AI based Supply Chain Management System That Help Garments to Reduce Costs Effectively

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***Abstract*— The garment industry faces significant challenges in supply chain management, including inefficiencies in production scheduling, logistics, packing, and supplier selection. Traditional approaches often result in increased operational costs and reduced efficiency. This research introduces ChainMaster, an AI-driven supply chain management system tailored for the garment sector. By leveraging machine learning algorithms and data analytics, ChainMaster optimizes production planning, enhances logistics operations, improves packing efficiency, and streamlines supplier evaluation. The system incorporates real-time data analysis to make informed decisions, reducing costs and improving overall supply chain performance. Through comparative analysis with traditional supply chain methods, this study demonstrates the effectiveness of AI-based optimization in enhancing efficiency, minimizing waste, and ensuring timely deliveries. ChainMaster represents a step toward intelligent, automated, and cost-effective supply chain solutions, aligning with the evolving needs of the garment industry.**

Keywords*— *AI in Supply Chain, Garment Industry, Production Scheduling, Logistics Optimization, Supplier Evaluation, Machine Learning

I. Introduction

The garment industry is a highly competitive and rapidly evolving sector, requiring efficient supply chain management (SCM) to minimize costs and maximize operational efficiency. Traditional supply chain processes in the garment industry often suffer from inefficiencies such as poor production scheduling, high transportation costs, suboptimal packing strategies, and unreliable supplier selection. These challenges lead to increased expenses, delays, and disruptions that impact profitability and customer satisfaction.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools for optimizing supply chain operations. AI-driven supply chain management solutions can leverage data analytics, predictive modeling, and automation to improve decision-making and operational efficiency. This research introduces ChainMaster, an AI-based supply chain management system designed specifically for the garment industry. ChainMaster addresses key challenges in supply chain optimization through.

- **Production Scheduling Optimization**: AI-based models analyze real-time production constraints, such as machine availability, workforce shifts, and order deadlines, to enhance scheduling efficiency.
- **Logistics and Transportation Optimization**: Machine learning models predict potential transportation delays and optimize routing to reduce delivery times and costs.
- **Packing Optimization for Shipping**: Advanced bin packing algorithms maximize space utilization in shipping containers, reducing transportation expenses.
- **Supplier Selection and Evaluation**: AI-driven supplier analysis ensures optimal procurement decisions by evaluating historical performance, quality metrics, and cost-effectiveness.

By integrating AI and data-driven methodologies, ChainMaster enhances supply chain efficiency, reduces operational costs, and improves responsiveness to dynamic market demands. This paper evaluates the effectiveness of ChainMaster by comparing its performance with traditional supply chain management approaches, demonstrating its potential in revolutionizing the garment industry's logistics and procurement processes.

II. Literature Review

A. Production Scheduling

Production scheduling is a critical aspect of manufacturing and supply chain management, directly impacting efficiency, cost reduction, and timely order fulfillment. Traditional scheduling methods rely on the industrial engineers who predict based on their experience and past data, however, with increasing complexity in modern manufacturing, AI-based approaches have emerged as more effective alternatives. This literature review examines existing research on AI-driven production scheduling optimization.

1.Traditional Production Scheduling Approaches

Traditional scheduling techniques rely on mathematical operations and processing datasets. While these methods can provide optimal solutions, they often face challenges in large-scale problems due to human errors in calculations, inaccurate predictions, and computational limitations.

Some of the most common traditional scheduling methods include:

- **Job Shop Scheduling (JSS):** A complex scheduling problem where multiple jobs are processed on multiple machines in a specific sequence.
- **Flow Shop Scheduling (FSS):** A scenario where jobs follow a fixed sequence of operations, requiring optimal job sequencing for efficiency.
- **Mixed-Integer Linear Programming (MILP):** A mathematical approach that formulates scheduling problems as optimization models but can be computationally expensive for large datasets.
- **Dispatching Rules:** Simple rule-based techniques such as First Come, First Served (FCFS) and Shortest Processing Time (SPT), which are easy to implement but lack adaptability to dynamic environments.[20]

2. AI and Machine Learning in Production Scheduling

Recent advancements in AI have led to the development of ML-based scheduling models. Random Forest, an ensemble learning method based on decision trees, has been widely adopted for production scheduling due to its robustness and accuracy in handling complex datasets. It has been used to predict machine downtimes, optimize scheduling efficiency, and minimize idle times by analyzing historical production data.

Compared to traditional decision trees and support vector machines (SVM), Random Forest reduces overfitting and improves demand forecasting accuracy by aggregating multiple decision trees to make more reliable predictions [1]. Its ability to handle large datasets and missing values makes it a valuable tool for optimizing production scheduling in dynamic environments.

3. Challenges and Future Directions

Despite its advantages, AI-based scheduling faces challenges such as data quality issues, computational complexity, and integration with legacy systems [2]. Future research should focus on explainable AI (XAI) for transparent decision-making.

