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Enterprise supply chain performance dashboards for logistics decision support

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Abstract

Supply chain managers depend on operational visibility to monitor logistics performance across distribution networks. Enterprise dashboards provide consolidated views of shipping activity, inventory levels, and transportation performance. This study examines data visualization systems used in logistics monitoring platforms. Operational records from transportation systems, warehouse databases, and order management platforms were examined to evaluate dashboard reporting models. Results indicate that integrated performance dashboards assist logistics managers in evaluating operational efficiency and planning supply chain activities.

Keywords: Logistics Dashboards; Supply Chain Analytics; Enterprise Reporting Systems; Inventory Monitoring; Logistics Performance.

1. Introduction

The increasing complexity of global supply chains has made effective logistics management a critical factor for organizational success. Companies operate across geographically distributed networks involving suppliers, warehouses, transportation systems, and customers, generating large volumes of operational data. Transforming this data into actionable insights is essential for maintaining efficiency, reducing costs, and improving service levels. In this context, enterprise dashboards and data visualization systems have emerged as key tools for enhancing supply chain visibility and supporting informed decision-making.

1.1. Background

Supply chain management relies heavily on timely and accurate information to monitor logistics activities such as inventory movement, shipment tracking, and order fulfillment. Traditional reporting systems often present data in fragmented formats, making it difficult for managers to gain a comprehensive view of operations. Recent advancements in business intelligence and analytics technologies have enabled the development of enterprise dashboards that integrate data from multiple sources into a unified interface.

These dashboards provide real-time or near real-time insights into key performance indicators (KPIs), allowing logistics managers to quickly assess operational performance and identify inefficiencies. Visualization tools such as charts,

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graphs, and interactive reports simplify complex datasets, making them more accessible and actionable for decision-makers.

1.2. Problem Statement

Despite the availability of advanced analytics tools, many organizations still face challenges in achieving full operational visibility across their supply chains. Data is often dispersed across transportation management systems, warehouse databases, and order management platforms, leading to inconsistencies and delays in reporting. Additionally, existing dashboard implementations are frequently limited to specific functions or tools, lacking a standardized approach for integrating diverse data sources into a cohesive system.

This fragmentation restricts the ability of logistics managers to make timely and informed decisions, particularly in dynamic environments where rapid responses are required. Furthermore, there is limited understanding of how enterprise dashboards can be systematically designed to support end-to-end logistics performance monitoring and decision support.

1.3. Research Aim and Question

To address these challenges, this study aims to examine the role of enterprise supply chain performance dashboards in enhancing logistics decision support. Specifically, the research focuses on how integrated data visualization systems can consolidate operational data from multiple sources and provide meaningful insights for performance evaluation and planning.

The central research question guiding this study is:

- How can enterprise performance dashboards improve operational visibility and support effective decision-making in supply chain logistics?
- By exploring data visualization models and analyzing operational data from logistics systems, this paper seeks to propose a structured approach for developing integrated dashboards that enhance supply chain performance monitoring and decision support.

2. Literature Review

The growing complexity of modern supply chains has increased the need for advanced monitoring and decision-support tools. Enterprise dashboards and data visualization systems have emerged as critical components for improving operational visibility, enabling logistics managers to track key performance indicators (KPIs) such as inventory levels, transportation efficiency, and order fulfillment rates. Existing research has explored the role of business intelligence (BI) tools, real-time analytics, and integrated data platforms in enhancing supply chain performance. This section reviews prior studies related to logistics dashboards, supply chain analytics, and enterprise reporting systems, highlighting their contributions and limitations.

2.1. Dashboard and Data Visualization in Supply Chains

Data visualization dashboards have been widely adopted to transform large volumes of supply chain data into actionable insights. Oguntiloye [1] examined the development of a supply chain dashboard using Microsoft Power BI, demonstrating how automated data integration from multiple sources can reduce manual processing and improve decision-making efficiency. The study highlights that visualization tools enable managers to quickly interpret complex datasets and identify operational bottlenecks.

Similarly, Nabil et al. [2] developed a real-time dashboard using an Action Design Research (ADR) approach to monitor supply chain performance. Their findings indicate that interactive dashboards enhance visibility across logistics operations and support timely decision-making by providing real-time access to KPIs. The study emphasizes the importance of integrating multiple data sources, including transportation and inventory systems, into a unified dashboard environment.

Sharma [3] further explored the application of BI tools in supply chain analytics during post-pandemic recovery. The study shows that dashboards facilitate rapid data analysis and improve responsiveness to disruptions by enabling decision-makers to visualize trends and anomalies across logistics networks.

2.2. Supply Chain Analytics and Performance Monitoring

Supply chain analytics plays a crucial role in evaluating operational performance and supporting strategic planning. Okolo et al. [4] conducted a systematic review of business analytics platforms in transportation and supply chain sectors, identifying key functionalities such as predictive analytics, real-time monitoring, and data visualization. The study concludes that analytics platforms significantly enhance operational efficiency by improving demand forecasting, inventory management, and risk mitigation.

