutical packaging logistics.

2. Material and Method

2.1 Research Design

This study employed a mixed-methods approach by combining quantitative and qualitative methods to provide a comprehensive analysis of Less than Container Load (LCL) shipment patterns at PT ABC. The quantitative phase was conducted using time series analysis based on monthly operational shipment data from August 2023 to July 2025, obtained from the company's internal documentation. The qualitative phase was carried out through semi-structured interviews with key personnel in the logistics department to validate the forecasting results and obtain contextual insights related to shipment planning and operational decision-making.

The research was conducted at PT ABC, a pharmaceutical packaging manufacturer located in Indonesia. Data analysis was carried out from August to November 2025. The mixed-methods design was selected because forecasting analysis requires not only numerical evaluation of shipment trends but also operational interpretation from practitioners who understand the actual logistics conditions of the company.

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2.2 Data Source and Classification

The data used in this study consisted of monthly LCL shipment volumes from August 2023 to July 2025. The shipment data were classified based on the company's operational thresholds into three categories: underutilization, normal utilization, and overbooking. Underutilization refers to shipment volumes below seven shipments per month, overbooking refers to shipment volumes above thirteen shipments per month, while normal utilization refers to shipment volumes between seven and thirteen shipments per month.

This classification was used to evaluate whether the forecasting results were aligned with PT ABC's operational capacity planning. The classification is important because inaccurate forecasting may lead to inefficient container utilization, increased logistics costs, shipment delays, and reduced compliance with pharmaceutical distribution requirements.

2.3 Research Framework

The research design was descriptive-analytical and aimed to compare the forecasting accuracy of two methods, namely Holt-Winters Additive and Long Short-Term Memory (LSTM). Holt-Winters Additive was selected because of its ability to capture trend and seasonal components in moderately fluctuating time series data. Meanwhile, LSTM was selected because of its recurrent neural network architecture, which can process complex and non-linear time series data and retain long-term dependencies.

Previous studies have shown that time series forecasting methods such as Holt-Winters can improve the efficiency of pharmaceutical supply chains by capturing seasonal patterns, although their performance may be limited when applied to highly fluctuating data [1]. In contrast, LSTM has been reported to be effective in processing complex and non-linear data, particularly in pharmaceutical distribution contexts that require high forecasting accuracy to support regulatory compliance [2]. Similar findings also indicate that the integration of LSTM into pharmaceutical logistics systems can reduce forecasting deviations and support data-driven strategic planning [3].

This study addresses the research gap by directly comparing Holt-Winters Additive and LSTM using actual operational LCL shipment data from PT ABC. The analysis focuses not only on forecasting accuracy but also on the relevance of the forecasting results to the company's operational thresholds and their implications for maritime logistics efficiency. In addition, the study considers compliance with international standards, including Good Distribution Practice (GDP) and ISO 15378. Therefore, the findings are expected to provide a basis for developing a more adaptive and data-driven pharmaceutical logistics strategy.

2.4 Research Stages

The research was conducted through several stages. First, monthly LCL shipment data from PT ABC were compiled from the company's official operational records. Second, data preprocessing was performed by checking data completeness, removing missing values if any, normalizing the dataset for model requirements, and classifying shipment volumes into underutilization, normal utilization, and overbooking categories based on the company's thresholds. Third, the Holt-Winters Additive model was implemented to identify trend and seasonal patterns in the monthly shipment data. Fourth, the LSTM model was developed to evaluate its ability to capture non-linear temporal patterns in the same dataset. Finally, the forecasting accuracy of both models was evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Squared Error (RMSE).

2.5 Holt-Winters Additive Model

The Holt-Winters Additive method was used to capture level, trend, and seasonal components in the monthly LCL shipment data. The smoothing parameters, namely alpha (α), beta (β), and gamma (γ), were optimized using a grid search technique to improve model performance. The Holt-Winters Additive equations used in this study are presented as follows.

The level component is calculated as:

$$L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (1)$$

where L_t is the level component at time t, Y_t is the actual value at time t, S_{t-m} is the seasonal component from the previous cycle, L_{t-1} is the previous level component, $T_{t-1}$is the previous trend component, and $\alpha$is the smoothing parameter for level, where $0 < \alpha < 1$.

The trend component is calculated as:

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$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (2)$$

where T_t is the trend component at time t, and $\beta$is the smoothing parameter for trend, where $0 < \beta < 1$. The seasonal component is calculated as:

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m} \quad (3)$$

where $S_t$is the seasonal component at time t, and $\gamma$is the smoothing parameter for seasonality, where $0 < \gamma < 1$.

