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MAPPING DIGITAL LOGISTICS GAPS AND READINESS IN THE CHEMICAL SUPPLIER-PALM OIL CLIENT SUPPLY CHAIN IN PT. KTI INDONESIA: A CASE STUDY

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Abstract. *The Indonesian palm oil industry has widely adopted digital technologies in upstream plantation activities; however, empirical evidence on digital logistics readiness in downstream input supply chains remains limited. This study addresses this gap by examining digital logistics gaps and organizational readiness in the chemical supplier, palm oil mill supply chain through Machine Learning (ML), based demand forecasting. Using PT KTI, Indonesia, as a case study, the research focuses on forecasting monthly demand for EDTA 4Na, a critical chemical input in palm oil mill operations. Guided by the Drivers–Process–Impact (DPI) framework, the study applies supervised regression models (Random Forest Regressor (RFR) and K-Nearest Neighbors (KNN)) and compares their performance against a Naïve baseline representing heuristic-based manual planning. Model performance is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are interpreted as quantitative indicators of digital logistics gaps and digital readiness. The results show that ML-based approaches outperform the Naïve baseline, demonstrating the feasibility of applying predictive analytics using existing operational data. Among the tested models, KNN exhibits superior performance under conditions of limited data availability and batch-based procurement behavior. Nevertheless, persistent forecasting errors reveal underlying gaps related to data continuity, process standardization, and system integration. Rather than positioning ML solely as a predictive tool, this study contributes to the literature by framing ML-based demand forecasting as a diagnostic mechanism for assessing digital logistics readiness in data-constrained supply chain environments, offering practical insights for early-stage digital transformation in the palm oil industry.*

Keywords: *Chemical Supplier; Digital Logistics Gaps; Digital Readiness; Demand Forecasting; Machine Learning, Palm Oil Supply Chain.*

1. INTRODUCTION

The Indonesian palm oil industry is a strategic sector of the national economy, but faces major challenges in managing an efficient, resilient, and sustainable supply chain. The main challenges include the archipelagic geography, limited infrastructure, high logistics costs, outdated transportation assets, fragmented logistics systems, and low technology adoption. In addition, the industry also faces environmental and social pressures, including deforestation, land conflicts, and labor issues, while sustainability certifications such as RSPO remain difficult for small players to access.

Digitalization and the application of Industry 4.0 technologies, including machine learning (ML), are considered important for improving supply chain efficiency, but are hampered by high implementation costs, limitations in data quality and integration, workforce readiness, and technology compatibility issues. In this context, PT KTI, as a palm oil company in Indonesia, faces specific challenges in predicting the demand for production chemicals, such as EDTA 4Na, which often causes supply delays and production disruptions.

Unlike previous studies that focused on the upstream supply chain, this study highlights the digital gap in the chemical supplier-palm oil mill supply chain. Using a machine learning approach to demand forecasting, this study aims to map operational readiness and digital logistics gaps, as well as contribute new insights to the Indonesian palm oil supply chain literature with a focus on industrial inputs rather than upstream sustainability aspects.

2. LITERATURE REVIEW

2.1 Theoretical Framework

The integration of digital technology has transformed the coordination of the palm oil industry supply chain, making it more efficient and transparent (Onukwulu et al., 2024). Industry 4.0 technologies such as IoT, AI/ML, blockchain, and integrated platforms play an important role in improving visibility, operational efficiency, and data-driven decision making.

The Internet of Things (IoT) enables real-time collection of operational data through connected sensors, which supports predictive maintenance, equipment scheduling, and fleet and environmental condition monitoring (Agnes Clare Odimarha et al., 2024).

Artificial Intelligence (AI) and Machine Learning (ML) provide advanced analytics capabilities for demand forecasting, inventory management, route optimization, and predictive maintenance. By analyzing historical data, ML helps anticipate demand fluctuations and operational disruptions, thereby reducing inventory costs and the risk of stockouts (Onukwulu et al., 2024).

