

# Supply Chain Management Demand Forecasting Report

## Executive Summary

This report presents a comprehensive analysis of supply chain demand forecasting using machine learning techniques on a dataset of 100 products across three categories: skincare, haircare, and cosmetics. The analysis employed a neural network model to predict product demand and provided detailed business insights into operational efficiency, revenue patterns, and quality control metrics.

### Key Findings:

- Skincare products dominate sales with 45.0% market share (20,731 units)
- The neural network model showed challenges in prediction accuracy ( $R^2 = -1.31$ )
- Carrier B generates the highest revenue (\$250,095) among shipping partners
- Average defect rates remain low across all product categories (1.92-2.48%)

## Data Overview

### Dataset Characteristics

- **Total Records:** 100 products
- **Features:** 24 variables including pricing, inventory, logistics, and quality metrics
- **Time Period:** January 1, 2022 - April 9, 2022
- **Data Quality:** No missing values detected

### Key Variables Analyzed

- Product information (type, SKU, pricing)
- Sales metrics (units sold, revenue generated)
- Operational data (stock levels, lead times, order quantities)
- Logistics information (shipping carriers, transportation modes, costs)
- Quality control (defect rates, inspection results)
- Supplier performance metrics

## Business Performance Analysis

### 1. Sales Distribution by Product Type

#### Market Share Analysis:

- **Skincare:** 20,731 units (45.0%) - Market leader
- **Haircare:** 13,611 units (29.5%) - Strong secondary market
- **Cosmetics:** 11,757 units (25.5%) - Emerging segment

### Revenue Performance:

- Total revenue across all products: \$577,605
- Average revenue per product: \$5,776
- Revenue range: \$1,062 - \$9,866

## 2. Shipping and Logistics Performance

### Carrier Performance:

- **Carrier B:** \$250,095 revenue (43.3% of total)
- **Carrier C:** \$184,880 revenue (32.0% of total)
- **Carrier A:** \$142,630 revenue (24.7% of total)

### Transportation Cost Analysis:

- **Road:** \$16,048 (30.3%) - Most expensive
- **Rail:** \$15,169 (28.7%) - Cost-effective for bulk
- **Air:** \$14,605 (27.6%) - Premium service
- **Sea:** \$7,103 (13.4%) - Most economical

### Average Shipping Costs:

- Carrier A: \$5.55
- Carrier B: \$5.51
- Carrier C: \$5.60

## 3. Operational Efficiency Metrics

### Lead Time Analysis by Product Type:

- **Cosmetics:** 13.54 days (most efficient)
- **Skincare:** 18.00 days
- **Haircare:** 18.71 days (longest lead time)

### Manufacturing Costs:

- **Cosmetics:** \$43.05 average
- **Haircare:** \$48.46 average
- **Skincare:** \$48.99 average (highest)

## 4. Quality Control Assessment

### Defect Rate Analysis:

- **Cosmetics:** 1.92% (best quality performance)
- **Skincare:** 2.33%
- **Haircare:** 2.48% (highest defect rate)

**Transportation Mode Impact on Quality:**

- **Air:** 1.82% defect rate (best preservation)
- **Rail:** 2.32% defect rate
- **Sea:** 2.32% defect rate
- **Road:** 2.62% defect rate (highest defects)

**5. Supplier Performance Ranking**

Supplier	Units Sold	Revenue	Defect Rate	Lead Time
Supplier 1	11,080	\$157,529	1.80%	16.78 days
Supplier 2	11,068	\$125,467	2.36%	16.23 days
Supplier 5	8,662	\$110,343	2.67%	14.72 days
Supplier 3	8,083	\$97,796	2.47%	14.33 days
Supplier 4	7,206	\$86,469	2.34%	17.00 days

**Demand Forecasting Model Analysis**

**Model Architecture**

The neural network model implemented consists of:

- **Input Layer:** 15 features after preprocessing
- **Hidden Layers:** 128, 64, and 32 neurons with ReLU activation
- **Dropout Layers:** 0.3, 0.3, and 0.2 for regularization
- **Output Layer:** Single neuron with linear activation for regression

**Model Performance Metrics**

**Critical Finding - Model Performance Issues:**

- **Mean Squared Error (MSE):** 220,425
- **Root Mean Squared Error (RMSE):** 469.49
- **Mean Absolute Error (MAE):** 371.05
- **R-squared Score:** -1.31 (indicating poor model fit)

**Model Interpretation:** The negative R-squared value indicates that the model performs worse than a simple mean-based prediction. This suggests significant overfitting or inappropriate model architecture for the given dataset size and complexity.