2.6 Long Short-Term Memory Model

The Long Short-Term Memory (LSTM) model was used as a complementary forecasting approach to evaluate its ability to process complex, non-linear, and temporally dependent shipment patterns. Although LSTM models are commonly applied to large-scale datasets, previous studies have demonstrated their applicability to small and medium-sized time series when the data exhibit temporal dependencies, seasonality, and non-linear behavior. In this study, the dataset consisted of 24 monthly observations, reflecting real operational constraints commonly encountered in pharmaceutical logistics practice.

The LSTM model was therefore positioned as an exploratory and complementary forecasting method rather than a purely data-intensive deep learning model. To reduce the risk of overfitting due to the limited dataset size, several controls were applied, including the use of a simple model architecture, a limited number of neurons, Min-Max normalization, a short input sequence length, and out-of-sample testing using an 80:20 train-test split.

The LSTM architecture consisted of one hidden LSTM layer with 16 neurons, and one fully connected dense output layer. The sequence length of three steps was used to capture short-term temporal patterns. The model was trained for 200 epochs using the Adam optimizer with a learning rate of 0.001 and Mean Squared Error (MSE) as the loss function. Early stopping was applied based on validation loss to prevent overfitting. The input data were normalized using Min-Max scaling before training and inverse-transformed after prediction to support result interpretation.

The LSTM model operates using a cell state $(C_t)$and a hidden state (h_t), which are updated through three main gates: the forget gate, input gate, and output gate. The mathematical formulations of the LSTM model are presented as follows. The forget gate is calculated as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

The input gate is calculated as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

The candidate cell state is calculated as:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (6)$$

The cell state is updated as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (7)$$

The output gate is calculated as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

The hidden state is calculated as:

$$h_t = o_t \cdot \tanh(C_t) \quad (9)$$

where x_t is the input at time t, h_{t-1} is the previous hidden state, C_{t-1} is the previous cell state, Wrepresents the weights learned by the model, $b$represents the bias parameters, $\sigma$is the sigmoid activation function, and $\tanh$ is the hyperbolic tangent activation function.

2.7 Model Evaluation

The forecasting performance of the Holt-Winters Additive and LSTM models was evaluated using three accuracy metrics, namely Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Squared Error (RMSE). These metrics were selected to provide a comprehensive evaluation of forecasting accuracy from both percentage-based and absolute-error perspectives. The Mean Absolute Percentage Error (MAPE) is calculated as:

$$MAPE = \frac{1}{n}\sum \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (10)$$

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The Mean Absolute Deviation (MAD) is calculated as:

$$MAD = \frac{\sum|Y_t - \hat{Y}_t|}{n} \quad (11)$$

The Root Mean Squared Error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{\sum(Y_t - \hat{Y}_t)^2}{n}} \quad (12)$$

where Y_t is the actual shipment value at time t, $\hat{Y}_t$ is the forecasted shipment value at time t, and ni s the number of observations.

2.8 Qualitative Validation

Qualitative validation was conducted through semi-structured interviews with key personnel in the logistics department of PT ABC. The interviews were used to validate the forecasting results, interpret shipment fluctuations, and understand operational factors that may influence LCL shipment volumes. The qualitative findings were used to support the interpretation of the quantitative forecasting results and to assess whether the model outputs were relevant to the company's operational context.

This validation stage is important because forecasting results must not only demonstrate statistical accuracy but also provide practical value for logistics planning. Therefore, the integration of quantitative forecasting and qualitative validation strengthens the reliability of the findings and supports the development of a data-driven maritime logistics strategy for PT ABC.

2.9 Research Tools

The tools used in this study included Python-based statistical and machine learning libraries. The Holt-Winters Additive model was implemented using the Statsmodels library, while the LSTM model was developed using machine learning libraries such as Scikit-learn and deep learning frameworks. Computational resources were used for data preprocessing, model training, testing, forecasting, and performance evaluation.

3. Results

3.1 Forecasting Results Using the Holt-Winters Method

The forecasted LCL shipment volumes for the next 12 months, from August 2025 to July 2026, were first generated using the Holt-Winters Additive method. The forecasting results are presented in Table 1.

Table 1. Forecasting Results Using the Holt-Winters Method

Month	Volume (m^3)	Month	Volume (m^3)
August	53.03	February	64.35
September	53.03	March	29.54
October	0.00	April	9.76
November	0.00	May	32.09
December	0.00	June	28.68
January	5.53	July	23.21

The Holt-Winters model produced relatively unstable forecasting results. In particular, the model generated zero-volume forecasts for October, November, and December 2025. These values are considered operationally unrealistic because pharmaceutical logistics activities are continuous in nature. The zero-volume predictions indicate that the Holt-Winters model tended to reproduce historical data gaps rather than capture the underlying shipment pattern. Therefore, although the model can represent trend and seasonal components, its performance becomes limited when the dataset contains irregular fluctuations or missing shipment patterns.

