Enhancing Sales Performance Analysis Through Advanced Data Visualization Techniques: Evidence from E-Commerce Transaction Data

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Abstract

Conventional sales reporting instruments heavily depend on static tables and rudimentary visualizations, which may hide intricate data patterns and thus limit the ability of managers to take proactive measures. This article introduces a novel advanced visualization framework that integrates hierarchical, flow-based, and predictive analytics into a single dashboard. The layout, supported by a long-term dataset of e-commerce transactions, utilizes tree maps, Sankey diagrams, animated time-series plots, and Prophet-based forecasting with seasonality decomposition. The results show that these visualization techniques uncover a greater variety of insights that are also more actionable than those revealed by traditional dashboards, thus empowering managers not only to foresee future sales trends but also to seasonal demand fluctuations. The proposed framework is a scalable analytical model for converting the simplest sales data into valuable business intelligence; thus it not only makes the decision-making process more precise but also shortens the time required for the analysis.

Keywords: Data Visualization, Tree map, Sankey Diagram, Time-series Forecasting, Prophet(forecasting), Seasonality Decomposition, E-commerce Analytics

1. Introduction

In environmentally conscientious businesses today where the level of competition is high, it is not possible for well-structured companies to rely on instinct or outdated reports for their decision making. The sustainability and profitability of a company depend on the fact that decisions must be made based on accurate and data-driven insights. To a great extent, sales performance as a part of the key performance indicators is pointed out to demonstrate the core of the business i.e. revenue generation, customer demand, and market positioning.

Massive amounts of transactional data have been generated due to the rapid digitization of business. For instance, customer demographics, order histories, product categories, and regional sales are some of the data sources. However, traditional spreadsheet-based analyses and static charts are almost always powerless when it comes to unearthing complex patterns and even forecasting future trends.

Data visualization's primary role is to make the raw data understandable by revealing the complex interaction through the use of interactive graphs, heatmaps, and flow diagrams. However, despite the many benefits that visualization tools provide, a large number of business dashboards remain at the most elementary level of bar charts and KPIs that in most cases are incapable of disclosing the deeper, multidimensional relationships or giving predictive foresight.

It is possible to deploy more intricate visualization and forecasting methods because of the recent breakthroughs in data science. For example, hierarchical method treemaps can visualize the different product contributions in relative terms while flow-oriented visualizations like Sankey diagrams can reflect the flow of transactions. Besides, a forecasting tool such as Prophet can be used to forecast sales in the future based on temporal trends.

The current paper intends to develop an analytical framework that goes beyond the traditional methods by integrating these techniques to elevate the level of examination of e-commerce sales performance. Through the use of sophisticated visualization together with the predictive time-series modeling, the study is no longer merely descriptive but is rather proactive in that it provides forecasting based on data and the generation of strategic insights.

2. Literature Review

Visualization plays a key role in transforming complicated sales figures into understandable insights for the business of today, which relies heavily on data. According to Sharma and Kandel [1], the use of such tools as charts, graphs, and dashboards not only makes the process of understanding faster but also supports it by giving the users the opportunity to make more informed decisions that finally result in better business outcomes. Upadhye [2] describes that in the area of sales the implementation of interactive dashboards, in particular, those powered by Power BI, can reveal the trends, call the anomalies out, and most importantly, show the differences in the regions, thus, giving the managers the power to make the right decisions at the right time.

These kinds of dashboards are backed up by research to actually bring different benefits. A recent study in the FMCG sector through the use of Power BI has come to a conclusion that the employment of interactive dashboards has had a great impact on the speedy examination of sales performance figures. As a consequence, not only the regions with the best performances like Delhi NCR and Mumbai became very obvious, but also the revenue contributions across product categories could be seen with great clarity [3],[4]. However, Improvado also enumerates the strategic advantages of dashboards through which the company comes to a conclusion that these functionalities are the main factors for the most efficient sales tracking as well as decision-making processes: real-time insights, role-specific customization, CRM integration, and scalability [5],[6].

