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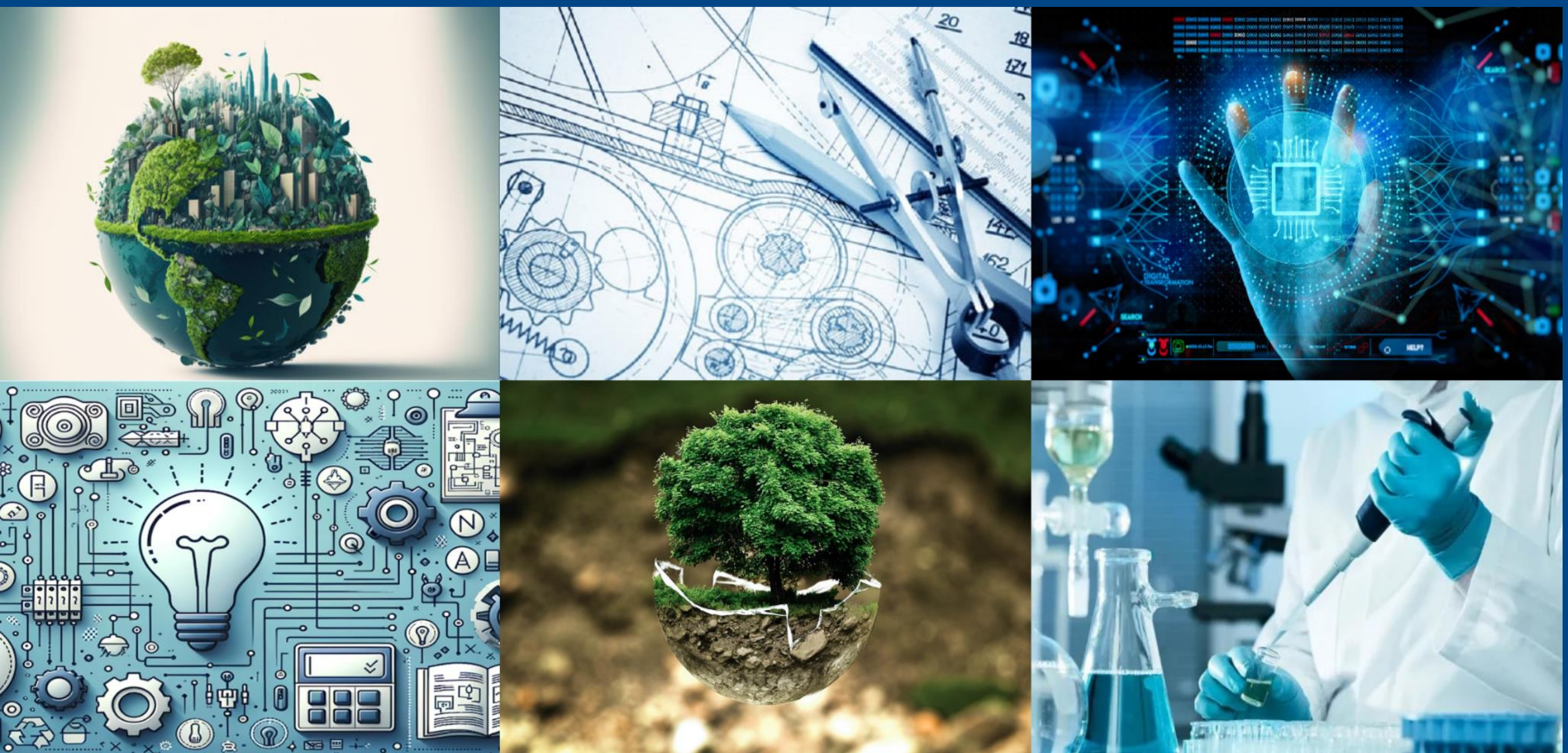

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Healthcare Supply Chain Optimizer: Predicting Medical Inventory By using Demand Forecasting Models

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ABSTRACT: Digital platforms in the healthcare sector are experiencing rising bounce rates resulting in diminished patient satisfaction lower engagement levels and financial losses when users exit without completing critical interactions such as appointment scheduling or service exploration it signals missed opportunities for healthcare providers this initiative proposes a data-centric approach combining machine learning and predictive analytics to minimize bounce rates without escalating operational costs the proposed framework involves deploying an intelligent model to examine user interaction patterns detect underlying causes of premature exits and formulate intervention strategies key enhancements may involve dynamic content personalization interface optimization and streamlined user pathways to foster engagement project efficacy will be assessed against three benchmarks achieving a 30 decrease in bounce rates operational improvement developing a predictive model with 90 reliability algorithmic performance and generating additional revenue exceeding 20 lakhs financial outcome through the
strategic fusion of behavioral analytics and resource-efficient inventory control, this solution targets threefold benefits: strengthened patient loyalty, elevated platform usability and sustainable organizational expansion within the digital healthcare landscape.

