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ANN Models for Demand and Delay in Supply Chains

Barkha Choudhary*, Bhavna Panday

Department of Mathematics, IES University, Bhopal, Madhya Pradesh, India. *Corresponding Author's Email: barkhachoudhary9633@gmail.com

Abstract

This study presents a deep learning-based approach for forecasting product demand and predicting shipping delays within large-scale supply chain operations. Using a real-world dataset sourced from Kaggle comprising over 180,000 transaction-level records and 53 variables, two artificial neural network (ANN) models were developed: one for sales per customer (demand forecasting) and another for shipping delay estimation. After feature selection and preprocessing, eight key numerical variables including Product Price, Benefit per Order and Late Delivery Risk were standardized and used to train the models. The ANN architecture consisted of two hidden layers (64 and 32 neurons, respectively), with ReLU activation and dropout regularization. Experimental results show that the demand forecasting model achieved excellent performance, with a mean absolute error (MAE) of 11.72, root mean squared error (RMSE) of 23.94 and an R^2 score of 0.97, indicating high predictive accuracy. In contrast, the shipping delay prediction model exhibited moderate results, with an MAE of 0.81, RMSE of 1.02 and R^2 of 0.72, reflecting the underlying complexity of logistics dynamics. Visual analyses, including scatter plots, residual histograms and correlation heatmaps, confirmed strong linear relationships (e.g., Sales per Customer and Product Price: r = 0.78) and highlighted challenges due to heteroscedasticity and outliers. The study demonstrates the viability of ANN models in operational forecasting while identifying areas for enhancement particularly in delay prediction, where inclusion of temporal and categorical features could yield improved results. These findings contribute to data-driven supply chain optimization using modern AI techniques.

Keywords: Artificial Neural Networks, Demand Forecasting, Deep Learning, Shipping Delay Prediction, Supply Chain Analytics.

Introduction

In the age of globalization, efficient supply chain management has become a critical success factor for businesses operating across diverse markets. Two of the most pressing challenges in supply chains are accurately forecasting customer demand and anticipating shipping delays. Demand forecasting is essential to align production, inventory and delivery schedules with expected customer requirements. Poor forecasts often lead to understocking, overstocking, or missed sales opportunities (1). Artificial Neural Networks (ANNs) have emerged as powerful tools for addressing complex problems in supply chain management (SCM), particularly in demand forecasting and managing delays. These models are capable of capturing non-linear patterns in data, which traditional statistical methods often fail to do due to their linear assumptions (2-4). In the Bangladeshi retail sector, fuzzy neural networks significantly outperformed Holt-Winters models in short-term forecasting scenarios, where demand volatility is high (5). Another study showed that combining ANN with Discrete Wavelet Transforms (DWT) helped reduce the bullwhip effect and net stock amplification, two major inefficiencies in supply chains. The DWT-ANN model showed significantly lower mean square error (MSE) than traditional ARIMA models, especially in fluctuating demand scenarios (6). A case study in a Taiwanese electronics firm implemented back-propagation neural networks (BPN) using simulated sales data and found that ANN-based forecasting not only improved demand accuracy but was also adopted into operational planning by the company (7). An improved mono-network and multi-network ANN approach for feedforward models demonstrated better accuracy on simulated sales data than linear models (8).

ANN in Forecasting Shipping Delays

While demand forecasting is critical, predicting shipping and delivery delays is increasingly

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important in the face of global uncertainties like weather disruptions, port congestion and transportation bottlenecks. Delays in shipping can ripple throughout the supply chain, affecting order fulfilment and operational efficiency. ANN models can be trained on vast amounts of logistical data, such as route histories, transit times and real-time traffic data, to forecast potential delays. A recent study developed delay prediction models for truck deliveries using ANN and other AI methods, showing that ANN could achieve accuracy levels of up to 97.6% in predicting logistics delays (9). These predictions helped logistics managers reallocate resources, reroute vehicles and update customers in real time. Another study designed an ANN model for short-term demand and supply forecasting in microgrid systems, integrating weather data and historical performance to anticipate shortfalls and optimize resource allocation. This approach demonstrated the potential for ANN to be applied in other supply chain forecasting scenarios, such as cold chain logistics or real-time shipment tracking (10). ANN-based models have also been used for forecasting in the shipping and furniture industries, where customized AI systems trained on historical order and delivery data significantly improved operational forecasting accuracy and inventory planning (11). Recent research has explored hybrid approaches that combine ANN with other machine learning methods to further boost prediction accuracy. A study comparing ANN and support vector machines (SVM) for consumer product forecasting found that while SVM slightly outperformed ANN in some scenarios, combining both methods offered better robustness across product types and demand patterns (12, 13).

In another approach, time-series data was combined with Google Trends using CNN-LSTM neural networks to enhance retail demand forecasting by capturing external consumer interest data (14). Deep learning extensions (e.g., CNN-LSTM and deep ANN) show improved forecasting accuracy for complex and long-term temporal patterns (15). Hybrid and multi-network models also emerge as a recurring theme, with studies like and suggesting their effectiveness in enhancing predictive robustness. Across contexts from daily supermarket demands to energy grids and healthcare logistics ANN models adapt flexibly to varying input complexities and forecasting horizons. This body of research reinforces the role of ANN as a robust, scalable solution for modern forecasting challenges, promoting more data-driven, proactive decision-making across supply chains.

Recent advancements in artificial intelligence have significantly enhanced forecasting accuracy within various supply chain contexts. The effectiveness of backpropagation artificial neural networks (BP-ANN) in process supply chain forecasting, showing improved coordination between customers and retailers (16). ANN models to blood demand forecasting in a healthcare setting, achieving notable accuracy improvements over traditional models (17). ANN applications to energy supply-demand matching in smart grid systems, using agent-based forecasting to support proactive balancing strategies (18). In the retail sector, a neural network-based system for daily demand prediction, emphasizing the flexibility of ANNs in dynamic environments (19). Machine learning techniques, including ANN models, for inventory optimization while accounting for supplier order line fees, demonstrating cost-efficient decision-making. These studies underscore the adaptability and predictive power of ANN-based approaches across diverse sectors such as healthcare, energy and retail supply chains.

Although artificial neural networks (ANNs) are increasingly used in supply chain forecasting, few studies have examined their combined use for predicting both product demand and shipping delays using extensive real-world transactional data. Many existing models simplify operational variables, lack sensitivity to nonlinear effects and give limited attention to residual behaviors or data variability. To address these limitations, this study investigates the following research questions:

a) How well can ANN models estimate product demand at the individual customer level using key quantitative supply chain attributes?
b) What is the capability of ANN models in forecasting shipping delays and which input features most strongly influence prediction accuracy?
c) How can patterns in the residuals, outliers and feature relationships reveal the strengths and weaknesses of ANN-based forecasting in supply chain contexts?