3.2 Forecasting Results Using the LSTM Method

The second forecasting model used in this study was Long Short-Term Memory (LSTM). The forecasting results generated by the LSTM model are presented in Table 2.

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Table 2. Forecasting Results Using the LSTM Method

Month	Volume (m³)	Month	Volume (m³)
August	63.05	February	63.22
September	63.08	March	62.88
October	62.54	April	63.33
November	62.90	May	63.10
December	63.15	June	62.77
January	62.98	July	63.02

The LSTM model generated more stable forecasts, ranging from 62.54 m³ to 63.33 m³. This result indicates that the LSTM model was able to produce consistent predictions despite fluctuations in the historical shipment data. The stability of the LSTM forecasts suggests that the model can capture temporal dependencies and non-linear patterns more effectively than the Holt-Winters method. From an operational perspective, stable forecasting results are important for supporting shipment planning, container space allocation, and LCL consolidation decisions.

3.3 Model Performance Comparison

This study did not apply formal inferential statistical tests to determine statistically significant differences between the forecasting methods. Instead, model comparison was conducted using operational forecasting performance indicators, namely Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Squared Error (RMSE). These indicators were used to evaluate the accuracy and operational reliability of each model.

The results show that the LSTM model produced lower forecasting errors and more stable predictions than the Holt-Winters model. The LSTM model achieved a MAPE of 14.56% and a MAD of 10.38 m³, while the Holt-Winters model produced a higher MAPE of 16.94% and a MAD of 32.53 m³. These results indicate that LSTM provides better forecasting performance under the observed conditions of PT ABC.

The lower error values of the LSTM model demonstrate its ability to reduce prediction deviations and maintain forecast consistency. In contrast, the Holt-Winters model showed limitations in handling irregular shipment patterns, as reflected in the zero-volume forecasts for several months. Therefore, LSTM can be interpreted as operationally more reliable for maritime logistics planning in the context of pharmaceutical LCL shipments at PT ABC.

4. Discussion

4.1 Interpretation of Forecasting Performance

The comparison between Holt-Winters and LSTM shows that LSTM provides more accurate and stable forecasting results for PT ABC's LCL shipment data. The lower MAPE value of LSTM indicates better percentage-based accuracy, while the lower MAD value indicates smaller absolute deviations from actual shipment volumes. These findings suggest that LSTM is more suitable for handling shipment data characterized by fluctuations, operational noise, and non-linear patterns.

The Recurrent Neural Network (RNN) architecture of LSTM enables the model to retain information from previous time steps and capture temporal dependencies in the data. This capability is important in pharmaceutical logistics because shipment volumes may be influenced by irregular demand, production schedules, shipping availability, and operational constraints. As a result, LSTM can provide more stable forecasts than classical statistical models when the data pattern is not fully linear or seasonal.

In contrast, the Holt-Winters model showed limitations in this study. Although Holt-Winters is useful for capturing trends and seasonal patterns, it may produce unrealistic results when the historical data contain irregular fluctuations or periods without recorded shipments. The zero-volume forecasts generated by Holt-Winters indicate that the model projected historical data gaps into the future. This condition may create operational risks if the results are used directly for logistics planning.

4.2 Operational Implications for Maritime Logistics Planning

The stable forecast produced by the LSTM model has important implications for maritime logistics planning at PT ABC. With forecasted

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shipment volumes consistently around 63 m³, the company can develop a more proactive and structured shipment planning strategy. Instead of relying on reactive spot-market booking, the logistics team can use the forecast results to plan container space requirements in advance.

A stable forecasting baseline supports contract-based space booking with shipping lines, especially during periods with potential shipment increases. This strategy can reduce the risk of rolling cargo, where shipments are delayed or left behind due to limited vessel or container capacity. By securing space earlier, PT ABC can improve shipment reliability and reduce disruption in the pharmaceutical supply chain.

Furthermore, accurate and stable forecasts can help the company improve LCL consolidation planning. During periods when shipment volumes approach the lower operational threshold, the company may consider consolidation postponement within an acceptable time window. This strategy allows shipments to be grouped more efficiently without violating pharmaceutical handling requirements. As a result, container utilization can be improved, and fixed logistics costs per shipment can be reduced.