KEYWORDS: Python Programming, Exploratory Data Analysis, Machine Learning, Data Preprocessing, Data Visualization, Transportation Cost Reduction

I. INTRODUCTION

The evolution of digital healthcare platforms has elevated user engagement as a key determinant of success a significant operational hurdle facing these platforms is escalating bounce rates the tendency of visitors to exit before completing critical actions like appointment scheduling virtual consultations or service inquiries this pattern of early departure undermines both service quality and financial performance creating urgent need for intervention our solution implements a three-tiered analytical approach intelligent user behavior analysis machine learning algorithms process interaction patterns
real-time tracking of navigation pathways identification of abandonment triggers adaptive interface enhancement ai-driven content personalization context-aware service recommendations responsive design optimization conversion funnel refinement simplified appointment workflows reduced procedural friction points smart call-to-action placement performance benchmarks include engagement 30 decrease in bounce rates technical 90 model prediction accuracy financial 20 lakh revenue

improvement the implementation emphasizes cost-conscious resource deployment continuous performance monitoring iterative improvement cycles this methodology offers healthcare providers enhanced digital patient satisfaction improved operational efficiency sustainable revenue growth scalable engagement solutions the framework maintains flexibility across multi specialty hospital portals niche healthcare services telemedicine applications preventive care platforms by converting transient visits into meaningful engagements this approach establishes new standards for digital healthcare interactions while delivering measurable organizational benefits the systems modular architecture allows customization for diverse healthcare delivery models and patient demographics new chat.

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The proposed intelligent system follows CRISP ML assurance methodology11 which is publicly available on the 360Digitmg[fig1]

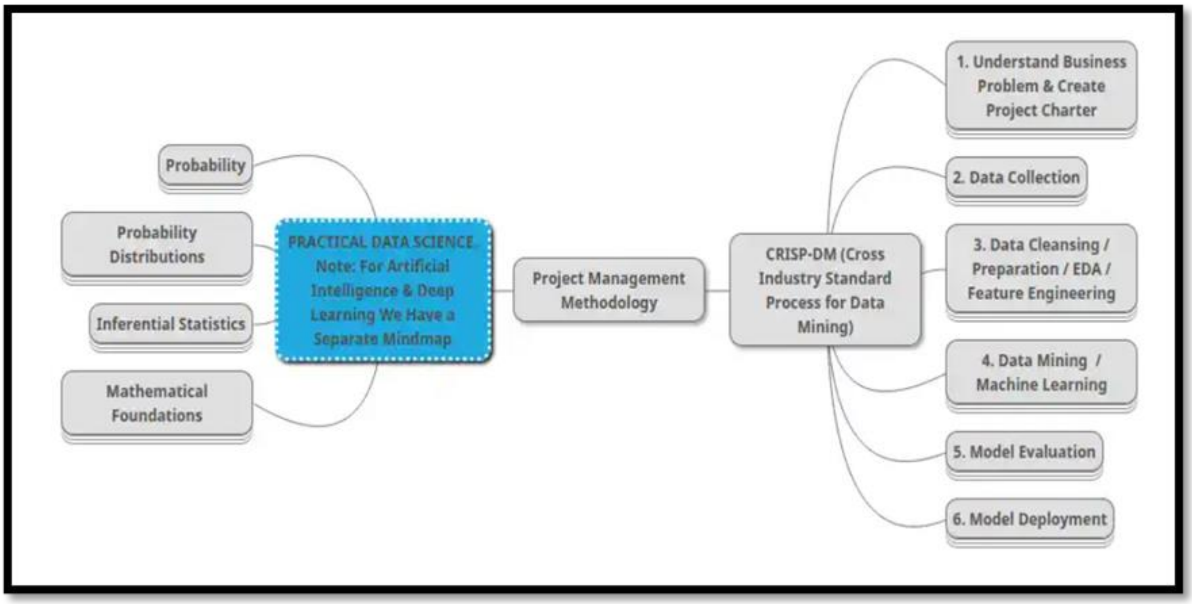

Fig1 CRISP-ML(Q) Methodology (Source: 360DigiTMG)

Business Problems: Bounce rate is increasing significantly leading to patient dissatisfaction.

Business Objective: Minimize Bounce Rate. 1.3 **Business Constraint:** Minimize Inventory Cost.

Success Criteria:

Business success Criteria: Reduce bounce rate by at least 30%.

ML Success Criteria: Achieve an Accuracy of at least 90%

Economic Success Criteria: Increase revenue by at least 20 lacs INR by reducing bounce rate.