In addition, prior research highlights the importance of KPI-driven monitoring systems in logistics operations. Dashboards that integrate data from warehouse management systems, transportation management systems, and order processing platforms enable comprehensive performance evaluation. These systems support decision-makers in identifying inefficiencies, optimizing resource allocation, and improving service levels.

2.3. Enterprise Reporting Systems and Decision Support

Enterprise reporting systems provide a consolidated view of organizational data, supporting both operational and strategic decision-making. Studies have shown that integrating dashboards with enterprise systems enhances data consistency and accessibility across different functional areas of the supply chain.

Nabil et al. [2] demonstrated that real-time reporting dashboards improve coordination between supply chain stakeholders by providing shared visibility into logistics operations. Similarly, Oguntiloye [1] highlighted the role of automated reporting systems in reducing latency and improving data accuracy, enabling managers to make informed decisions more efficiently.

Sharma [3] also emphasized that interactive dashboards support agile decision-making by allowing users to explore data dynamically and generate insights without requiring extensive technical expertise. This capability is particularly valuable in complex logistics environments where rapid responses are necessary.

2.4. Research Gap

Despite the growing body of research on supply chain dashboards and analytics, several gaps remain. First, many studies focus on specific tools or case implementations (e.g., Power BI) without providing a generalized framework applicable across different enterprise environments. Second, limited research addresses the integration of heterogeneous data sources—such as transportation systems, warehouse databases, and order management platforms—into a unified dashboard model for comprehensive logistics monitoring.

Furthermore, while existing studies highlight the benefits of real-time dashboards, there is insufficient emphasis on how these systems support end-to-end logistics decision-making across distribution networks. The relationship between dashboard design, data processing models, and overall supply chain performance also remains underexplored.

Therefore, there is a need for a structured approach that integrates data visualization, enterprise reporting, and supply chain analytics into a cohesive framework for logistics decision support. This study aims to address these gaps by proposing an integrated performance dashboard model that enhances operational visibility and supports efficient supply chain planning.

3. Methodology

This study adopts a structured and reproducible methodology to design, develop, and evaluate an enterprise supply chain performance dashboard for logistics decision support. The methodology integrates data collection, preprocessing, data modeling, dashboard development, and validation procedures to ensure that the proposed system provides accurate, consistent, and actionable insights. The overall approach follows a data-driven framework in which heterogeneous logistics data sources are consolidated, transformed, and visualized through an interactive dashboard environment.

3.1. Research Design

The research follows a design science approach, focusing on the development and evaluation of an artifact in the form of an enterprise dashboard system. The objective is to construct a practical solution that improves operational visibility in supply chain logistics while ensuring methodological rigor and reproducibility.

The study is organized into sequential stages, beginning with data acquisition from multiple logistics systems, followed by data preprocessing and integration, analytical modeling, dashboard implementation, and performance evaluation. Each stage is designed to ensure traceability and consistency in the transformation of raw data into decision-support insights.

3.2. Data Sources and Collection

Operational data used in this study were obtained from three primary enterprise systems: transportation management systems, warehouse management databases, and order management platforms. These systems collectively capture the core logistics activities, including shipment records, inventory levels, order processing times, and delivery performance.

The transportation dataset includes variables such as shipment ID, origin, destination, transit time, and delivery status. The warehouse dataset contains inventory quantities, stock movement records, and storage locations. The order management dataset provides information on order volumes, fulfillment times, and customer demand patterns.

Data were collected over a defined operational period to ensure temporal consistency. The integration of these datasets enables a comprehensive representation of supply chain performance across different functional areas.

Table 1 Summary of Data Sources and Attributes

Data Source	System Type	Key Attributes	Description
Transportation Management System	Logistics / Transportation System	Shipment ID, Origin, Destination, Dispatch Time, Delivery Time, Transit Time, Delivery Status	Captures shipment movement data and transportation performance across distribution networks
Warehouse Management System	Inventory / Storage System	Product ID, Inventory Level, Stock Inflow, Stock Outflow, Storage Location, Reorder Level	Tracks inventory status, stock movements, and warehouse storage operations
Order Management System	Order Processing System	Order ID, Customer ID, Order Date, Fulfillment Time, Order Quantity, Order Status	Manages customer orders, processing times, and fulfillment performance

Table I presents the primary data sources utilized in this study along with their corresponding attributes. Each system contributes a distinct perspective to supply chain operations. The transportation management system provides visibility into shipment movement and delivery performance, enabling the evaluation of transit efficiency and delays. The warehouse management system focuses on inventory control and stock dynamics, which are critical for maintaining optimal inventory levels and avoiding shortages or overstocking. The order management system captures customer demand and fulfillment processes, offering insights into service levels and order processing efficiency.