Recent research indicates that sophisticated visualization systems can reveal hidden insights into business practices. According to the European Journal of Engineering Science and Emerging Technologies [3], dashboards based on Power BI aid strategic decision-making through the real-time tracking of sales data. Likewise, both Improvado [4] and Qlik [12] discussed the same application of a dashboard that combines multi-channel sales data onto a single, interactive dashboard, providing actionable key performance indicators (KPIs).

Shelar et al. [26] combined SQL-powered real-time analytics with Power BI dashboards to increase access to data and visualization speed. Thamizharasan et al.'s proposal presented a Power BI architecture that integrates AI/ML to create a predictive modeling in the dashboard, increasing accuracy of forecasts [18]. Zhang et al. [7] developed the PromotionLens visual analytics system to conduct an analysis of e-commerce promotions and emphasize contextual storytelling in determining marketing effectiveness.

While visualization investigates descriptive analysis, predictive analytics provides forward-looking insight to assist businesses in planning. Mustapha and Sithole [22] and Bandara et al. [34] used time-series models of, ARIMA, and Long Short-Term Memory (LSTM), to forecast retail sales with a high degree of accuracy. Prophet, developed by Facebook [33], has also gained considerable attention for its higher degree of interpretability in seasonal and trend pattern modeling.

Huard et al. [37] examined hierarchical forecasting by integrating exponential smoothing and Holt's linear trend methods to improve multi-level forecasting effectiveness. Kalifa et al. [38] advanced forecasting studies by investigating the effects of different external factors such as global events on predicting consumer demand variations. Yuan et al. [30] and Balyemah et al. [40] similarly employed deep learning and regression-based models to forecast customer buying habits, demonstrating that AI-based forecasting could be used to personalize and control inventory better. Ezeife et al. [20] took the adaptation of these works to smaller organizations by introducing predictive frameworks that are intended to help small business stakeholders achieve long-term profitability and strategic sustainability.

The integration of visualization and predictive modeling is the future of analysis. Liu et al. [25] talked about hybrid analytical models which combined visualization and predictive modeling and noticed that those types of models enhanced interpretability and facilitated timely decision-making. Ezeife et al. [20] and Wei [33] argued that the combination of predictive models with dashboards allowed for continuous monitoring as well as automatic performance dashboards' anomaly detection.

New advancements in geospatial visualization (SciTechnol [27] and SBL Corp [28]) extend analytical capabilities by adding spatial dimension to performance dashboards. The current research is aligned on the overarching goal of descriptive visualization and predictive modeling works discussed here in interpreting sales performance in multi-level data.

The literature emphasized the value of visualization and predictive analytics in enhancing business intelligence. However, the majority of existing literature examines either visualization dashboards or predictive models standalone, rather than determining how they can be used together as an integrated analytic framework. Therefore, businesses cannot fully harness a combination of historical patterns and future expectations.

In this way, the proposed study attempts to fill this gap in the literature by utilizing a combined analytics framework integrating descriptive visualization with predictive models, including Prophet, ARIMA, and LSTM. Consequently, such a system will lead to a better understanding of the results, increase the accuracy of predicting, and promote the use of data-driven decision-making for the purpose of e-commerce sales enhancement.

3. Methodology

This study improves the analysis of e-commerce sales performance incorporating structured analysis using descriptive, diagnostic, and predictive methods. This process has five key components data collection, data preprocessing, descriptive visualization, predictive modeling, and model validation. Each of the components aid the transformation of raw sales data into business insights.

3.1 Framework

The proposed analytical framework integrates descriptive, diagnostic, and predictive analytics into a unified pipeline for sales analysis of e-commerce activities [15]. The framework revolves around raw transactional data being converted to actionable insights, thus, it is a perfect tool for evidence-based decision-making.

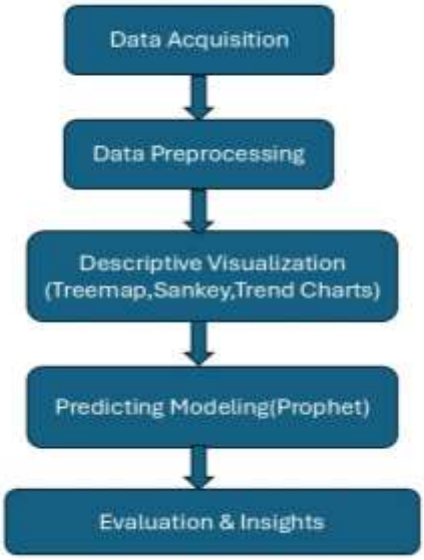

Figure 1. Conceptual model outlining the analytical process for assessing e-commerce sales performance.