II. METHODS AND METHODOLOGY

To effectively minimize the bounce rate while maintaining cost efficiency a structured approach integrating data analysis machine learning techniques and strategic inventory management will be employed the methodology consists of the following key steps

1.Data collection and preprocessing gather user interaction data from the platform including session duration pages visited click-through rates and exit points collect demographic an behavioral data to understand user preferences perform data cleaning normalization and feature engineering to prepare the dataset for analysis.

2.Exploratory data analysis edge analysis patterns in user behavior to identify key factors contributing to a high bounce rate use visualization techniques to interpret trends and correlations in user interactions segment users based on engagement levels to tailor strategies accordingly.

3.Machine learning model development select appropriate classification or regression models eg logistic regression decision trees random forest or deep learning models to predict bounce probability train the models on historical data optimizing hyperparameters to improve accuracy validate model performance using techniques such as cross-validation and ab testing to achieve a minimum accuracy of 90.

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4.Implementation of optimization strategies personalize user experiences by recommending relevant content or services based on behavior analytics improve platform design by optimizing navigation, reducing loading time and enhancing uiux elements to implement targeted interventions such as chatbot assistance pop-ups or reminders to retain users.

5.Inventory cost optimization: analyze demand patterns to align inventory management with user needs, use predictive analytics to forecast service demand and reduce unnecessary stockpiling implement cost-effective resource allocation strategies without compromising service quality.

6.Performance evaluation and monitoring track changes in bounce rate user engagement metrics and revenue growth post-implementation continuously refine machine learning models based on real-time user data measure success against predefined criteria a 30 reduction in bounce rate at least 90 model accuracy and a revenue increase of at least 20 lacs in this structured methodology ensures a data-driven cost-conscious approach to reducing bounce rates while improving user satisfaction and business profitability.