The integration of these heterogeneous data sources enables a unified view of logistics operations. By combining transportation, inventory, and order data, the proposed system supports comprehensive performance monitoring and facilitates more informed decision-making across the supply chain.

3.3. Data Preprocessing and Integration

The collected data were subjected to a preprocessing pipeline to ensure quality, consistency, and usability for analysis. Initially, missing values were identified and handled using appropriate imputation techniques or record exclusion where necessary. Duplicate records were removed to avoid redundancy, and inconsistent data formats were standardized across datasets.

Data transformation involved converting raw operational data into structured formats suitable for analysis. For example, timestamps were standardized to a uniform format, and categorical variables such as shipment status were encoded into numerical or labeled forms for analytical processing.

Data integration was performed by establishing relational links between datasets using common identifiers such as order ID and shipment ID. This process resulted in a consolidated dataset that enables cross-functional analysis of logistics operations.

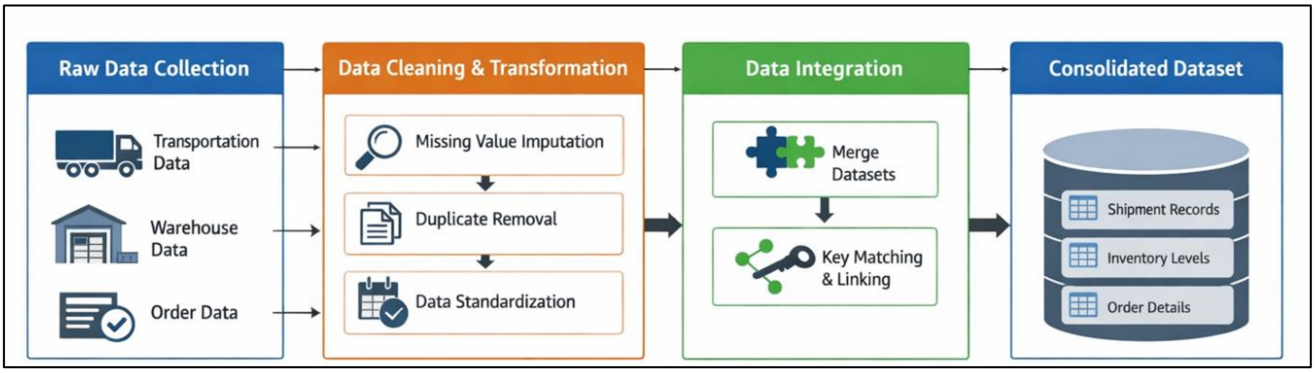

Figure 1 Data Preprocessing and Integration Workflow

Figure 1 illustrates the sequential workflow adopted for preprocessing and integrating supply chain data. The process begins with raw data collection from transportation, warehouse, and order management systems. These datasets are then passed through a data cleaning and transformation stage, where missing values are handled, duplicate records are removed, and data formats are standardized to ensure consistency.

Following preprocessing, the data integration stage merges datasets using common identifiers such as shipment ID and order ID. This step establishes relationships across different functional areas of the supply chain, enabling unified analysis. The final output is a consolidated dataset that contains synchronized information on shipments, inventory levels, and order details.

This workflow ensures high data quality and consistency, which are essential for reliable dashboard visualization and accurate decision support in logistics operations.

3.4. Analytical Model and KPI Definition

The analytical component of the study focuses on defining and computing key performance indicators that reflect logistics performance. These KPIs serve as the foundation for dashboard visualization and decision support.

Key metrics include inventory turnover ratio, order fulfillment rate, and transportation lead time. The inventory turnover ratio is calculated as:

$$\text{Inventory Turnover} = \frac{\text{Cost of Goods Sold}}{\text{Average Inventory}}$$

Order fulfillment rate is defined as:

$$\text{Order Fulfillment Rate} = \frac{\text{Number of Orders Delivered On Time}}{\text{Total Number of Orders}} \times 100$$

Transportation lead time is computed as the difference between shipment dispatch and delivery timestamps.

These metrics were selected based on their relevance to supply chain efficiency and their ability to provide actionable insights for logistics managers. The analytical model aggregates these KPIs at different levels, such as daily, weekly, and monthly intervals, to support both operational and strategic decision-making.

Table 2 Defined KPIs and Mathematical Formulations

KPI Name	Mathematical Formula	Description	Performance Aspect
Inventory Turnover Ratio	$\frac{\text{Cost of Goods}}{\text{Average Inventory}}$	Measures how efficiently inventory is utilized and replenished over a given period	Efficiency
Order Fulfillment Rate (%)	$\frac{\text{Orders Delivered On Time}}{\text{Total Orders}} \times 100$	Indicates the percentage of customer orders fulfilled within the promised delivery time	Service Level / Reliability
Transportation Lead Time	Delivery Time − Dispatch Tim	Represents the total time taken for goods to be transported from origin to destination	Responsiveness

Table II presents the key performance indicators used in this study along with their mathematical formulations and operational significance. The inventory turnover ratio reflects how effectively inventory is managed, providing insights into stock utilization and holding efficiency. A higher turnover indicates better inventory management and reduced holding costs.