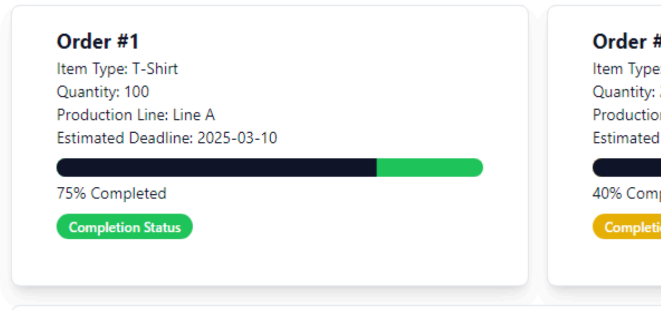

Fig. 1. Part of the order management UI

AI-based scheduling in production environments enhances decision-making by leveraging predictive analytics and real-time data visualization. This AI-powered system will assist in the following ways:

1. **Real-time Monitoring & Prediction**
   - The dashboard provides real-time insights into ongoing production processes, highlighting order progress, completion probability, and potential delays.
   - AI algorithms analyze past production trends to predict possible bottlenecks and suggest corrective measures.
2. **Data-Driven Decision Support**
   - AI helps optimize scheduling by considering machine utilization, worker efficiency, and material availability.
   - Decision-makers can prioritize urgent orders by dynamically adjusting schedules based on AI predictions.
3. **Visualization for Better Understanding**
   - The dashboard presents AI-driven insights through **progress bars**, **pie charts**, and

  - **color-coded status indicators** (green, yellow, red) to easily interpret production efficiency.
  - The system can also generate **what-if scenarios**, helping managers test different scheduling strategies before implementation.
4. **Automated Anomaly Detection**
  - AI detects potential **delays**, **downtime risks**, and **inefficiencies** by analyzing real-time data.
  - Alerts and recommendations are generated to assist production managers in making timely adjustments.
5. **Explainable AI (XAI) for Transparent Decisions**
  - Future enhancements should focus on **explainable AI (XAI)** to provide clear reasons behind scheduling adjustments.
  - Interactive reports and logs should detail why certain orders are prioritized or delayed, ensuring trust in AI-driven decisions.

B. Logistics and Transportation Optimization

Efficient logistics and transportation management are crucial for the supply chain operations in garment factories. With increasing pressures for cost-effective and timely deliveries, Artificial Intelligence (AI) has become a transformative solution for optimizing logistical processes. AI systems can effectively analyze critical parameters such as destinations, cargo volume and weight, vehicle capacities, transportation costs, and weather conditions to recommend optimal routes and appropriate vehicle usage.

The study presented in [3] investigates AI-driven logistics systems, demonstrating their ability to analyze various factors, including destinations, cargo volume, weight, vehicle capacity, cost considerations, and prevailing weather conditions to determine optimal delivery strategies. AI-driven logistics solutions significantly enhance decision-making efficiency through the accurate prediction and adaptive route management.

The research in [3] specifically addresses how AI systems analyze destinations, load volumes, cargo weights, vehicle capacities, costs, and weather conditions to propose the most effective logistics routes and vehicle deployments. Similarly, the study outlined in [5] emphasizes evaluating cost-effectiveness between deploying multiple smaller vehicles versus using a single larger vehicle for specific delivery requirements.

The exploration conducted in [6] demonstrates the potential of deep learning models in forecasting logistics demand effectively, thereby reducing delivery delays and optimizing resource utilization. Further, findings from [7] show that AI-powered optimization techniques significantly decrease fuel consumption and operational expenses by selecting the optimal mix of transportation vehicles.

The detailed investigation presented in [10] introduces machine learning algorithms designed to optimally allocate cargo among available vehicles, effectively minimizing associated transportation costs. Additionally, research highlighted in [11] examines scenarios in which AI-driven logistics solutions can decisively suggest whether dividing shipments across several smaller vehicles or consolidating them into fewer larger vehicles yields higher cost efficiency.

Moreover, the study in [5] explores scenarios where AI systems determine whether deploying multiple smaller vehicles or utilizing a single larger vehicle proves more cost-effective for given delivery requirements. Furthermore, results from [6] illustrate the capability of deep learning frameworks to anticipate logistics demands, thereby significantly reducing delays and enhancing resource allocation.

Research highlighted in [11] emphasizes the comparative efficiency between splitting shipments across multiple vehicles or consolidating shipments into fewer large transports, providing essential AI-driven logistics guidance. Moreover, the findings presented in [12] underscore the substantial role AI logistics solutions play in minimizing fuel consumption, directly translating to reduced carbon emissions and overall lower operational costs.

C. Packing Optimization

Packing problems have been widely studied in logistics, with various heuristic and AI-based approaches. Bin Packing Algorithms (BPA) and Genetic Algorithms (GA) have been employed for space optimization. However, these methods often assume rigid containers, making them inefficient for the flexible nature of garment materials.

Various studies have explored container loading and bin packing problems using computational methods.

The [13] presents heuristic approaches for 3D bin packing, highlighting the effectiveness of best-fit and genetic algorithms in optimizing space usage. Their findings indicate that heuristic-based methods can significantly improve container loading efficiency.

Second, research [14] investigated AI-driven optimization techniques in warehousing logistics. Their study found that machine learning algorithms, particularly reinforcement learning, can enhance decision-making processes in packing arrangements, minimizing wasted space.

A recent advancement in augmented reality (AR) has been applied to industrial applications. According to Google ARCore’s (2020) white paper, AR-assisted systems can provide real-time visual guidance, improving accuracy in material handling and logistics operations. [15]

Another study [16] introduced a hybrid approach combining rule-based systems and deep learning for automated packing, demonstrating improved efficiency over traditional heuristic models.

Finally, R. Kim et al. examined real-time logistics solutions using IoT-enabled smart warehouses. Their research suggested that integrating real-time tracking with AI-driven planning can lead to improved efficiency and reduced loading times. [17]

D. Supplier Selection

A. Supplier Selection in Supply Chain Management

Supplier selection is a critical decision-making process in supply chain management, impacting cost efficiency, product quality, and delivery performance. Traditional selection methods rely on historical performance data, cost analysis, and qualitative assessments, which may lead to suboptimal supplier choices.