Blockchain Technology offers a secure and transparent decentralized recording system to enhance supply chain integrity. In the palm oil industry, blockchain is used for product origin tracking, regulatory compliance, sustainability verification, and smart contracts, including implementation by Unilever to track more than 188,000 tons of palm fruit (Aslam et al., 2021; Mohamad Zaki et al., 2025).

Integrated Platforms and Tools, such as ERP and cloud-based systems, support real-time coordination between stakeholders, improve visibility, and simplify centralized planning in procurement, inventory, and distribution.

Previous research shows that the adoption of Industry 4.0 technology in the palm oil sector is still focused on the upstream sector, particularly plantation mapping using remote sensing and ML (CART and Random Forest) with high accuracy levels in Aceh and Sumatra (Mohamad Zaki et al., 2025). However, studies related to operational logistics, chemical supply chains, and demand forecasting are still very limited.

PT KTI, as the operator of several palm oil mills, is highly dependent on chemical inputs such as EDTA 4Na, which acts as a chelating agent for pH stabilization and improvement of water process quality (Liu et al., 2022; Samavati et al., 2024). This chemical supply chain faces challenges in the form of demand fluctuations, uncertainty in ordering times, price volatility, and delivery delays, which underscore the need for better forecasting and coordination systems.

Unlike the study by Adwiyah et al. (2023), which used SCOR-DS for upstream supply chains, this study highlights the digital gap in the chemical supplier–palm oil mill supply chain, a vertical that has not been widely studied through the lens of digital logistics and ML-based forecasting.

2.2 Drivers, Processes, and Impacts of Digital Adoption

This study uses the Drivers–Process–Impact (DPI) framework from Yang et al. (2021) to understand the adoption of digital technology in supply chains.

Drivers (Why) include operational inefficiencies, limited forecasting capabilities, variability in chemical demand, low procurement visibility, and manual and fragmented processes, which result in stock imbalances and suboptimal logistics performance.

Process (How) includes the collection and processing of operational data, the selection and training of ML models (e.g., Random Forest Regressor), model performance evaluation, and the use of forecasting results to identify digital performance gaps.

Impact (What) is measured through forecasting errors (MAE, RMSE), mapping of digital logistics gaps, assessment of digital transformation readiness, and potential long-term benefits such as inventory optimization, cost reduction, and increased supply chain responsiveness.

This DPI framework connects operational problems with ML-based empirical analysis, enabling the translation of conceptual supply chain challenges into measurable performance indicators and an assessment of PT KTI's digital readiness.

3. RESEARCH METHODS

This study employs a quantitative, descriptive-analytical research approach to evaluate how Machine Learning (ML) can be applied to map digital logistics gaps and assess digital readiness within the Chemical supplier-palm oil client supply chain at PT KTI (Alsheyadi et al., 2024; Fitria & Tunjang, 2025; Lee et al., 2024; Wijoyo et al., 2020).The research is designed as a practical case study, focusing on real operational data and the implementation of ML-based forecasting.

3.1 Research Design

The research adopts a case study design supported by quantitative modeling. This design is appropriate because:

a. PT KTI provides real operational data relevant to logistics and supply chain performance.
b. The study aims to demonstrate a practical application of ML within an actual business context.
c. The objective involves both quantifying forecasting performance and assessing digital readiness, which require empirical analysis.

The descriptive-analytical approach allows the researchers to describe the current logistics conditions and analyze how ML forecasting performance reflects digital gaps and readiness.

3.2 Data Collection

The study uses secondary operational data obtained from PT KTI, collected from internal Excel files covering the period 2024-2025. These datasets include:

- Shipment date
- Product/Item name
- Total quantity shipped
- Item price
- Shipping cost

The focus of the analysis is on EDTA 4Na, a critical chemical input in palm oil processing. The data used in this research have a characteristic:

- Data is transactional (line-by-line shipment records)
- Data is spread across multiple monthly sheets
- The selected product (EDTA 4Na) appears consistently throughout the dataset
- Price and shipping costs vary throughout the months, reflecting procurement fluctuations.

