

Faculty of Engineering



Exposé for a case study for the attainment
of the degree of

Master of Science in Logistics Engineering

on the Topic

Data Analytics for the Strategic Decision-Making in Logistics

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1. Introduction of the Case Study

The logistics sector has seen profound changes through the adoption of data analytics and advanced technologies. These tools are transforming decision-making processes, enabling organizations to respond effectively to challenges, optimize operations, and improve overall efficiency. This report examines the integration of data-driven methods and artificial intelligence (AI) in logistics, emphasizing practical applications, benefits, challenges, and conclusions. Key insights include the role of open-source tools in democratizing access to innovative technologies.

In today's data-driven environment, advances in internet technology, mobile usage, and cloud computing have expedited data collection, generating great prospects for strategic logistics decision-making. Big Data analytics has become critical for generating insights that improve productivity and strategy. In logistics and supply chain management, these tools help with network design, procurement, and distribution. This study examines how data analytics and artificial intelligence are transforming supply chain management, with a focus on efficiency and decision-making.

Data analytics and artificial intelligence are transforming strategic decision-making in logistics, allowing businesses to optimize operations, improve control, and precisely respond to global dynamics. Leveraging sophisticated technologies such as Artificial Intelligence, Data Analytics, Machine Learning, and the Internet of Things is crucial for gaining a competitive edge, but it requires a strategic assessment of costs, benefits, and implementation to improve decision-making and resilience.

Market needs and a focus on customer service are driving logistics businesses to develop smarter, more responsive supply chains. Automation, robotics, and artificial intelligence are helping to streamline processes, reduce lead times, and cut costs. AI provides proactive decision-making, helping logistics professionals to optimize procedures while remaining competitive in the face of escalating costs and global supply chain difficulties.

2. Supply Chain Analytics: Data-Driven Insights for a Fashion & Beauty Startup.

2.1 Introduction

Supply chain analytics is a valuable part of data-driven decision-making in various industries such as manufacturing, retail, healthcare, and logistics. It is the process of collecting, analyzing and interpreting data related to the movement of products and services from suppliers to customers.

Here is a dataset we collected from a Fashion and Beauty startup. The dataset is based on the supply chain of Makeup products.



SUPPLY_CHAIN_DATASET.xlsx

In modern supply chain management, leveraging Data Analytics and Artificial Intelligence (AI) plays a crucial role in optimizing logistics operations, improving efficiency, and reducing costs.

2.2 Objectives and Analysis of the Case Study:

This case study focuses on five key areas where data-driven decision-making enhances supply chain performance:

1. Inventory Optimization
2. Lead Time Analysis
3. Supplier Performance
4. Carbon Emissions Analysis
5. Defect Rate and Waste Analysis

By utilizing Excel, we analyzed logistics data to derive actionable insights and recommend strategic improvements.

2.2.1 Inventory Optimization

Objective: To improve stock management by balancing inventory levels, reducing holding costs, and ensuring product availability.

Key Metrics & Analysis

1. Stock Turnover Ratio: Measures how often inventory is sold and replaced.
 - Formula: $\text{Stock Turnover Ratio} = \text{Total Products Sold} / \text{Average Stock Levels}$
 - Excel Calculation: Use $\text{=Number of Products Sold} / \text{Average (Stock Levels)}$

- Created a Pivot table to highlight Average Stock Turnover Ratio for each Product Type.
- Insights: Higher turnover suggests efficient inventory management; low turnover indicates overstocking.

Product Type	Average of Stock Turnover Ratio
cosmetics	9.466
haircare	8.380
skincare	10.849
Grand Total	9.650

Table 1: Stock Turnover Ratio

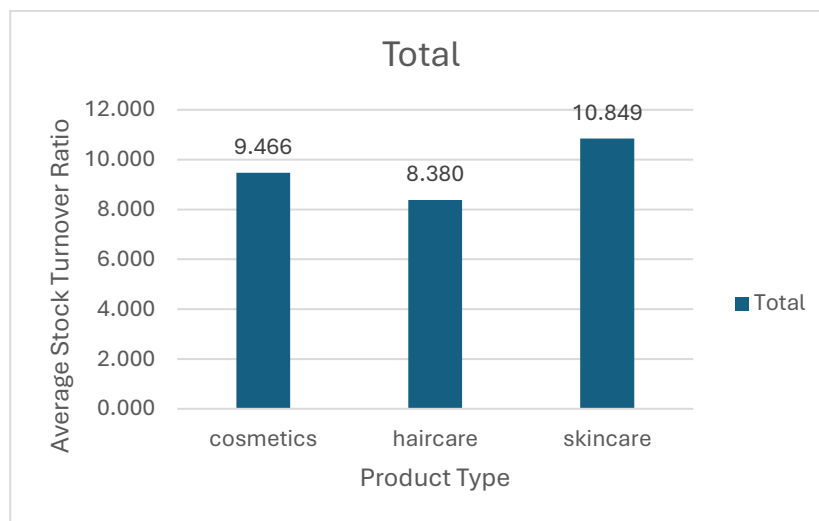


Figure 1: Comparison of Stock Turnover ratio for all Product Type

2. Critical Stock Levels

- Applied Conditional Formatting in Excel to highlight products below threshold. (Red Color)
- Threshold determined using the formula: $\text{Reorder Point} = (\text{Average Daily Usage} \times \text{Lead Time}) + \text{Safety Factor}$.
- Suggested action: Increase reorder frequency for critical items.

