Analytical Study of an Online Commerce Brand

A End-Term report for the BDM capstone Project

Submitted by

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Contents

1 Executive Summary 2
2 Detailed Explanation of Analysis Process/Method 3
2.1. Method for Financial Overview 3
2.2. Method for Margin Analysis 4
2.3. Method for Credit Analysis 6
3 Results and Findings 7
3.1. Financial Overview of the business 7
3.2. Profit-Margin Analysis 11
3.3 Credit Analysis 14
4 Interpretation of Results and Recommendations 16
4.1. Financial Overview of the Business 16
4.2. Credit Overview of the Business 16
4.3. Ideal Margins for Desired Profit 17
4.4. Expand Product Variety: 17
4.5. Implement a Structured Credit Management System: 18
4.6. Enforce Strict Repayment Practices: 18
5 Additional 18

1 Executive Summary

Molcha by Babita Singh is a women's ethnic apparel brand (saree blouses, palazzos, etc.) selling on Myntra. Despite its wide reach, the business faces severe inefficiencies from **excessive returns, logistics losses, and inventory misallocation**, which have eroded profits. In particular, high-return categories like kurtis see up to 80% of items returned, creating a large gap between gross revenue and net earnings.

Over a nine-month period (June 2024–Feb 2025) of Myntra portal data, key variables (order status, article type, price, payment method, return type, courier, region, etc.) were aggregated and cleaned for analysis. Using Python (Pandas) for transformation and Matplotlib/Seaborn for visualization, we computed descriptive statistics, trend analyses, return profiling, margin calculations, and courier performance metrics. This revealed ₹92.7 lakh total sales revenue but only ₹28.3 lakh net profit after returns – a **75.2% gross margin collapsing to 30.6%** after return-related costs. The overall return rate was **52.01%**, with returns causing ~₹41.38 lakh in combined lost revenue, handling costs, and tax.

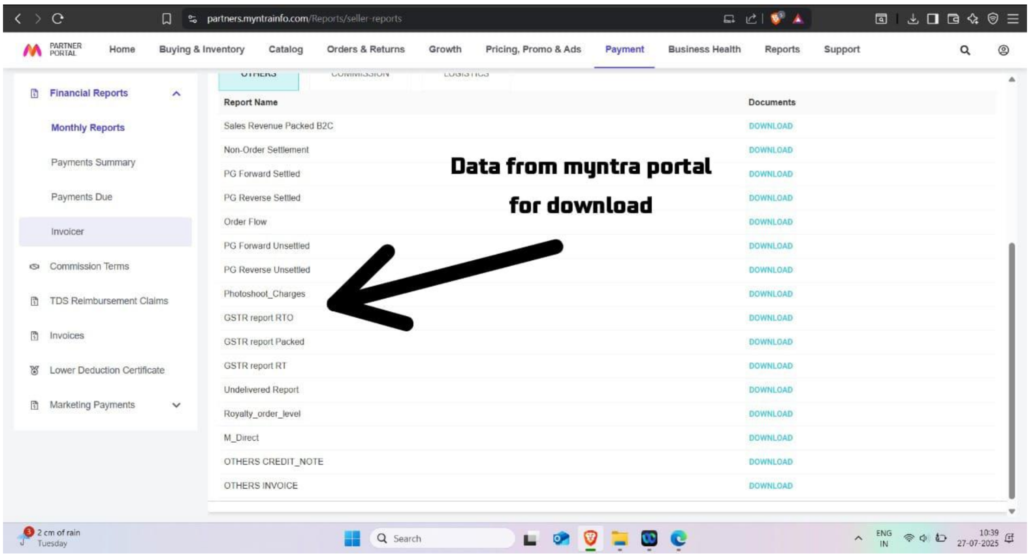
Key findings show stark contrasts: low-return products like Cushion Covers (12.16% return) and Churidars (30.91%) are very profitable, whereas high-return lines like Kurtis (80%) and Co-ords (64.8%) break even at best. We also observed that orders with deep discounts (71–100%) actually had much lower returns (~17.2%) than moderate discounts (51–70%, ~52.3%). These patterns highlight that **return rates are the primary drag on profitability** (in fact, return rate and margin had a correlation of –0.97).

Based on these insights, the report recommends immediate and strategic actions: shift inventory toward low-return lines, implement a tiered restocking fee and stricter return window to discourage frivolous returns, adjust pricing/discount strategies, and reroute shipments through more reliable couriers in high-RTO regions. Early implementation of such measures has already shown preliminary improvement in net margin. For example, reducing the return rate from ~52% to ~35% could recoup much of the ₹41 lakh loss, **potentially boosting annual profit by ₹1.5–2.0 million**. Together, these steps promise to realign operations with demand and restore healthy profitability.

2 Detailed Explanation of Analysis Process/Method

2.1. Data Collection

The analysis began with gathering nine months of transactional data (June 2024–February 2025) from the **Myntra Seller Portal** for *Molcha by Babita Singh*. Specifically, we extracted and worked with three primary data sources: the **Order Flow Report**, which detailed all customer orders including pricing, discounts, payment methods, and fulfillment status; the **RTO (Return to Origin) Report**, which provided insights into failed deliveries and logistics reversals; and the **RT (Return Transaction) Report**, which captured post-delivery customer returns along with reasons and item conditions.



Each of these reports offered a distinct operational lens—Order Flow for sales and fulfillment, RTO for pre-delivery returns, and RT for post-delivery returns—making it critical to **consolidate them into a unified dataset** for holistic analysis.

Before merging, each dataset was reviewed to ensure consistency in timeframes, with all records strictly falling between June 2024 and February 2025. Redundant rows and duplicate exports were removed to prevent overcounting. Uniform formatting, schema alignment, and data deduplication ensured that the final integrated dataset offered a complete and non-overlapping view of the business performance over the selected period.

