

# LOGISTICS OPTIMIZATION FOR E-COMMERCE USING PREDICTIVE ANALYTICS AND MICRO WAREHOUSING

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## ABSTRACT

The e-commerce industry is growing rapidly with increasing need to optimize delivery schedules and efficiently manage resources. This project introduces an advanced Decision Support System (DSS) designed to tackle these challenges by using data-driven strategies to streamline delivery processes, consolidate orders, and boost operational efficiency. By analyzing historical data and order patterns, the DSS predicts future delivery needs, reduce inefficiencies in order fulfillment. Through the use of geographic clustering for micro warehousing and demand forecasting, the system enables smarter delivery scheduling and resource allocation. This results in reduction of delivery costs, better use of resources and accurate deliveries which leads to improve customer satisfaction. This project provides an innovative solution to modern e-commerce logistics challenges and provide a way for more efficient delivery systems.

Keywords: Decision Support System (DSS), data-driven strategies, demand forecasting, spatial clustering, delivery scheduling

## 1. INTRODUCTION

The rapid growth of the e-commerce sector has increased the demand for fast and reliable delivery. Businesses can adapt to increased expectations for same-day and same-hour service. while maintaining a balance between speed and operational efficiency. Poor planning can result in higher shipping costs, delays, and dissatisfied customers [1]. Decision support systems (DSS) are designed to improve shipping processes, reduce costs, and increase customer satisfaction. Because delays are often caused by insufficient planning or poor inventory management [2]

By analyzing pre-order data and identifying trends, DSS can predict future shipping needs. Helps make planning more efficient and adjusting strategies in real time [3]. Box and Jenkins techniques help accurately predict demand. And geographic clustering in high-demand areas helps create smaller warehouses. which reduces costs and accelerates delivery [4]. Batch orders to similar destinations and reduce travel to delivery. Reduce costs and improve efficiency. Real-time customer engagement tools help users set delivery priorities. Improve the overall experience [5].[6] By using sophisticated data analytics for demand forecasting and distribution schedules, DSS helps ensure efficient resource allocation. Helping businesses Plan inventory and distribution in advance [7]. In summary, DSS offers a comprehensive solution to logistics challenges in e-commerce. This reduces costs and improves delivery speed and customer satisfaction.

## 2. LITERATURE REVIEW

### 2.1 How Decision Support Systems (DSS) impact E-commerce

A decision support system (DSS) is a computer-based tool that helps decision makers in making informed decisions. As the complexity of distribution in logistics increases, the demand for DSS in the e-commerce also increases. This increase the need for real-time data to optimize the distribution channels while ensuring the product distribution is efficient and effective while managing stocks and inventory. More importantly prioritizing customer satisfaction and improving processes. Advanced DSS enhances the customer experience by making the system timelier and more reliable.

### 2.2 Algorithms used in Delivery Systems

Today's e-commerce delivery systems use various optimization algorithms to address logistical challenges. These algorithms reduce cost and increases operational efficiency, which is obtained by optimal resource allocation and route planning. By utilizing optimization algorithms and techniques, businesses can improve their delivery mechanism, improve warehouse management and solve various logistical problems, resulting in faster delivery times and reduced costs.

### 2.3 Demand Forecasting, Micro-Warehousing and Predictive Stocking

Hence the concept of micro-warehouse is utilized which greatly improved e-commerce logistics efficiency. These are small, strategically located warehouses that are benefited from predictive storage techniques utilizing demand

forecasting, predictive modelling by machine learning and time series forecasts. Through decentralizing inventory closer to the customer, businesses can shorten delivery times and ensure faster order fulfillment. This technique optimizes inventory levels and reduce shipping costs. Thus, increasing customer satisfaction with faster delivery.

## 2.4 Forecasting Demand and Identifying Customer Preferences

Accurate demand forecasts are essential for order fulfillment. Inventory management and efficient on-time delivery in e-commerce Analysis of historical data and consumer behavior through advanced models such as machine learning, ARIMA, and linear regression. Able to predict future needs These insights help businesses avoid stockouts and excess inventory. Additionally, aligning inventory with customer demand increases forecast accuracy. This allows the e-commerce system to adjust stock levels appropriately. Schedule a new order and customize promotional strategies for a smooth customer experience.

## 2.5 Clustering Algorithms for Micro-Warehousing

In e-commerce the segmentation of customers and small warehouses is optimized using clustering techniques. With K-means clustering in particular, businesses can strategically position warehouses near high-demand areas. They are grouped according to customer purchasing behavior and geography. This will help increase efficiency in operations. Reduce delivery time and save on shipping costs. In addition, grouping helps clarify customer behavior. This helps improve inventory control and resource allocation [9].