In [Fig2] is an architecture that defines workflow of methodologies

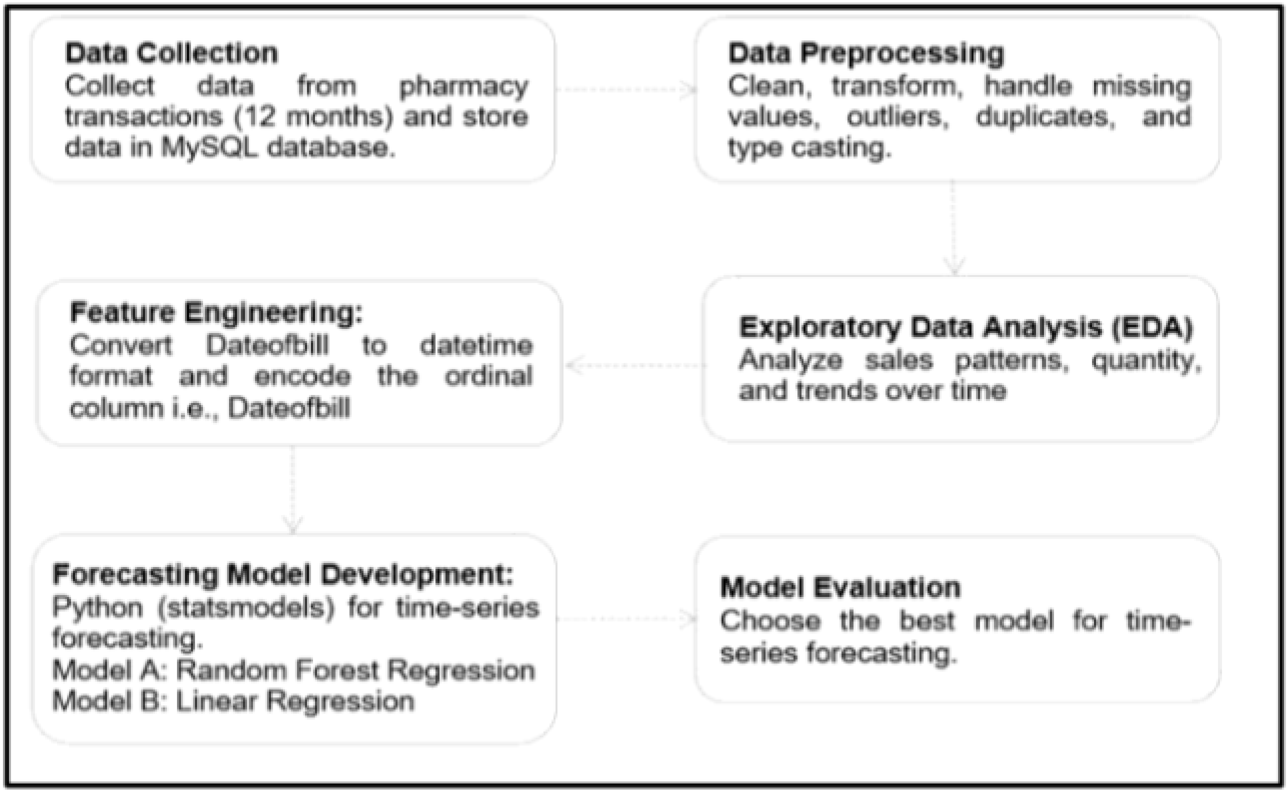

Fig 2: Architecture

2.1 Data Collection and Source

Revolutionizing healthcare inventory through intelligent data integration
modern healthcare systems require a sophisticated approach to inventory management that addresses three fundamental objectives:
1 Eliminating care interruptions from supply shortages
2.Guaranteeing treatment consistency through resource availability
3 Maximizing value across the procurement lifecycle our pioneering model employs a unified data architecture that

synthesizes information from diverse operational touchpoints strategic data channels:

Operational tracking systems: correlate material usage with patient throughput and revenue cycle data

Clinical workflow platforms: record provider decisions to project future supply requirements **Vendor intelligence:** assess supplier consistency and market price dynamics

Operational feedback: collect frontline insights on inventory performance

Digital footprint analysis: uncover hidden demand signals through user engagement data **execution methodology:** real-time data fusion from clinical systems and external sources systematic gathering of practitioner and patient perspectives advanced temporal modeling of utilization trends.

Contemporary healthcare systems require sophisticated inventory control mechanisms to maintain service excellence patient retention and fiscal responsibility stockouts and supply chain disruptions contribute substantially to patient attrition rates creating both operational and financial challenges this investigation develops a data-centric methodology to balance inventory availability with cost containment through comprehensive analytics

Primary data domains

1 Stock control metrics real-time quantity monitoring across therapeutic categories reorder interval analysis and fulfillment success rates perishability management with expiry date tracking vendor transaction archives with performance benchmarks.

2 Clinical demand indicators patient flow analytics with treatment documentation prescription volume trends by specialty and seasonality patient-reported availability concerns

2.2. Data Dictionary

There are in total 14 columns defining types of sales, patient ID, Specialization of Doctors, Department, Date of Bill, Quantity, Return Quantity, what is Final Cost and Final Sales of Drugs, MRP of returned Drug, Formulations and Subcategories. Now, the following table [Table 1] shows the detailed variable name and variable description.

Field Name	Description	Data Type
Typeofsales	Type of sales transaction (e.g., Sale, Return)	Categorical
Patient_ID	Unique ID for each patient	Numeric
Specialisation	Specialization of medical professional	Categorical
Dept	Department in pharmacy	Categorical
Dateofbill	Date of the sales transaction	Date
Quantity	Quantity of medicine sold	Numeric
ReturnQuantity	Quantity of medicine returned	Numeric
Final_Cost	Final cost after discounts/adjustments	Numeric
Final_Sales	Final sales amount	Numeric
RtnMRP	Maximum Retail Price of returned medication	Numeric
Formulation	Medication formulation	Categorical
DrugName	Name of the drug	Categorical
SubCat	Subcategory of the drug	Categorical
SubCat1	Secondary subcategory of the drug	Categorical

Table1

2.3 Data Types

The above Following [Table 1] After preprocessing dataset we get the following information like non-null values, Count and Datatype.

2.4 Data Preprocessing

Data preprocessing methodology for bounce rate reduction to develop an effective solution for minimizing bounce rates. A robust data preprocessing pipeline is essential. This systematic approach transforms raw data into a refined dataset suitable for machine learning applications while maintaining data integrity the methodology consists of six key phases.

1.Comprehensive data acquisition aggregate multi-source data including web server logs and clickstream analytics patient interaction histories appointment scheduling records user device metadata extract critical features temporal metrics session duration time-per-page navigation patterns pages visited click paths contextual data device type geolocation historical engagement indicators.

2.Data quality enhancement addresses missing data through context-aware imputation medianmode substitution targeted record deletion for incomplete cases implement deduplication protocols standardize temporal formats and measurement units resolve data type inconsistencies.

3.Feature space optimization encode categorical variables using one-hot encoding for nominal categories ordinal encoding for ranked variables normalize numerical features via min-max scaling for bounded ranges z-score standardization for parametric models engineer predictive features composite engagement indices temporal usage patterns behavioral frequency metrics.

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4.Anomaly management detects statistical outliers using iqr-based filtering 25th-75th percentile ranges standard deviation thresholds apply corrective measures historization for extreme values robust scaling for skewed distributions.

5.Strategic data partitioning create evaluation subsets 70 training corpus 20 validation set 10 holdout test data address class imbalance with smote for minority class augmentation cluster based under sampling.