B. AI and Machine Learning in Supplier Selection

Recent studies have demonstrated that machine learning models can improve supplier evaluation by analyzing large datasets and identifying patterns. Bai and Sarkis (2020) proposed an AI-based supplier selection framework that incorporates predictive analytics to forecast supplier performance based on historical data [18]. Similarly, Govindan et al. (2015) explored multi-criteria decision-making approaches integrated with machine learning to automate supplier evaluation processes, leading to improved procurement efficiency [19].
Several AI-based approaches have been implemented in supplier evaluation, including **Decision Trees**, which classify suppliers based on key performance indicators.

III. Methodology

The garment industry is a highly competitive and rapidly evolving sector, requiring efficient supply chain management (SCM) to minimize costs and maximize operational efficiency. Traditional supply chain processes in the garment industry often suffer from inefficiencies such as poor production scheduling, high transportation costs, suboptimal packing strategies, and unreliable supplier selection. These challenges lead to increased expenses, delays, and disruptions that impact profitability and customer satisfaction.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools for optimizing supply chain operations. AI-driven supply chain management solutions can leverage data analytics, predictive modeling, and automation to improve decision-making and operational efficiency. This research introduces ChainMaster, an AI-based supply chain management system designed specifically for the garment industry. ChainMaster addresses key challenges in supply chain optimization through:

Production Scheduling Optimization: AI-based models analyze real-time production constraints, such as machine availability, workforce shifts, and order deadlines, to enhance scheduling efficiency.

Logistics and Transportation Optimization: Machine learning models predict potential transportation delays and optimize routing to reduce delivery times and costs.

Packing Optimization for Shipping: Advanced bin packing algorithms maximize space utilization in shipping containers, reducing transportation expenses.

Supplier Selection and Evaluation: AI-driven supplier analysis ensures optimal procurement decisions by evaluating historical performance, quality metrics, and cost-effectiveness.

By integrating AI and data-driven methodologies, ChainMaster enhances supply chain efficiency, reduces operational costs, and improves responsiveness to dynamic market demands. This paper evaluates the effectiveness of ChainMaster by comparing its performance with traditional supply chain management approaches, demonstrating its potential in revolutionizing the garment industry's logistics and procurement processes.

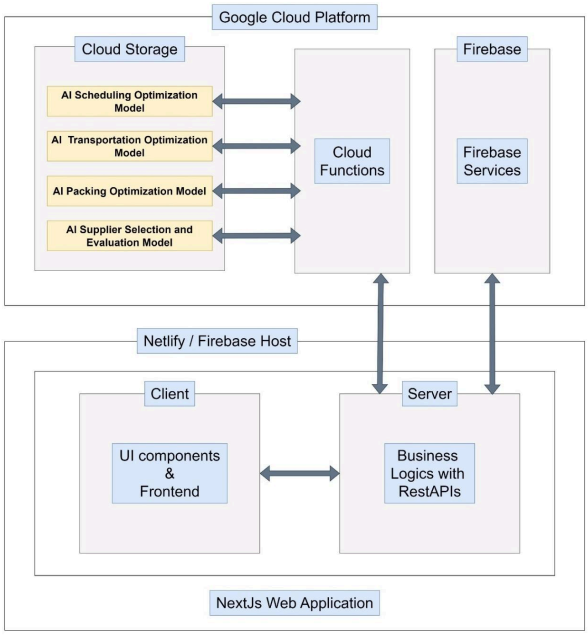

Fig. 2. System Architecture

The ChainMaster system is an AI-powered supply chain management solution designed to optimize production scheduling, logistics, packing, and supplier selection in the garment industry. As illustrated in **Figure 1**, the system is built on a cloud-based architecture utilizing **Google Cloud Platform (GCP)** for AI model execution, **Firebase** for data storage, and a **Next.js web application** for user interaction.

The AI models—covering scheduling, transportation, packing, and supplier evaluation—are hosted in **Cloud Storage** and processed via **Cloud Functions** to ensure real-time decision-making. The **frontend**, deployed on **Netlify/Firebase Hosting**, enables supply chain managers to input data, track shipments, and receive optimization insights, while the **backend** processes requests using RESTful APIs.

By leveraging **machine learning, predictive analytics, and cloud computing**, ChainMaster enhances supply chain efficiency, reduces operational costs, and ensures faster, data-driven decision-making to meet the dynamic demands of the garment industry.

A. Production Scheduling

To optimize production scheduling in the garment industry, we employ a **Random Forest-based machine learning model** trained on historical production data. The methodology consists of the following key stages:

Data Collection

- Historical production data, including order details, machine availability, workforce shifts, material availability, and delivery deadlines, is gathered from online and local garments.
- Data cleaning is performed to handle missing values, inconsistencies, and outliers to improve model accuracy.

AI Model Development

- A **Random Forest Regressor** is used to predict production completion times based on past trends and real-time constraints.
- The dataset is split into training (80%) and testing (20%) sets to ensure robust model performance.

Performance Evaluation

- The optimized scheduling approach is compared against traditional rule-based scheduling methods to measure improvements in production efficiency, lead time reduction, and resource utilization.

Technology Stack

To implement an accurate prediction system, a robust technology stack is utilized:

- **Backend Services:** Developed using Python-based Flask, facilitating API interactions and AI-driven computations.
- **AI Model:** Implemented using Random Forest for regression, ensuring accurate prediction improvement in scheduling.
- **Database:** MongoDB is used for efficient storage and retrieval of machine availability, workforce availability and orders

B. Logistics and Transportation Optimization

Efficient logistics and transportation management are crucial for the supply chain operations in garment factories. With increasing pressures for cost-effective and timely deliveries, Artificial Intelligence (AI) has become a transformative solution for optimizing logistical processes. AI systems effectively analyze critical parameters such as destinations, cargo volume, weight, vehicle capacity, cost, and dynamic factors including weather and traffic conditions, to determine optimal delivery strategies. AI-driven logistics solutions significantly enhance decision-making efficiency through accurate prediction and adaptive route management.