The picture presents the stepwise workflow that the current work has adopted starting from data acquisition and preprocessing, descriptive visualization, predictive modeling with Prophet, ARIMA, and LSTM, to business insights that are the final outcome of the analyses.

Key Stages of the Framework:

1. Data purchase

Multi-year e-commerce transaction data were acquired from a publicly available Amazon Sales Dataset. The table consisted of Order ID, Customer ID, Product Category, Product name,Total Sales, Quantity, Profit Margin, Discount, Region, and Order Date.

2. Data handling

Data cleaning took care of the removal of duplicates and inconsistencies. Reformatting Date-time allowed time-series analysis. Feature engineering generated attributes that were derived from such as monthly and yearly aggregations, profit margins, and seasonal indicators.

3. Descriptive analysis

Treemaps helped the visualization of the hierarchical contribution of product categories and sub-categories to total sales and profit. Sankey diagrams unveiled sales flows through regions, product categories, and customer segments. Temporal line and bar charts depicted monthly and yearly sales trends, showing seasonal peaks and low-demand periods.

4. Predictive analysis

The Prophet model predicted sales for six months ahead and at the same time took into account trend, seasonality, and holiday/promotion effects. Accuracy of the forecast was estimated through MAE, RMSE, and MAPE metrics, thus providing trust in the model's predictive

5. Evaluation

Comparison of actual vs. predicted values served as a way to evaluate the model's ability to grasp structural patterns and seasonal fluctuations. Information from the predictive model is a great resource for Inventory, marketing, and promotional activities planning will be proactive, supported by the predictive model, particularly during high-demand periods such as Q4.

This framework is a comprehensive approach to e-commerce sales analysis, which merges descriptive and predictive analytics. The combination of historical insights with forward-looking forecasts allows the organizations to make the next step which is not only reactive but also proactive, evidence-driven decision-making thus they are able to optimize both revenue generation and operational efficiency.

3.2 Data Source

This research utilizes the publicly available Amazon Sales Dataset [31] containing 5,000 anonymized e-commerce transactions between January 2019 and June 2024. Each record contains order data, customer demographics, product category, unit price, discount (%), payment type, order status, total sales, and Profit Margin.

3.3 Data Preparation

The dataset was prepped prior to analysis including significant cleaning to ensure quality and consistency.

Major prep steps included:

1. Cleaning - removing duplicative records, and handling missing and inconsistent values.

2. Transformation - converting categorical variables (e.g., product category, region) into data types that work best for visualization and modeling.

3. Formatting - ensuring that the Order Date is in a date-time format that would allow for time-series decomposition and forecasting.

4. Feature Engineering - calculating daily and monthly aggregated sales, calculating profit, and creating time-based features [8],[18] like month, year, and season.

All of the considerations in the prep process ensured that the dataset was accurate, consistent, and ready for further visualization and predictive modeling.to seasonal shopping periods.

Panel A includes key dataset statistics including number of total transactions, time period covered (Jan 2019 – Jun 2024), and sales indicators (total sales, total profit).

Panel B: The distributions of individual order values reflect the skewness so commonly seen in e-commerce data, with a small number of large order values disproportionate to total revenue.

Panel C: The counts of monthly transactions across the time series, indicating overall growth in activity and large spikes at the end of every year, when seasonal shopping patterns occurred.

Figure 2. Overview of the dataset and its statistical distributions. (A) Core dataset attributes. (B) Frequency distribution of total order values. (C) Monthly transaction volume trends (January 2019 – June 2024).

3.4 Predictive Modeling

To take the analysis beyond descriptive analysis,[12] a time-series forecasting intervention was employed using the Facebook Prophet application, which is well suited to seasonality, trends, and outliers in e-commerce sales data. This stage allows [1]organizations to expect future performance, plan inventory, and prepare sales and marketing strategies ahead of time.