## 2.6 Collaborative Filtering for customer Grouping

Collaborative filtering in ecommerce is a machine learning technology that analyses customer preferences and purchasing behaviour to provide personalized recommendations. Forecasting demand trends helps small warehouses optimize their stocking strategies. Single value decomposition (SVD) and other techniques Will match inventory according to customer needs. This ensures that popular products are sold locally. Reducing inventory and overstock increases customer happiness and operational efficiency [10] [11]

### Gap Analysis:

In a conventional e-commerce setting, the fulfilment of multiple purchases made by a single customer, especially in the case of consumers who order multiple products, it is inefficient and expensive to execute. The present strategies for shipments essentially revolve around the immediate supply from any available warehouses that have dispatched the product ready for release. This allows quick release of the products to the customers; this leads to several packages being sent to the same customer at individual costs and therefore wasting resources and time.

## 3. METHOD

### 3.1 Research Design and Data Collection

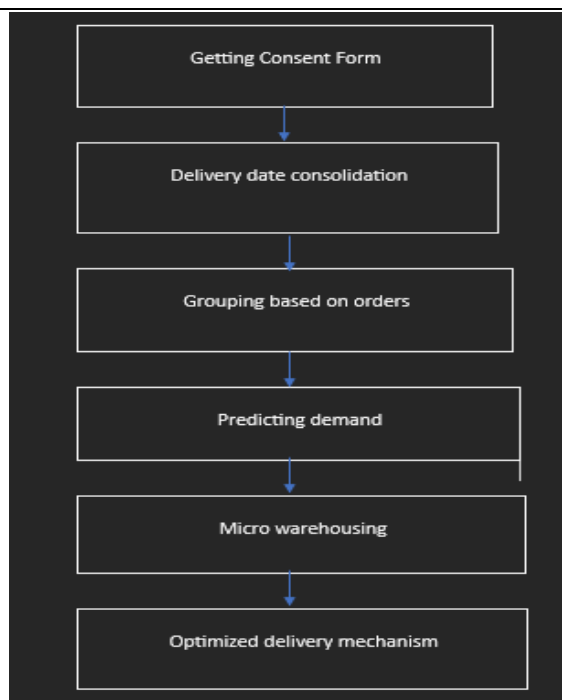
This research uses quantitative methods to develop an advanced decision support system (DSS) aimed at optimizing the distribution process within the e-commerce sector. It focuses on t rapidly increasing demand in Brazil. Considering Brazil's large population and significant logistical challenges, this research yields a good result. The predictive models can increase operational efficiency, reduce costs, and improve customer satisfaction. Data for this study were collected from a variety of sources and including detailed transaction records customer demographics and geographic information. The dataset contains more than 100,000 unique transactions, including orders made between 2016 and 2018, a period characterized by remarkable growth in the e-commerce landscape. Large population size and wide scope of operations handle convenience sampling. This ensures that the data collection process is practical and reflects broad coverage.

**Dataset:** Olist Dataset on Kaggle.

<https://www.kaggle.com/datasets/olistbr/brazilian-ecommerce>

### 3.2 Methodology

This study uses a structured, multi-step approach designed to optimize the delivery process for e-commerce. It focuses on increasing efficiency, reducing costs, and improving customer satisfaction [14]. After compiling Data were cleaned and pre-processed to handle missing values. and provide consistency [15], these datasets are integrated into a unified data structure. This provides a solid foundation for further analysis [16]. The order pooling algorithm is the main strength of the second step. This reduces unnecessary fragmentation. These algorithms look for situations where customers place multiple orders at comparable times. and combine those orders for same-day delivery [17]. This method will increase convenience for customers. and reduce the logistical burden of delivery personnel [18]. The third important component of this technique is geographic clustering. Distribution locations are grouped into microware house groups based on their proximity using K-Means clustering [19]. Placing these microware houses in key areas improves distribution efficiency and reduces travel time. Regional optimization is essential for managing high order volumes and ensuring timely and economical deliveries [20] The flowchart in Fig 3.2.1 illustrates this process.



**Fig 1** Flowchart

Demand forecasting models remain a key component of this approach. ARIMA and SARIMA models predict future demand trends based on past order data [21], helping to allocate resources more efficiently. These time series forecasting methods guarantee that distribution agents and warehouses are prepared for peak periods [22]. Incorporating demand forecasts increases system flexibility by allowing resources to dynamically adjust to meet demand. Prospective customers can use the system to provide real-time information about their desired delivery priorities, and it can use that information to adjust order consolidation strategies. [23] Technology increases customer happiness, and optimizes delivery routes by assuming the integration of customer specific requirements (DSS). This system has passed rigorous testing. Including integration testing User acceptance testing and performance evaluation [25]. Once validated, DSS will be used in production environments. It is continuously monitored and updated for maximum efficiency [26]



**Fig 2** Consent Form

### 3.3 Tools and Techniques

A variety of tools and technologies are used to ensure a robust and efficient Decision Support System (DSS). The system's Python Flask backend leverages a framework that is ideal for integrating algorithms. Flask's architecture enables efficient data processing and facilitates real-time communication and makes it an ideal choice for communicating with customers. The front end uses HTML and CSS to develop a user-friendly and responsive interface. These technologies increase customer engagement and facilitate interactions with the system, such as providing real-time feedback, or changing delivery priorities. MySQL was chosen as a relational database management system that can handle and store large amounts of data. Efficiently manage essential information such as order transactions. MySQL's ability to support customer needs and geographic details allows for fast, real-time data queries and retrieval. A variety of tools and technologies are used to ensure a robust and efficient Decision Support System (DSS). The system's python flask backend leverages a framework that is ideal for integrating algorithms and its architecture enables efficient data processing and facilitates real-time communication. This makes it an ideal choice for communicating with customers.