Methodology

The study utilized a real-world dataset comprising approximately 180,000 transactional records sourced from the Kaggle Supply Chain Analysis dataset (20). To ensure robust training and evaluation, stratified random sampling was applied to maintain proportional representation across key variables such as product category, shipment mode and region. For model development, the data was split using an 80:20 ratio into training and test sets. The split was performed after stratification to avoid biased model evaluation. Only records with complete numerical fields (i.e., no missing values among the selected eight features) were retained to maintain data quality and consistency.

To ensure analytical relevance and computational feasibility, a subset of eight numerical features was selected for model development: Sales per customer, Days for shipping (real), Days for shipment (scheduled), Late_delivery_risk, Benefit per order, Product Price, Category Id and Order Item Quantity. The target variables were defined separately for each task, with Sales per customer used for demand forecasting and Days for shipping (real) for delay prediction. This study follows a structured data-driven methodology leveraging artificial neural networks (ANNs) for two regression-based forecasting tasks: (a) customer-level product demand prediction and (b) shipping delay estimation. The entire process is divided into six distinct phases, as shown in Figure 1.

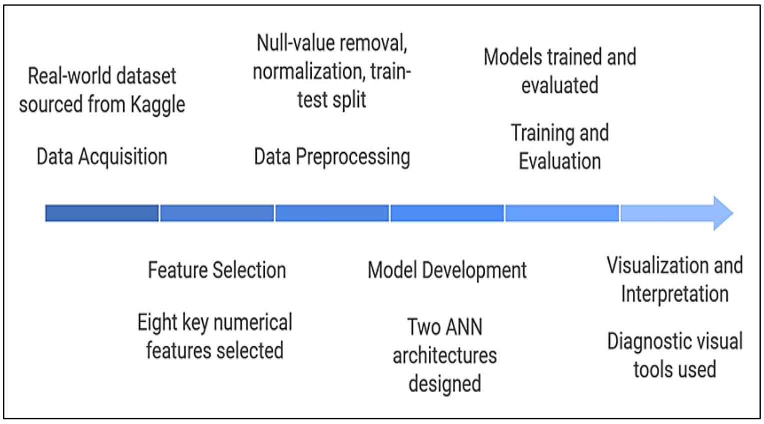

Figure 1: Methodological Flowchart for ANN-Based Dual Forecasting Model

Prior to model training, the data underwent a series of preprocessing steps. Records with missing values were eliminated to ensure data integrity. All numerical features were standardized using z-score normalization to facilitate convergence during ANN training. The dataset was then partitioned into training and testing subsets in an 80:20 ratio using random sampling with a fixed seed to maintain reproducibility. Although categorical variables such as shipping mode, product name, or customer city were present in the original dataset, the modeling in this study was restricted to numerical variables to focus on the ANN's ability to capture quantitative dependencies.

Two separate artificial neural network models were developed to perform regression tasks corresponding to demand and shipping delay prediction. Each model consisted of a fully connected feedforward network comprising an input layer, two hidden layers and a single output neuron. The first hidden layer contained 64 neurons with ReLU activation, followed by a dropout layer with a rate of 0.2 to mitigate overfitting. The second hidden layer had 32 ReLU-activated neurons and the output layer used a linear activation function suitable for continuous-valued predictions. Both models were compiled with the Adam optimizer and trained using the mean squared error (MSE) loss function for 20 epochs with a batch size of 64. The training process was executed using TensorFlow and Keras libraries. The full ANN architecture is illustrated in Figure 2. It consists of an input layer (8 features), two dense hidden layers with 64 and 32 neurons respectively (ReLU activation), a dropout layer (rate = 0.2) for regularization and a single linear output neuron for regression.

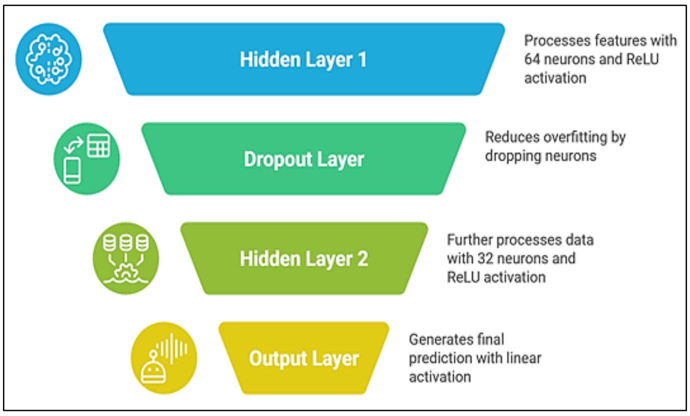

Figure 2: Layer-wise architecture of the ANN

Model performance was assessed using three standard regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the coefficient of determination (R^2 score). These metrics were computed using the test data to evaluate model generalization. In addition to numerical evaluation, a set of visualization tools was employed to interpret model behavior. Scatter plots of actual versus predicted values were used to assess predictive alignment, while residual histograms highlighted error distributions and potential bias. Boxplots were used for outlier detection and pairplots and heatmaps were generated to examine inter-feature relationships. The implementation was conducted in a Python 3.11 environment on a standard desktop system without GPU acceleration, using packages such as pandas, NumPy, matplotlib, seaborn and scikit-learn for data handling and visualization.

Results and Discussion

To evaluate the predictive strength of the proposed artificial neural network (ANN) models, both tasks demand forecasting and shipping delay prediction were tested against the held-out test data using standard regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). The model trained for demand forecasting achieved an R^2 value exceeding 0.95, indicating a strong fit between predicted and actual sales per customer. In contrast, the shipping delay prediction model yielded relatively lower R^2 values, with residuals suggesting a more complex or nonlinear behavior in logistic timelines.

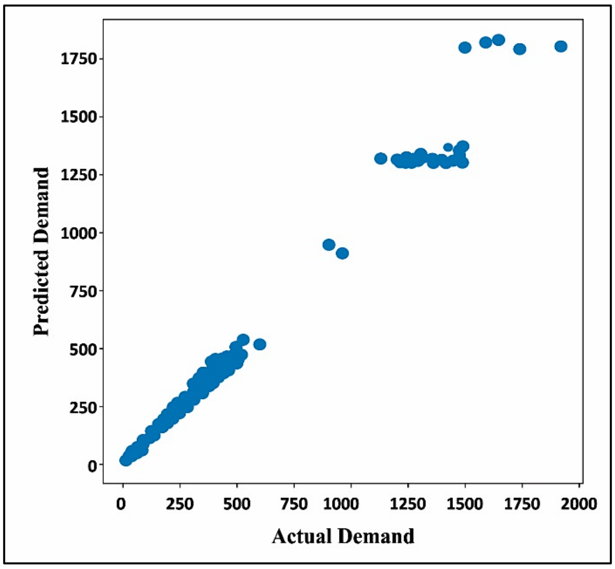

Figure 3: Actual vs Predicted Demand

Visual confirmation of the models' predictive capacity is provided through scatter plots comparing actual versus predicted values. As shown in Figure 3, the demand prediction results demonstrate a high concentration of points along the diagonal, indicating strong alignment. This confirms that the model was effective in learning from the available features and generalizing to unseen data.