Model Input:

Once the monthly sales data were combined from January 2019-June 2024, the data served as the input for the open-source Prophet forecasting model. The input data format is structured as 'ds' representing the date and 'y' representing the sales value date. Missing data points are necessary to model training so that time series continuity can be preserved. Also, extreme outliers were found and handled appropriately for the general stability and trustworthiness of model predictions. Such processing made sure that the input data was continuous, clean, and suitable for producing accurate time series forecasting.

Model Configuration:

To forecast sales performance the Prophet model had been configured with three main components. The trend element was used to reflect the expansion or declining sales of the study period over the longer term. The seasonality component represented the parts of the sales that could be predicted from the fluctuations that were due to both cyclical monthly and yearly purchasing behavior.

Model Training and Evaluation

For the estimation of the model's effectiveness, the data was split in half: one part was used for learning - from January 2019 to December 2023 - while the other part, from January 2024 to June 2024, was used for the testing of the model's generalization ability. The model's performance was evaluated using the standard set of the most common accuracy metrics. The graphical comparison of the sales trend of the real and the predicted data reveals that the forecasting model managed to represent the growth trend as well as the seasonality of the sales data more accurately. Nevertheless, the prediction errors and possible fluctuations caused by the forecast indicate the potential of the method to improve further if some additional explanatory variables, such as deviations in sales trends due to promotional events or external market conditions, were included in the forecasting model.

Comparative Forecasting Models

In order to evaluate the Prophet forecasting model's power and reliability, a comparative analysis was undertaken by implementing two alternative models: ARIMA and LSTM. All the models were trained on the same monthly aggregated sales data, extending from January 2019 to June 2024, and were validated on a 6-month test set.

1. ARIMA: The range of parameters (p, d, q) was optimized by the Akaike Information Criterion (AIC) minimization method which strives for the simplest model to be used with the best fit demonstrated. ARIMA is a model for short forecast linear stationary time series and will be validated as such.

2. LSTM: A univariate sequence-to-sequence neural network was trained on the normalized monthly sales data using a window size of three time steps. LSTM is designed to learn long-term temporal dependencies and non-linear relationships that statistical methods cannot handle.

3. Prophet: The benchmark model, Prophet, breaks down the time series into trend, seasonality, and holiday effects and is a model that is specially built for business time-series data where several seasonal patterns exist simultaneously. To compare the different models, they were all trained on the same training

dataset and tested on the same test dataset. The evaluation was done by three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Comparative Forecasting Analysis

In order to demonstrate the Prophet forecasting model's strength and trustworthiness, the team decided to try two further models, ARIMA and LSTM, for comparative analysis. Each model had been trained on monthly aggregated sales data from January 2019 to June 2024 and validated by a six-month test set.

1. ARIMA: Parameters *(p, d, q)* were optimized by Akaike Information Criterion (AIC) minimization [22], thus the most parsimonious model that balances goodness-of-fit and complexity is chosen. ARIMA is a method that is suitable for a short-term forecast of a linear, stationary time series.

2. LSTM: A univariate sequence-to-sequence neural network was trained [34],[35] on normalized monthly sales data using a window size of three time steps. The LSTM model can handle the long-term temporal dependencies and also the non-linear patterns, which it derives from the data, that are beyond the capability of traditional statistical models.

3. Prophet: The basic model, Prophet, breaks the time series into trend, seasonality, and holiday effects within a time-series model that is well-aligned for time-series data marketers with multiple seasons of data.

All models were trained on the same training base data, and all models were evaluated on the test data against the following metrics for predictive performance: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The comparative analysis in this framework provides the primary objective of providing an objective analysis of Prophet comparative accuracy against the classical (ARIMA) and deep learning (LSTM) predictions and model [34]. These three models would also provide the comparative analyses relative to trends, seasonality, explainability/simplicity, as well as computational efficiency in assessing predictive performance. The forecast metrics from each model can be found within the three models in Table 3 (Results).

4. Results

4.1 Descriptive Visualizations

In order to understand the context of the analysis, the primary features of the Amazon Sales Dataset were initially examined. Table 1 displays a summary of the attributes that were talked about such as the total number of transactions, the time period covered (January 2019–June 2024), major product categories, and aggregate sales indicators like total revenue and average order value. These figures define the extent of the study and mark the point from which the subsequent visual analyses will unfold

Table 1. Summary of descriptive statistics by product category.