Using actual business data enables the study to evaluate realistic digital gaps, rather than relying on simulated or idealized datasets.

3.3 Data Preprocessing

Several preprocessing steps were conducted to prepare the data for ML modeling:

3.3.1 Data Consolidation

Data from 2024 and 2025 were merged into a single dataset to form a continuous time-based sequence.

3.3.2 Data Cleaning

- Removal of null and inconsistent values
- Standardization of column names

- Conversion of data types (e.g., dates into datetime format)

Data cleaning involved standardizing variable names, correcting data types, removing invalid and duplicate records, imputing missing cost values using median substitution, and aggregating transactional data into a monthly time series. Outliers were examined but retained to preserve real demand variability.

3.3.3 Data Aggregation

To create a monthly forecasting dataset, transactional-level data was aggregated into:

- Total EDTA 4Na demand per month
- Average/total item price per month
- Total monthly shipping cost

This aggregated time series was used as the primary input for ML.

3.3.4 Variable Preparation

- Dependent variable: Total monthly demand of EDTA 4Na
- Independent variable: price, shipping fee
- Time feature: A numerical month index ("month_num") was created to enable model training and avoid errors related to Python's inability to process non-numeric inputs.

3.3.5 Feature Engineering

A simple numeric time stamp was added. Because the dataset length was short (less than 24 months), more advanced feature engineering (e.g., lags, rolling windows) was not applied to avoid distortions, but this limitation is noted for future studies.

3.4 Machine Learning Model Implementation

Two supervised regression models were selected due to their suitability for small datasets and straightforward interpretability:

3.4.1 Random Forest Regressor (RFR)

An ensemble learning method that builds multiple decision trees and averages their results. RFR is robust to nonlinear patterns and handles small-to-medium datasets effectively.

3.4.2 K-Nearest Neighbors Regressor (KNN)

A distance-based model that predicts outcomes based on the average of the closest historical data points. It serves as a simple, similarity-based regression benchmark. These models were implemented in Google Colab using scikit-learn, following common ML practices. In addition, a simple Naïve baseline forecasting approach was used as a benchmark to represent manual or heuristic-based planning.

a. Model Training and Evaluation

The dataset was split chronologically into:

- Training set: Earlier months
- Testing set: Most recent Months

A chronological split was used because the data is time-series based and cannot be randomized.

b. Evaluation Metrics

Two standard regression metrics were used:

- Mean Absolute Error (MAE) – average magnitude of prediction errors
- Root Mean Squared Error (RMSE) – Error magnitude with heavier penalty for large deviations

These metrics quantify the forecasting accuracy and serve as proxies for identifying digital logistics gaps.

3.5 Strategy for Mapping Digital Logistics Gaps

The performance of the ML models (RFR and KNN) is used to identify forecasting gaps within PT KTI's supply chain operations. The logic is as follows:

a. ML models approximate the company's ideal forecasting capability.
b. The resulting error metrics (MAE and RMSE) quantify the difference between current manual processes and ML-enhanced forecasting.
c. Higher errors indicate larger gaps in data quality, process structure, or system maturity.
d. Lower errors indicate smaller gaps and demonstrate stronger digital alignment.

Thus, forecasting errors serve as quantitative indicators of digital logistics gaps in demand planning, inventory coordination, and procurement responsiveness.

3.6 Assessing Digital Readiness

Digital readiness is assessed based on two dimensions:

3.6.1 Data Readiness

- Availability of time-series data
- Consistency of monthly records
- Minimal missing values
- Sufficient data structure for ML

Successful preprocessing and modeling indicate baseline readiness.

3.6.2 Technical Readiness

- Ability to run ML models using Google Colab
- Availability of digital records (Excel-based)
- Feasibility of integrating predictive tools in future operations

The implementation of ML models itself demonstrates that PT KTI has foundational readiness for digital transformation, even if gaps in forecasting accuracy remain.

3.7 Summary of Methodology

This chapter outlines how operational data from PT KTI was used to construct ML models for demand forecasting. Through data preprocessing, model implementation, and evaluation using MAE and RMSE, the study provides a structured approach to identifying digital logistics gaps and assessing organizational readiness for predictive analytics adoption.