6.Dimensionality reduction implement feature selection through correlation-based elimination recursive feature importance ranking principal component transformation remove multicollinear and low-variance predictors this preprocessing framework ensures the development dataset exhibits high predictive signal-to-noise ratio optimal feature representation statistical robustness computational efficiency the refined data structure enables accurate model training while controlling for potential biases ultimately supporting the development of effective bounce rate reduction solutions the methodology maintains adaptability across various healthcare platform architectures and scales efficiently with increasing data volumes

III. RESULTS AND DISCUSSION

After EDA (A method for examining and condensing data collections is called exploratory data analysis, or EDA. Prior to statistical modeling or machine learning, this is an important stage.). There are following observation:

Four Business Moment Decision:

There are three business moment decisions, here in the research paper to find out the outliers and other visualizations focused on co-relation matrix.

• FIRST MOMENT BUSINESS DECISION: Includes Measure of central Tendency (Mean, Median, Mode),
• SECOND MOMENT BUSINESS DECISION: Includes Variance, Standard Deviation, Range,

• THIRD BUSINESS DECISION: Includes Skewness

• FOURTH MOMENT BUSINESS DECISION: Includes Kurtosis. Following [Table 2] and [Table 3] contains the four-business moment decision result before processing and after pre-processing respectively.

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Column_Name	First Moment Business Decision			Second Moment Business Decision			Third Moment Bussiness Decision	Fourth Moment Bussiness Decision
	Mean	Median	Mode	Variance	Standard Deviation	Range	Skewness	Kurtosis
Qunatity	1.96	1	1	6.34	2.51	18	0	19.48
ReturnQuantity	0.22	0	0	0.57	0.75	5	4.33	20.956
Final_Cost	109.583	53.65	49.352	42251.4	205.55	1479	5.13	27.969
Final_Sales	209.96	86.242	0	155041	393.752	2248	3.31	14.68
RtnMRP	20.045	0	0	5974.73	77.296	578	5.31	31.62

Table 2: Before Removing Outliers Four Moment Business Decision: Readings Unprocessed Data

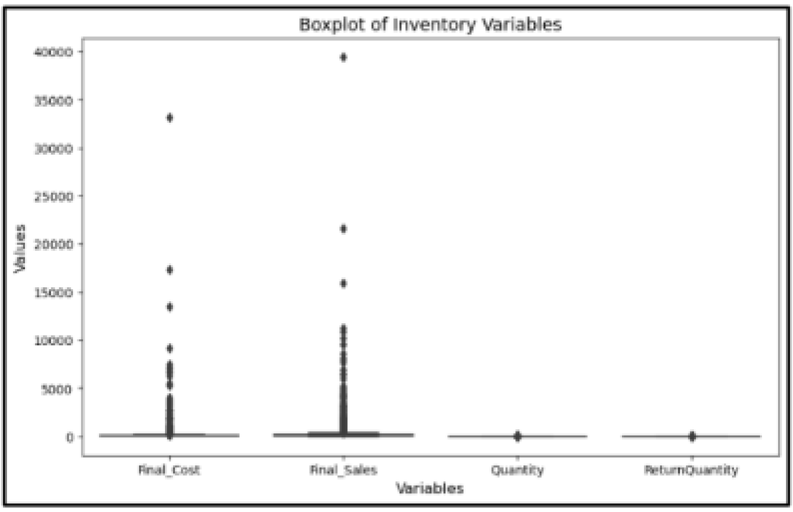
Column_Name	First Moment Business Decision			Second Moment Business Decision			Third Moment Bussiness Decision	Fourth Moment Bussiness Decision
	Mean	Median	Mode	Variance	Standard Deviation	Range	Skewness	Kurtosis
Qunatity	2.23	1	1	26.34	5.13	150	11.34	183.09
ReturnQuantity	0.29	0	0	2.7	1.64	50	17.17	341.5
Final_Cost	124.82	53.65	49.352	216007.9	464.77	33138	34.5	2064.98
Final_Sales	234.04	83.44	0	450560.4	671.24	39490	21	980.93
RtnMRP	29.13	0	0	33218.35	182.26	8014	15.8	415.82

Table 3: Removing Outliers Four Moment Business Decision: Readings Processed Data

From Table 2 and Table 3, the result indicates that the unclean data exhibits higher mean variance standard deviation, range skewness and kurtosis values compared to the clean data. Cleaning this data set has resulted in a more stable and normalized distribution with reduced variability and potential basis and statistically best making it more reliable for business making decisions.

Data Visualization

Data visualization plays a crucial role in optimizing medical inventory by uncovering patterns, trends, and inefficiencies.