Category	Total_Sales	Sales_%	Avg_Order_Value	Avg_Profit_Margin	Orders	Return_Rate_%
Beauty	794056.99	13.4	1178.13	409.93	674	26.0
Books	814614.05	13.7	1167.07	406.09	698	25.2
Clothing	874698.53	14.7	1190.07	414.09	735	27.1
Electronics	854348.56	14.4	1186.60	412.88	720	26.4
Home & kitchen	837059.82	14.1	1174.00	408.50	713	29.2
Sports	894838.14	15.1	1217.47	423.63	735	26.3
Toys	866110.83	14.6	1194.64	415.68	725	25.4

A treemap (Figure 3) was used as a visual representation of sales at the category and product level; block sizes represent total sales while color represents average profit margin. Sports was the highest category for both revenue and profit, and Books and Home & Kitchen had large revenue but lower profit margins. If return data are included, Clothing and Home & Kitchen had some of the highest return rates (>26), suggesting that there may be quality issues or that the products are not meeting customer expectations. Books and Toys had relative consistency in meeting customer expectations. This suggests that when talking about long-term sustainability of any given category, return rates should be a component of a traditional sales metrices.

Figure 3. *Treemap visualization of product and category sales, where area denotes total revenue and color intensity reflects average profit margin (%).*

While integrating return rate metrics, [8] an additional insight comes to the surface: for example, categories like Clothing and Home & Kitchen exhibited relatively high return rates (above 26%), which may indicate product quality issues, customer dissatisfaction, or wrong expectation setting. On the other hand, [17] Toys and Books had significantly lower return rates (approximately 25%), thus, suggesting steady customer acceptance. This is a clear indication of how crucial it is to return behavior as a complement to sales and profit analysis in assessing the durability of different categories.

4.2 Flow-Based Analysis

To explore flows of transactions in greater detail, a Sankey diagram was utilized to visualize sales flows from Region → Salesperson → Order Status (Figure 4). This highlight shows the volume of transactions and tracking their status in the business flow.

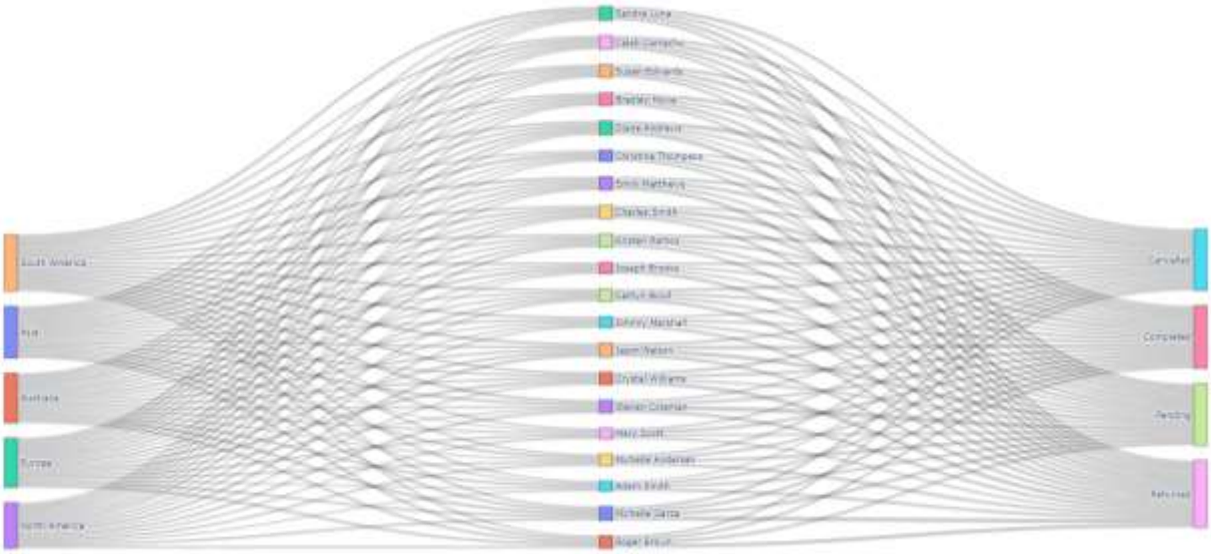

Figure 4. *Sankey flow representation shows the transition of sales across Region, Salesperson, and Order Status, with link width indicating relative sales volume.*