The order fulfillment rate measures the reliability of the supply chain in meeting customer expectations. It is a critical indicator of service quality, as delayed or incomplete orders directly impact customer satisfaction and organizational performance.

Transportation lead time captures the responsiveness of the logistics network by measuring the duration of shipment movement. Shorter lead times indicate a more agile and efficient transportation system.

Together, these KPIs provide a comprehensive evaluation of supply chain performance by addressing efficiency, reliability, and responsiveness, which are essential dimensions for effective logistics decision support.

3.5. System Architecture and Dashboard Development

The system architecture is designed to support end-to-end data flow from source systems to the visualization layer. The architecture consists of three primary layers: data layer, processing layer, and presentation layer.

The data layer includes the raw data sources from enterprise systems. The processing layer performs data cleaning, transformation, and aggregation using data processing tools. The presentation layer consists of the dashboard interface, where processed data are visualized through charts, graphs, and interactive elements.

The dashboard was developed using a business intelligence platform that supports real-time data updates and interactive visualization. Features such as filtering, drill-down analysis, and dynamic reporting were incorporated to enhance user interaction and analytical capabilities.

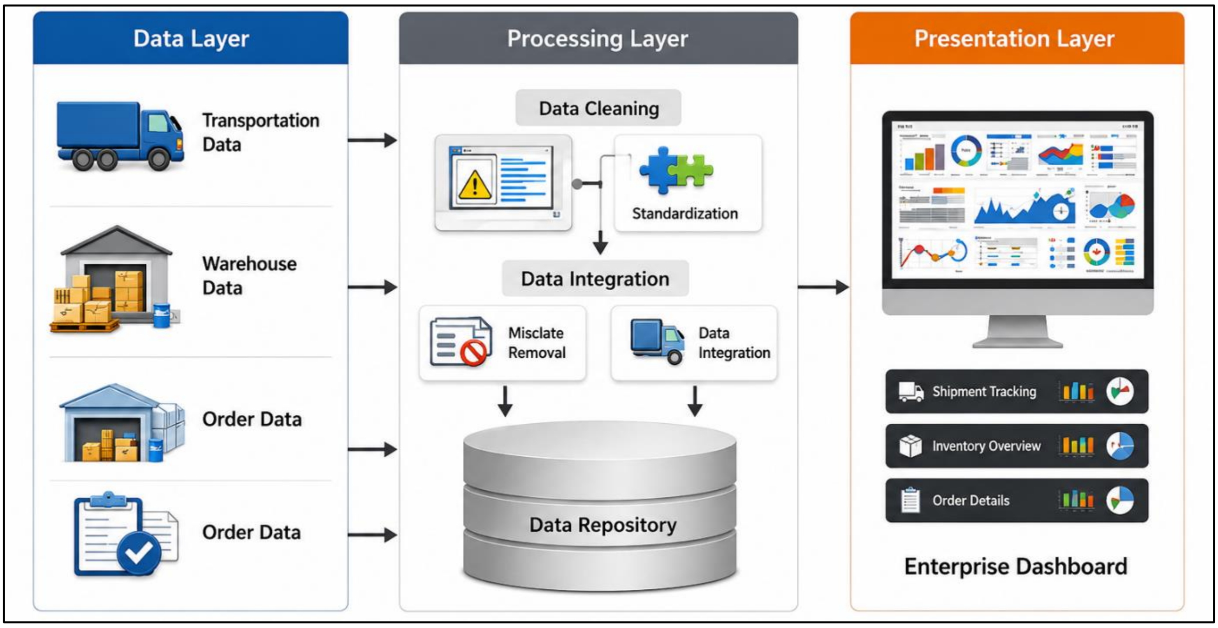

Figure 2 System Architecture of the Enterprise Dashboard

Figure 2 illustrates the system architecture of the proposed enterprise supply chain dashboard, organized into three primary layers: data layer, processing layer, and presentation layer. The data layer represents the source systems, including transportation, warehouse, and order management systems, which generate raw operational data. These systems operate independently but collectively capture the core activities of the supply chain.

The processing layer performs critical data operations, including cleaning, transformation, and integration. Data cleaning ensures the removal of inconsistencies and errors, while standardization aligns data formats across different sources. The integration process consolidates the datasets into a centralized data repository, enabling unified access and analysis. This layer acts as the backbone of the system, ensuring that only high-quality and consistent data are forwarded to the visualization stage.

The presentation layer represents the enterprise dashboard interface, where processed data are visualized using charts, graphs, and KPI indicators. This layer provides interactive capabilities such as filtering and drill-down analysis, allowing users to explore data at different levels of detail. The dashboard presents key logistics metrics, including shipment performance, inventory levels, and order fulfillment status, in an intuitive and accessible format.