2.2 Data Cleaning and Preprocessing

Before analysis, I performed extensive data cleaning. First, I **inspected for duplicates and inconsistencies** – for example, I used Pandas functions like `drop_duplicates()` to remove repeated rows and `isin()` or `unique()` to check category codes for typos. Any records with clearly invalid values (negative prices, impossible dates) were flagged and corrected or in some cases discarded. We also standardized column types: dates were parsed into a datetime format, prices and discounts cast to numeric types, and categorical fields (like payment method or article type) converted to consistent string categories. Missing or null values were handled methodically. For instance, if essential fields (order status, price) were null, the rows were dropped; otherwise, missing optional fields were filled or noted for exclusion, depending on context. Finally, we **derived new fields** needed for analysis: for example, calculating the *return* *rate* required marking each order as sold or returned, and computing **month** or **week** from the order date for trend analysis.

Importance of Cleaning: In this project, data cleaning was essential to ensure accurate identification of return-driven losses. For instance, duplicate entries or inconsistent product labels (like "Kurti" vs "Kurtis") would misstate return rates, leading to flawed category analysis. Misparsed dates could misplace returns in the wrong month, affecting trend accuracy. Since our decisions—like shifting inventory or penalizing couriers—were based on these metrics, clean data was crucial to avoid misleading conclusions and ensure that profit-loss patterns reflected real operational gaps.

2.3 Comprehensive Explanation for each Method/Analysis Used:

Following data cleaning, we performed a multi-layered Exploratory Data Analysis (EDA) to extract meaningful business insights. The goal of this phase was to understand sales patterns, identify inefficiencies, and determine key profitability drivers. This section covers summary statistics, category-wise breakdowns, return behavior, and temporal/spatial patterns using Python's **Pandas**, **Matplotlib**, and **Seaborn** libraries.

1. Descriptive Statistics and Distributions:

Using df.describe() and value_counts(), we first explored the **central tendencies** and **distribution** of numerical and categorical fields:

- Count, mean, median, min, max for fields like Price, Discount, Margin, and BaseAmount.
- For example , for article-wise order distribution using df['ArticleType'].value_counts() reveals that saree blouses are the most sold product tyes.

We used df.describe() and value_counts() to quickly understand key statistical properties and identify dominant categories, enabling data-driven insights into pricing trends and high-performing product types.

2. Profit Matrix and Margin Profiling:

To assess the true financial performance of the business, we built a **granular profitability framework** that went beyond simple revenue-minus-cost calculations. The analysis aimed to factor in all return-related costs that impact net profitability, including logistics, refund losses, and tax components.

- Return Shipping Costs - For all returned orders, we assumed the shipping cost is either explicitly provided or defaults to ₹50. This cost was treated as a **sunk cost** due to the reverse logistics involved
- Return Handling Cost - To model warehouse restocking, manpower, and repackaging, we applied a **15% handling fee** on the amount paid by the customer for every return
- Lost Revenue - If a returned item was refunded (not exchanged), the full paid amount was considered a **lost revenue**
- Tax Component (temporary) - We captured the **loss of TCS (IGST, SGST, CGST)** associated with refunded transactions
- Net Profit Calculation - The final **net profit** per order was computed by subtracting all return-related costs from the basic profit.

```python
# Calculate return-related costs
# Shipping costs lost for returns
df['return_shipping_cost'] = np.where(df['is_returned'],
                                      df['shipping_amount'].fillna(50), # Use actual shipping or default to 50
                                      0)

# Potential restocking/handling costs for returns (typically 10-15% of item value)
df['return_handling_cost'] = np.where(df['is_returned'],
                                      df['customer_paid_amount'] * 0.15, # 15% handling cost
                                      0)

# Lost revenue from returns (if refunded)
df['lost_revenue'] = np.where(df['is_returned'] & (df['return_type'] == 'return_refund'),
                              df['customer_paid_amount'],
                              0)

# Tax loss on returns (TCS components)
df['tax_loss'] = np.where(df['is_returned'] & (df['return_type'] == 'return_refund'),
                          df['tcs_igst_amt'] + df['tcs_sgst_amt'] + df['tcs_cgst_amt'],
                          0)

# Calculate true net profit including tax losses
df['net_profit'] = df['basic_profit'] - df['return_shipping_cost'] - df['return_handling_cost'] - df['lost_revenue'] - df['tax_loss']

print("Profit metrics calculated successfully")
```

```
Profit metrics calculated successfully
```

- Margin Analysis:
    - Basic Profit Margin = (Total Basic Profit / Total Revenue) * 100
    - Net Margin = (Total Net Profit / Total Revenue) * 100

This approach of calculating the profit and margin is justified as it aggregates all controllable and uncontrollable return costs, providing the most realistic picture of take-home profitability.

3. Return Behavior and Analysis:

A. Return Reasons Analysis

Objective: Understand which return types (refunds, exchanges, RTOs) hurt the business most in terms of both frequency and profitability.

Method:

- Filtered the dataset to include only returned orders (df[df['is_returned']]).
- Grouped by return_type to calculate:
    - **return_count**: Number of returns per reason.
    - **loss_per_return**: Average loss in net_profit per return.
    - **tax_per_return**: Hidden tax loss associated with each return.
    - **percent_of_returns**: Each return reason's share of total returns.

Justification:
This granular breakdown helped pinpoint that **'return_refund'** was:

- The **most frequent** reason (69.6% of returns),
- And **also the most damaging**, with a **loss of ₹456 per item**.