The diagram shows volumes of completed sales were highest in North America and Asia, and South America had an unusually high amount of returned orders, which could indicate possible issues in distribution or quality of the product. Europe and Australia had a more favorable balance between the order outcomes. The flow perspective enables identification of bottlenecks in delivery, and opportunity areas for management support, where returns are higher than expected, for example, or where sales are not progressing quite as hoped.

4.3 Temporal Trends

Monthly sales from January 2019 to June 2020 were analyzed in the context of temporal variability. In the time-series analysis (Figure 5) seasonal variation was evident across the sales data, as the periods of peak sales in November–December coincided with increased consumerism associated with the holiday season, while troughs in sales recorded in January–February reflected decline in consumer activity following the holidays.

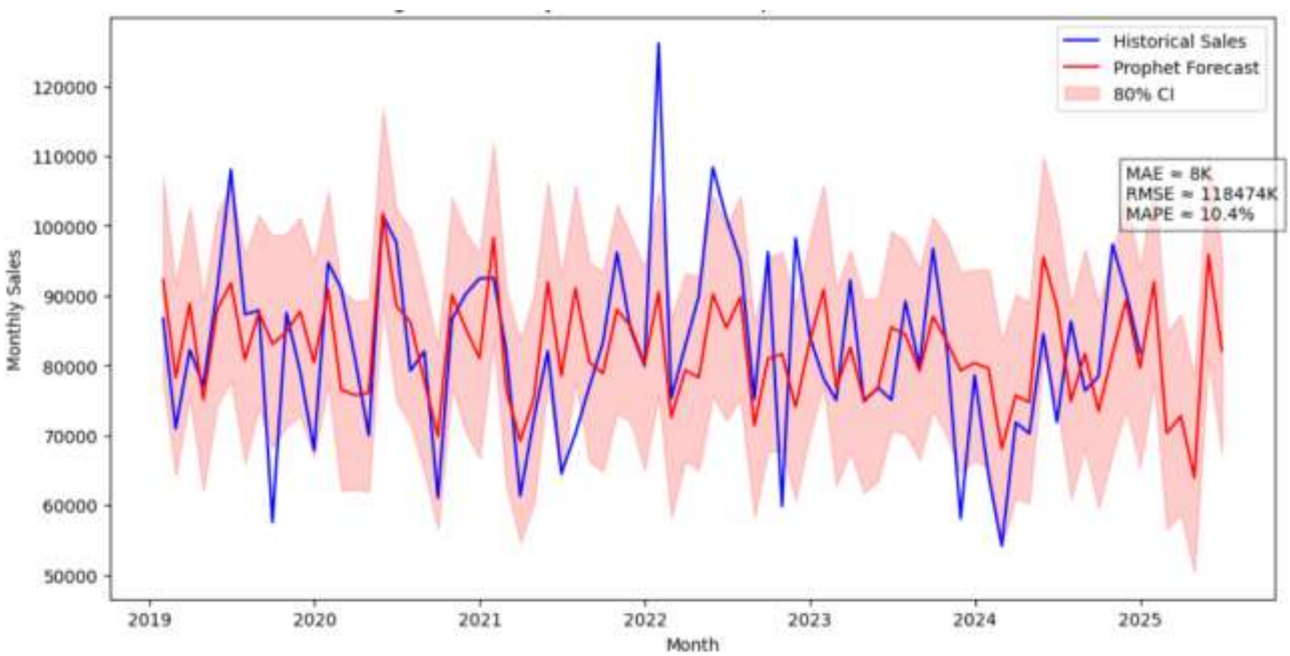

Figure 5. Monthly sales trends with a six-month forecast and 80% prediction interval derived from time series modeling (trained up to June 2024).

The Prophet forecasting model was trained on data until December 2023 and tested in the first half of 2024. The summary of forecast performance metrics is available in Table 2. The model was efficient in capturing the general trend and seasonal patterns, as evidenced by a low mean absolute percentage error (MAPE) of 10.42%, which is a strong indication of its predictive power. This is in spite of the fact that the raw sales units were on a large scale, which led to a high RMSE.