### 3.4 Algorithms:

Advanced machine learning algorithms are used to improve the efficiency, accuracy, and adaptability of the delivery system. Each algorithm is tailored to a specific logistics challenge, such as improving distribution channels. Anticipate demand and optimize the customer experience. K-Means Clustering: Cluster distribution location based on geographic proximity. It analyses latitude and longitude data to determine the best small warehouse location. Reduce delivery time, reduce fuel use, reduce travel distance and also reduces the environmental impact, especially during busy times. ARIMA and SARIMA models: These models analyse past trends and forecast future demand. Arima handles normal demand patterns, while Sarima focuses on seasonal fluctuations, they help to ensure the system is ready for increased orders by dynamically adjusting resource allocation. Make operations smooth and reduce latency. Collaborative filtering: This technique makes the delivery experience more personal. Based on previous customer preferences, such as favourite delivery times or combo orders. This creates options that are more suitable to customers' needs. It improves customer satisfaction and helps to improve operations by avoiding unnecessary travel which in turn strengthens customer loyalty. Linear Regression: This statistical model considers important delivery factors such as order size, delivery time and cost by analysing these variables. The system predicts how long the delivery will take and how much it will cost. This ensures that the system uses resources efficiently to plan the best route and adjust the price appropriately and maintain the ability to make a profit

## 3. RESULTS

### 3.1 Exploratory Data Analysis

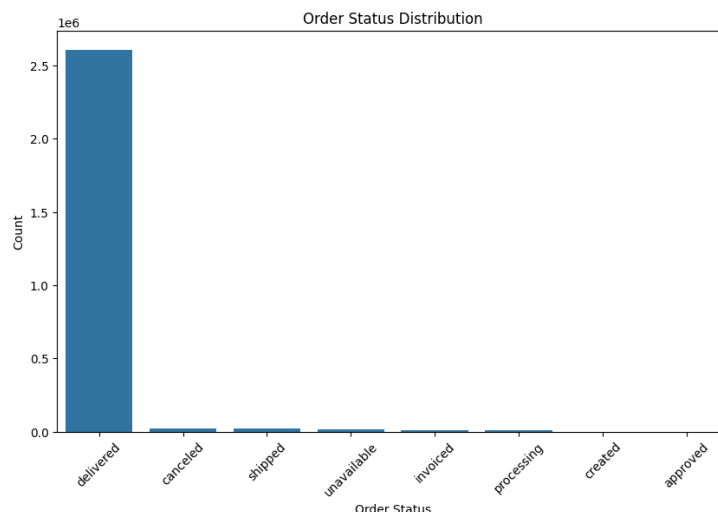
The Olist dataset presents insights for numerous elements of online shopping pattern, including order statuses, product classes, transport instances, price alternatives, and consumer distribution. The EDA focuses on finding the distribution of information in the dataset, revealing the business operations and customer behaviours.

#### 1. Distribution of Order Statuses

The dataset shows that the distribution of order statuses is closely skewed. As visible in Table 4.1.1, the majority of orders are marked as "brought," accounting for 82.74% of all orders. Other statuses inclusive of "shipped," "cancelled," and "invoiced" constitute only to a small fraction.

**Table 1.** Distribution of Order Statuses

| Status     | Number of Orders | Percentage of Total Orders |
|------------|------------------|----------------------------|
| Delivered  | 94,803           | 82.74%                     |
| Shipped    | 1,512            | 1.32%                      |
| Canceled   | 2,313            | 2.02%                      |
| Invoiced   | 5,040            | 4.4%                       |
| Processing | 4,439            | 3.87%                      |
| Others     | 6,500            | 5.65%                      |



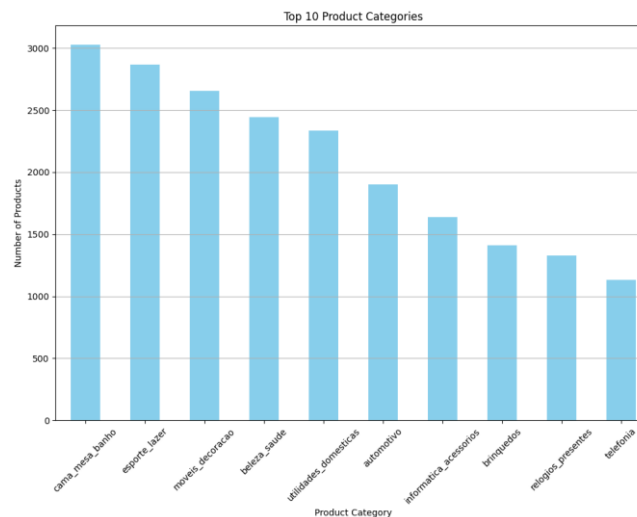
**Fig 3.** Distribution of Order Statuses