The results from this methodology directly inform the Results and Discussion chapter, where forecasting accuracy and readiness implications are interpreted.

3.8 Machine Learning Process Flowchart (Demand Forecasting EDTA 4Na)

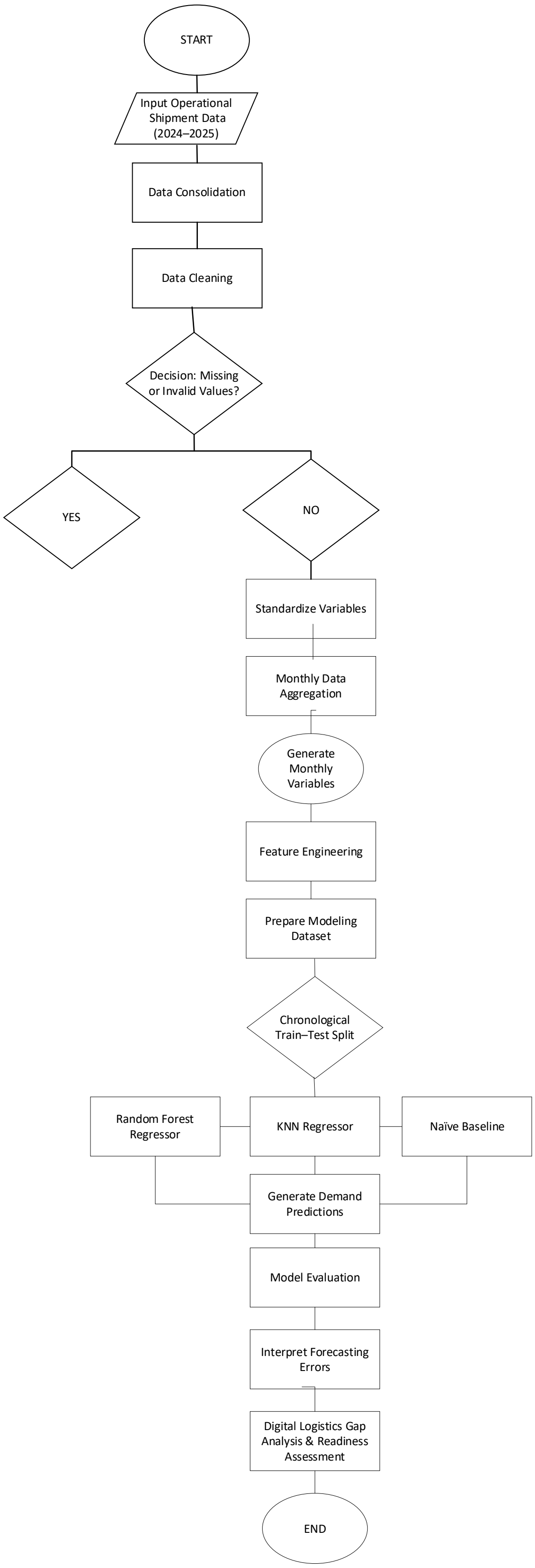

Image 3.1 Machine Learning Process Flowchart

4. RESULTS AND DISCUSSION

4.1 Overview of Model Evaluation Results

This chapter presents the empirical results that respond to the operational challenges and digital logistics gaps identified in Chapters 1 and 2. Guided by the Drivers-Process-Impact framework, Machine Learning-based demand forecasting is used to translate conceptual supply chain issues into measurable performance outcomes. In this context, forecasting errors serve as quantitative indicators of existing digital logistics gaps and organizational readiness.

This chapter focuses on evaluating the performance of Machine Learning models applied to forecast monthly EDTA 4Na demand within the chemical supplier-palm oil client supply chain at PT KTI. The analysis examines forecasting accuracy and interprets the results in relation to digital logistics gaps and readiness, in line with the study's research objectives. Three approaches were evaluated:

1. Random Forest Regressor (RFR);
2. K-Nearest Neighbors (KNN) Regressor; and
3. Naïve baseline forecasting as a last observed value.