Bar graph of inventory metrics provides insights into variations in **Final_Cost, Final_Sales, Quantity, and ReturnQuantity** across individual records. The logarithmic scale The boxplot reveals significant outliers in Final_Cost and Final_Sales, indicating variability in pricing and sales across different medicines.

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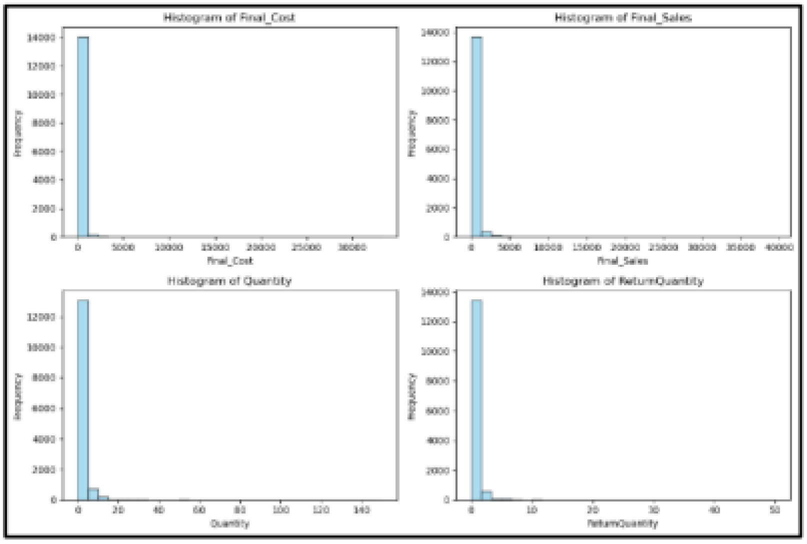
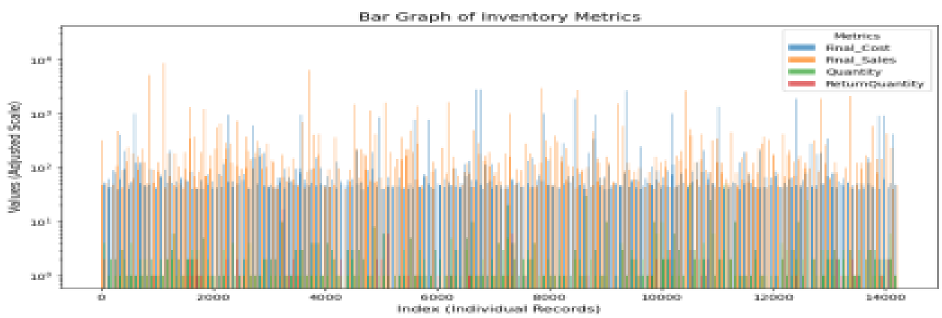


This has direct implications for medical inventory optimization. Histograms show that Final_Cost, Final_Sales, Quantity, and ReturnQuantity are highly skewed, with most values concentrated near zero and a few extreme values. This indicates significant right-skewed distributions, which can affect medical inventory optimization. used in the y-axis helps visualize differences more clearly, especially since the values vary significantly



7

Model Deployment

Deploying a model for medical inventory optimization is a critical step to ensure that your predictive models are available for real-time decision-making and impact the business process. Here's a breakdown of the key steps in **model deployment**, along with best practices tailored to your inventory optimization project:

Model Development & Testing

• **Finalizing the model**: Ensure that the model has met the business success criteria (e.g., 90% accuracy, reducing bounce rates by 30%, etc.).
• **Performance evaluation**: Test the model with real or simulated data to confirm it performs well under different scenarios (seasonality, demand fluctuations, etc.).
• **Version control**: Keep track of different versions of the model, as optimizations and adjustments might be required over time.

Containerization

• **Docker**: Use Docker to package the model and all dependencies (e.g., libraries, configurations, etc.) into a container, which makes deployment more consistent and easier to scale.
• **Kubernetes**: If you're planning to deploy across multiple servers, Kubernetes can help manage container orchestration, scaling, and load balancing.

Create an API (Application Programming Interface)

• **Flask/FastAPI (for Python models)**: Wrap the model in a web service (API) to handle incoming requests such as inventory data, sales data, etc., and return optimized inventory recommendations.

o Example: A RESTful API where you can send input data like

product IDs, usage patterns, and receive back recommendations (e.g., reorder quantities, safety stock levels).

• **Input format**: The API should accept inputs (e.g., CSV, JSON) that represent the real-time data you're using for inventory decisions.

• **Output format**: The API should return predictions or recommendations in a standardized format.

Model Hosting/Environment Setup

• **Cloud-based services**: Host the model on cloud platforms like AWS (SageMaker), Azure (Machine Learning), or Google Cloud (AI Platform).

o **AWS Lambda**: For lightweight models, you can use AWS Lambda to run your predictions as serverless functions.

o **Google AI Platform**: Easy deployment for large-scale

o machine learning models with built-in scalability.

o **Azure ML**: Offers model deployment, versioning, and monitoring tools. Choose based on your infrastructure and scalability needs.