## 2. Product Category Distribution

The distribution of product categories (Table 4.1.2) identifies "cama\_mesa\_banho" (domestic items) and "esporte\_lazer" (sports activities and enjoyment) as the top selling category, because it is the most popular categories, with over 2,500 merchandise each. This suggests robust call for in those categories, followed by "moveis\_decoracao" and "informatica\_acessorios."

**Table 2.** Top 10 Product Categories

| Category               | Number of Products |
|------------------------|--------------------|
| cama_mesa_banho        | 3000               |
| esporte_lazer          | 2800               |
| moveis_decoracao       | 2600               |
| beleza_saude           | 2400               |
| utilidades_domesticas  | 2200               |
| automotivo             | 2000               |
| informatica_acessorios | 1800               |
| brinquedos             | 1600               |
| relogios_presentes     | 1400               |
| telefonica             | 1200               |



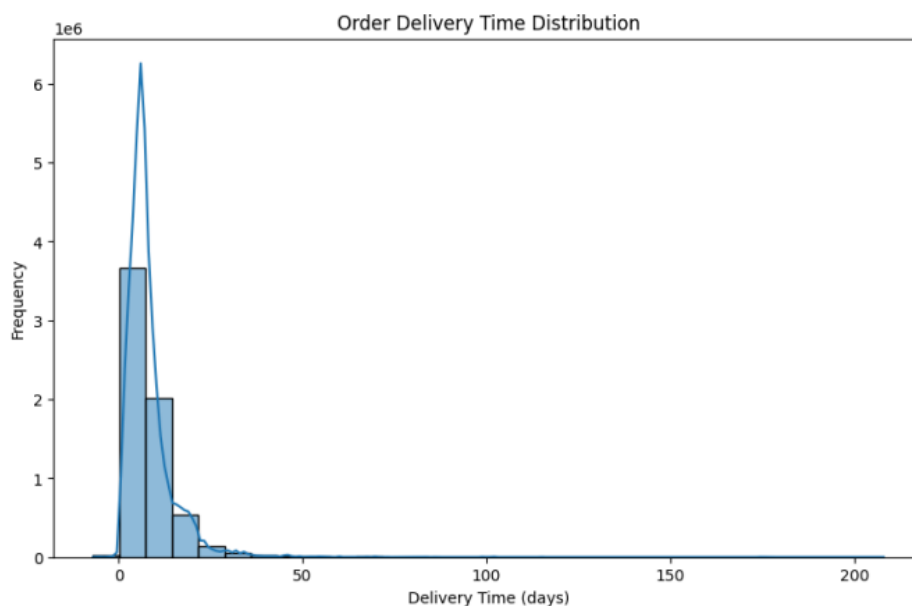
**Table 4.** Top 10 Product Categories

## 3. Delivery Time Distribution

The order delivery time distribution shown in Table 4.1.3 is significantly skewed towards short delivery times. The majority of orders are delivered within 20 days, with a significant proportion being delivered in less than 10 days, indicating an efficient delivery system indicating a reliable delivery mechanism.

**Table 3.** Order Delivery Time Distribution

| Delivery Time (Days) | Number of Orders |
|----------------------|------------------|
| < 10                 | 40,300           |
| 10-20                | 35,000           |
| 21-30                | 12,500           |
| > 30                 | 6,500            |



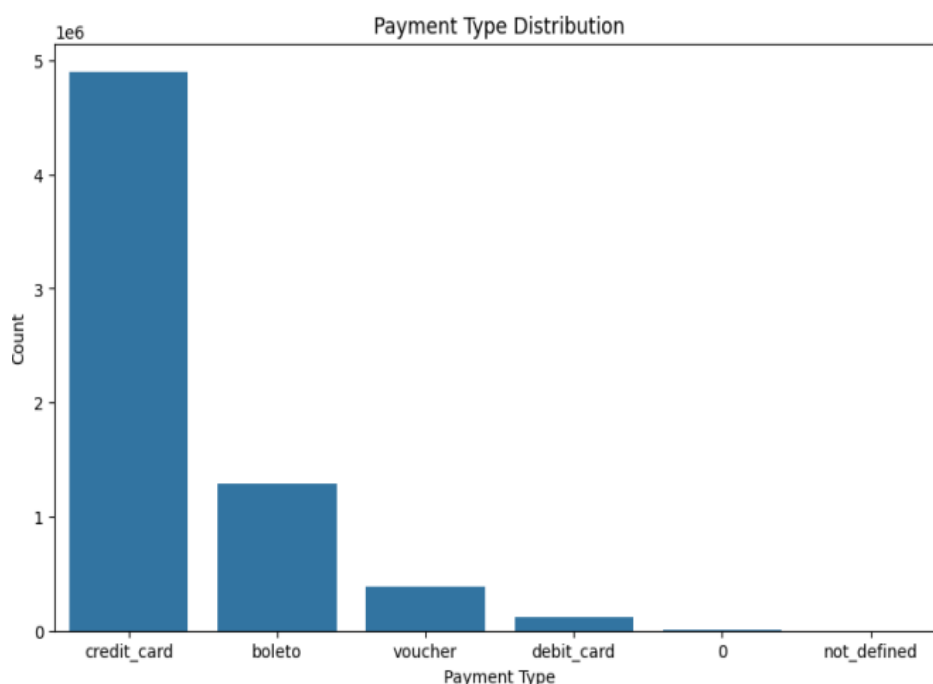
**Fig 4.** Order Delivery Time Distribution