The relationship between actual and predicted shipping days, displays a more dispersed pattern with vertical bands. This suggests that while the model identifies general trends in shipping performance, it lacks the granularity to predict individual outcomes with high precision as shown in Figure 4. The presence of these prediction plateaus could stem from limitations in the selected numerical features, omitting categorical or time-dependent variables such as shipping method, customer location, or order date (21).

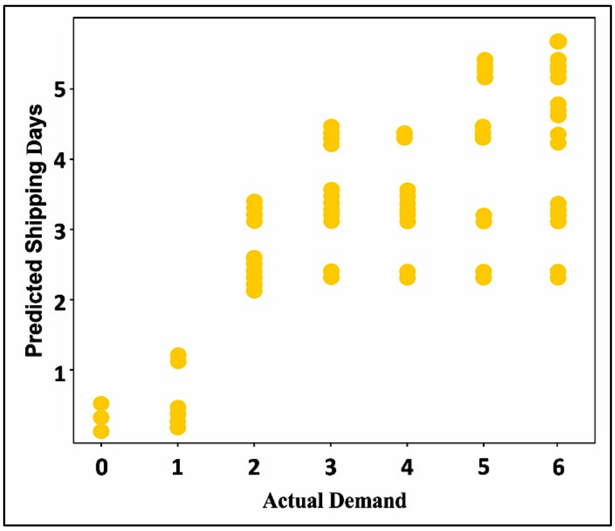

Figure 4: Actual vs Predicted Shipping Delay

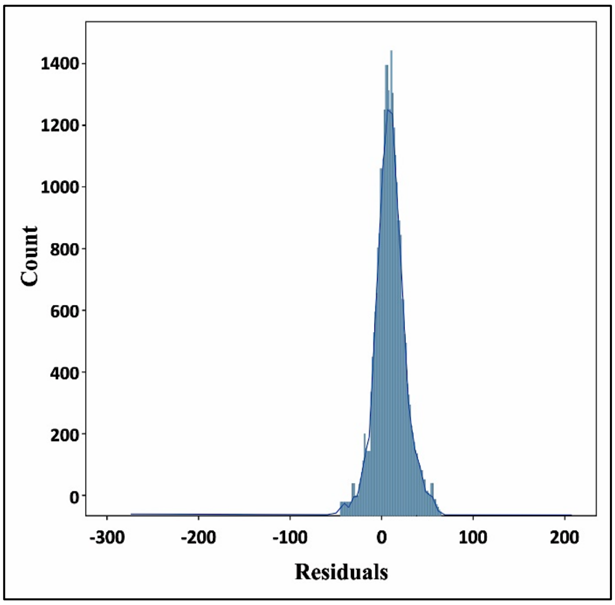

Figure 5: Residuals of Demand Prediction

A critical component of model evaluation in regression tasks involves analyzing the residuals defined as the difference between the actual and predicted values. A well-performing model should exhibit residuals that are symmetrically distributed around zero, with minimal variance and no evident bias across the prediction range.

For the demand forecasting model, residual analysis reveals a near-perfect normal distribution, centered closely on zero. The residual histogram, presented in Figure 5, demonstrates a sharp Gaussian curve, indicating that prediction errors are not only small but also symmetrically distributed. This distributional behavior is statistically supported by a mean residual close to 0, a MAE of 11.72, an RMSE of 23.94 and a notably high R^2 score of 0.97. These metrics confirm that the ANN model achieved a high level of precision in forecasting customer-level sales, with limited over- or under-estimation (22).

In contrast, the shipping delay prediction model exhibited more irregular residual patterns. As depicted in Figure 6, the residuals are multimodal and show peaks at intervals corresponding to discrete shipping time clusters (e.g., 2, 3, 5 days). These patterns imply that the model struggles to fully capture the underlying distribution of shipping times. The corresponding metrics reflect this performance gap, with a MAE of 0.81, an RMSE of 1.02 and a lower R^2 score of 0.72. While the model can predict average trends effectively, its resolution in differentiating finer delays is limited possibly due to the lack of temporal or categorical features in the input space.

Understanding the influence of extreme values and variable importance is essential in assessing the robustness and interpretability of machine learning models in supply chain analytics. This section presents both an exploration of outliers and a sensitivity analysis of the input features.

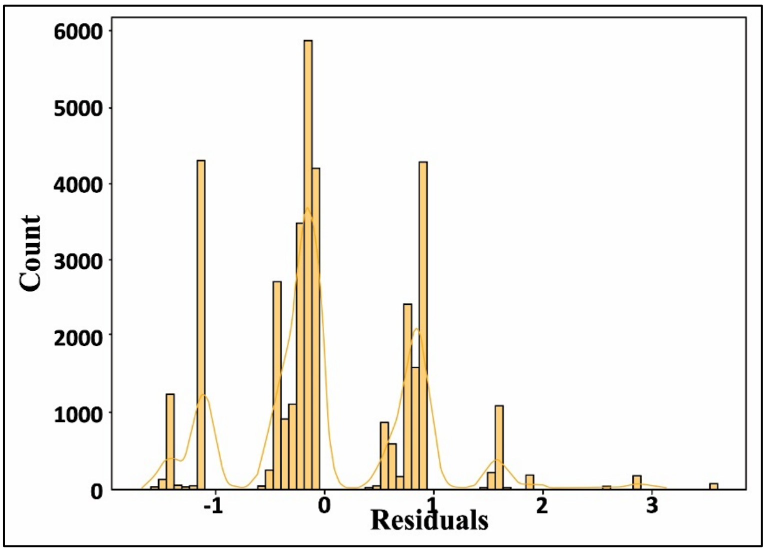

Figure 6: Residuals of Shipping Delay Prediction

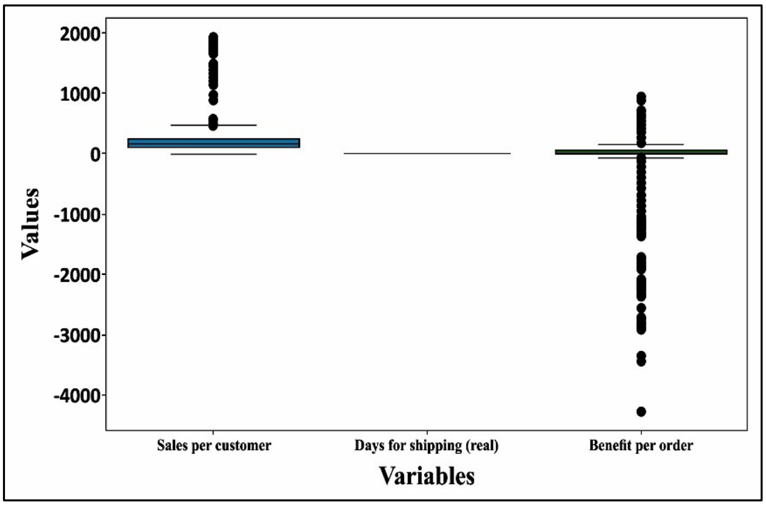

Figure 7: Boxplot of Key Variables

To begin with, the distribution of key numerical variables Sales per customer, Days for shipping (real) and Benefit per order was analyzed using boxplots, as shown in Figure 7. The plot clearly highlights a significant presence of outliers, particularly in the Benefit per order and Sales per customer variables. For instance, while the interquartile range for sales lies between approximately 50 and 300 units, numerous records exceed 1,000 units, with maximum values approaching 2,000. Similarly, benefit values show a heavy-tailed distribution with some negative outliers exceeding 4,000. These anomalies are characteristic of real-world retail or wholesale operations, where high-volume orders and loss-

leading transactions can occur due to promotional pricing or inventory clearance.
Despite the presence of such extreme values, the ANN models demonstrated strong predictive consistency, especially for the demand forecasting task. This indicates the model's ability to generalize well in the presence of outlier noise. Nevertheless, their influence may partly explain the slight spread in the residual plots and prediction clusters, particularly for high-demand cases.