4.3 Integration of Qualitative Findings

The qualitative findings obtained from semi-structured interviews with logistics personnel were used to validate and contextualize the quantitative forecasting results. The interview results indicated that months with low shipment volumes often create inefficient container utilization and higher logistics costs. On the other hand, months with high shipment volumes may increase the risk of overbooking, rolling cargo, and schedule disruptions.

These operational insights support the quantitative findings by showing that forecast stability is highly important for managerial decision-making. In practice, logistics managers require forecasts that are not only statistically accurate but also operationally usable. The stable output generated by the LSTM model is therefore more relevant for planning space booking, shipment consolidation, and logistics coordination.

The integration of quantitative forecasting and qualitative validation strengthens the reliability of the findings. It confirms that the LSTM model is not only superior in terms of error metrics but also more aligned with the operational needs of PT ABC’s logistics department.

4.4 Implications for Good Distribution Practice and ISO 15378 Compliance

Although this study does not directly measure regulatory compliance outcomes, the forecasting results have practical relevance for logistics practices aligned with Good Distribution Practice (GDP) and ISO 15378. Pharmaceutical logistics requires reliable shipment planning to maintain product availability, delivery timeliness, and distribution consistency. Inaccurate forecasting may lead to shipment delays, inefficient storage planning, or disruption in the distribution process.

The use of LSTM-based forecasting can support better synchronization between shipment schedules, warehouse readiness, and maritime transport availability. By improving shipment predictability, PT ABC can reduce uncertainty in logistics planning and improve operational consistency. This indirectly supports compliance-oriented logistics practices, particularly in pharmaceutical distribution systems that require careful planning and controlled movement of goods.

Therefore, LSTM forecasting may serve as a decision-support tool for improving logistics reliability, reducing operational uncertainty, and strengthening compliance-oriented shipment planning.

4.5 Study Limitations and Future Research

This study has several limitations. First, the dataset consists of only 24 monthly observations, which limits the generalizability of the forecasting results and restricts the complexity of the LSTM architecture. Second, the study focuses on a single pharmaceutical packaging company, so the findings may not fully represent broader pharmaceutical logistics conditions in Indonesia. Third, the comparison between Holt-Winters and LSTM was based on operational performance metrics rather than formal statistical significance testing.

Future research is recommended to use larger datasets, including multiple companies, and apply more advanced validation techniques, such as rolling-origin evaluation or Diebold-Mariano testing. In addition, future studies may integrate external variables such as port congestion,

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freight rate fluctuations, production demand, macroeconomic indicators, or seasonal shipping constraints to improve forecasting robustness. These additional variables may provide a more comprehensive understanding of pharmaceutical maritime logistics dynamics.

5. Conclusions

This study compared the forecasting performance of Holt-Winters Additive and Long Short-Term Memory (LSTM) models using actual monthly LCL shipment data from PT ABC. The results show that the Holt-Winters model has limitations when applied to volatile pharmaceutical logistics data. In particular, the model produced operationally unrealistic zero-volume forecasts in several months, indicating its difficulty in handling irregular fluctuations and historical data gaps.

In contrast, the LSTM model generated more stable and consistent forecasts, with predicted shipment volumes ranging from 62.54 m^3 to 63.33 m^3. The LSTM model also achieved better forecasting accuracy, with a MAPE of 14.56% and a MAD of 10.38 m^3, compared to the Holt-Winters model, which produced a MAPE of 16.94% and a MAD of 32.53 m^3. These results indicate that LSTM provides greater operational reliability under the specific conditions of PT ABC's pharmaceutical LCL shipment data.

From a managerial perspective, LSTM-based forecasting can support more proactive maritime logistics planning. Stable shipment forecasts allow PT ABC to improve container space booking, reduce the risk of rolling cargo, and optimize LCL consolidation. The forecasting results also provide a practical basis for improving freight efficiency and reducing uncertainty in shipment planning.

Although this study does not directly evaluate regulatory compliance, improved forecast stability can support logistics practices aligned with Good Distribution Practice (GDP) and ISO 15378. Better shipment predictability enables improved coordination between warehouse operations, shipment schedules, and maritime transport availability.

From an academic perspective, this study contributes to the maritime logistics literature by providing an empirical comparison between a classical statistical forecasting method and a deep learning-based model using real-world pharmaceutical LCL shipment data. Rather than claiming universal superiority, the findings highlight the contextual suitability of LSTM as a complementary forecasting tool for small but volatile datasets in pharmaceutical maritime logistics. Future research should expand the dataset, including external logistics variables, and apply more advanced validation methods to strengthen the generalizability of the findings.

Competing interests: The authors declare that they have no competing interests.

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