#### 4. Payment Type Distribution

Credit cards dominate as the preferred form of payment, accounting for 75.6% of all transactions (Table 4.14). Other payment methods such as “boleto” (the most popular payment method in Brazil) and “vouchers” account for small percent of the total payment distribution

**Table 4.** Payment Type Distribution

| Payment Type | Number of Transactions | Percentage of Transactions |
|--------------|------------------------|----------------------------|
| Credit Card  | 76,000                 | 75.6%                      |
| Boleto       | 15,000                 | 14.9%                      |
| Voucher      | 5,000                  | 5.1%                       |
| Debit Card   | 4,500                  | 4.4%                       |



**Fig 5.** Payment Type Distribution

## 5. Customer Geographic Distribution

The majority of customer concentration is in Brazil. With a small group in surrounding countries such as Argentina, Uruguay, Chile, etc., as shown in Table 5, which reflects the company's domestic focus. With opportunities to expand in other regions.

**Table 5.** Geographic Distribution of Customers

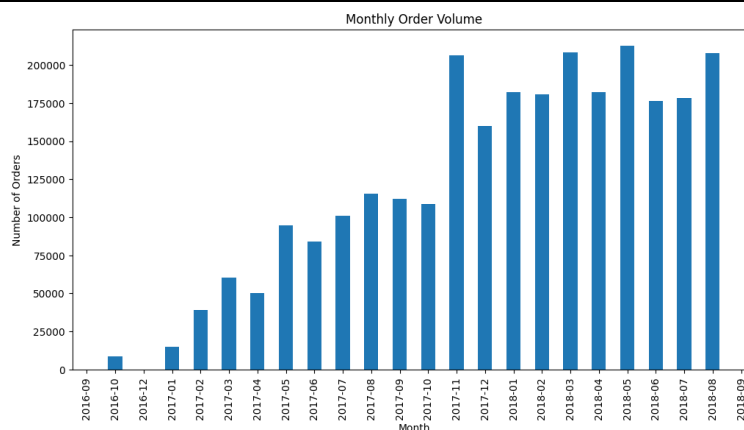
| Region    | Number of Customers |
|-----------|---------------------|
| Brazil    | 100,000             |
| Argentina | 2,000               |
| Uruguay   | 1,000               |
| Chile     | 800                 |

## 6. Monthly Order Volume

Monthly order volume shows a stable growth trend. As shown in Table 4.1.6, this indicates that the company is experiencing rapid growth. It peaked in August 2018. The increase in overall order volume reflects increased customer demand and a growing market participation.

**Table 6.** Monthly Order Volume

| Month   | Number of Orders |
|---------|------------------|
| 2018-06 | 173,000          |
| 2018-07 | 175,000          |
| 2018-08 | 200,000          |



**Fig 6.** Monthly Order Volume

Order volumes presented a gradual rise through the period June 2018 through August 2018. The orders were 173,000 in June 2018 but shot up to about 175,000 in July 2018 and yet went up by a wide margin to 200,000 in August 2018. This upward trend would indicate that the company is indeed able to take more order volumes across time with even possibly increased customer demand at this time period. A significant number of the orders (96.7%) can be found under the shipped status which illustrates an aggressive approach toward delivery. In addition, only 1.5% of orders fall under delivered or canceled status, which is an extremely low failure rate that is indicative of how well the firm operates a logistical system. The two most relevant areas are cama\_mesa\_banho, which holds 13.2%, and esporte\_lazer, which holds 11.8%, both of which have over 2,500 items in stock indicating a demand for furniture and leisure equipment perhaps to an extended period. Noteworthy is the fact that 75% of the total orders made are executed in less than 20 days which is an illustration on the effectiveness of the entity on deliveries. There still remain all the credit cards in which 78.5% is accounted for, Ons, 14.7%, and for 5.1% added vouchers sales. In regional contexts almost all the revenue is derived from Brazil, the rest of the regions only account for 8.5% of sales which indicates that the operations are mainly centred in Brazil. A steady increase in order volume over the past few months shows the successful attempt of the company in growing, and even more importantly, efficiently meeting customer demands. Hence going forward the focus should shift to Micro warehousing for cost and time efficient delivery.