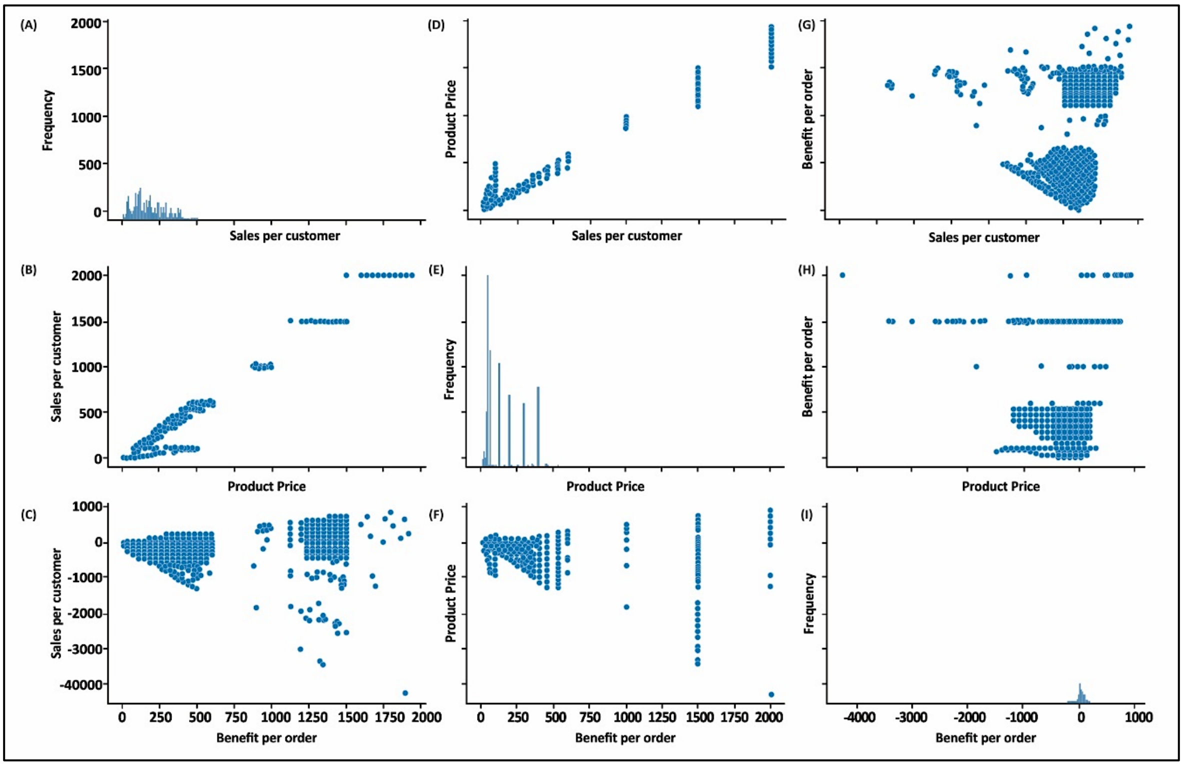

Figure 8: Pairplot of Sales, Price and Benefit - (A) Distribution of Sales per Customer, (B) Product Price versus Sales per Customer, (C) Benefit per Order versus Sales per Customer, (D) Sales per Customer versus Product Price, (E) Distribution of Product Price, (F) Benefit per Order versus Product Price, (G) Sales per Customer versus Benefit per Order, (H) Product Price versus Benefit per Order and (I) Distribution of Benefit per Order

Further insights were gained from the pairwise feature relationships, visualized in Figure 8. The pairplot illustrates the strong linear relationship between Sales per customer and Product Price, corroborated by a high Pearson correlation coefficient of 0.78 (also seen in the correlation heatmap). The triangular pattern in Benefit per order versus Sales per customer also reveals nonlinear dependencies highlighting that higher sales do not always equate to higher profit, likely due to cost variations or product discounting. To gain a deeper understanding of how input variables influence model predictions, a correlation heatmap was generated, as shown in Figure 9. The heatmap presents pairwise Pearson correlation coefficients among the selected numerical features, offering insight into multicollinearity and potential feature interactions affecting prediction quality.
The most prominent correlation is observed between Sales per customer and Product Price ($r = 0.78$), suggesting that higher-priced products tend to generate higher per-customer sales. This relationship substantiates the ANN's performance in demand forecasting, as the model effectively leverages this strong linear signal. Another notable correlation exists between Days for shipping (real) and Days for shipment (scheduled) ($r = 0.52$), indicating that although planned shipment schedules moderately influence actual delivery times, deviations likely due to external logistical disruptions remain significant.