We used a **bar chart with color mapping (RdYlGn)** to visually correlate frequency with financial damage. Redder bars indicated higher losses per return — allowing stakeholders to *visually prioritize high-cost return types*.

This directly supports the problem statement: returns are eroding profit not just due to frequency, but due to *which types of returns are dominant.*

B. Price Sensitivity Analysis

Objective: Determine how product price influences return rates and net profit.

Method:

- Created price buckets: 0-500, 501-1000, etc.
- Aggregated by price_range to get:
    - **return_rate**: Percentage of orders in each range that were returned.
    - **avg_profit** and **profit_margin**.
    - **tax_per_order** and **order_count** for context.

Visualization:
Used a **dual-axis bar/line chart** to compare:

- Return rate (bar, left y-axis)
- Profit margin (line, right y-axis)

Justification:
This allowed us to see that **higher price ≠ lower returns**; mid-range items had both high sales and high return rates. This suggests the need to **rethink return policies or product quality standards in mid-tier SKUs**.

C. Discount Impact Analysis

Objective: Explore how different discount levels influence return behavior and margins.

Method:

- Calculated discount_percentage, then binned it into ranges: 0–10%, 11–30%, etc.
- Grouped by discount_range to assess:
    - **Return rate**
    - **Profit margin**
    - **Average price and tax per order**

Visualization:
Again used **dual-axis bar/line charts** to contrast return rate with profit margin across discount levels.

Justification:

This showed that *not all discounts hurt profitability*. In fact, **strategic discounting may reduce returns** and improve margins, contrary to typical assumptions.

D. Delivery Delay Impact

Objective: Investigate how delivery performance influences return rates and profitability.

Method:

- Calculated delay in days between promised_delivery_date and actual_delivery_date.
- Bucketed it into: *Very Early*, *Early*, *On Time*, *Slight Delay*, *Major Delay*.
- Grouped by delay category to analyze:
  - Return rate
  - Average profit
  - Profit margin

Justification:
Reveals a **strong link between logistics reliability and financial outcome**, validating the need for better SLA tracking and courier selection — particularly for high-value items.

E. Category Level Relationship

Objective: Test for a statistical correlation between return rate and profit margin across product categories.

Method:

- Scatter plot of return_rate vs. net_margin, bubble size scaled by revenue.
- Regression line overlaid with sns.regplot.
- Annotated top and bottom outliers for further study.
- Correlation coefficient calculated: **-0.71**, suggesting a **strong negative relationship**.

Justification:
This correlation confirmed the business hypothesis: **categories with high returns consistently have lower margins**, guiding strategic SKU pruning and return policy refinement.

F. Courier Partner Performance

Objective: Evaluate the reliability and efficiency of courier partners to detect weak links in the reverse logistics chain.

Justification: Since RTOs (Return to Origin) often result from delivery failure or operational delays, comparing courier-wise return rates helps identify vendors contributing disproportionately to returns — enabling strategic courier selection.

G. Return Mode v/s Payment Method

Objective: Assess how return logistics and payment methods influence return and RTO behavior.

Justification: Orders paid via COD tend to have more fraud risk or delivery rejection, while return mode (pickup vs online drop-off) affects reverse logistics cost and experience. Studying this informs **return policy design and prepaid incentives**.

4. Temporal (Day , Week , Month) Analysis

Objective: Analyze time-based trends in order volume, cancellations, and article-wise sales to detect **seasonal patterns** or **operational bottlenecks** over time.

Method:

- Converted order_created_date to datetime and used it as the index for time series analysis

```
df['order_created_date'] = pd.to_datetime(df['order_created_date'], format='%Y%m%d', errors='coerce')
df.set_index('order_created_date', inplace=True)
```

- Created a new column order_info to classify each order as **Completed** or **Cancelled** based on its order_status:

```
df['order_info'] = df['order_status'].apply(lambda x: 'Cancelled' if ('C' in x or 'RTO' in x) else 'Completed')
```

- Resampled data monthly using .resample('M')

```
monthly_cancellation_rate = monthly_cancelled / (monthly_completed + monthly_cancelled)
```

- Plotted these trends over time using Matplotlib with dual y-axes (primary for order volume, secondary for cancellation rate).

- For product-wise seasonality:
  - Grouped sales by month and article type, then selected **top 5 article types** by total sales.
  - Visualized monthly trends for these using a multi-line plot.

```
monthly_article_sales = df[df['order_info'] == 'Completed'].groupby([pd.Grouper(freq='M'), 'article_type']).size().unstack(fill_value=0)
top5_articles = monthly_article_sales.sum().sort_values(ascending=False).head(5).index
monthly_article_sales[top5_articles].plot(...)
```

5. Revenue v/s Count of Returns (Product Level Profitability Check)

Objective: To **correlate product-level revenue with return frequency**, identifying products that appear profitable by sales volume but become **net-negative due to excessive returns**.

Method:

- Grouped data by product category (e.g., article_type) to calculate:

- **Total Revenue** (customer_paid_amount.sum())
- **Number of Returns** (is_returned.sum())

- Plotted a **scatterplot or barplot** with:
  - X-axis: Number of Returns per Article Type
  - Y-axis: Total Revenue per Article Type
- Optional color/size encoding for net profit or return rate.

```
returns_vs_revenue = df.groupby('article_type').agg({
    'customer_paid_amount': 'sum',
    'is_returned': 'sum'
}).rename(columns={'customer_paid_amount': 'total_revenue', 'is_returned': 'return_count'})

returns_vs_revenue.plot(kind='scatter', x='return_count', y='total_revenue', figsize=(10,6))
plt.title('Returns vs Revenue by Article Type')
plt.xlabel('Number of Returns')
plt.ylabel('Total Revenue (₹)')
plt.grid(True)
plt.show()
```

Justification: High-order volumes can falsely indicate strong performance. However, if certain products (e.g., **Kurtis**) also experience a high return rate, they may **erode net profit**. This analysis helps identify **"return-heavy" products** that require quality checks, sizing adjustments, or delisting.