Automation and Scheduling

• **Batch predictions**: If the optimization process is not real-time, schedule batch jobs (e.g., once a day or week) that process inventory data and generate recommendations for procurement and stock levels.

• **Real-time predictions**: For on-demand optimizations, the model should be available 24/7, allowing the API to process real-time data (e.g., new sales data, stock in/out transactions).

Model Monitoring & Logging

• **Track model performance**: Set up monitoring tools to track how well the model is performing in the live environment. This includes:

o Monitoring accuracy over time.

o Tracking any discrepancies in predicted vs. actual demand.

o Watching for model drift (e.g., the model's predictions get worse over time as new patterns emerge).

• **Logging**: Use logging frameworks to capture errors, model predictions, and user interactions for troubleshooting and continuous improvement.

Future Scope and Insights

The future scope of medical inventory optimization and bounce rate is to leverage data driven approaches and advanced machine learning techniques to forecast drug demand, optimize inventory levels, and reduce waste and costs. Some of the **benefits** of this approach are:

• Minimize drug shortages and stockouts, which can lead to improved patient care and satisfaction, as well as reduced bounce rate.

• Maximize the availability and utilization of drugs, which can increase sales and profits, as well as customer loyalty and retention.

• Reduce inventory costs and waste, which can improve cash flow and sustainability, as well as reduce the environmental impact of expired or unused drugs

Business Insights

Here we can understand that around 30 plus percent (approx. 30.548%) of customer in the data set based on a situation where they returned medicine with a final_sales value of zero this means that a significant portion of our customer did not get the medicine they needed which could lead to dissatisfaction of a customer so to improve business criteria we can increase our revenue and It's important to reduce the bounce rate by ensuring customer service at its best.

Statistical Insights

Unprocessed data shows the noise in all four moment business decision like mean, standard deviation, variance, range, skewness, and kurtosis.

• Final_Cost: The average final cost is 124.82, with a high standard deviation (464.78), indicating variability in costs. The distribution is highly skewed (34.51) and has a high kurtosis (2,025.87), suggesting extreme outliers.
• Final_Sales: The average final sales are 234.04, with a high standard deviation (671.26). The mode is 0.0, indicating that many transactions have no sales. The distribution is less skewed (21.01) compared to Final_Cost.
• Quantity: The average quantity sold is 2.23, with a mode of 1. The distribution is highly skewed (11.34) and has a high kurtosis (180.15), indicating a concentration of low quantities with some extreme values.
• Return_Quantity: The average return quantity is 0.29, with a mode of 0. The distribution is highly skewed (17.17) and has a very high kurtosis (409.42), indicating most transactions have no returns, but some have significant returns.

Recommendations:

After analysing whole research, in recommendations section, there are some improvements in dataset, • Thorough examination of the "TABLETS & CAPSULES" and "INJECTIONS" subcategories to pinpoint and solve the root causes of high return rates.
• A thorough evaluation of the "Form1" formulation to pinpoint areas in need of modification or replacement.
• Assessment and potentially revaluation of suppliers, particularly for products related to Department1 and "Form1" formulation.
• To maximize stock levels and prevent returns, Department 1 enhanced inventory control. Development of efficient return management practices in Department1.

IV. CONCLUSION

The optimization of medical inventory is a critical component of efficient healthcare management. It ensures the timely availability of medical supplies while minimizing waste, reducing costs, and improving patient care. Effective inventory management in the healthcare industry requires a strategic blend of demand forecasting, technology integration, supplier coordination, and regulatory compliance. As healthcare institutions strive to enhance efficiency and reduce operational costs, optimizing medical inventory has emerged as a key priority.

• Through various strategies such as demand forecasting, classification techniques (ABC and VED analysis), automation, and real-time tracking, healthcare facilities can significantly improve their inventory management systems. The adoption of Just in-Time (JIT) inventory models helps reduce storage costs, while AI-driven forecasting minimizes the risk of stockouts and overstocking. Additionally, automation through RFID, IoT, and integrated inventory management systems ensures real-time monitoringreducinghumanerrorsandimprovingaccuracy
• Effective supplier relationship managment has also proven to be a crucial factor in inventory optimization. By collaborating with multiple suppliers, healthcare institutions can
• ensure a steady supply chain, negotiate better pricing, and mitigate risks of shortages due to supplier failures. Furthermore, adopting centralized or decentralized inventory management systems based on the specific needs of a healthcare facility helps improve accessibility and efficiency in stock management.
• The implementation of advanced analytics and predictive modeling will further optimize inventory levels, helping healthcare institutions balance supply and demand dynamically.
• Effective inventory management in hospital supply chains is crucial to ensuring the continuous availability of essential medicines while minimizing costs and waste. The study highlights the importance of demand forecasting, data-driven inventory control, and supply chain coordination to mitigate drug shortages.