Conclusion

1. Skincare products have the highest stock turnover (10.849), indicating strong demand and efficient inventory management.
2. Haircare products have the lowest turnover (8.380), suggesting potential overstocking or slower sales.
3. The overall average stock turnover ratio is 9.650, reflecting a moderately efficient inventory system.

4. Critical stock monitoring helps prevent stockouts by identifying low-stock products using conditional formatting.

2.2.2 Lead Time Analysis

Objective: To analyze and reduce lead times for improving order fulfillment and operational efficiency.

Key Metrics & Analysis

1. Average Lead Time Calculation:

- Formula: `=AVERAGE (Lead Time in Days) `
- Created a Pivot Table in Excel to group products by lead times and identify bottlenecks.

Product Type	Average of Product Lead Times
cosmetics	15.385
haircare	15.529
skincare	16.700
Grand Total	15.96

Table 2: Product Lead Time in Days

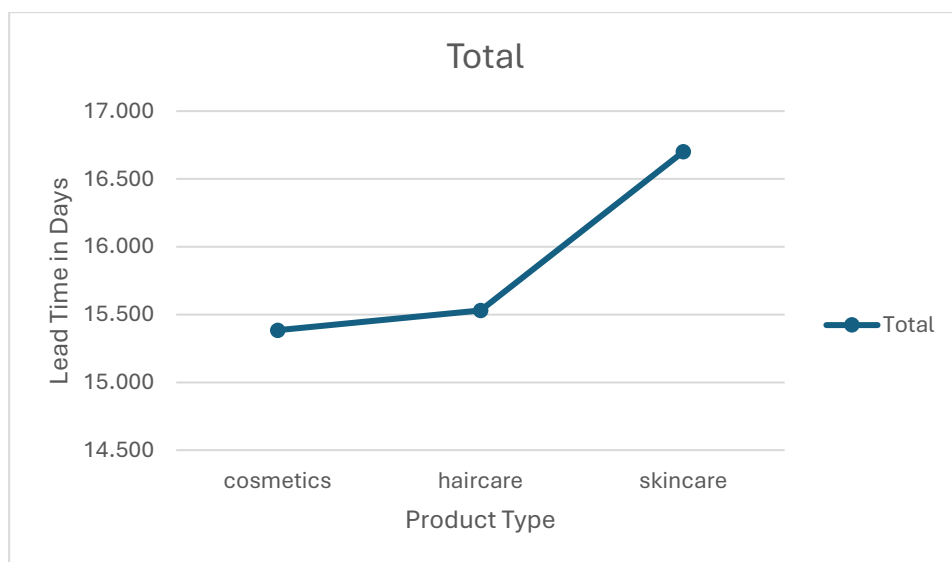


Figure 2: Line Graph for lead time by Product Type

2. Supplier Lead Time Analysis:

- Used a Pivot Table to compare lead times across suppliers.
- Identified suppliers with consistently high lead times.
- Suggested alternatives for high-lead-time suppliers to reduce delays.

Average of Supplier Lead Time	Column Labels			
Suppliers	cosmetics	haircare	skincare	Grand Total
Supplier 1	13.429	21.2	13.267	14.778
Supplier 2	11.286	21	23.800	18.545
Supplier 3	28.000	21.4	18.556	20.133
Supplier 4	13.250	14.5	19.000	15.222
Supplier 5	14.000	17	22.714	18.056
Grand Total	13.538	18.706	18	17.08