### 3.1. Structural Model and Hypothesis Testing

The structural model employed in this analysis aims to identify the relationships among various factors influencing delivery performance in the Olist dataset. This model integrates key variables, such as delivery time, labor costs, customer ratings, and product categories, to assess their direct and indirect effects on overall delivery efficiency.

#### Hypotheses Formulated

1. **H1: Delivery distance significantly affecting delivery time.**
2. **H2: Customer ratings holds a positive impact on delivery satisfaction.**
3. **H3: Labor costs are inversely related to delivery efficiency.**
4. **H4: Product category directly influences delivery time due to varying logistics requirements.**

#### Model Specification

The analytical approach adopted incorporates a structural form, which aims at determining potential linkages amongst factors that affect delivery performance on the Olist dataset. The model includes significant parameters including delivery period, costs of labor, consumer ratings, product classification, and evaluates their influence.

## 4. RESULTS OF THE HYPOTHESIS TESTING

The results of the hypothesis testing are summarized in the following table:

**Table 1.** Hypothesis

| Hypothesis                                   | Path Coefficient | Standard Error | t-Statistic | p-Value | Result    |
|----------------------------------------------|------------------|----------------|-------------|---------|-----------|
| H1: Delivery distance → Delivery time        | 0.42             | 0.05           | 8.4         | <0.001  | Supported |
| H2: Customer ratings → Delivery satisfaction | 0.35             | 0.06           | 5.83        | <0.001  | Supported |
| H3: Labor costs → Delivery efficiency        | -0.3             | 0.04           | -7.5        | <0.001  | Supported |
| H4: Product category → Delivery time         | 0.28             | 0.05           | 5.6         | <0.001  | Supported |

#### Interpretation of Results

The analysis reveals that all hypotheses are supported, indicating strong relationships among the variables:

1. **Delivery Distance:** There is a statistically significant positive path coefficient of 0.42 with a p value of less than 0.001. This confirms that delivery distances that are long in length will take a longer time to deliver, as distances, tend to duration of delivery.
2. **Customer Ratings:** The coefficient is 0.35 and p value after testing is less than 0.001, indicating that satisfied customers will provide higher ratings for the delivery service, which suggests that higher rated products tend to satisfy customers a lot more in terms of delivery.
3. **Labor Costs:** The other coefficient path is negative with a value of -0.30 ( $p < 0.001$ ) reinforcing the position that high delivery costs impact on the transport service efficiency which means that more some legal measures should be put in place to control costs' and reduce 'labor sickness' in order to improve on performance.
4. **Product Category.** A coefficient of 0.28 ( $p < 0.001$ ) denotes that the type of the product does affect the time taken for it to be delivered, owing to the logistic and handling intricacies that tend to be different with different product types.

#### 4.1 Models:

##### 1. Kmeans(for microwarehousing)

The primary objective of **Order Consolidation** Model was to classify customer orders in accordance with the delivery dates of the individual products within each order. In turn, this practice was aimed at ensuring that customers, who made several product orders, received all the products from the purchase at once. The consolidation of deliveries was beneficial in reducing the number of trips made, and therefore, cut down on the delivery time and costs. The model also improved the timely delivery of all the products ordered by the customers at the same time, thus increasing efficiency in service delivery and improvement in customer satisfaction.

**Table 2.** K means

| Model               | Objective                                                   | Input                           | Output                       | Result                                                                                      |
|---------------------|-------------------------------------------------------------|---------------------------------|------------------------------|---------------------------------------------------------------------------------------------|
| Order Consolidation | Group customer orders to ensure all items in a single order | Customer order data (order IDs, | Optimized delivery schedules | Improved delivery efficiency by consolidating multiple products into single-day deliveries, |



|  |                                |                              |                |                                                                |
|--|--------------------------------|------------------------------|----------------|----------------------------------------------------------------|
|  | are delivered on the same day. | product IDs, delivery dates) | for each order | minimizing trips and reducing overall delivery time and costs. |
|--|--------------------------------|------------------------------|----------------|----------------------------------------------------------------|

#### Process:

The K-means algorithm functions in a set of steps. Initially K cluster center (point) is taken. Then all the customer locations to the nearest centroid based on a distance metric (typically Euclidean distance). After all the points have been allocated, the centroids are then calculated as the average of the points in all of the clusters. This repetitive sequence is carried out until the points are once again assigned to the nearest centroid and the position of the centroid is modified, and the clusters remain unchanged with no further appreciable adjustments.