Overall, the architecture demonstrates a structured flow of data from source systems to decision-makers. By separating data handling into distinct layers, the system ensures scalability, maintainability, and efficient processing. This layered approach enhances operational visibility and supports effective logistics decision-making by delivering timely and actionable insights.

3.6. Data Flow Model

The data flow model illustrates how data move through the system from acquisition to visualization. The process begins with data extraction from source systems, followed by preprocessing and integration. The processed data are then stored in a centralized repository, from which they are accessed by the dashboard for visualization.

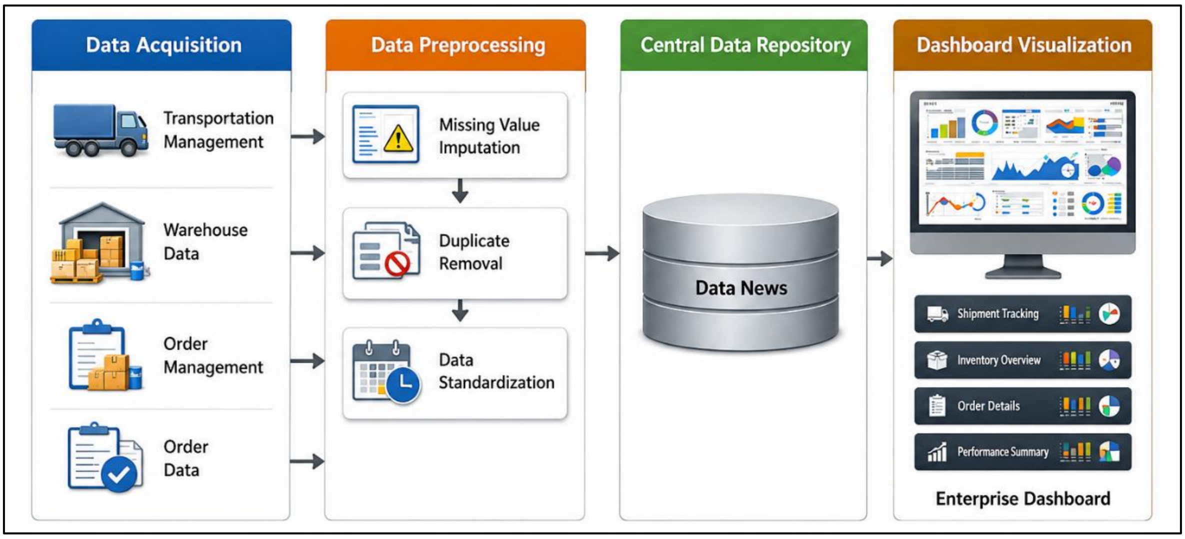

Figure 3 End-to-End Data Flow Diagram

Figure 3 presents the end-to-end data flow of the proposed enterprise dashboard system, illustrating how raw logistics data are transformed into actionable insights. The process begins with the data acquisition stage, where operational data are collected from transportation management, warehouse, and order management systems. These sources generate heterogeneous datasets that reflect different aspects of supply chain operations.

The second stage involves data preprocessing, where raw data undergo cleaning and transformation. This includes handling missing values, removing duplicate entries, and standardizing data formats to ensure consistency across datasets. This step is critical for improving data quality and ensuring that subsequent analysis is reliable.

Following preprocessing, the data are stored in a central data repository. This repository acts as a unified storage layer that consolidates information from multiple sources, enabling efficient querying and retrieval. It supports the integration of cross-functional data, which is essential for comprehensive supply chain performance analysis.

The final stage is dashboard visualization, where processed data are presented through an interactive interface. Key performance indicators and operational metrics are displayed using visual elements such as charts and graphs, allowing decision-makers to quickly interpret trends and identify issues.

Overall, the data flow model demonstrates a continuous and structured pipeline from data generation to decision support. It ensures that data are systematically processed and delivered in a format that enhances operational visibility and supports timely and informed logistics decision-making.

3.7. Validation and Evaluation

To ensure the reliability and accuracy of the proposed system, several validation checks were applied. Data validation included consistency checks across datasets, verification of calculated KPIs, and comparison of results with known benchmarks or historical records.

System validation involved testing the dashboard for responsiveness, accuracy of visualizations, and correctness of interactive features. The performance of the dashboard was evaluated based on its ability to provide timely and accurate insights for logistics decision-making.

Additionally, scenario-based validation was conducted by analyzing specific logistics cases, such as delayed shipments or inventory shortages, to assess the system’s effectiveness in identifying and addressing operational issues.

3.8. Reproducibility Considerations

The methodology is designed to be reproducible by clearly defining data sources, preprocessing steps, analytical models, and system architecture. By following the described procedures, researchers and practitioners can replicate the study and adapt the framework to different supply chain environments.