Table 3: Supplier Lead Time for all Product Types

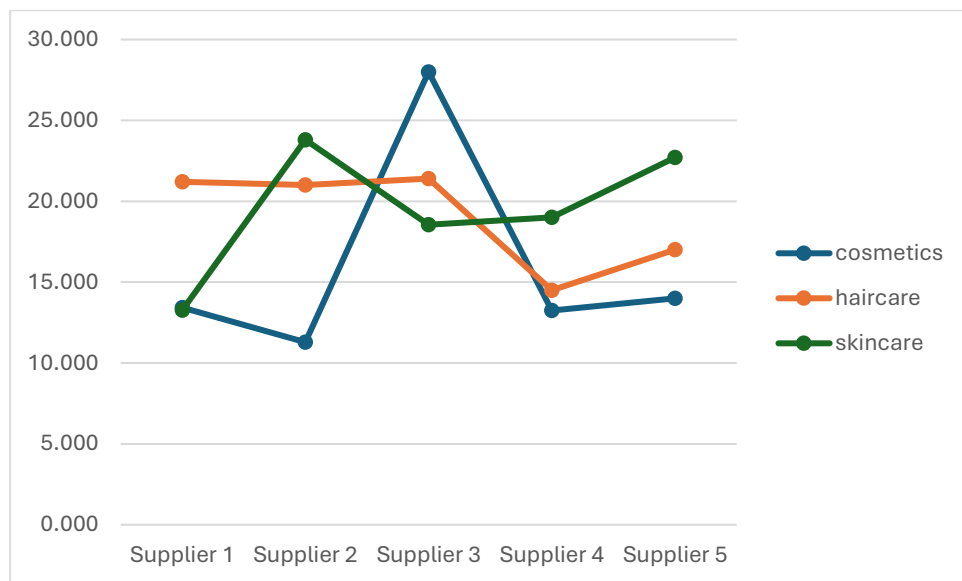


Figure 3: Comparison of Lead Times for all Product Types by all Suppliers

Conclusion

1. Skincare has the highest average lead time (16.7 days), while cosmetics have the lowest (15.385 days).
2. Supplier 3 has the longest lead time (20.133 days), impacting overall efficiency.
3. Haircare lead times are inconsistent across suppliers, with Supplier 1 and Supplier 2 exceeding 21 days.

2.2.3 Supplier Performance

Objective: To evaluate supplier efficiency based on delivery performance and product quality.

Key Metrics & Analysis

1. Average Lead Time per Supplier:

- Formula: `=AVERAGE (Lead Time)`
- Created a Pivot Table with “Supplier Name” in rows and “Lead Time” and “Defect Rates” as values.

2. Defect Rate Calculation:

- Formula: `Defect Rate = (Defective Units / Total Units) × 100%`
- Used `=SUM(Defective Units) / SUM(Total Units)` in Excel.

Suppliers	Average of Supplier Lead Time	Average of Defect Rates
Supplier 1	14.778	1.80
Supplier 2	18.545	2.36
Supplier 3	20.133	2.47
Supplier 4	15.222	2.34
Supplier 5	18.056	2.67
Grand Total	17.08	2.28

Table 4: Lead Time and Defect Rates for all Suppliers

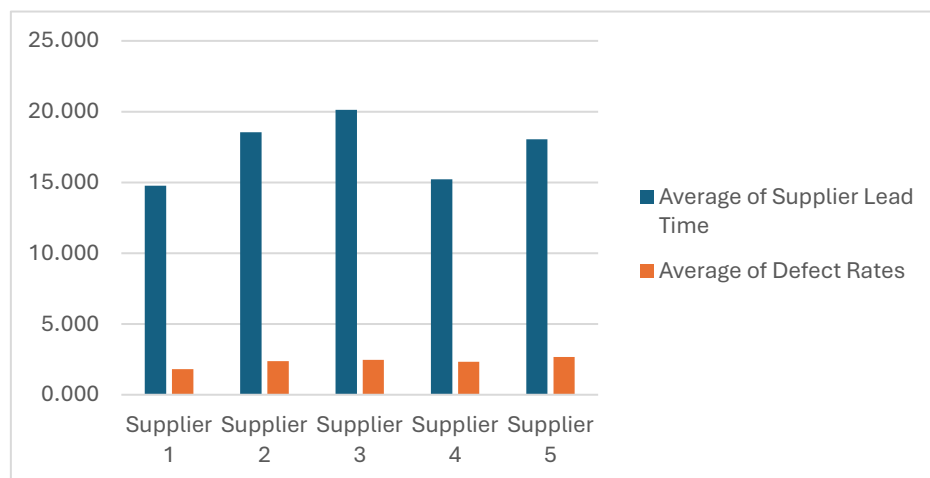


Figure 4: Comparison between Lead Time and Defect Rates for all Suppliers

Conclusion

1. Supplier 3 has the longest lead time (20.133 days) and a high defect rate (2.47%), indicating inefficiency.
2. Supplier 5 also shows high defect rates (2.67%) and long lead times (18.056 days), impacting quality and delivery.
3. Supplier 1 is the most efficient with the lowest defect rate (1.80%) and a shorter lead time (14.778 days).

2.2.4 Carbon Emissions Analysis

Objective: To estimate and reduce carbon emissions from logistics activities.