3 Results and Findings

A. Order Distribution by Category

The pie chart shows that Saree Blouses dominate the product mix, accounting for **66.2%** of total orders (5,481 of 8,279). The next largest categories are Palazzos (~9.4%) and Salwar (~8.2%), while all other categories together make up only about 10%. In monetary terms, Saree Blouses also contribute about 65% of total revenue (≈₹6.03M of ₹9.27M). The weighted average order value is roughly **₹1,120**. This concentration indicates the business relies heavily on a single major product line (women’s ethnic wear) for both sales volume and revenue.

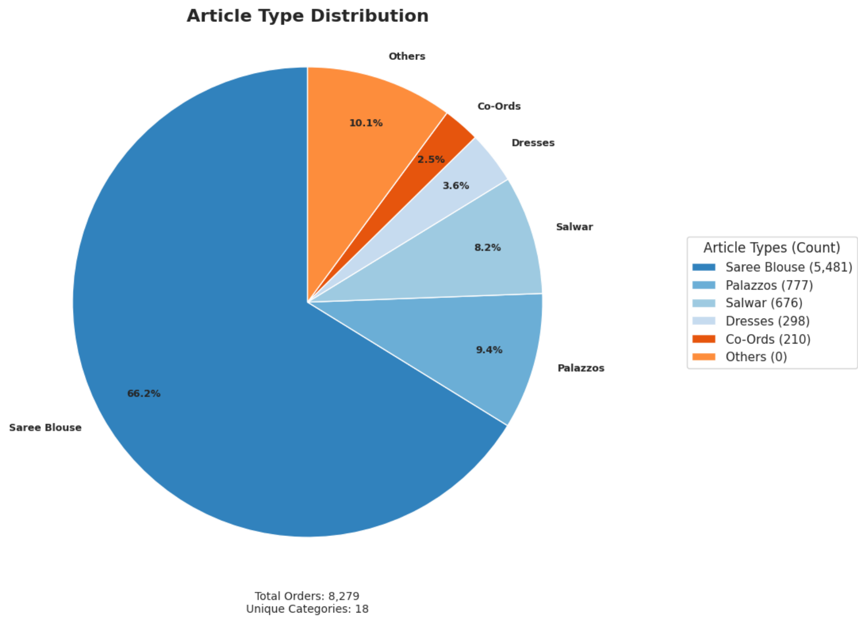


Fig 1. Distribution of orders by article type.

B. Return Reasons and Profit

The stacked bar chart shows that **refund returns** constitute the vast majority of return cases (~69%), and these are associated with large losses (red color). By contrast, **exchanges** (green, ~12% of returns) actually generate profit, since the retailer retains revenue while still satisfying the customer. An intermediate category "release to refund" (~18%) also causes loss (orange). The key insight is that refund-driven returns (red portion) dominate and lead to the biggest profit hit. Focusing on reducing simple refunds (for example, by offering exchanges or better sizing information) could significantly improve margins.

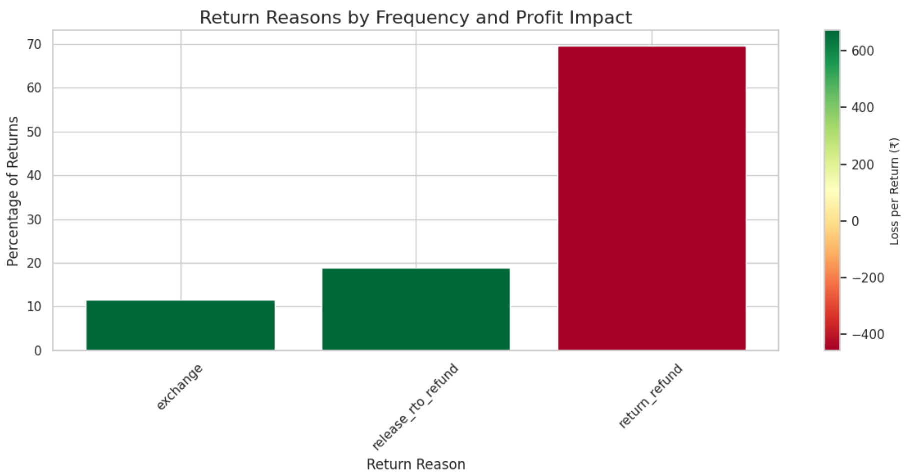


Fig 3. Return reasons by frequency and profit impact.

C. Return Rate and Price Rang

We see that **mid-priced items (₹500–2,000)** have the highest return rates (~50–52%) and the lowest profit margins (~29–30%). In contrast, the highest price range (₹2,001–5,000) has a somewhat lower return rate (~47%) and a higher margin (~44%). This suggests that more expensive items tend to be more satisfying (fewer returns) and/or carry higher markups. By pricing or upselling customers into higher price bands, the business might reduce returns and improve margin

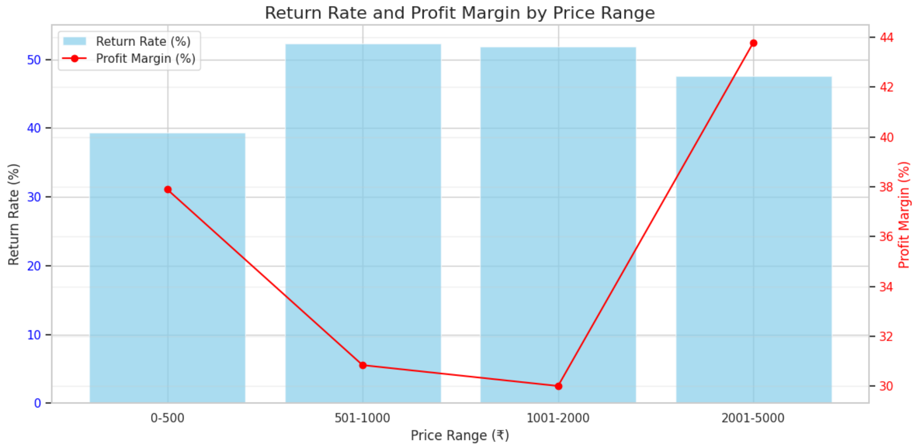


Fig 4. Return rate (bars) and profit margin (line) by product price range.