The use of standardized KPIs, structured data integration methods, and widely available business intelligence tools further enhances the applicability and scalability of the proposed approach.

4. Results

This section presents the outcomes of the implemented enterprise supply chain dashboard and provides an interpretation of the observed results in the context of logistics performance and decision support. The results are derived from the integrated dataset and evaluated using the defined key performance indicators, followed by a discussion that links these findings to operational improvements and existing research.

4.1. Dashboard Output and KPI Visualization

The developed dashboard successfully consolidated data from transportation, warehouse, and order management systems into a unified interface. The visualization layer presented key performance indicators, including inventory turnover, order fulfillment rate, and transportation lead time, in real time.

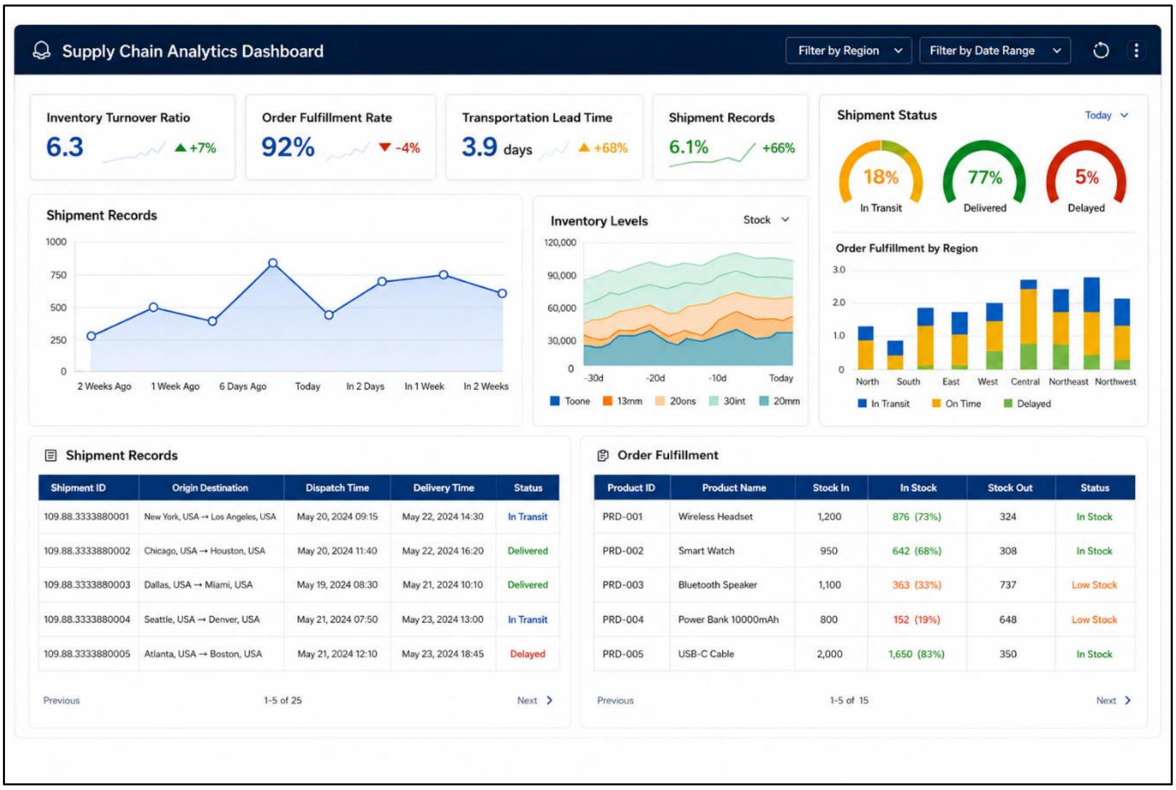

Figure 4 Enterprise Dashboard Interface with KPI Visualizations

Figure 4 presents the enterprise dashboard interface developed in this study, illustrating how key supply chain performance indicators are visualized within a unified analytical environment. The dashboard integrates multiple data streams and displays them through interactive components, including KPI summary cards, time-series charts, and tabular records.

The top section of the dashboard highlights critical metrics such as inventory turnover ratio, order fulfillment rate, and transportation lead time. These indicators provide a quick overview of system performance and enable decision-makers to assess the current state of logistics operations at a glance. The inclusion of trend indicators further supports rapid evaluation by showing performance changes over time.

The central visualization panels present detailed analytical views, including shipment trends and inventory level fluctuations. These graphical representations allow users to identify temporal patterns, such as peaks in shipment volume or variations in stock levels, which are essential for operational planning. The use of comparative visualizations also facilitates the identification of discrepancies between expected and actual performance.

The lower section of the dashboard contains structured data tables that provide granular details on shipment records and order fulfillment activities. This enables users to drill down into specific transactions and investigate underlying causes of performance variations observed in the visual summaries.