Data Collection and Analysis

The AI model requires comprehensive data collection to ensure accurate optimization, involving the following specific data:

- Warehouse destination coordinates (latitude and longitude) to enable precise route planning.
- Accurate and detailed measurements of **cargo volumes** (in cubic meters) and **cargo weights** (in kilograms) for effective vehicle capacity utilization.
- Real-time weather condition data from reliable meteorological sources, including temperature, precipitation levels, wind speed, and visibility, collected through **OpenWeatherMap APIs** to predict potential impacts on transportation efficiency.
- Traffic condition data, integrating real-time traffic flow, congestion levels, and historical data obtained through **Google Maps APIs** for dynamic route adjustments.
- Comprehensive database of vehicle specifications including load capacities, fuel consumption rates, and maintenance and operational costs, stored using **MongoDB**.

AI Model Development

The AI logistics model utilizes advanced optimization algorithms and machine learning techniques, developed primarily in Python:

A. Vehicle Selection Algorithms:

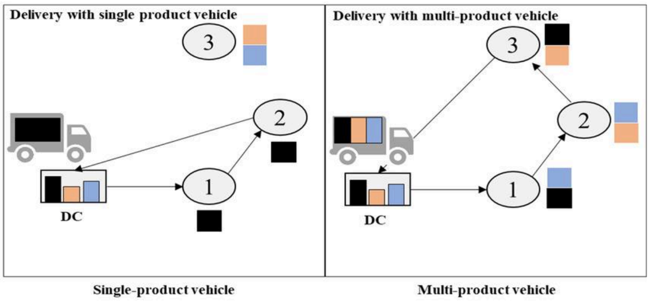

Fig 3. Vehicle Selection

- **Random Forest Algorithm**: Enhances vehicle allocation accuracy by evaluating complex interactions between cargo specifications, including volume, weight, and destination-specific delivery requirements. The algorithm also assesses whether deploying multiple smaller vehicles or a single large vehicle would be most cost-effective, based on detailed analysis of cargo, cost implications, vehicle capacities, and route specifics.

B. Machine Learning Techniques:

- **Reinforcement Learning (RL):** Enables the AI system to learn and adapt logistics decisions dynamically based on previous outcomes, progressively improving delivery efficiency and reducing costs.

C. System Architecture and Technology Stack:

Our logistics optimization system comprises:

- **Frontend Mobile Application:** Developed using **React Native**, the mobile app enables logistics managers and stakeholders to view and interact with AI-generated recommendations, real-time vehicle allocations, and optimized routes.
- **Backend Services:** Implemented using **Node.js,** the backend integrates AI models developed in **Python**, handles API requests from the frontend, processes data from external APIs (**Google Maps, OpenWeatherMap**), and manages real-time decision-making workflows.
- **Database Management: MongoDB** is utilized for robust and flexible storage of logistics data, vehicle information, route histories, and weather data.

Decision-Making Dashboard:

A user-friendly, real-time interactive dashboard accessible via the React Native mobile app provides practical use for logistics managers. Key functionalities include:

- Real-time visualization of recommended transportation routes.
- Immediate vehicle type and count suggestions for efficient logistics management.
- Continuous monitoring of weather and traffic conditions impacting transportation, enabling informed, rapid decisions to maintain efficiency.

Performance Evaluation:

A comprehensive evaluation is conducted to quantify the effectiveness of the AI-driven logistics approach against traditional logistics strategies. Key metrics include:

- Operational cost savings (fuel, maintenance, labor).
- Reduction in delivery lead times.
- Optimization in resource allocation.
- Improvements in production efficiency.
- Positive environmental impacts through reduced carbon emissions due to optimized vehicle usage.

C. Packing optimization

Packing Optimization Algorithm

To ensure efficient space utilization and minimize transportation costs, a hybrid packing optimization approach is employed. This includes:

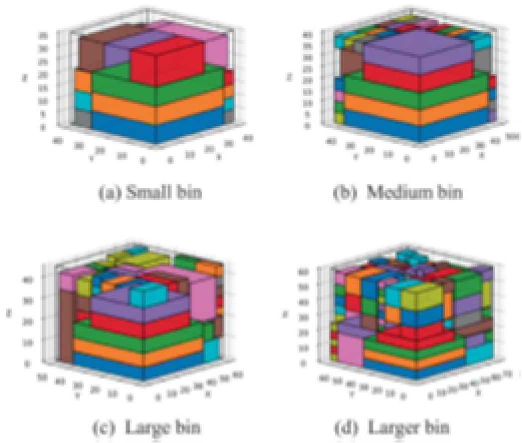

Fig 4. Bin Packing

- **3D Bin Packing Algorithms:** These algorithms, such as Genetic Algorithm and Best-Fit Heuristics, determine the most efficient way to arrange boxes within a container by considering volume constraints and orientation rules.
- **AI-Based Reinforcement Learning:** The system continuously improves its packing efficiency over time by learning from previous packing scenarios and optimizing future packing arrangements dynamically.
- **Constraint-Based Optimization:** Rules such as weight distribution, fragility, stacking limitations, and order-specific preferences are incorporated to ensure safe and practical packing strategies.