D. Return Rate by Discount Level

Interestingly, **heavily discounted items (71–100% off)** see a *much lower* return rate (~17%) but a very high profit margin (~64%). Conversely, items with low discounts (0–10%) have very high return rates (~60%) and slim margins (~22%). This indicates that deep discounts (e.g. clearance sales) not only preserve profit per item but also reduce returns, perhaps because customers have lower expectations or simply the items move out of inventory. In sum, higher discounts in this data are associated with significantly fewer returns and higher margins.

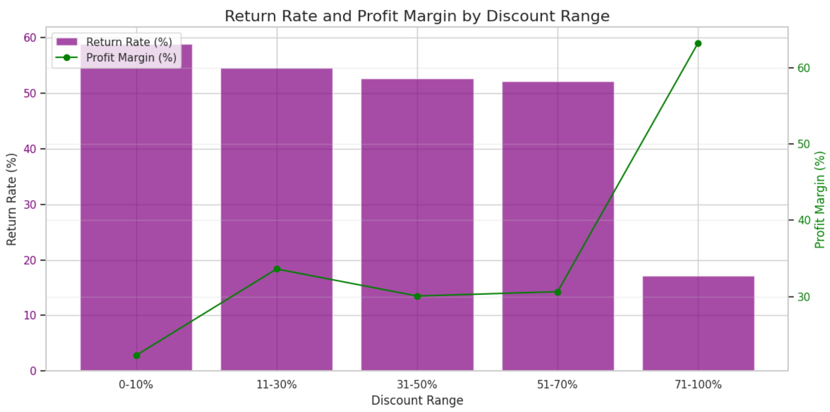


Fig 5. Return rate (purple bars) and profit margin (green line) by discount level.

E. Return Count by Return Method And Payment Type

The bar graph depicting the distribution of returns based on payment methods and return modes highlights a pronounced pattern. Orders paid through Cash-on-Delivery (COD) consistently experience a significantly higher number of returns compared to prepaid orders. Among these, the most frequent return mode is physical pickup, which suggests that customers largely prefer the convenience of a pickup facility rather than taking the effort to drop off returned items. Interestingly, prepaid drop-off returns appear to be the least common, indicating either better product satisfaction or greater purchasing intent in prepaid transactions. These insights underscore the behavioral difference between COD and prepaid customers, with the former being more return-prone, potentially due to impulse buying or lower perceived commitment to the order.

F. Return Related Deduction and Net Profit Impact

The chart clearly shows that returns significantly erode profitability. While Molcha generates a basic profit of around ₹6.9 million, major deductions—especially from lost revenue and handling costs—reduce the net profit to just ₹2.8 million. Lost revenue is the most damaging component, highlighting the need to urgently control return rates. This emphasizes that reducing returns is not optional but essential for sustaining profit margins. Strategic actions like restocking fees, better product content, and courier optimization can directly improve bottom-line performance.

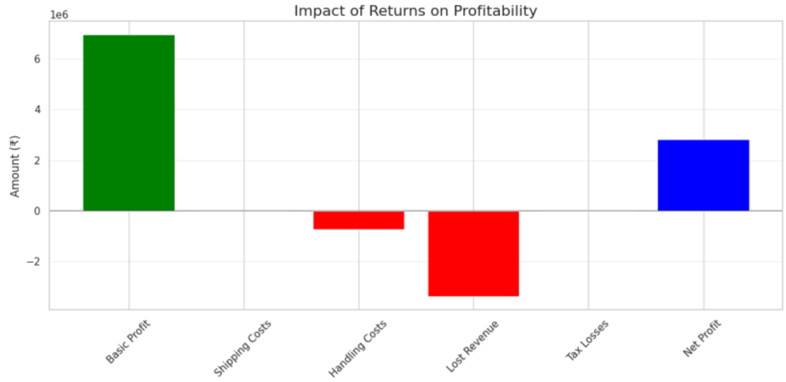


Fig 6: Breakdown of Profit Erosion Due to Returns

G. Influence of Delivery Timing on Returns and Profit Margin

This chart reveals a critical relationship between delivery timing, return rates, and profit margins. Surprisingly, while return rates remain steady across early and on-time deliveries (~46%), they spike dramatically to over 80% when orders are **delayed significantly**. Interestingly, **slightly delayed deliveries show the highest profit margin (~42%)**, suggesting that moderate flexibility doesn't harm profitability. However, **major delays drastically reduce margin efficiency despite high sales volume**, due to the surge in returns. These findings emphasize the importance of maintaining timely—though not necessarily rushed—deliveries and avoiding major delays to optimize profitability.