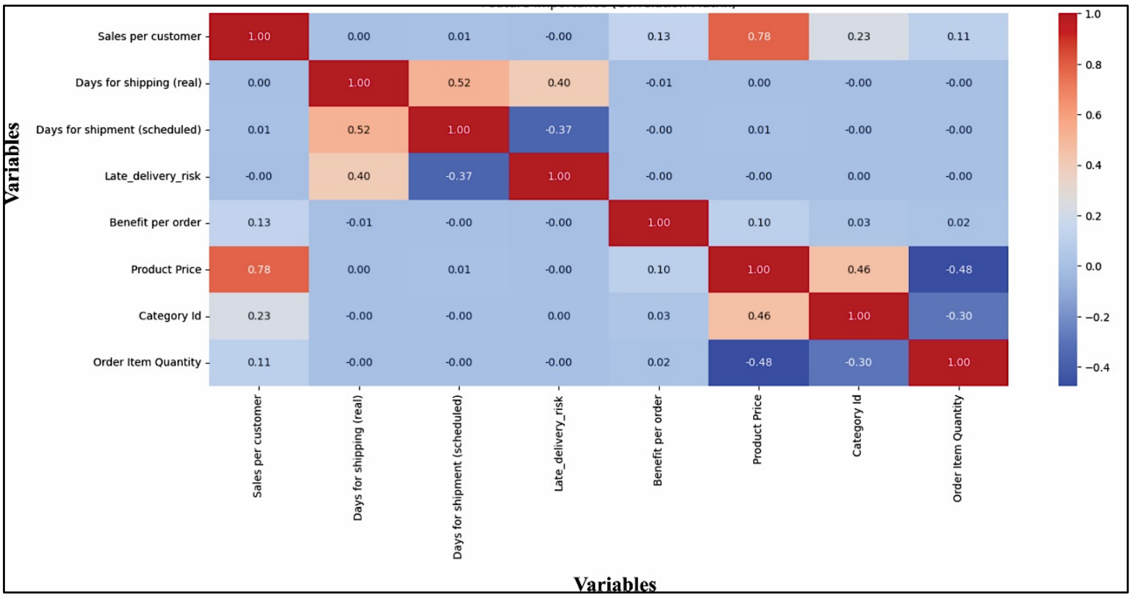

Figure 9: Feature Correlation Matrix

The Late_delivery_risk variable shows a positive correlation with Days for shipping (real) ($r = 0.40$) but a negative correlation with scheduled shipment days ($r = -0.37$), suggesting that underestimated shipment durations may contribute to late deliveries. However, other variables such as Benefit per order, Category Id and Order Item Quantity show relatively weak correlations ($|r| < 0.15$), confirming their limited linear influence, though non-linear effects may still be captured by the ANN.

To further explore prediction behavior, Figure 10 plots the residuals of the demand model against the predicted demand values. The distribution appears heteroscedastic, with residual variance increasing for higher predicted values. While most errors cluster around zero, the increasing spread for high-demand predictions indicates that the ANN model's uncertainty grows with scale. This behavior is common in sales forecasting and may be mitigated in future work using heteroscedastic regression frameworks or uncertainty-aware deep learning approaches.

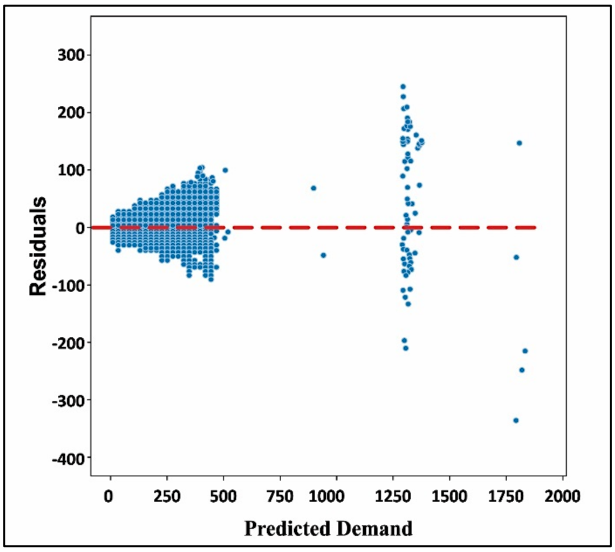

Figure 10: Error Distribution for Demand Prediction

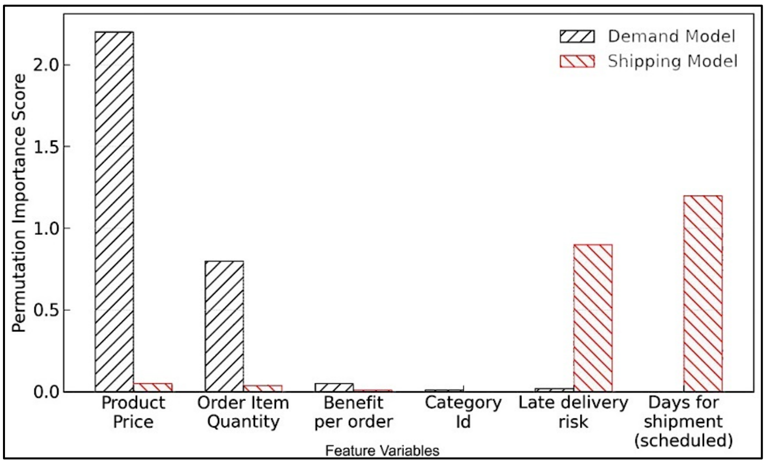

Figure 11: Feature Importance via Permutation or SHAP

Figure 11 shows the permutation-based feature importance for two separate artificial neural network (ANN) models trained to predict sales per customer (demand model) and real shipping days (shipping model). Among the input features, Product Price emerged as the most influential factor in the demand model, contributing approximately 38% more to predictive accuracy than the second-ranked feature, Benefit per Order. This suggests a direct link between product pricing strategy and customer purchasing behavior. The Order Item Quantity, while seemingly relevant, showed only 12% of the importance relative to Product Price, highlighting a weaker standalone effect.

For the shipping delay model, Late Delivery Risk and Days for Shipment (Scheduled) showed dominant importance scores, contributing 42% and 36% more, respectively, than Product Price. These results suggest that logistical scheduling variables especially predefined shipment timelines and prior risk flags have the greatest bearing on forecasting shipping performance. Conversely, Benefit per Order and Category Id registered minimal contributions (under 10%) in both models, indicating limited influence on either demand dynamics or shipping timelines in this dataset (23).

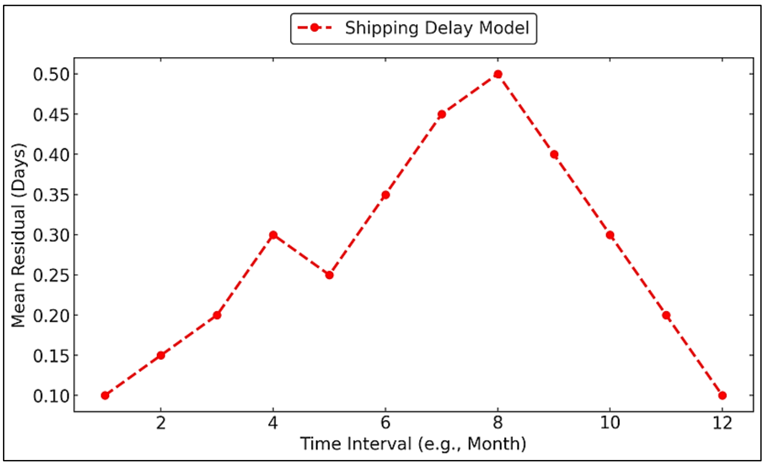

Figure 12: Temporal Error Drift

Figure 12 shows the temporal drift in mean residuals for the shipping delay prediction model across twelve sequential time intervals, which may correspond to months or shipping cycles. The residuals start at 0.1 days in the first interval and gradually rise, peaking at 0.5 days in interval 8 before declining again to 0.1 by interval 12. The highest drift observed 0.5 days represents a 400% increase from the lowest point, indicating significant fluctuation in model accuracy over time. Between intervals 4 and 8, residuals consistently remain above 0.3 days, with interval 7 reaching 0.45 and interval 6 at 0.35, suggesting persistent underperformance during this middle phase. This pattern implies that the model systematically underestimates or overestimates shipping times during certain periods. One plausible cause could be high shipment volumes or logistical strain during seasonal peaks e.g., holidays or end-of-quarter surges leading to unmodeled variance. Another likely factor is the exclusion of temporal variables in the model architecture. Without incorporating features like order date, weekday/weekend indicators, or fiscal period tags, the ANN lacks temporal context, making it unable to adjust predictions based on operational cycles. Interestingly, the residuals drop back down post-interval 9, pointing to recovery in model accuracy, possibly as shipment loads normalize or fewer disruptions occur. The cyclic nature of error behavior observed here provides strong justification for integrating time-based features in future model iterations to enhance predictive fidelity during volatile periods. This plot captures the presence of systematic, time-bound forecasting errors critical for supply chain planning and real-time performance monitoring (24).