**Top Performing Products (Demand Analysis)**

SKU	Product Type	Units Sold	Revenue
SKU10	Skincare	996	\$2,331
SKU94	Cosmetics	987	\$7,888
SKU9	Skincare	980	\$4,971

SKU	Product Type	Units Sold	Revenue
SKU36	Skincare	963	\$7,573
SKU37	Skincare	963	\$2,438

## Seasonal Demand Patterns

### Monthly Demand Trends:

- **February:** 532 units (peak demand)
- **April:** 521 units
- **January:** 428 units
- **March:** 410 units (lowest demand)

The limited 4-month dataset shows February as the strongest sales month, potentially indicating seasonal preferences or promotional activities.

## Strategic Recommendations

### 1. Model Improvement Priority

#### Immediate Actions Required:

- Redesign the neural network architecture with fewer parameters to prevent overfitting
- Implement cross-validation techniques for better model validation
- Consider alternative algorithms (Random Forest, Linear Regression) for comparison
- Expand dataset size for more robust training

### 2. Operational Optimization

#### Supply Chain Efficiency:

- **Partner with Carrier B** for primary logistics given superior revenue performance
- **Prioritize Supplier 1** for new contracts based on volume and quality metrics
- **Optimize cosmetics production** to leverage shorter lead times and lower defect rates

### 3. Inventory Management

#### Product Focus Areas:

- **Increase skincare inventory** allocation given 45% market dominance
- **Monitor top 5 SKUs** closely for stockout prevention
- **Implement seasonal adjustments** based on February demand spike patterns

### 4. Quality Control Enhancement

#### Transportation Quality Optimization:

- **Prefer air transportation** for high-value, quality-sensitive products

- **Implement additional quality checks** for road transportation shipments
- **Establish quality benchmarks** below 2% defect rate across all suppliers

## 5. Cost Management

### Transportation Cost Strategy:

- **Utilize sea transportation** for non-urgent, bulk shipments (13.4% of total costs)
- **Balance road and rail options** based on urgency and cost constraints
- **Negotiate improved rates** with underperforming carriers

## Risk Assessment and Mitigation

### High-Risk Areas Identified

1. **Model Reliability:** Current forecasting model requires complete reconstruction
2. **Lead Time Variability:** 14-19 day range creates inventory planning challenges
3. **Single Carrier Dependency:** Over-reliance on Carrier B for revenue generation
4. **Limited Historical Data:** 4-month dataset insufficient for seasonal analysis

### Mitigation Strategies

- Implement ensemble forecasting methods combining multiple algorithms
- Establish safety stock levels based on lead time uncertainty
- Diversify carrier partnerships to reduce dependency risk
- Collect at least 12 months of historical data for comprehensive seasonal modeling

## Conclusion and Next Steps

This analysis reveals significant opportunities for supply chain optimization, particularly in demand forecasting model development and operational efficiency improvements. While the current neural network model requires substantial revision, the business intelligence derived from the data provides valuable insights for strategic decision-making.

### Immediate Priority Actions:

1. **Rebuild forecasting model** with appropriate complexity for dataset size
2. **Strengthen partnership with top-performing suppliers and carriers**
3. **Expand data collection** for more robust future analyses
4. **Implement recommended operational optimizations** for cost and quality improvements

### Long-term Strategic Goals:

- Achieve demand forecasting accuracy above 85% ( $R^2 > 0.85$ )
- Reduce average defect rates below 2% across all product categories
- Establish automated inventory optimization based on reliable demand predictions
- Develop comprehensive seasonal demand planning capabilities

The foundation for data-driven supply chain management has been established, requiring focused execution on model improvement and operational optimization to realize the full potential of predictive analytics in demand forecasting.