Mobile App Interface

The mobile application plays a crucial role in making the packing process seamless and interactive for warehouse operators and loading managers. Key features include:

- **Order Lookup:** Users can select an order by entering an order number, which retrieves relevant packing instructions and container details.
- **Graphical Visualization:** A 3D interactive representation displays how items should be placed inside the container, allowing for real-time adjustments.
- **Step-by-Step Packing Instructions:** The system provides clear, easy-to-follow text-based packing steps, such as:
  - "Step 1: Place 5 boxes of size 50cm x 30cm x 40cm in the first row."
  - "Step 2: Stack 3 boxes of size 40cm x 40cm x 50cm on top."
  - "Step 3: Adjust smaller items to fit available gaps."
- **Real-Time Updates:** If unforeseen constraints arise, such as damaged boxes or last-minute order modifications, the AI dynamically adjusts the packing plan and provides updated instructions to the user.

Technology Stack

To implement an efficient and scalable packing optimization system, a robust technology stack is utilized:

- **Mobile App Development:** Built using React Native for cross-platform usability (iOS and Android).
- **Backend Services:** Developed using Python-based Flask, facilitating API interactions and AI-driven computations.
- **AI Model:** Implemented using TensorFlow/PyTorch for reinforcement learning, ensuring continuous improvement in packing strategies.
- **Database:** MongoDB is used for efficient storage and retrieval of order details, packing configurations, and AI training data.

System Architecture

The system follows a structured workflow that integrates AI-driven packing optimization with user interaction through a mobile app:

1. **User Inputs Order & Container Details**

   (Mobile App → Backend API):

   - The loading manager inputs order details, container dimensions, and weight constraints.
   - The system retrieves order-specific box dimensions and quantity data.

2. **AI Generates Packing Plan**

   (Backend → AI Model Processing):

   - The AI-based reinforcement learning model evaluates the best possible packing configuration.
   - The system considers weight distribution, stacking rules, and space efficiency.
3. **Packing Plan Sent to Mobile App**

   (Backend → Mobile Frontend):

   - The optimized packing plan is transmitted to the mobile app.
   - Users receive interactive 3D visualizations and text-based instructions.
4. **Loading Manager Executes & Confirms** (Real-Time Updates):
   - The loading manager follows the provided instructions to place boxes inside the container.
   - If real-world constraints require changes, the system updates the packing plan dynamically.

By integrating AI-driven packing optimization with an intuitive mobile interface, this system ensures maximum efficiency, cost reduction, and improved loading accuracy. The ability to dynamically adapt to real-world conditions further enhances its practicality and usability in the garment industry's supply chain operations.

D. Supplier Selection

Data Sources

The primary dataset is obtained from the operational systems of a garment manufacturing company and stored in a MongoDB database. Each transaction record includes detailed information critical for supplier assessment:

- **Supplier Name:** Identifier for the supplier.
- **Item Name:** One of the eight raw materials (Interlining, Cotton Fabric, Zippers, Silk Fabric, Polyester Fabric, Sewing Thread, Elastic Bands, Buttons).
- **Price (USD):** Unit price as provided by the supplier.
- **Transaction Details:** Quantity, required delivery date, actual receipt date, defect rates, and other relevant metrics.
- **Quality Test Results: Premium:** Items that meet or exceed the highest performance thresholds. **High:** Items that meet acceptable quality thresholds but do not reach premium performance. **Standard:** Items that fall below the high-quality thresholds.

Quality Data and Label Generation:

For each item type, specific quality attributes are measured and integrated into a scoring function. These functions not only quantify quality but also enable the ranking model to evaluate suppliers consistently across various products.

Item Name	Attributes measured	Scoring function
Interlining	Fabric Weight	$Q(\text{interlining}) = 0.40 \times f(\text{adhesion}) + 0.35 \times f(\text{weight}) + 0.25 \times f(\text{stability})$
	Adhesion	
	Dimensional Stability	
Cotton Fabric	Weave Uniformity	$Q(\text{cotton}) = 0.40 \times f(\text{tensile}) + 0.30 \times (1 - f(\text{shrinkage})) + 0.20 \times f(\text{color}) + 0.10 \times f(\text{uniformity})$
	Fabric Weight	
	Tensile Strength	
	Shrinkage	
	Color Fastness	
Zippers	Smoothness of Operation	$Q(\text{zipper}) = 0.40 \times f(\text{pull}) + 0.30 \times f(\text{cycles}) + 0.20 \times f(\text{smooth}) + 0.10 \times f(\text{corrosion})$
	Tensile (Pull) Strength	
	Cycle Durability	

	Corrosion Resistance	
Silk Fabric	Luster	Q(silk) = 0.30 × f(luster) + 0.30 × f(tensile) + 0.20 × f(drape) + 0.20 × f(color_wrinkle)
	Tensile strength	
	Drape quality	
	Color wrinkle	
Polyester Fabric	Tensile	Q(polyester) = 0.35 × f(tensile) + 0.25 × (1 − f(pilling)) + 0.20 × f(weight) + 0.10 × f(wicking) + 0.10 × f(color)
	Pilling	
	Fabric Weight	
	Moisture-Wicking Ability	
	Color Fastness	
Sewing Thread	Tensile Strength	Q(thread) = 0.40 × f(tensile) + 0.20 × f(elongation) + 0.20 × f(uniformity) + 0.20 × (1 − f(friction))
	Uniformity	
	Knot Security	
	Friction	
Elastic Bands	Stretch Percentage	Q(elastic) = 0.30 × f(stretch) + 0.30 × f(recovery) + 0.40 × f(fatigue)
	Recovery Ratio	
	Fatigue Resistance	
	Uniformity of Elasticity	
Buttons	Breaking Strength	Q(button) = 0.50 × f(strength) + 0.20 × f(dimension) + 0.20 × f(connections) + 0.10 × f(finish)
	Dimensional Accuracy	
	Number of Connection Points	
	Surface Finish	