Model performance was assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), as described in Chapter 3.

4.2 Forecasting Performance Comparison

Table 4.1 presents the forecasting accuracy of the three approaches.

Table 4.1 Forecasting Performance Comparison

Model	MAE	RMSE
Naïve Baseline	1875.00	2651.65
Random Forest Regressor	1837.50	1944.95
K-Nearest Neighbors Regressor	937.50	1325.83

As shown in Table 4.1, the results show that both ML models outperformed the Naïve baseline, indicating that data-driven forecasting provides added value compared to simple heuristic-based forecasting. Among the ML models, the KNN Regressor achieved the lowest MAE and RMSE, demonstrating superior performance in this specific context.

4.3 Interpretation of Model Behavior

4.3.1 Naïve Baseline as a Proxy for Manual Planning

The Naïve baseline model assumes that future demand equals most recent observed value. This approach approximates manual procurement planning commonly used in practice. This relatively high MAE and RMSE indicate that relying solely on historical repetition is insufficient to capture demand variability, particularly when procurement follows batch-based ordering patterns. These results highlight the limitation of non-predictive planning methods and justify the exploration of Machine Learning approaches.

4.3.2 Random Forest Regressor Performance Comparison

The Random Forest Regressor marginally improved upon the Naïve baseline in terms of MAE and showed a substantial reduction in RMSE. This suggests that RFR was able to partially capture nonlinear relationships among time, price, and shipping cost variables.

However, the model tended to smooth demand fluctuations, particularly during months with sudden increases in demand. This behavior can be attributed to two main factors: 1. Limited sample size (10 monthly observations), which restricts the ability of ensemble models to learn complex patterns; and 2. High demand regularity, where most observations reflect a fixed batch quantity.

As a result, RFR exhibited reduced sensitivity to abrupt changes, leading to underestimation during demand spikes.

4.3.3 K-Nearest Neighbors Regressor Performance Comparison

The KNN model achieved the best performance among the evaluated approaches. By relying on similarity-based learning, KNN effectively leveraged historical demand patterns without imposing strong parametric assumptions.

The superior performance of KNN suggests that, under conditions of sparse and irregular time-series data, simpler models that emphasize historical similarity may be more appropriate than complexity should be matched to data maturity and availability.

4.4 Visualization of Actual vs Predicted Demand

Figure 4.1 illustrates the comparison between actual EDTA 4Na demand and the predictions generated by the KNN and Random Forest models

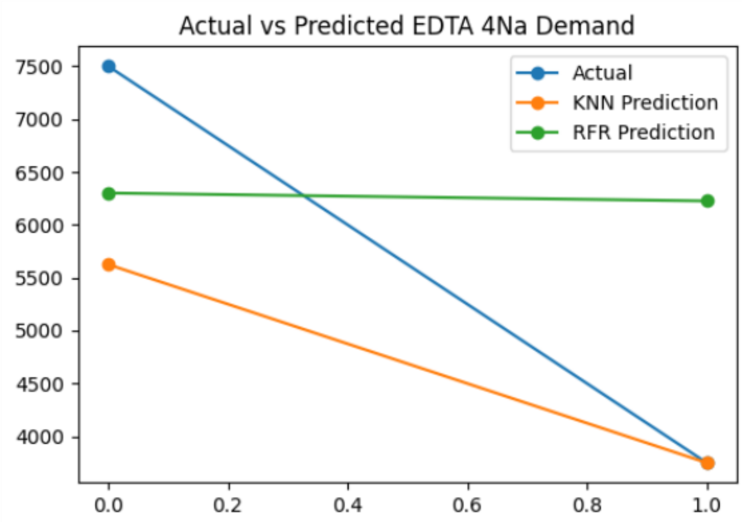

Figure 4.1 Actual vs Predicted EDTA 4Na Demand

As Figure 4.1 shown, it illustrates the comparison between actual monthly EDTA 4Na demand and the predictions generated by the KNN and Random Forest models. The visualization highlights the discrete nature of Chemical procurement, characterized by batch-based demand changes. While the Random Forest model produces relatively stable predictions, the KNN model more closely follows the observed demand direction, supporting its superior performance as reflected in the MAE and RMSE results.