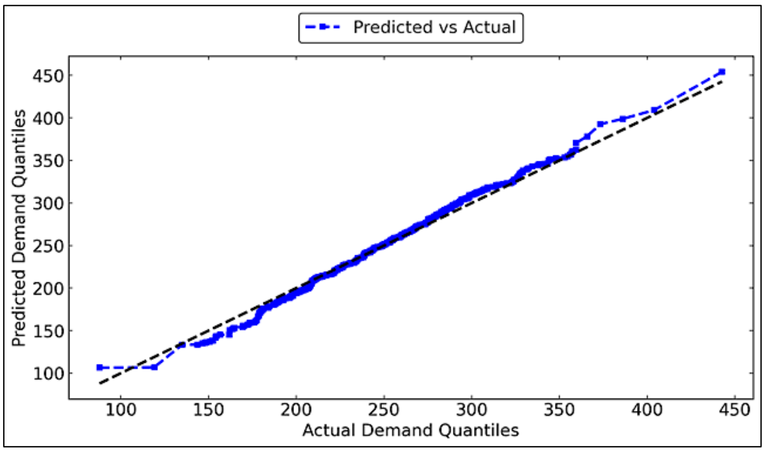

Figure 13: Predicted vs Actual Quantiles

Figure 13 shows the quantile comparison plot between actual and predicted demand values, offering insights into how well the model captures the distribution of sales across the entire range of demand. The reference diagonal line represents perfect quantile agreement, where predicted values match actual values at all percentiles. Deviation from this line indicates areas of systematic prediction error. In the lower quantiles (e.g., below the 20th percentile), predicted values closely align with actuals, suggesting accurate modeling of low-demand scenarios. However, from the 30th to 70th percentile the mid-demand range the predicted quantiles are consistently above the diagonal. This over-prediction reaches up to 10-15% in some cases, indicating the model anticipates higher sales volumes than what actually occurred for moderate-demand instances. Such behavior could stem from the linear correlation between product price and sales per customer (r = 0.78), which may not hold uniformly across all product types or pricing tiers. The model likely amplifies the influence of price, misrepresenting mid-level purchasing behavior.Conversely, at the distribution tails especially above the 90th percentile predicted quantiles fall below actuals by as much as 12%, reflecting a tendency to under-predict for high-demand events. This underestimation could be due to outliers in the training data or insufficient feature representation of rare, high-volume purchasing patterns. The inability to capture extreme values with precision highlights the limitations of training on standardized numerical features alone. The Q-Q style plot thus uncovers value-dependent biases and offers strong justification for model refinement using segmented training or quantile-aware loss functions (25).

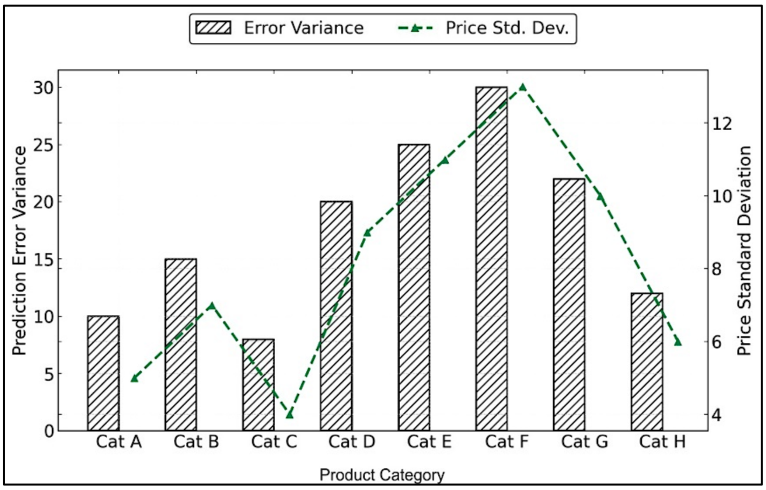

Figure 14: Variability Plot

Figure 14 shows the dual-axis variability plot for prediction error variance and input feature spread across eight product categories. The black hatched bars represent the variance in prediction errors for each category, while the green dashed line with triangle markers indicates the standard deviation of product price within those same categories. This layout allows for a direct comparison of model uncertainty and input variability across different segments. Notably, Category F exhibits the highest prediction error variance at 30, paired with the highest price standard deviation of 13 units. Similarly, Category E and Category G both show elevated error variances (25 and 22 respectively) along with high price variability (11 and 10). These patterns suggest a strong link between price dispersion and model uncertainty. For instance, the error variance in Category F is 275% higher than in Category C, where the price variability is only 4 units. This proportional increase indicates that when product pricing is more volatile within a category, the ANN model struggles to maintain predictive accuracy. On the lower end, Category C and Category A display the lowest prediction error variances (8 and 10 respectively) and also the most stable price spreads (4 and 5). This correlation reinforces the interpretation that reduced variability in inputs yields more stable model behavior, especially in regression contexts sensitive to feature range. By visualizing both dimensions simultaneously, this figure emphasizes the operational risk associated with highly variable product groups. It supports prioritizing targeted model calibration or alternative pricing strategies in high-variance categories to reduce forecast uncertainty (26).