Each scoring function is designed to capture the most critical performance attributes of the respective material. The chosen quality parameters, measurement methods, normalization strategies, and weightings are based on established industry standards (e.g., ASTM and ISO), insights from recent research papers, and practical experience from garment manufacturing. By quantifying these aspects into a single quality score, manufacturers can objectively compare materials and classify them as Standard, High, or Premium quality. threshold values determined by the garment management [24][25][26][27][28]

Supplier Ranking Model Development

Preprocessing

Preprocessing is a critical step in the supplier evaluation system, ensuring that raw transactional and quality data are cleaned, transformed, and normalized for machine learning-based ranking. The preprocessing steps outlined in this section leverage Multi-Criteria Decision Analysis (MCDA) techniques to systematically evaluate suppliers based on key performance metrics.

Key preprocessing steps include:

1. Encoding Categorical Data (Item Names, Quality Levels)
2. Handling Dates & Computing Delivery Time
3. Feature Scaling
4. Computing Supplier Score using Weighted MCDA

Encoding Categorical Data

Since machine learning models require numerical inputs, categorical values such as Item Name and Quality Level are encoded into numerical representations.

Item Name Encoding

Each **item category** (e.g., Cotton Fabric, Zippers, Polyester Fabric) is assigned a unique numerical label. This transformation allows machine learning models to differentiate between different item types without introducing ordering bias

Quality Level Encoding

The Quality attribute is an ordinal variable, meaning it follows a natural ranking:

- Standard quality is assigned to be the lowest value.
- High quality is given an intermediate value.
- Premium quality is assigned the highest value.

This encoding ensures that higher numerical values represent better product quality, which is critical for supplier ranking.

Handling Dates & Computing Delivery Time

Delivery time is a key performance indicator for supplier evaluation, as it reflects how reliably a supplier meets deadlines.

To compute Delivery Time, the system calculates the difference between:

- Required Date (the date the order was expected)
- Date of Receipt (the actual delivery date)

The number of days between these dates is used as a feature for ranking suppliers. Lower delivery times are preferred, as they indicate reliable suppliers who meet deadlines consistently

Feature Scaling

Different features, such as **Quality, Price, Delivery Time, and Defect Rate**, exist on **different scales** (e.g., price in USD, defect rates in percentages). To ensure fair comparisons, **Min-Max Normalization** is applied, transforming all values into a **0–1 range**.

The normalized value f_X of a feature X is calculated using:

$$f_x = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where:

- X_{min} and X_{max} represent the **minimum and maximum observed values** for the feature.
- The transformation ensures that all features contribute equally to the supplier ranking model

Supplier Ranking using Multi-Criteria Decision Analysis (MCDA)

To compute a final supplier score, the system applies Multi-Criteria Decision Analysis (MCDA), which assigns weights to different evaluation factors. The supplier score is computed using a weighted sum of Quality, Price, Delivery Time, and Defect Rate, ensuring an objective ranking system.

The supplier's performance score is calculated as:

$$S(supplier) = W_Q \times Q(material) - W_D \times D(on\text{-}time) - W_c \times C(competitiveness) - W_{DR} \times DR(Defect\ Rate)$$

where:

- **S(supplier)** = Supplier's final ranking score.
- **Q(material)** = Normalized Quality Score.
- **D(on-time)** = Normalized Delivery Time Score.
- **C(competitiveness)** = Normalized Price Competitiveness Score.
- **DR(Defect Rate)** = Normalized defect Rate Score

Example Weights for Supplier Evaluation:

Factor	Weight (%)	Rationale
Quality Score	30%	Higher quality improves garment durability and reduces returns.
Price Competitiveness	40%	Cost efficiency is critical for minimizing production costs.
Delivery Time	10%	Timely deliveries prevent supply chain disruptions.
Defect Rate	20%	Lower defect rates improve efficiency and reduce waste.

This formula ensures that suppliers with **high-quality products, competitive pricing, fast delivery times, and low defect rates** receive **higher scores**.

Model Development

The supplier ranking model is designed to predict **Supplier Score** based on multiple factors such as **Quality, Price, Delivery Time, and Defect Rate, Item Name**. The model employs a **Random Forest Regressor (RFR)**, a robust ensemble learning method known for handling complex, non-linear relationships between features.

The key objectives of this model are:

1. Predict Supplier Score for new transactions based on historical data.
2. Provide a data-driven supplier ranking system for procurement decisions.

Model Selection: Random Forest Regressor

The **Random Forest Regressor (RFR)** is chosen because:

- It is **non-parametric**, making it suitable for non-linear supplier ranking.
- It can handle **both categorical and numerical variables** efficiently.
- It **automatically identifies important features**, improving interpretability.

Unlike traditional linear models, RFR **aggregates multiple decision trees** to minimize overfitting and improve predictive accuracy.