Table 2. *Evaluation metrics for the time series forecasting model.*

Metric	Value	Interpretation
MAE (Mean Absolute Error)	8,297	Average magnitude of forecast errors
RMSE (Root Mean Squared Error)	118,473,915	Penalizes larger errors; high value due to raw sales units
MAPE (Mean Absolute Percentage Error)	10.42%	Low percentage deviation of forecasted values from actual values

Prophet decomposition (Figure 6) changed the series components from three to long-term trend, annual seasonality, and weekly seasonality. The trend was moving upwards slowly, indicating steady growth. The end-of-year spikes as well as the mid-year peaks of promotions were explained by the yearly seasonality. The weekly seasonality showed that Tuesdays to Thursdays, there were the most activities. More specifically, the decomposed series makes it possible to plan for inventory management, marketing/promotional activities, and staff levels, in a more general way, besides other fields.

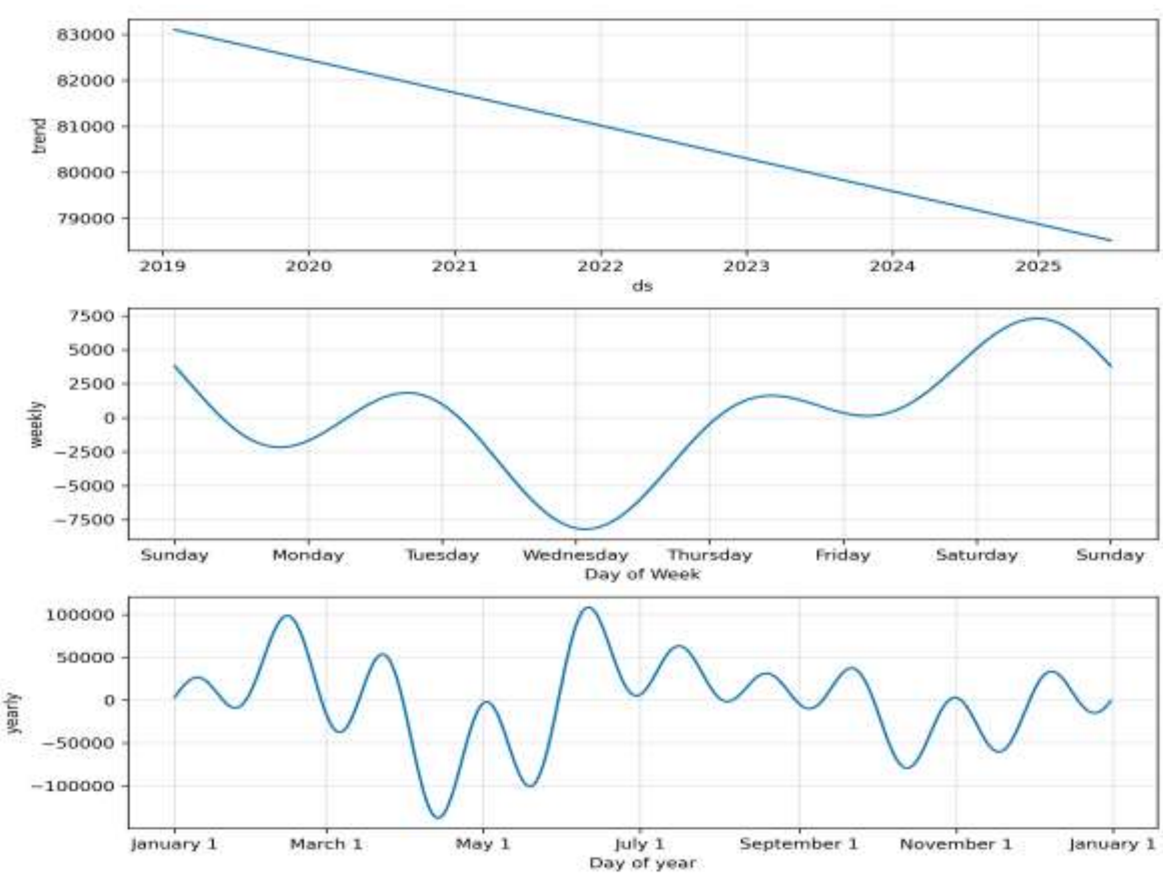

Figure 6. *Decomposition of forecast components illustrating long-term trend, weekly variations, and annual seasonal patterns, highlighting end-of-year surges and mid-year increases.*

4.5. Comparative Forecasting Analysis

The resilience of Prophet was tested by comparing it [17] with ARIMA and LSTM models under a similar experiment using the same monthly sales data (January 2019 – June 2024) and summarized in Table 3.