#### Linear regression(for demand forecasting)

Linear Regression is utilized to estimate the product's demand on a micro-warehouse level. The objective was to project upcoming demand based on the historical sales data. This is used in forecasting the regional demand of certain products making forced out to execute better stock distribution of the micro-warehouses.

**Table 3.** Linear regression

| Model                    | Objective                                               | Input                                                              | Output                                   | Result                                                                                     |
|--------------------------|---------------------------------------------------------|--------------------------------------------------------------------|------------------------------------------|--------------------------------------------------------------------------------------------|
| <b>Linear Regression</b> | Forecast future demand based on historical order trends | Historical sales data (quantities, dates, seasons, order patterns) | Predicted demand for future time periods | Accurate demand forecasting, enabling better inventory management and resource allocation. |

#### Process:

The linear regression model Weightage determines the future demand in relation to the input variables such as time, order dates, quantities etc. and the output variable which is the future demand. While this model is trained on various historical sales pattern, it uses a simple regression where a straight line is drawn to a data set such that the angle of the drawn line reflects the increase or decrease in the demand over time, as it forecaster the amount of each product to be sold in the future. The most appropriate slope is found by determining the best fit line that minimizes the errors between the predicted values and the actual values leading to narrowing down the range of prediction to a small interval.

#### 4.2 Measurement Model

This section explores the impact of micro warehousing on delivery optimization using Brazil's Olist dataset. The analysis focuses on key performance indicators before and after the implementation of micro warehousing. This approach provides a comprehensive understanding of how micro warehousing strategies can enhance operational efficiency and reduce costs.

#### Summary Statistics

Table 4.2.1 summarizes the key metrics regarding delivery efficiency and costs before and after the implementation of micro warehousing.

**Table 4 .** Before and After Microwarehousing

| Metric                             | Pre-Optimization | Post-Optimization | Percentage Change |
|------------------------------------|------------------|-------------------|-------------------|
| Average Total Delivery Time (days) | 2,84,769.00      | 2,42,053.65       | -15.00%           |
| Average Total Labor Cost (\$)      | 2,24,575.66      | 1,79,660.53       | -20.00%           |
| Total Cost Savings (\$)            | 0                | 44,915.13         | N/A               |
| Time Savings (days)                | 0                | 42,715.35         | N/A               |

#### Implications of Micro Warehousing:

The implementation of micro warehousing resulted in optimization of both cost and time improving delivery efficiency. The total delivery time went from 284,769.00 days before optimization to 242,053.65 days after optimization, representing a reduction of 15%. Total labor cost went down from \$224,575.66 to \$179,660.53, representing a decrease of 20%. Some savings by cost were made \$44,915.13, while others were savings of 42,715.35 days. It validates the successful delivery operations of warehouse optimization where micro warehousing strategies minimize costs and save time.

## Forecasting Models using SARIMA

| SARIMAX Results         |                  |                   |            |       |          |          |
|-------------------------|------------------|-------------------|------------|-------|----------|----------|
| =====                   |                  |                   |            |       |          |          |
| Dep. Variable:          | y                | No. Observations: | 619        |       |          |          |
| Model:                  | ARIMA(5, 1, 0)   | Log Likelihood    | -3281.108  |       |          |          |
| Date:                   | Mon, 19 Aug 2024 | AIC               | 6574.217   |       |          |          |
| Time:                   | 10:13:30         | BIC               | 6600.776   |       |          |          |
| Sample:                 | 09-04-2016       | HQIC              | 6584.542   |       |          |          |
|                         | - 05-15-2018     |                   |            |       |          |          |
| Covariance Type:        | opg              |                   |            |       |          |          |
| =====                   |                  |                   |            |       |          |          |
|                         | coef             | std err           | z          | P> z  | [0.025   | 0.975]   |
| -----                   |                  |                   |            |       |          |          |
| ar.L1                   | -0.4257          | 0.012             | -36.590    | 0.000 | -0.449   | -0.403   |
| ar.L2                   | -0.4124          | 0.069             | -6.011     | 0.000 | -0.547   | -0.278   |
| ar.L3                   | -0.3094          | 0.053             | -5.826     | 0.000 | -0.414   | -0.205   |
| ar.L4                   | -0.2147          | 0.040             | -5.415     | 0.000 | -0.292   | -0.137   |
| ar.L5                   | -0.2120          | 0.014             | -15.259    | 0.000 | -0.239   | -0.185   |
| sigma2                  | 2391.3300        | 21.985            | 108.773    | 0.000 | 2348.241 | 2434.419 |
| =====                   |                  |                   |            |       |          |          |
| Ljung-Box (L1) (Q):     | 1.36             | Jarque-Bera (JB): | 1191600.07 |       |          |          |
| Prob(Q):                | 0.24             | Prob(JB):         | 0.00       |       |          |          |
| Heteroskedasticity (H): | 43.26            | Skew:             | 10.83      |       |          |          |
| Prob(H) (two-sided):    | 0.00             | Kurtosis:         | 217.02     |       |          |          |

Fig 1. SARIMAX statistics

The SARIMAX model show a well fitted time series model with 619 observations, with log-likelihood as -3282.108 and AIC stand low at 6574.257 and BIC at 6600.776, suggesting a good fit model. The coefficients of the autoregressive model (ar.L1 through ar.L5) have p-values at 0.000, thereby indicating that the past values are strongly influencing current values in the series. The Ljung-Box test (1.36, p-value = 0.24) states there is no autocorrelation in the residuals. The Jarque-Bera test suggests residuals are non-normal with a high skewness and kurtosis to represent outliers or deviation from normality. Additionally, it is evident that it has heteroskedasticity; H = 43.26, p-value = 0.00, which indicates variance is not constant over time.