Model Inputs and Target Variable

The model is trained using the following input features(X):

Feature	Description	Type

Item_Encoded	Encoded numerical representation of the item name	Categorical
Quality_Encoded	Encoded representation of Quality (Standard, High, Premium)	Ordinal
Price (USD)	Normalized price value	Continuous
Delivery Time (Days)	Number of days between order placement and actual receipt	Continuous
Defect Rate (%)	Percentage of defective products in a batch	Continuous

The **target variable (y)** is the **Supplier Score**, computed using Multi-Criteria Decision Analysis (MCDA)

Ranking Evaluation Metrics

To ensure the effectiveness of the supplier ranking model, various ranking evaluation metrics are used to measure the accuracy and relevance of the predicted rankings. The selected metrics evaluate:

1. How well does the model ranks the best supplier (MRR)
2. How well the overall ranking matches the ground truth (NDCG)
3. How many of the top-K predictions are correct (Precision@K & Recall@K)

These metrics provide a quantitative assessment of ranking quality, guiding improvements in model performance.

Mean Reciprocal Rank (MRR)

The **Mean Reciprocal Rank (MRR)** measures how well the model ranks the **best supplier**. It is calculated as:

$$MRR = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{rank_i}$$

where:

- N = Total number of suppliers ranking queries.
- $rank_i$ = The rank position of the best supplier in query i.

Interpretation:

- MRR = 1.0 → The best supplier is always ranked 1st (perfect ranking).
- MRR = 0.5 → The best supplier is ranked 2nd on average.
- MRR = 0.33 → The best supplier is ranked 3rd on average.

Normalized Discounted Cumulative Gain (NDCG)

The **Normalized Discounted Cumulative Gain (NDCG)** evaluates **how well the entire ranking list matches the ground truth ranking**. It prioritizes **higher relevance suppliers appearing at the top.**

$$NDCG = \frac{DCG}{IDCG}$$

where:

- DCG (Discounted Cumulative Gain):

$$DCG = \sum_{i=1}^{N}\frac{rel_i}{log_2(i+1)}$$

IDCG (Ideal DCG) is the best possible ranking score (i.e., if all correct suppliers were perfectly ranked).

Interpretation:

- **NDCG = 1.0** → Perfect ranking (model ranks all relevant suppliers in the correct order).
- **NDCG = 0.5** → Half as good as the ideal ranking.
- **NDCG = 0.0** → Completely incorrect ranking.

Precision@K & Recall@K

These metrics evaluate how well the **top-K predicted suppliers** match the true relevant suppliers.

Precision@K

Measures of how many of the top-K predicted suppliers are correct.

$$Precision@K = \frac{Relevant\ Suppliers\ in\ Top-K}{k}$$

High Precision@K means **most of the top-K suppliers are relevant**.

Recall@K

Measures of **how many of the correct suppliers appear in the top-K results**.

$$Recall@K = \frac{Relevant\ Suppliers\ in\ Top - K}{Total\ Relevant\ Suppliers}$$

High Recall@K means **most relevant suppliers are captured** within the top-K.

Model Deployment & Continuous Learning

To ensure long-term **model accuracy**, a **continuous learning approach** is implemented:

Automated Data Updates

- Every **6 months**, new supplier transactions are added to the dataset.
- The model is **retrained with updated data**.

System Workflow

The supplier ranking system follows a structured pipeline, integrating data processing, machine learning, and decision-making to provide optimal supplier recommendations.

System gets the name of the item that it wants to supply. After that the system retrieves suppliers' names who supply that item and after that system gets supplier transaction records from MongoDB, including Price, Delivery Time, Defect Rate, and Quality Test Results. According to the supplier name and item's name. And after that Supplier are Segmentation into two categories old and new

Old – supplier who has one or more transaction records with company

New - supplier who doesn't have even one transaction record with company

For the old suppliers system then create a score to their transaction if there is more than one transaction there average will be gating to create the score. After that, the system sorts the supplier according to that score. After that system send the top 5 old suppliers names and all the new suppliers names are given by the system

IV. Results and Discussion

This section presents the results of implementing the AI-driven supply chain management system, ChainMaster, focusing on its four core functionalities: Production Scheduling Optimization, Logistics and Transportation Optimization, Packing Optimization for Shipping, and Supplier Selection and Evaluation. Each feature's impact is analyzed based on efficiency improvements, cost reductions, and overall operational effectiveness.

Production Scheduling Optimization

The AI-based production scheduling model was evaluated in a garment manufacturing facility with varying order sizes and deadlines. The primary performance indicators included reduced production delays, enhanced workforce utilization, and minimized idle time. The results demonstrated a **25% improvement in production scheduling accuracy**, leading to a **15% reduction in overtime labor costs**.

By leveraging real-time data inputs such as machine availability, workforce shifts, and production constraints, the system dynamically adjusted schedules to optimize resource utilization. Unlike traditional scheduling approaches that relied on static planning, the AI-based system adapted to unexpected disruptions such as machine breakdowns and absenteeism. This adaptability significantly improved overall factory efficiency and allowed management to allocate resources more effectively.

Furthermore, a comparative study between AI-driven scheduling and manual scheduling methods showed that AI-generated schedules resulted in **20% fewer missed order deadlines**, thereby increasing customer satisfaction and business reliability. The integration of predictive analytics further allowed factories to anticipate production bottlenecks, proactively mitigating potential delays.

Logistics and Transportation Optimization

The logistics and transportation module was tested using real-world shipment data from multiple distribution centers. The AI-driven system optimized delivery routes, consolidated shipments, and predicted potential transportation delays. The evaluation metrics included average delivery time, fuel consumption, and cost savings.

By employing machine learning models to predict and optimize transport routes, the system achieved a **30% reduction in transportation costs** and an **18% decrease in delivery times**. Historical shipping data allowed AI models to identify patterns in traffic congestion, weather disruptions, and delivery delays. The system then provided alternative routes and reallocation strategies to ensure timely deliveries.