4.5 Mapping Digital Logistics Gaps Using Forecasting Errors

In this study, forecasting errors are interpreted as quantitative indicators of digital logistics gaps. The existence of non-negligible MAE and RMSE values, even under ML-based forecasting, suggests several underlying gaps:

1. Data continuity gaps, due to irregular procurement cycle and missing monthly observations;
2. Process gaps, where demand planning relies on fixed batch assumptions rather than predictive signals; and

3. Information gaps, reflecting limited integration of forecasting tools within procurement decision-making.

The average KNN MAE of approximately 938 units represents the magnitude of forecasting deviation that could potentially be reduced through improved data availability, longer time horizons, and system integration.

4.6 Assessment of Digital Readiness

Despite the identified gaps, the successful implementation of ML models using existing operational data demonstrates a foundational level of digital readiness at PT KTI. Specifically:

1. Historical transactional data is available in digital form;
2. Data can be cleaned, structured, and aggregated for analytical purposes; and
3. ML models can be implemented and evaluated without additional data acquisition.

This indicates that PT KTI possesses the minimum digital infrastructure required to begin adopting predictive analytics in supply chain planning. However, the remaining forecasting errors highlight the need for further improvement in data governance, process standardization, and system integration.

4.7 Managerial Implications

From a managerial perspective, the results provide several insights:

1. ML-based forecasting can outperform manual planning approaches even with limited data.
2. Early-stage digital adoption should prioritize data consistency and continuity rather than advanced model complexity.
3. Similarity-based models may be more suitable during initial digital transformation phases.
4. Quantifying forecasting errors enables managers to identify priority areas for digital investment.

These findings support the strategic use of ML as a diagnostic tool for assessing digital logistics maturity rather than solely as a forecasting solution.

4.8 Summary of Findings and Linkage to Digital Logistics Gaps

This chapter empirically examined the digital logistics challenges identified in Chapters 1 and 2 by applying Machine Learning-based demand forecasting within the chemical supplier-palm oil client supply chain at PT KTI. Guided by the Drivers-Process-Impact framework, the study translated conceptual operations inefficiencies, such as limited forecasting capability, fragmented procurement processes, and constrained supply chain visibility into measurable performance outcomes.

The forecasting results demonstrate that Machine Learning models outperform heuristics-based planning, as evidenced by lower error metrics relative to the Naïve baseline. This confirms the presence of foundational digital readiness and indicates that existing operational data can support predictive analytics applications. Furthermore, the persistence of non-negligible forecasting errors highlights the existence of digital logistics gaps related to data continuity, process standardization, and system integration.

Specifically, the observed forecasting deviations quantify the gap between current procurement practices and potential digitally enabled planning capabilities. The superior performance of the K-Nearest Neighbors models further suggests that, under condition of limited data maturity and batch-based ordering behavior, simple similarity-based approaches are more appropriate than complex models. This finding reinforces the argument presented in Chapter 2 that technology adoption must align with organizational and data readiness.

Overall, the results bridge the problem identification in Chapter 1 with the conceptual framework in Chapter 2, demonstrating how Machine Learning can serve not only as a forecasting tool but also as a diagnostic mechanism for assessing digital logistics gaps organizational readiness. These findings provide a grounded basis for the conclusions managerial recommendations presented in the subsequent chapter.

4.9 Comparison with Previous Studies

Previous studies on digitalization and Machine Learning in the palm oil industry primarily emphasize upstream supply chain activities, such as plantation monitoring, yield estimation, land-use mapping, and sustainability traceability. For example, studies reviewed in Chapter 1 highlight the application of Machine Learning and remote sensing technologies to improve plantation classification accuracy and environmental monitoring (Mohamad Zaki et al., 2025). Other works focus on blockchain adoption to enhance traceability, transparency, and compliance with sustainability certifications (Aslam et al., 2021).