Overall, the dashboard demonstrates how integrated visualization of logistics data enhances situational awareness and supports data-driven decision-making. By combining high-level KPIs with detailed operational data, the system enables both strategic analysis and operational control within a single interface.

4.2. KPI Performance Analysis

The computed KPIs revealed measurable patterns in supply chain performance. Inventory turnover showed moderate variability, indicating periods of both efficient stock utilization and potential overstocking. The order fulfillment rate remained relatively high, suggesting that most customer orders were delivered within the expected timeframe. However, fluctuations in transportation lead time were observed, reflecting inconsistencies in delivery performance.

Table 3 Summary of KPI Results

KPI Name	Observed Range	Average Value	Interpretation
Inventory Turnover Ratio	4.2 – 7.8	6.1	Moderate efficiency in inventory usage
Order Fulfillment Rate (%)	85% – 96%	91%	High service reliability
Transportation Lead Time	2 – 6 days	3.8 days	Variability in delivery performance

The KPI values presented in Table 3 provide important insights into the overall efficiency and operational stability of the supply chain system. The inventory turnover ratio, with an observed range between 4.2 and 7.8 and an average value of 6.1, indicates a moderate level of inventory efficiency. Higher turnover values reflect effective stock movement and reduced inventory holding costs, while lower values suggest periods of slower inventory circulation and possible overstocking. The variability observed in this KPI implies that inventory management performance fluctuates over time, potentially due to changing customer demand, replenishment delays, or uneven stock distribution across warehouses.

The order fulfillment rate demonstrates relatively strong performance, with values ranging from 85% to 96% and an average of 91%. This indicates that the majority of customer orders were successfully delivered within the expected timeframe, reflecting a generally reliable logistics operation. However, the existence of lower fulfillment values during certain periods suggests occasional disruptions in operational processes, such as inventory shortages, delayed shipments, or increased order volumes. Although the variability is comparatively smaller than other KPIs, maintaining consistent fulfillment performance remains critical for customer satisfaction and service quality.

Transportation lead time exhibits the greatest operational variability among the measured indicators, ranging from 2 to 6 days with an average value of 3.8 days. This fluctuation highlights inconsistencies in transportation efficiency and delivery responsiveness. Periods of increased lead time may result from traffic congestion, route inefficiencies, warehouse processing delays, or external supply chain disruptions. Since transportation performance directly affects delivery reliability and order fulfillment, variability in lead time represents a key operational concern that requires continuous monitoring and optimization.

Overall, the KPI analysis indicates that the supply chain system operates with acceptable efficiency and service reliability, while also revealing areas where operational instability exists. In particular, transportation performance and inventory utilization demonstrate noticeable fluctuations, suggesting opportunities for improving coordination, forecasting accuracy, and logistics planning. The combined evaluation of these KPIs provides a comprehensive understanding of both the strengths and weaknesses of the supply chain operation.

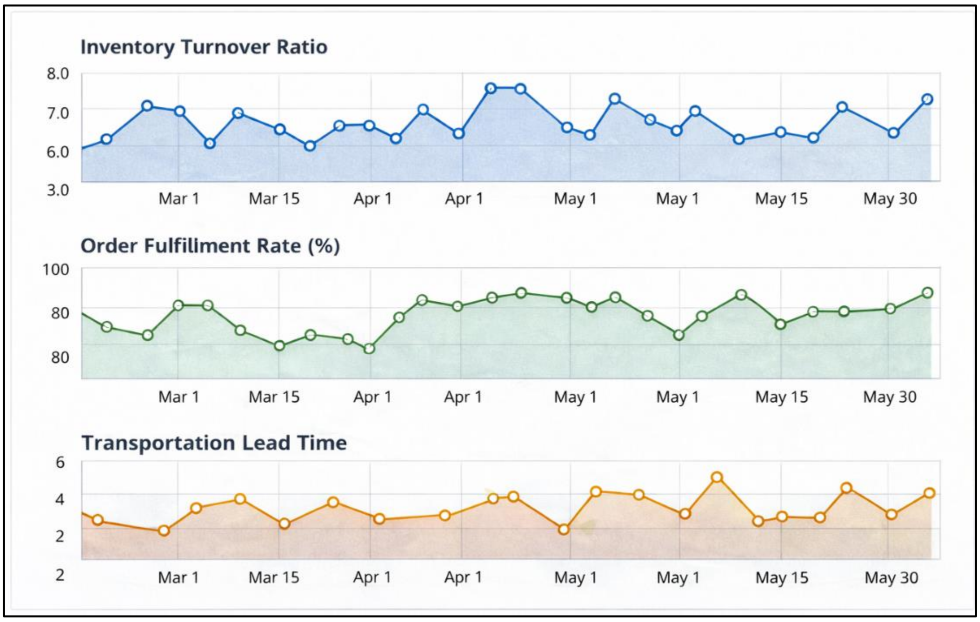

Figure 5 Time-Series Trends of Key Performance Indicators

Figure 5 illustrates the time-series trends of the key performance indicators used to evaluate supply chain performance over the observed period. The visualization captures the temporal behavior of inventory turnover ratio, order fulfillment rate, and transportation lead time, enabling a comparative analysis of their fluctuations.