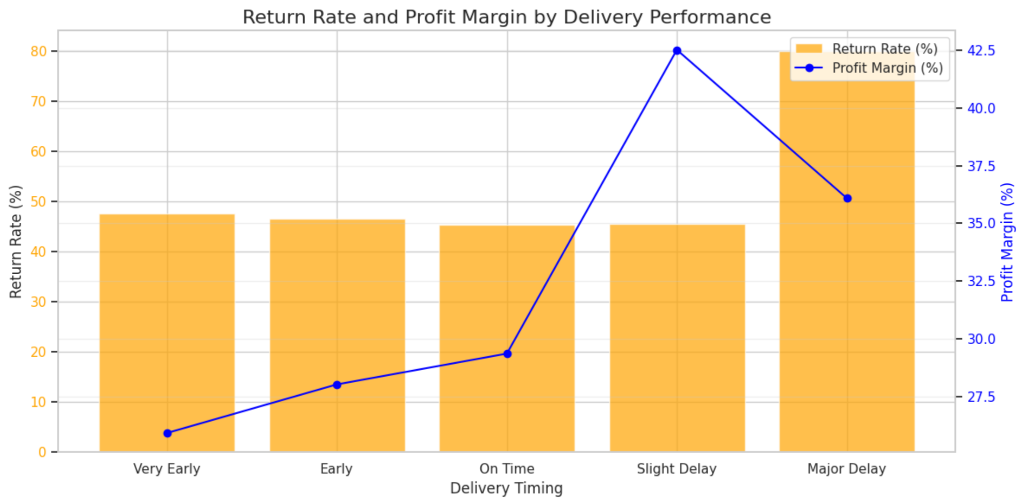


Fig 7: Delivery Timing v/s Return Rates v/s Profit Margin

H. RTO Rate Comparision: COD v/s Prepaid Orders

This chart highlights a stark difference in **Return-to-Origin (RTO)** rates based on payment methods. **Cash-on-Delivery (COD) orders exhibit an RTO rate exceeding 45%,** nearly four times higher than **prepaid orders (~12%)**. This suggests that COD transactions carry a significantly higher fulfillment risk and operational cost. To reduce RTO losses, the business should actively **incentivize prepaid payments**—through discounts or loyalty points—and **limit COD options** in high-RTO regions. Shifting the payment mix toward prepaid could directly enhance order reliability and profitability.

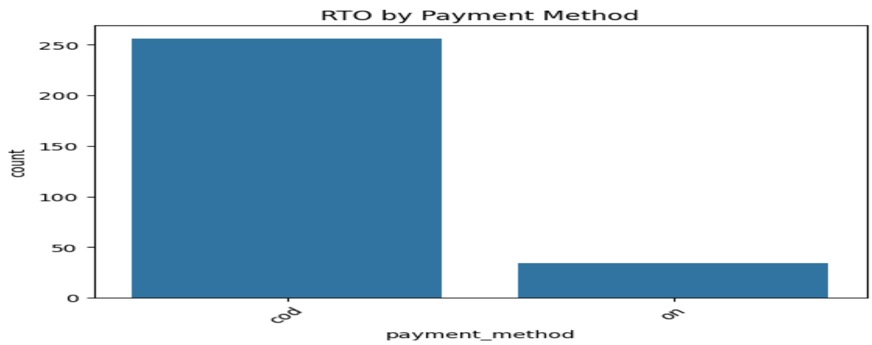


Fig 7 : Payment methods used by return customers

I. Courier Wise Failure Counts in Order Fulfilment

This chart shows a significant concentration of order failures with **Flipkart Logistics**, which accounts for the majority of 'F' (failed delivery) counts—over 400 instances. In contrast, other courier partners like EK_E2E, EcomExpress, and Delhivery show far fewer failures. This disproportion suggests operational or service inefficiencies specific to Flipkart Logistics. To improve fulfillment performance and reduce return-to-origin rates, the business should **audit**

Flipkart Logistics' delivery accuracy, consider **rebalancing shipment volumes across better-performing couriers**, or **set performance SLAs** to reduce dependency on a single underperforming partner.

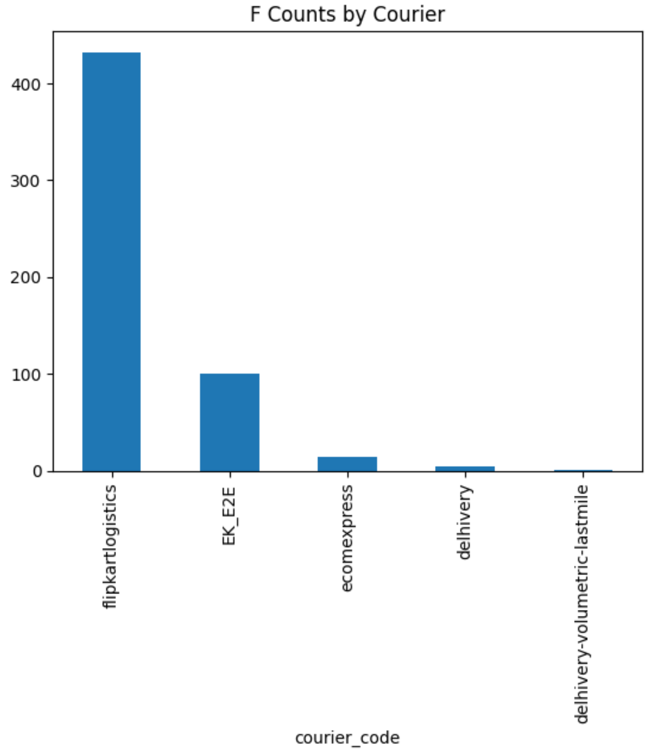


Fig 8: Courier Company v/s Orders Delivered

J. Temporal Trends in Order Volume and Refund Activity

The time-series plots reveal a synchronized trend between order creation and refund volumes over time. A noticeable surge in orders is observed in **late September to early October 2024**, likely tied to promotional campaigns or seasonal events. However, this period also sees a spike in **refund activity**, suggesting fulfillment or product quality issues during peak demand. Post-October, both metrics decline steadily before stabilizing. The correlation between high order volume and rising refunds underscores the need for **scalable quality control, fulfillment reliability**, and **proactive customer support during sales events** to preserve customer trust and prevent margin erosion.