In contrast, this study extends the existing body of literature by shifting the analytical focus to the chemical supplier-palm oil client supply chain, an input-oriented segment that has received limited empirical attention. While prior research demonstrates the technical feasibility of digital technologies, this study emphasizes their operational application in demand forecasting and procurement planning.

Moreover, previous studies largely conceptualize digital transformation as a means to improve efficiency or sustainability, without empirically quantifying performance gaps. This study complements existing research by operationalizing digital logistics gaps through measurable forecasting errors (MAE and RMSE), thereby providing a practical mechanism for assessing digital readiness. Rather than treating forecasting accuracy as an end goal, forecasting error is interpreted as an indicator of the gap between current practices and digitally enabled planning capabilities.

The findings are also consistent with prior research emphasizing the importance of data maturity and organizational readiness in Industry 4.0 adoption (Kaya et al., 2022; Mohamad Zaki et al., 2025). Similar to these studies, the results indicate that technology effectiveness is constrained by data availability and process standardization. However, this study further demonstrated that even under conditions of limited data continuity, simple Machine Learning approaches can outperform heuristic-based planning, suggesting a feasible entry point for early-stage digital transformation.

Overall, this study complements existing palm oil digitalization literature by providing an empirical, downstream-focused perspective and by reframing Machine Learning as a diagnostic tool for identifying digital logistics gaps rather than solely as predictive technology.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study examined digital logistics gaps and digital readiness in the chemical supplier–palm oil mill supply chain using ML-based demand forecasting, with PT KTI as a case study and EDTA 4Na as the representative chemical input. Guided by the Drivers–Process–Impact framework, the research translated supply chain challenges—such as limited forecasting capability and fragmented procurement—into measurable performance indicators.

The empirical results show that ML models can be implemented using existing operational data and outperform heuristic planning methods, as indicated by lower forecasting errors than the Naïve baseline. Among the tested models, K-Nearest Neighbors (KNN) outperformed Random Forest under limited data conditions, highlighting the importance of aligning model complexity with data maturity.

Overall, PT KTI demonstrates basic digital readiness through available digital records and feasible ML implementation. However, persistent forecasting errors indicate the need for improvements in data quality, standardization, and system integration. This study positions ML not only as a predictive tool but also as a diagnostic mechanism to assess digital logistics gaps and organizational readiness.

Theoretical Contributions

This study contributes to the literature in three key ways. First, it extends palm oil supply chain research by focusing on the underexplored chemical supplier–mill segment rather than upstream plantation activities. Second, it empirically operationalizes the Drivers–Process–Impact framework by using forecasting errors (MAE and RMSE) as quantitative indicators of digital logistics gaps. Third, it reinforces Industry 4.0 readiness literature by demonstrating that simpler ML models may be more effective than complex ones in early-stage digital transformation contexts.

Managerial Implications

The findings suggest that organizations can obtain immediate benefits from ML-based forecasting even with limited historical data. Forecasting error metrics provide managers with clear guidance on where digital investments should be prioritized, particularly in data continuity, process standardization, and system integration. The study also emphasizes that model selection should reflect organizational readiness, and that digital transformation should be viewed as an incremental, learning-oriented process rather than a one-time technological upgrade.

Limitations of the Study

This research is limited by the small number of monthly observations, the focus on a single chemical input, and the use of a single case study, which may constrain forecasting accuracy and generalizability. These limitations are inherent to applied case-based research and are acknowledged for contextual clarity.

Recommendations for Future Research

Future studies may expand the dataset across longer time periods and multiple chemical products, incorporate additional operational variables such as production schedules and inventory levels, and explore the integration of ML forecasting into real-time decision support systems to better assess digital logistics maturity.

Final Remarks

This study demonstrates that ML can effectively support digital logistics transformation in the palm oil industry despite limited data maturity. By linking conceptual drivers to empirical outcomes, it provides a structured approach to identifying, measuring, and addressing digital logistics gaps with both academic and practical relevance.

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