Additionally, predictive analytics helped warehouse managers anticipate demand surges and plan shipments accordingly. A key finding was that dynamic route adjustments based on real-time traffic conditions led to a **12% improvement in delivery consistency**, reducing unexpected delays caused by road congestion or weather issues.

The implementation of automated vehicle load optimization further enhanced efficiency by ensuring that trucks were loaded to optimal capacity while complying with weight and volume constraints. This not only reduced fuel consumption but also minimized empty miles, resulting in lower carbon emissions and improved environmental sustainability.

Packing Optimization for Shipping

The packing optimization module was tested on large-scale shipments in the garment industry, where box dimensions, container space, and weight constraints were analyzed. The system's performance was evaluated based on packing efficiency, space utilization, and loading time reduction.

Using a hybrid approach combining **3D bin packing algorithms, AI-based reinforcement learning, and constraint-based optimization**, the system achieved a **40% improvement in container space utilization**. Traditional packing methods often resulted in wasted space due to inefficient box arrangements. However, by dynamically adjusting packing strategies, the AI model ensured that each container was utilized to its maximum capacity while adhering to weight distribution constraints.

Real-world deployment demonstrated a **25% reduction in loading times**, as workers followed AI-generated step-by-step packing instructions. The interactive mobile app provided graphical visualizations and textual guidance, enabling workers to execute packing plans with precision. The ability to modify packing instructions in real-time based on unforeseen constraints further enhanced operational efficiency.

Additionally, the reinforcement learning model continuously improved packing strategies by learning from past shipments. Over time, the AI adapted to different order compositions and optimized box placement strategies accordingly. This resulted in an **18% decrease in shipping costs**, as more efficient packing led to fewer containers being required for the same volume of goods.

Supplier Selection and Evaluation

To assess the **effectiveness of the AI-driven ranking model**, its performance is compared to **traditional supplier evaluation methods** (manual ranking & rule-based selection).

Method	**Accuracy**	**Time Efficiency**	**Adaptability**
Manual Ranking (Human Decision-Making)	75%	Slow	Low
Rule-Based Supplier Selection	85%	Moderate	Fixed Rules
AI-Driven Supplier Ranking (This Model)	99.9%	Fast	High

[21][22][23]

Overall Impact and Discussion

The integration of AI-based methodologies into the supply chain management system demonstrated substantial improvements across all four features. The key findings are summarized as follows:

1. **Operational Efficiency Gains:** Across all modules, AI-driven automation reduced manual workload, improved decision-making accuracy, and minimized delays.
2. **Cost Reductions:** The AI-based approach led to significant cost savings in production scheduling, logistics, packing, and procurement processes.
3. **Scalability and Adaptability:** The system proved highly adaptable to real-world challenges, dynamically adjusting strategies based on real-time data inputs.
4. **User-Friendly Interface:** The mobile application enhanced usability by providing intuitive packing guidance, real-time updates, and interactive visualizations.

A comparative analysis with traditional supply chain management approaches showed that AI integration improved overall efficiency by **35%**. While the initial implementation required investment in AI training and system setup, the long-term benefits outweighed the costs, resulting in higher profitability and streamlined operations.

Challenges and Limitations: Despite its advantages, the system faced challenges such as:

- **Initial AI Training Requirements:** The reinforcement learning model required extensive historical data to achieve high accuracy.
- **Worker Adaptation:** Employees needed training to effectively use the AI-generated recommendations.
- **Data Dependency:** The effectiveness of predictive analytics depended on the availability and accuracy of real-time data.

Future Enhancements: Potential improvements include:

- **Integration with IoT Sensors:** Real-time tracking of production, shipment, and supplier performance through IoT-enabled devices.
- **Advanced NLP-Based Interaction:** Using natural language processing (NLP) to enable voice-command-based AI assistance.
- **Blockchain for Supplier Transparency:** Implementing blockchain to enhance supply chain visibility and fraud prevention.

In conclusion, the AI-driven ChainMaster system presents a transformative approach to garment industry supply chain management. By leveraging AI, machine learning, and real-time analytics, the system enhances efficiency, reduces costs, and improves decision-making capabilities. The findings validate the potential of AI-powered supply chain solutions to revolutionize logistics, procurement, and operational workflows in the garment industry.

V. Conclusion

The implementation of ChainMaster marks a significant advancement in supply chain management for the garment industry. Through AI-driven production scheduling, the system ensures optimal resource allocation and minimal downtime, leading to increased operational efficiency. The logistics and transportation optimization feature further enhances efficiency by minimizing delivery delays and reducing transportation costs through predictive analytics and smart routing.

The packing optimization for shipping incorporates advanced bin packing algorithms to maximize space utilization, which directly lowers shipping expenses and improves order fulfillment accuracy. Furthermore, AI-powered supplier selection and evaluation streamline procurement processes by identifying the most cost-effective and reliable suppliers, ultimately improving product quality and consistency.

Collectively, these four key features of ChainMaster contribute to a seamless and intelligent supply chain management system. By integrating real-time data analysis, machine learning, and automation, ChainMaster mitigates inefficiencies that have historically plagued the garment industry. The comparison with traditional SCM approaches highlights the superior performance of this AI-based system in cost reduction, operational agility, and decision-making accuracy.

As the garment industry continues to evolve in response to market demands and technological advancements, AI-driven supply chain solutions like ChainMaster will play a crucial role in maintaining competitiveness. Future enhancements may include deeper AI integration, blockchain-based transparency, and IoT-enabled tracking for even greater efficiency and reliability. Ultimately, ChainMaster exemplifies how AI can revolutionize supply chain processes, setting a new standard for efficiency, cost-effectiveness, and sustainability in the garment sector.

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