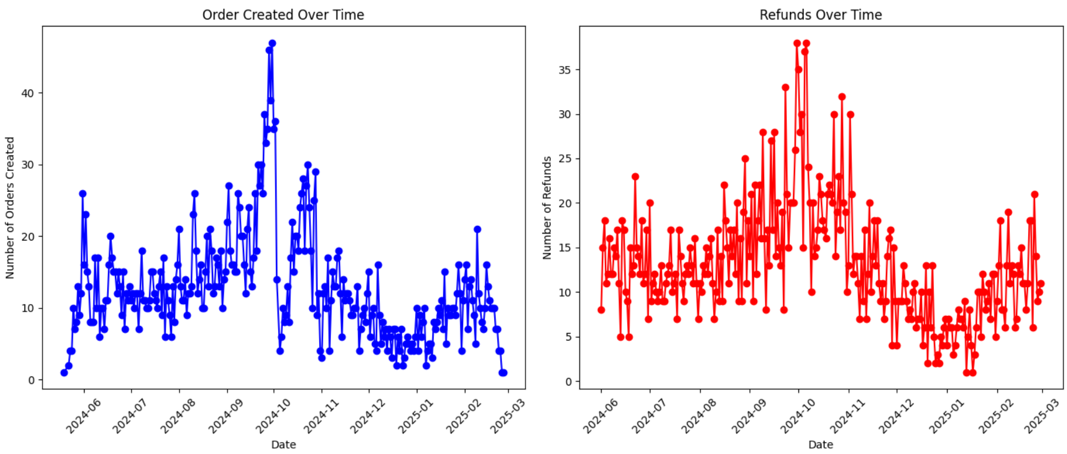


Fig 9: Time Series Comparision of total orders made and Return

K. Revenue Loss Distribution per Returned Item

The histogram reveals that a majority of returned items result in a **revenue loss centered around ₹950–₹1000**, with a strong peak indicating this is the most frequent loss range. However, a noticeable tail toward higher values—extending up to ₹2500—suggests that **certain high-value products disproportionately contribute to revenue loss**. This calls for a more selective return policy, especially for premium items, and a re-evaluation of packaging, sizing, and quality assurance practices for products in the ₹1500+ range. Addressing these high-loss outliers can meaningfully improve overall profitability.

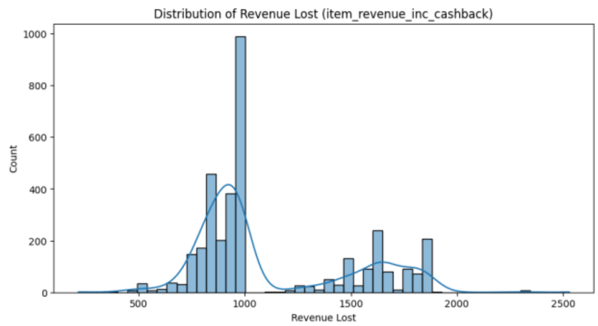


Fig 10: Revenue Loss per Returned item

L. Refund Volume Distribution by Refund Mode

The chart indicates that **Order Reversal (OR)** is the most commonly used refund method, accounting for the vast majority of refund transactions. In comparison, **NEFT (bank transfers)** and **Myntra Credit** are significantly less utilized. This pattern may reflect a customer preference for direct reversals or a company policy bias. However, relying heavily on OR could delay customer resolution if systemic issues arise. **Encouraging Myntra Credit**, especially through incentives, could not only **retain refunded revenue within the ecosystem** but also **enhance repurchase rates**, offering a strategic opportunity to recover potential losses.

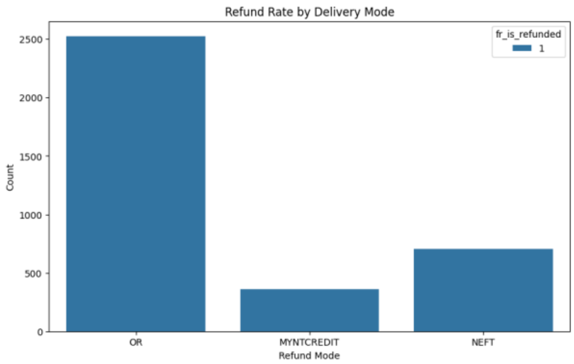


Fig 11: Return Rate by Delivery Mode

4 Interpretation of Results and Recommendations

A detailed product-level analysis indicates that while **Saree Blouses** are the top revenue contributor (₹60.3 lakh) and generate the highest net profit (₹17.1 lakh), their **return rate of 54.90%** poses a major threat to sustained profitability. This high return volume significantly erodes the realized margins (28.46%), signaling potential mismatches in **fit, fabric expectation, or product representation online**. Similarly, **Palazzos, Salwar, and Dresses**, despite contributing substantial revenue and profits, show elevated return rates exceeding **40%**, which diminishes their margin efficiency.

On the other hand, categories like **Cushion Covers**, **Churidar**, and **Trousers** offer a more promising mix of **higher margins (over 38%)** and **comparatively lower return rates**, making them better suited for scaled promotions. Particularly, **Cushion Covers** with a **69.25% profit margin** and only **12.16% returns** present a highly efficient category with minimal loss risk, ideal for aggressive marketing.