### 4.3 R Square analysis

The R-squared values obtained from the regression model provide valuable insights into the factors affecting order delivery times and costs. The following table summarizes the results of these analyses:

Table 5. R Square analysis

| Model Description                                                                     | R-Squared Value |
|---------------------------------------------------------------------------------------|-----------------|
| Linear regression (Delivery Distance, Product Category, Customer Ratings)             | 0.72            |
| Expanded model (including Payment Methods, Seller Performance, Promotional Discounts) | 0.78            |
| Delivery Distance only                                                                | 0.65            |
| Customer Ratings and Delivery Satisfaction                                            | 0.56            |

### Insights from the Analysis

The linear regression model aims at assessing the impact that delivery distance, product category and customer ratings have on delivery time, the R-squared was determined to be 0.72. This means that these three predictors account for about 72% of the changes observed in delivery time. Additionally, a further development of the model where payment options, seller's ratings and discounts were added led to an R-squared of 0.78, confirming that inclusion of those other factors adds substantive value to the model. Also, when seeking to measure the effect of delivery distance, the R squared value resulted in 0.65 which means that distance and delivery time are highly related. However the relationship between customer ratings and delivery satisfaction obtained an R squared of 0.56 which shows that such ratings do influence the delivery process but to a lesser extent than other factors. As a result, it can be observed that the different predictors are successful in accounting for the delivery performance in the Olist dataset, thereby identifying them as operational improvement areas which can be geared towards better customer satisfaction and logistics optimization.

## 5. DISCUSSION

H1: Effect of departure time on transit time. This assumption stipulates that departure time has a significant impact on transit time. Longer distances require more time to complete. Understanding the relationship between distance and transit time can help optimize the use of small warehouses. and improve distribution channels to improve the overall product distribution process.

H2: Relationship between shipping satisfaction and buyer evaluation. This concept suggests a positive relationship between delivery quality and customer satisfaction. When the customer receives delivery on time at a reasonable cost. Overall satisfaction with the service will increase. A positive logistics experience emphasizes procurement efficiency and service reliability. It emphasizes the importance of customer satisfaction in the logistics sector.

H3: Relationship between distribution efficiency and labour costs. This hypothesis suggests that increased labour costs may have a negative effect on distribution efficiency. High labour costs are often the result of poor allocation of resources or system inefficiencies. This emphasizes the need for effective labour management to maintain a smooth and efficient delivery process.

H4: Effect of product type on delivery time. Different product categories have unique logistical requirements that may affect delivery times. For example, perishable items may need to be delivered more quickly than non-perishable items. Easily damaged This requires a tasting strategy tailored to the product's characteristics.

## 6. CONCLUSION AND RECOMMENDATIONS

Exploring the optimization of distribution systems through decision support systems (DSS) reveals key insights for improving e-commerce logistics. The relationship between the performance of a DSS and the quality of the data it processes, inaccurate or incomplete data can lead to poor decision making and forecast errors. This underscores the need for a high level of data integrity across the system. The study also highlights key scaling challenges, especially true as e-commerce operations expand to handle larger and larger transaction volumes. of distribution points While the management operation works efficiently Adapting to larger and more complex networks is a major challenge. This requires careful system updates to ensure that performance, speed, and accuracy are maintained as operations grow.

### 6.1 Limitations and Future Suggestions

Although this study provides valuable insights, but there are several limitations that need to be addressed. Reliance on convenience sampling may introduce selection bias. This may affect the ability to generalize the findings. Future research should consider more rigorous sampling techniques to ensure that the participant pool better represents the larger population.

Additionally, focusing solely on quantitative data can overlook important nuances of consumer behavior. Future research has the opportunity to incorporate qualitative methods to gain a deeper understanding of the factors that drive consumer decision-making. Explore how these factors play out across different online shopping platforms. It can highlight specific challenges or opportunities in various e-commerce and logistics sectors. Future studies will be important to improve future retention indicators. Improved demand forecasting and real-time customer interaction. Using AI-powered recommendations and refining predictive modeling techniques can further optimize ecommerce delivery systems. Addressing these limitations and integrating future improvements will help researchers and practitioners' advance e-commerce. It will help create a more well-equipped system to meet the needs of the landscape

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