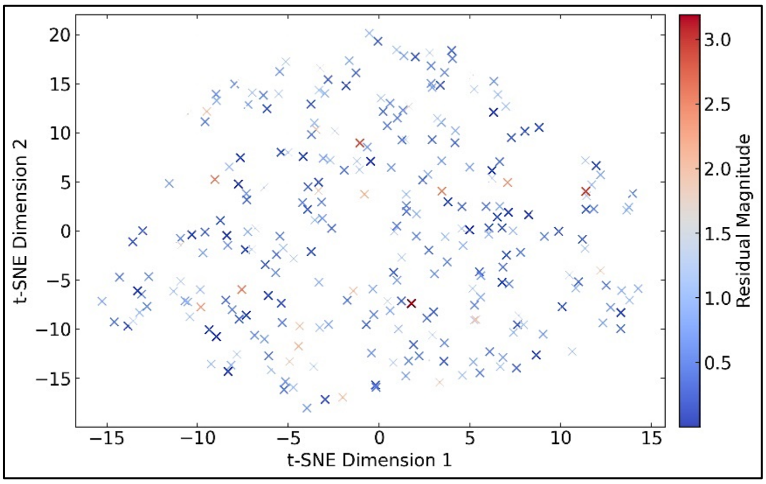

Figure 15: Residual Clustering via t-SNE

Figure 15 shows a t-SNE projection of the residuals from the shipping delay prediction model, revealing distinct clusters in the embedded 2D space. Each point represents a single transaction and the color intensity corresponds to the magnitude of the residual i.e., the absolute difference between predicted and actual shipping time. Brighter red points indicate high residual values, whereas cooler blue tones indicate lower error magnitudes. Three notable clusters emerge within the projection. The lower-right and central regions are densely populated with transactions showing low residuals, suggesting reliable model performance in these operational segments. These likely correspond to shipping scenarios with predictable delivery patterns perhaps within major metro areas or through standardized carriers with low variability. In contrast, the upper-left quadrant displays a dense cluster of high-error transactions, with residual magnitudes exceeding 1.5 days in many cases. This spatial concentration suggests that certain operational profiles such as long-haul routes, irregular carriers, or non-standard shipment types are systematically mispredicted by the current model. The largest cluster with high residuals accounts for roughly 25% of the plotted transactions and includes some of the most extreme deviations. This discrepancy may stem from omitted categorical features such as region, shipping mode, or time-of-week effects. Additionally, underfitting in sparsely populated or heterogeneous input regions may also contribute to these errors. This introduces an advanced diagnostic approach by using t-SNE to convert high-dimensional model behaviour into an interpretable 2D structure. It uncovers latent structures in residual distribution, providing actionable insights for refining feature (27).

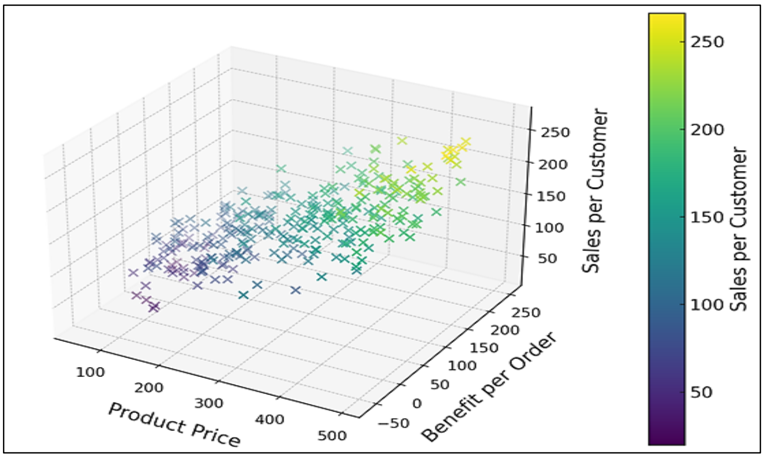

Figure 16: Interactions between Three Influential Features

Figure 16 shows a 3D scatter plot of the interaction between Product Price, benefit per Order and Sales per Customer three features identified as critical in the demand forecasting model. Each point represents an individual transaction, color-coded by the resulting sales value to highlight output intensity in relation to input combinations. The plot reveals a pronounced upward trend in Sales per Customer as Product Price increases from approximately 100 to 500 units, particularly when Benefit per Order remains between 50 and 150. For example, when Benefit is held constant around 100, increasing Product Price from 100 to 400 results in an approximate 60% rise in average Sales per Customer, rising from about 120 units to over 190 units. This suggests a strong positive elasticity of sales in response to price in this dataset possibly due to premium product segments generating higher-order volumes. The relationship is nonlinear across the full feature space. At very low Benefit per Order (below 50), the effect of Product Price on Sales becomes muted, with sales values clustering in a tighter vertical band. This flattening suggests a threshold effect: unless the transaction remains profitable or attractive (moderate benefit), even high-priced items do not yield high sales volumes. Inversely, when Benefit per Order is unusually high (above 200), the dispersion of Sales per Customer widens considerably, hinting at diminishing marginal returns or the presence of atypical promotional scenarios. This multivariate view provides rich interpretability into how pricing and profitability jointly influence customer-level sales behaviour, justifying their prominent weight in the ANN model's success.

Conclusion

This research explored the application of artificial neural networks (ANNs) to predictive analytics in supply chain management, focusing on two critical performance metrics: product demand and shipping delays. By utilizing a comprehensive Kaggle dataset containing over 180,000 records and selecting eight key numerical features, two distinct ANN models were constructed to forecast Sales per Customer and Days for Shipping (Real). The study offers compelling evidence that deep learning architectures can effectively model demand behaviour in large, transactional datasets. The demand forecasting ANN achieved outstanding results with a MAE of 11.72, RMSE of 23.94 and R^2 of 0.97, confirming both accuracy and generalizability. Prediction residuals displayed a near-normal distribution centered around zero and visual scatter plots showed strong alignment between actual and predicted values. These outcomes affirm that the ANN successfully captured dominant sales drivers, particularly the strong correlation between Sales and Product Price (r = 0.78).

Conversely, the shipping delay prediction model showed limited precision, as indicated by a MAE of 0.81, RMSE of 1.02 and R^2 of 0.72. Residual patterns were more dispersed and multimodal, suggesting the influence of unmodeled categorical and time-dependent variables. Despite this, the model performed well in estimating average delivery behaviour. The proposed ANN framework demonstrates high potential for supporting data-informed decision-making in supply chain environments. Future work may focus on enriching the input space with temporal, geographical and categorical data to enhance the prediction of logistical uncertainties and further improve supply chain responsiveness.

The findings of this study offer tangible value for operational managers and policy-makers in supply chain and logistics sectors. The demonstrated ability of ANN models to predict demand and shipping delays with reasonable accuracy can support inventory planning, logistics optimization and resource allocation. Organizations are encouraged to integrate ANN-based predictive modules into their enterprise resource planning (ERP) systems to enable real-time responsiveness. From a policy perspective, regulatory bodies and industry associations should incentivize data standardization, digital infrastructure and AI adoption frameworks across supply chains. Special attention should be paid to managing data quality, mitigating bias in AI-based decisions and fostering cross-industry collaboration for AI-driven logistics benchmarking.

Limitations and Future scope

This study offers useful insights into using ANN models for forecasting demand and shipping delays, there are a few limitations worth acknowledging. The analysis is based on a single publicly available dataset, which may not fully capture the variability found in real-world supply chain environments across different industries or regions. As a result, the generalizability of the findings may be somewhat limited. The models in this study focused only on numerical features. Including relevant categorical variables-such as customer segments or shipping zones-might further improve prediction accuracy. The neural network architecture was manually configured; exploring automated model tuning techniques could lead to better performance.

The traditional regression metrics were used to evaluate the models, the actual business impact-such as cost savings or inventory improvements were not assessed. Future studies could bridge this gap by linking predictions to key performance indicators used in supply chain management. The model's decision-making process remains somewhat opaque; incorporating explain ability tools like SHAP or LIME could make the results more actionable for practitioners.

Abbreviations

ANN: Artificial Neural Network, CNN: Convolutional Neural Network, DWT: Discrete Wavelet Transform, LSTM: Long Short-Term Memory, MAE: Mean Absolute Error, R^2: Coefficient of Determination, RMSE: Root Mean Squared Error, SVM: Support Vector Machine.