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• By implementing optimization techniques such as machine learning models, real-time tracking, and advanced replenishment strategies, hospitals can enhance efficiency and patient safety. Additionally, integrating Just-in-Time (JIT) inventory systems and supplier collaboration can further reduce risks associated with stockouts.

• Ultimately, a well-optimized medical inventory system contributes to better healthcare outcomes, improved operational efficiency, and cost savings. Hospitals and healthcare institutions must leverage technology and data analytics to create a more resilient and responsive supply chain.

REFERENCES

1. Kaakeh, R.; Sweet, B.V.; Reilly, C.; Bush, C.; DeLoach, S.; Higgins, B.; Clark, A.M.; Stevenson, J. Impact of drug shortages on U.S. health systems. Am. J. Health Syst. Pharm. 2011, 68, 1811– 1819. [Google Scholar] [CrossRef]
2. Fox, E.R.; Burgunda, V. Sweet, and Valerie Jensen, Drug shortages: A complex health care crisis. Mayo Clin. Proc. 2014, 89, 361–373.
3. Stevenson, W.J.; Hojati, M.; Cao, J. Operations Management, 6th ed.; Stevenson explains this well in chapter 12 page 455; Thomson Reuters: Toronto, ON, Canada, 2018.
4. Aptel, O., & Pourjalali, H. (2001). Improving activities and decreasing costs of logistics in hospitals. A comparison of U.S. and French hospitals. The International Journal of Accounting, 36, 65–90.
5. Beaulieu, M., & Landry, S. (2002). Comment gérer la logistique hospitalière? Deux pays, deux réalités. Gestion, 27, 91– 98.
6. Belien, J., & Demeulemeester, E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. European Journal of Operational Research, 176, 1185–1204.
7. Ahmed W., Huma S. Impact of lean and agile strategies on supply chain risk management. Total Qual. Manage. Business Excell. 2021;32:33–56.
8. Amoako-Gyampah K., Boakye K.G., Adaku E., et al. Supplier relationship management and firm performance in developing economies: a moderated mediation analysis of flexibility capability and ownership structure. Int. J. Prod. Econ. 2019;208:160–170.
9. Andaneswari, A. K. and Q. Rohmadiena, The Disruption of Personal Protection Equipment Supply Chain: What Can We Learn from Global Value Chain in the Time of Covid-19 Outbreak? Global South Review. 2, 171-188.
10. Aptel O., Pourjalali H. Improving activities and decreasing costs of logistics in hospitals: a comparison of US and French hospitals. Int. J. Account. 2001;36:65–90.
11. Kaakeh, R.; Sweet, B.V.; Reilly, C.; Bush, C.; DeLoach, S.; Higgins, B.; Clark, A.M.; Stevenson, J. Impact of drug shortages on U.S. health systems. Am. J. Health Syst. Pharm. 2011, 68, 1811– 1819.
12. Fox, E.R.; Burgunda, V. Sweet, and Valerie Jensen, Drug shortages: A complex health care crisis. Mayo Clin. Proc. 2014, 89, 361–373.
13. Stevenson, W.J.; Hojati, M.; Cao, J. Operations Management, 6th ed.; Stevenson explains this well in chapter 12 page 455; Thomson Reuters: Toronto, ON, Canada, 2018.
14. Wu I.C., Lin Y.C., Yien H.W., Shih F.Y. Constructing constraint-based simulation system for creating emergency evacuation plans: A case of an outpatient chemotherapy area at a cancer medical center. Healthcare. 2020;8:137. doi: 10.3390/healthcare8020137.
15. Liu Z.Y. The anti-hepatitis drug use effect and inventory management optimization from the perspective of the hospital drug supply chain. Pak. J. Pharm. Sci. 2017;30:1917–1922.
16. Alves R.J.V., Etges A., Neto G.B., Polanczyk C.A. Activity-based costing and time-driven activity-based costing for assessing the costs of cancer prevention, diagnosis, and treatment: A systematic review of the literature. Value Health Reg. Issues. 2018;17:142–147. doi: 10.1016/j.vhri.2018.06.001.
17. 17. Abbas S.A., Aslam A., Rehman A.U., Abbasi W.A., Arif S., Kazmi S.Z.H. K means and k-medoids: Cluster analysis on birth data collected in the city Muzaffarabad, Kashmir. IEEE Access. 2020;8:151847– 151855. doi: 10.1109/ACCESS.2020.3014021.

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