Products like **Shorts**, **Tops**, and **Co-Ords**, while generating moderate revenue, suffer from disproportionately high return rates (**65–68%**), suggesting that these categories may be contributing to **logistical and cost inefficiencies**. **Kurtis (entry 16)** stand out as a loss-making product, with a negligible net profit and an **alarming 80% return rate**, indicating it should either be **discontinued or significantly reworked**.

Overall, the data advocates for a **strategic reallocation of marketing and inventory efforts** toward high-margin, low-return categories, while **auditing or repositioning underperforming SKUs** to optimize profitability and reduce operational friction.

	Article Type	Count	Revenue (₹)	Net Profit (₹)	Margin %	Return %
10	Saree Blouse	5481	6032676.36	1717098.83	28.46	54.90
7	Palazzos	777	826812.55	306630.60	37.09	44.27
5	Salwar	676	783294.98	319624.47	40.81	44.53
8	Dresses	298	425223.54	130313.56	30.65	48.32
14	Co-Ords	210	347152.16	60764.10	17.50	64.76
2	Churidar	165	220479.78	104517.25	47.40	30.91
4	Shirts	153	152503.26	62423.34	40.93	45.10
9	Harem Pants	106	122062.27	35423.02	29.02	45.28
15	Shorts	94	112269.95	13729.29	12.23	68.09
12	Skirts	84	42516.16	10937.79	25.73	52.38
0	Cushion Covers	74	31110.14	21543.02	69.25	12.16
13	Tops	67	71563.10	18084.78	25.27	65.67
11	Ethnic Dresses	43	53986.02	15265.38	28.28	53.49
6	Trousers	28	32819.99	12692.07	38.67	39.29
3	Kurtas	12	11412.04	5120.60	44.87	33.33
1	Earrings	5	2995.00	1596.42	53.30	20.00
16	Kurtis	5	4825.00	136.99	2.84	80.00

Profitibility Summary:

The business generated a total revenue of ₹92.75 lakh, with commission costs of ₹22.99 lakh, resulting in a basic operating profit of ₹69.75 lakh before considering returns. However, the financial burden of returns significantly impacts this profitability. Return-related losses—including handling costs (₹7.27 lakh), lost revenue (₹33.92 lakh), and tax leakage (₹17.9k)—amount to a total loss of ₹41.38 lakh, effectively eroding 59% of the basic profit. This brings the final net profit down to ₹28.37 lakh, reducing the overall net profit margin to 30.59%, from a potential 75.20%. The margin reduction of 44.62% solely due to returns underscores the urgent need for corrective measures around product quality, return policies, and operational efficiency. Without addressing these inefficiencies, nearly half of the company's potential profit will continue to be lost to returns.

Strategic SMART Recommendations

1. Product Portfolio Optimization

- Specific: Delist or revamp SKUs with >60% return rates (e.g., *Kurtis, Shorts*).
- **Measurable**: Target a 25–30% inventory shift to low-return categories.
- **Achievable**: Begin with a 7-day audit and 30-day phase-out plan.
- **Relevant**: Prioritizes margin recovery.
- **Time-bound**: Phase out underperformers within 30 days.

2. Return Policy Restructuring

- Introduce **tiered return fees** to discourage casual returns.

- Promote **exchanges** with incentives (e.g., 10% discount on next purchase).
- Update return policies and communication within 2 weeks.

3. Payment Method Optimization

- Offer ₹X discount on prepaid orders to reduce COD usage.
- Restrict COD in high RTO PIN codes.
- Implement in stages across high-risk areas in 30 days.

4. Discount Strategy Overhaul

- **Avoid the problematic 51–70% discount range (52% return rate).**
- Use deep discounts (71–100%) for clearance.
- Apply 0–10% discounts on premium items.

5. Courier Performance Realignment

- Shift volume away from *Flipkart Logistics*; enforce SLA tracking.
- Reallocate volumes to top-performing partners within 30 days.

6. Customer Experience Enhancements

- Improve **product descriptions**, **size guides**, and **images** on top 20 returned SKUs.
- Add pre-shipping confirmations for orders >₹1000

7. Delivery Optimization

- Prioritize early/on-time delivery for high-value items.
- Target Friday promotions (lower return rate, higher margin).
- Set realistic delivery timelines to reduce expectation gaps.

8. Return Reason Tracking & Prediction Model

- Capture granular return reasons.
- Develop a risk-scoring model based on product/discount history.

9. Financial & Supply Chain Management

- Rebalance inventory investment away from high-return products.
- Streamline refund processing to recover tax credits faster.
- Negotiate rates with reliable delivery partners.

Implementation Timeline:

Phase	Timeline	Focus Areas
Critical (Days 0–30)	Immediate execution of quick-win strategies	- Implement tiered return policy - Discontinue or flag products with >60% return rate - Shift volumes away from underperforming couriers - Audit and correct discount brackets
Strategic (Days 31–90)	Medium-term structural improvements	- Rebalance inventory: increase stock for low-return, high-margin products - Launch geo-targeted campaigns - Roll out enhanced product pages with better sizing, descriptions, and photos
Systemic (Days 91–180)	Long-term process innovation and automation	- Deploy return reason tracking and return prediction model - Introduce loyalty program for low-return customers - Implement dynamic pricing engine based on return probability and margins

Expected Impact:

By implementing these strategies, return rates are projected to drop from 42% to 20-25% within six months, translating to ₹1.5–2 million in additional profit annually. The clear takeaway is that every 1% reduction in return rate directly lifts profitability, offering a highly leverageable improvement path.

Additional Documents:

- https://drive.google.com/drive/folders/11ixA6wQKDWSQ7XMH6mSj85wEu4Hih-FS?usp=drive_link
- https://drive.google.com/drive/folders/1Ovn31Ox-A-Q70J0iKKTZGxaBzBupR5E-?usp=drive_link