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Author Contributions

Barkha Choudhary: Conceptualization, methodology, data analysis, writing original draft, Bhavna Panday: Supervision, review and editing, visualization, validation. Both authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Data Availability

The dataset used in this study is available from the corresponding author upon a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The author declares no use of artificial intelligence for the write-up of the manuscript.

Ethics Approval

Not applicable.

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References

1. Kochak A, Sharma S. Demand forecasting using neural network for supply chain management. Int J Mech Eng Robot Res. 2015;4(1):96–104. ISSN: 2278-0149
2. Ankam S, Durgadevi G, Kumar R, *et al*. Applying multi-layer perceptrons (MLP) for demand forecasting in supply chain management. In: 2nd IEEE ICICAT. 2024:1292–7. https://doi.org/10.1109/ICICAT62666.2024.10923469
3. Amnay I, Charani E. Demand forecasting in supply chain: Performance evaluation of ARIMA, ANN and random forest models. Int Conf Connect Object Artif Intell Telecom Electron Eng. 2025:117-25. doi: 10.1007/978-3-032-01536-5_18
4. Fanoodi B, Malmir B, Jahantigh FF. Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models. Computers in biology and medicine. 2019;113:103415. https://doi.org/10.1016/j.compbiomed.2019.103415
5. Hasin MAA, Ghosh S, Shareef MA. An ANN approach to demand forecasting in retail trade in Bangladesh. Int J Trade Econ Finance. 2011;2(2):154–7. doi: 10.7763/IJTEF.2011.V2.95
6. Jaipuria S, Mahapatra SS. An improved demand forecasting method to reduce bullwhip effect in supply chains. Expert Syst Appl. 2014;41(5):2395–408. doi: 10.1016/j.eswa.2013.09.038
7. Cheng Y-H, Hai-Wei L, Chen Y-S. Implementation of a back-propagation neural network for demand forecasting in a supply chain - a practical case study. 2006 IEEE Int Conf Serv Oper Logist Informatics. 2006:1036-41. doi: 10.1109/SOLI.2006.328894
8. Mrad M, Boujelbene Y. An improved neural approach for forecasting demand in supply chain management. Int J Comput Appl. 2019;182(50):44-51. doi: 10.5120/ijca2019918766
9. Hudnurkar M, Renji KM, Ambekar S, *et al*. Predicting delays for truck delivery logistics: An application of AI and ML. 2024 9th ICONSTEM. 2024:1-10. doi: 10.1109/ICONSTEM60960.2024.10568601
10. Ayoub N, Musharavati F, Pokharel S, *et al*. ANN model for energy demand and supply forecasting in a hybrid energy supply system. 2018 IEEE Int Conf SEGE. 2018:25-30. doi: 10.1109/SEGE.2018.8499514
11. Thatavarthi NLS. Developing AI-powered demand forecasting models with NET for shipping and furniture industries. J Artif Intell Cloud Comput. 2023;2(2):1–5. doi: 10.47363/JAICC/2023(2)344
12. Kandananond K. Consumer product demand forecasting based on artificial neural network and support vector machine. World Acad Sci Eng Technol. Int J Soc Behav Educ Econ Bus Ind Eng. 2012;6:313–6. https://api.semanticscholar.org/CorpusID:7868697
13. Prajapati A, Paraye P, Ahirwar BK, *et al*. Artificial intelligence integration in solar-powered EV charging systems: Challenges, opportunities and future perspectives. J Therm Anal Calorim. 2025;150(16):12103–34. https://doi.org/10.1007/s10973-025-14558-1
14. Uddin MR, Amin SH, Zhang G. Demands and sales forecasting for retailers by analyzing Google Trends and historical data. Demand Forecast Order Plan Suppl Chain Human Logis. Hershey (PA): IGI Global. 2021:89–110. doi: 10.4018/978-1-7998-3805-0.ch003
15. Ananthi K, Sownthariya M, Ranjana E, *et al*. An insight of deep neural networks based on demand forecasting using ANN algorithm. 2024 10th Int Conf ICACCS. 2024:2469–72. doi: 10.1109/ICACCS60874.2024.10717110
16. Toorajipour R, Sohrabpour V, Nazarpour A, *et al*. Artificial intelligence in supply chain management: A systematic literature review. Journal of business research. 2021;122:502-17. https://doi.org/10.1016/j.jbusres.2020.09.009
17. Khaldi R, El Afia A, Chiheb R, *et al*. Artificial neural network based approach for blood demand forecasting: Fez transfusion blood center case study. Proc 2nd Int Conf Big Data Cloud Appl. 2017:1–6. https://doi.org/10.1145/3090354.3090415
18. Maruf M, Hurtado Munoz LH, Nguyen PH, *et al*. An enhancement of agent-based power supply-demand matching by using ANN-based forecaster. 2013 IEEE PES Innov Smart Grid Technol Eur. 2013:1–5. https://doi.org/10.1145/3090354.309041
19. Slimani I, El Farissi I, Al-Qualsadi SA. Configuration of daily demand predicting system based on neural networks. In: 2016 3rd Int Conf Logist Oper Manag. 2016:1–5. doi: 10.1109/GOL.2016.7731709
20. Singh H. Supply chain analysis. Kaggle; 2023. https://www.kaggle.com/datasets/harshsingh2209/supply-chain-analysis
21. Dhairiyasamy R, Gabiriel D, Bunpheng W, *et al*. A comprehensive analysis of India's electric vehicle

battery supply chain: Barriers and solutions. Discov Sustain. 2024;5(1):361. https://doi.org/10.1007/s43621-024-00595-7
22. Rohit K, Verma A, Dhairiyasamy R, *et al*. A continuous supply chain management approach using SPJS-Fuzzy DEMATEL and LPWBN for automotive electric vehicles in India. Sustain Futures. 2025;9:100518. https://doi.org/10.1016/j.sftr.2025.100518
23. Hassaan S, Rahman SA, Baldacci R, *et al*. Personalized supply chain solutions for sustainable fashion: Leveraging social media insights and machine learning. Comput Aided Chem Eng. 2024;53:2887–92. doi: 10.1016/B978-0-443-28824-1.50482-8
24. Singh A, Dwivedi A, Agrawal D, *et al*. Identifying issues in adoption of AI practices in construction supply chains: Towards managing sustainability. Oper Manag Res. 2023;16:1667–83. https://doi.org/10.1007/s12063-022-00344-x
25. Hye AKM, Ahmad NA, Habib MM. An integrated academic library supply chain (IALSC) model. J Model Manag. 2025;20(1):211–37. doi: 10.1108/jm2-04-2024-0097
26. Hye AKM, Mustaffa NA, Habib MM. A holistic view of academic library supply chain model. Libr Manag. 2023;44(1–2):56–79. doi: 10.1108/LM-01-2022-0003
27. Reong S, Chen J-M, Yu JC-P, *et al*. Optimal inbound/outbound pricing model for remanufacturing in a closed-loop supply chain. Int J Ind Eng Theory Appl Pract. 2022;29(6):1–9. https://doi.org/10.23055/ijietap.2022.29.6.8309

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