Key Metrics & Assumptions

1. Estimating Shipping Volumes

- Assumed average shipment size based on industry standards:

Transportation Mode	Shipment Volume (Kg)
Air	1000
Road	10000
Rail	60000
Sea	20000

Table 5: Shipment Volume for different Transportation Modes

2. Carbon Emissions Calculation:

- Formula: $\text{CO}_2 \text{ Emissions} = \text{Shipment Volume} \times \text{Distance} \times \text{Emission Factor}$

Transportation Mode	Emission Factor
Air	0.5
Road	0.15
Rail	0.04
Sea	0.02

Table 6: CO2 Emission Factor for different Transportation Modes

Mode of Transports	Sum of Carbon Emissions
Air	12143500
Rail	90816000
Road	43785000
Sea	9907200
Grand Total	156651700

Table 7: Carbon Emissions based on mode of Transports

Mode of Transports	Sum of Carbon Emissions
Air	12143500
Route A	5146500
Route B	3244000
Route C	3753000
Rail	90816000
Route A	45792000
Route B	37584000
Route C	7440000
Road	43785000
Route A	16530000
Route B	19770000
Route C	7485000
Sea	9907200
Route A	3009600
Route B	3489600
Route C	3408000
Grand Total	156651700

Table 8: Carbon Emissions based on mode of Transportation and Routes

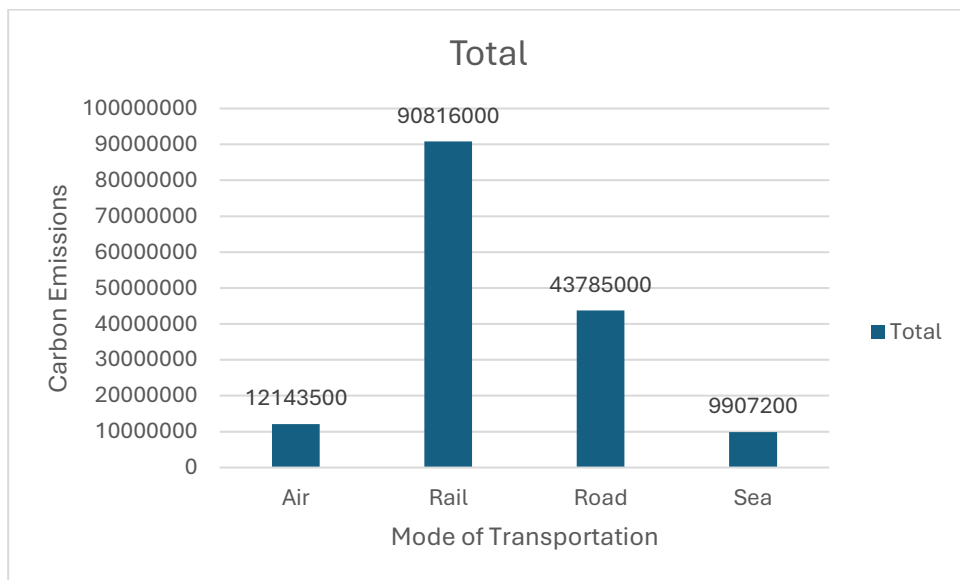


Figure 5: Graphical Representation of Carbon Emissions

Conclusion

1. Rail transport has the highest carbon emissions (90.8M), followed by road (43.78M) and air (12.14M).
2. Sea transport is the most eco-friendly mode, with the lowest emissions (9.9M).

3. Route A contributes the most emissions across all transport modes, requiring optimization.
4. Shifting shipments from air and road to rail and sea can significantly reduce carbon footprint.

2.2.5 Defect Rate and Waste Analysis

Objective: To minimize waste by identifying defect-prone products and suppliers.

Key Metrics & Analysis

1. Defect Rate Calculation (Same as Supplier Performance Section).

- Created Pivot Table to analyze waste by product category and supplier.

Product Type	Sum of Defective Units	Sum of Production Volumes	Sum of Defect Rate
cosmetics	218.48	12461	1.75%
haircare	536.17	19957	2.69%
skincare	583.64	24366	2.40%
Grand Total	1338.29	56784	2.36%

Table 9: Defect Rate based on Product Type

Suppliers	Sum of Defective Units	Sum of Production Volumes	Sum of Defect Rate
Supplier 1	259.67	13545	1.92%
Supplier 2	339.25	14105	2.41%
Supplier 3	220.27	7997	2.75%
Supplier 4	269.82	11756	2.30%
Supplier 5	249.28	9381	2.66%
Grand Total	1338.29	56784	2.36%

Table 10: Defect Rate based on Supplier

Conclusion

1. Haircare products have the highest defect rate (2.69%), requiring quality improvements.
2. Supplier 3 has the highest defect rate (2.75%), indicating the need for better quality control.
3. Cosmetics have the lowest defect rate (1.75%), showing better production consistency.