SAFETY STOCK OPTIMIZATION WITH SIMULATION-BASED INVENTORY MODELING IN R: A CASE STUDY FOR A U.S. APPAREL E-COMMERCE BRAND

1. Background

A fast-growing U.S. e-commerce apparel company struggled with inventory shortages during flash sales and holiday events. Their standard safety stock formula based on average demand often failed during high-variance weeks. The operations team needed a smarter model to simulate stockout risks under various demand and lead time conditions using R.

2. Objective

- To build a Monte Carlo simulation model in R to estimate inventory requirements
- To compute safety stock thresholds based on service level targets and demand variability
- To integrate simulation outputs into their seasonal buying plan

3. Data Used

Source: Shopify sales data, supplier schedules, and fulfillment logs

Structure:

- Weekly sales records from Jan 2022 to Dec 2023 for 50 SKUs
- Fields: SKU_ID, Date, Units_Sold, Lead_Time_Days, Restock_Date, Sale_Week_Flag, Returns

4. Modeling Methodology

4.1 Demand and Lead Time Analysis

- Calculated mean and standard deviation of weekly demand using dplyr
- Identified lead time variability by analyzing Restock_Date - Order_Date
- Created demand distribution assumptions per SKU (normal/lognormal based on Shapiro test)

4.2 Monte Carlo Simulation in R

- Simulated 10,000 demand scenarios per SKU using rnorm()

- Simulated variable lead times for each scenario using truncated normal distributions
- Defined stockout as Simulated_Demand > Stock_on_Hand + Safety_Stock

simulate_demand <- rnorm(10000, mean = mu_demand, sd = sd_demand)

simulate_lead <- rnorm(10000, mean = mu_lead, sd = sd_lead)

4.3 Safety Stock Formula (Simulation-Based)

- Safety Stock (SS) set at the percentile level of unmet demand that satisfies a service level (e.g., 95%)
- R code to calculate SS:
- safety_stock <- quantile(simulated_demand - expected_inventory, probs = 0.95)

4.4 Scenario Testing

- Ran simulations for sale vs. non-sale weeks
- Included return-adjusted demand forecasts for more accurate planning
- Compared simulation-based SS with historical stockout data

5. Results

SKU Type	Previous SS (units)	Simulated SS	Stockouts Reduced	Fulfillment Accuracy
Graphic T-shirts	220	310	↓ 41%	↑ 9.3%
Activewear Bottoms	160	190	↓ 34%	↑ 7.8%
Festival Jackets	280	360	↓ 52%	↑ 11.2%
Swimwear Tops	90	135	↓ 29%	↑ 6.1%

6. Interpretation and Recommendations

- Simulation-based safety stock provided **more resilience during sales events**
- Some high-return SKUs required extra buffer stock to accommodate reverse logistics
- Recommended **SKU-specific safety stock policy**, updated every quarter
- Suggested shifting from flat safety stock to **dynamic service-level-based thresholds**

- Shared insights with finance team to plan working capital during clearance cycles

7. Reporting Output

- **R Markdown Report (26 pages)**:
  - Simulation distribution plots per SKU
  - Stockout risk bands by service level
  - Weekly order fill rate projections under different reorder strategies
- **Excel Dashboard Export**:
  - Columns: SKU, Recommended SS, Current SS, Action Required
  - Filters for product category, lead time variability, return rate
- **Reusable Simulation Engine in R**:
  - inventory_simulation.R with 3 key functions:
    - simulate_demand_profile()
    - estimate_safety_stock()
    - compare_stockout_risk()

8. Business Outcome

- Achieved **20–25% improvement in fulfillment accuracy** during Black Friday–Cyber Monday
- **Reduced urgent air-freight costs by 18%** during peak season
- Used simulation insights in Q1 2024 to **negotiate better terms with third-party suppliers**
- Model adopted into the brand's **seasonal planning workflow**