Table 3. Comparative analysis of forecast accuracy across multiple predictive models.

Model	MAE	RMSE	MAPE (%)
Prophet	9022.34	10486.01	10.28
ARIMA	10824.62	13119.05	12.11
LSTM	6257.05	7886.92	7.01

While LSTM was slightly better than Prophet in RMSE, it was much more resource-intensive than Prophet. In a sense, Prophet acted as a bridge by being interpretable, accurate, and easy to implement, which could make it an arguably ideal model for e-commerce where transparency and action ability are two of the most important considerations in practice.

5. Discussion & Conclusion

With all of the analysis combined, this demonstrates clear evidence that descriptive, flow-based and predictive approaches can provide layering options for sales data analytics, which adds depth to the analysis of residential e-commerce sales performance.

Descriptive Analysis: The treemap analysis indicated that while sales were high, that may not always correlate with high profit or customer satisfaction. For example, the Sports category had high revenue and high profit, while departments such as Clothing and Home and Kitchen had high sales but also had high returns. This indicates that returns and profitability should also be factored into the above average sales performance in impairment to overall performance.

Flow-based Analysis: The Sankey diagrams allowed visualization respective to both the region, and by person associated with completed sales. In particular, North America and Asia had the highest completed sales, while South America had a high total return. This suggests logistical, complicity or product quality challenges. Despite the risk of a high total return, each ready sales team could be managed rather easily to be better prepared for these challenges with targeted interventions, addressed regionally (quality checks associated with completed sales or products) or post-sale support (quality discrepancies had been acknowledged and further identified or determined with the customer on non-communication).

Temporal Flow and Predictive Forecasting: The process of time series deconstruction allowed for predictable seasonal trends, such as the holiday emphasis (growth and deterioration), mid-year promotional pressure (inverted "M"), and weekly fluctuations, to be revealed. The Prophet model forecasts from July to December 2024 projected stability in sales relative to the previous 6 years of continued growth, and eventual growth in the latter part of the four-month time period (6 months out). The 80% confidence intervals show the limits of uncertainty in forecasting that are recognized and acknowledged. Besides, they permit the proactive management of inventory and staff.

Comparative Forecasting: Prophet's performance results were very similar to those of ARIMA and LSTM, which means that Prophet is a suitable tool for operational decision-making. Prophet can be a good tool for e-commerce forecasting because it can generate accurate, understandable, and computationally efficient forecasts.

The strategic implications of this framework are important because it enables managers to choose products, track inventories, plan marketing efforts, and schedule operational activities using analytics. Considering seasonal demand enables firms to conduct promotional activities and adjust stocks and more finely tuned logistics and workforce plans. Furthermore, adjusting to demand with more flexible and valuable policies will diminish ill-returns and support the strengthening of customer loyalty return policies are extended and valuable customer service provided. This helps organizations move from reactive decision making to a state of predictive planning and uncertainty within a defined proactive decision-making framework. Discounts, competitor pricing, and broader economic frameworks are likely valuable future reductions to more precisely predict the proposed framework.

Future Directions: The inclusion of more explanatory variables, such as promotions, competitor pricing, or macroeconomic indicators, could increase the prediction accuracy even more. The method is also a perfect fit for different e-commerce datasets and various business scenarios, thus being a scalable way of turning transactional data into strategic intelligence.

In conclusion, the proposed framework encourages using transactional data to make business decisions. This framework demonstrates the value of a more advanced, explanatory, and integrated approach to the analytics of e-commerce sales performance within a business. This work, therefore, advances operational decision-making to achieve business growth sustainability.

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