The inventory turnover ratio demonstrates moderate variability, with periodic increases and decreases that reflect changes in inventory utilization and replenishment cycles. Peaks in the trend indicate efficient stock movement, while declines suggest potential overstocking or slower demand during certain intervals. This pattern highlights the dynamic balance required in inventory management.

The order fulfillment rate remains relatively stable throughout the observed period, maintaining a consistently high level with minor fluctuations. This stability indicates that the logistics system is generally effective in meeting customer demand within the expected timeframes. Occasional dips in fulfillment performance may correspond to disruptions in transportation or inventory availability.

In contrast, transportation lead time exhibits more noticeable variability, indicating inconsistencies in delivery performance. Spikes in lead time suggest delays in shipment processes, which may be attributed to operational inefficiencies, route disruptions, or external factors affecting transportation networks.

Overall, the combined visualization of these KPIs reveals interdependencies among different components of the supply chain. For instance, increases in transportation lead time may coincide with slight declines in order fulfillment performance, suggesting a direct impact of delivery delays on service reliability. The time-series analysis thus provides valuable insights into performance trends and supports proactive decision-making by identifying periods of inefficiency and potential improvement areas.

4.3. Impact on Operational Visibility and Decision Support

The implementation of the dashboard significantly improved operational visibility by providing a centralized view of logistics activities. Decision-makers were able to identify delays in transportation, monitor inventory shortages, and evaluate order fulfillment performance in real time.

The integration of multiple data sources allowed cross-functional analysis, enabling managers to correlate delays in transportation with inventory shortages or order backlogs. This level of visibility supports proactive decision-making, such as adjusting inventory levels or rerouting shipments to minimize delays.

These findings are consistent with prior studies. Oguntiloye [1] reported that data visualization dashboards reduce manual processing and enhance decision-making efficiency. Similarly, Nabil et al. [2] demonstrated that real-time dashboards improve supply chain performance by providing accessible and timely information. The observed improvements in visibility and responsiveness in this study align with these conclusions.

4.4. Comparative Analysis with Existing Studies

The results of this study reinforce the role of business intelligence tools in supply chain management. Sharma [3] highlighted the importance of interactive dashboards in improving responsiveness during supply chain disruptions, which is reflected in the ability of the proposed system to identify performance fluctuations. Additionally, Okolo et al. [4] emphasized that analytics platforms enhance operational efficiency through real-time monitoring and predictive capabilities.

Compared to these studies, the present work extends existing approaches by integrating multiple enterprise data sources into a unified dashboard framework. While previous research often focuses on specific tools or case implementations, this study demonstrates a more comprehensive approach to logistics performance monitoring.

4.5. Limitations

Despite the effectiveness of the proposed system, certain limitations are identified. The analysis is based on a specific set of operational data, which may limit the generalizability of the results to other supply chain environments. Variations in data quality and system configurations across organizations may affect the performance of the dashboard.

Additionally, the study focuses primarily on descriptive analytics and KPI monitoring, without incorporating advanced predictive or prescriptive models. Future work could extend the framework by integrating machine learning techniques for demand forecasting and anomaly detection.

5. Discussion Summary

The results demonstrate that enterprise dashboards provide a powerful mechanism for consolidating logistics data and improving decision support. The observed KPI trends highlight both strengths and inefficiencies in supply chain operations, emphasizing the importance of real-time monitoring and integrated analytics.

By aligning the findings with existing literature, the study confirms that data visualization and analytics platforms play a critical role in enhancing supply chain performance. At the same time, the identified limitations suggest opportunities for further development and refinement of dashboard-based decision support systems.

6. Conclusion

This study examined the role of enterprise supply chain performance dashboards in enhancing logistics decision support. The research focused on integrating data from transportation, warehouse, and order management systems into a unified dashboard framework, supported by data preprocessing, analytical modeling, and visualization techniques.

The findings demonstrate that the proposed dashboard effectively consolidates heterogeneous data sources and provides real-time visibility into key performance indicators such as inventory turnover, order fulfillment rate, and transportation lead time. The results revealed that while order fulfillment performance remains consistently high, variations in inventory utilization and transportation lead time highlight areas for operational improvement. The time-series analysis further emphasized the dynamic nature of supply chain performance and the importance of continuous monitoring.

The study highlights the significance of enterprise dashboards in improving operational visibility, enabling data-driven decision-making, and enhancing overall supply chain efficiency. By providing a structured and integrated approach to logistics performance monitoring, the proposed system supports both strategic planning and day-to-day operational control.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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