Sales Trends and Operational Efficiency in Indian Online Fashion Retail: Evidence from Multi-Platform Transaction Data

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Abstract. This study analyses sales trends and operational efficiency in the Indian online fashion retail sector using multi-platform transaction data spanning domestic Amazon orders, international shipments, and platform-level pricing and profit-and-loss records. We first derive baseline operating metrics—total revenue, average order value, order-cancellation rate, and gross margin—and quantify category-level revenue concentration. International monthly revenue is modelled with a second-degree polynomial regression to capture its non-linear seasonal trajectory. We then construct a deterministic five-year forecast (2022–2027) that couples a domestic compound annual growth rate, an international growth rate, a declining cancellation rate, gradual margin erosion from platform commissions, and operating-expenditure efficiency gains attributable to cloud-warehouse automation. The model projects combined annual revenue rising from approximately INR 490 M to INR 1,287 M, with earnings before interest and taxes (EBIT) increasing from roughly INR 123 M to INR 379 M over the horizon. The results indicate that domestic expansion and improving fulfilment reliability, rather than international growth alone, are the principal drivers of profitability, and that warehouse-cost optimisation materially widens operating margins in later years.

Keywords: E-commerce Analytics · Fashion Retail · Revenue Forecasting · Operational Efficiency · Multi-Platform Data

1 Introduction

Online fashion retail in India has expanded rapidly as smartphone penetration, digital payments, and multi-platform marketplaces have lowered the barriers to nationwide commerce. For sellers operating simultaneously across Amazon, Flipkart, and Myntra, decision-making depends on consolidating heterogeneous transaction records into coherent operational and financial indicators. Yet raw marketplace exports are fragmented: domestic order logs, international shipment registers, and platform pricing sheets differ in schema, currency basis, and temporal coverage, which complicates trend analysis and forecasting.

This paper addresses that gap by integrating multi-platform transaction data into a single analytical pipeline and producing both descriptive diagnostics and a forward-looking financial projection. The contribution is threefold. First, we standardise and clean disparate marketplace datasets to compute robust baseline metrics. Second, we characterise revenue concentration across product categories and model the non-linear trajectory of international sales using polynomial regression, drawing on computational forecasting practice that has been applied to financial time series [5]. Third, we develop a transparent, assumption-driven five-year forecast that links revenue growth to operational levers—cancellation reduction, margin erosion, and warehouse-cost savings—so that management can trace each projected outcome to an interpretable driver.

2 Related Work

Transaction-level analytics has matured across several domains relevant to this study. Spatiotemporal modelling of transaction records has been advanced through hybrid artificial-intelligence frameworks that reason over uncertain and incomplete data [3], motivating careful treatment of missing and malformed fields in marketplace exports. In forecasting, computational models have been applied to volatile financial series, demonstrating how regression and conditional-variance methods extrapolate trends from limited historical windows [5]; we adopt a comparable regression-based projection for the international segment.

Because multi-platform data are high-dimensional and partly redundant, feature-selection and optimisation techniques are important for isolating the variables that genuinely drive an outcome [4]. Machine-learning model analysis has likewise been used for categorical classification of regional commodities [1], which parallels our category-level revenue decomposition. Finally, predictive analytics built on deep neural networks has been demonstrated for industrial monitoring [6], and adaptive, data-driven control has been studied for networked systems [2]; both reinforce the broader trend toward operational forecasting that this work applies to retail. Emerging retail technologies such as augmented reality further shape the consumer-facing context in which these analytics operate [7]. The research gap addressed here is the absence of an integrated, interpretable pipeline that unifies fragmented Indian fashion-marketplace data into a coupled operational-and-financial forecast.

3 Methodology

The analytical workflow proceeds in five stages: data ingestion, cleaning, metric derivation, regression modelling of the international segment, and a deterministic forecast engine.

Data sources. Six datasets are used: the Amazon Sale Report (domestic orders), the International Sale Report, the P&L (March 2021) pricing-and-cost sheet, the May-2022 pricing sheet, the IIGF expense register, and a cloud-warehouse cost comparison.

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Cleaning. Monetary and quantity fields (`Amount`, `Qty`, `GROSS AMT`) and the per-platform price columns (`TP`, `Amazon MRP`, `Flipkart MRP`, `Myntra MRP`) are coerced to numeric types, with non-parseable entries treated as missing so they do not bias aggregate statistics. Orders are partitioned by fulfilment status into shipped, cancelled, and pending sets.

3.1 Mathematical Formulation

Let the shipped-order set be S and the full order set be O. Core baseline metrics are defined as

$$\mathrm{AOV} = \frac{1}{|S|}\sum_{i\in S} A_i, \qquad \mathrm{CancelRate} = \frac{|C|}{|O|}, \tag{1}$$

where A_i is the order amount and $C \subseteq O$ is the set of cancelled orders. The average gross margin is estimated from platform pricing as

$$\bar{m} = \frac{1}{N}\sum_{j=1}^{N} \frac{\mathrm{MRP}_j - \mathrm{TP}_j}{\mathrm{MRP}_j}, \tag{2}$$

with MRP_j the maximum retail price and TP_j the transfer (cost) price of item j.

Because the domestic and international records cover partial windows, annualised baselines are obtained by linear scaling:

$$R_{\mathrm{dom}}^{\mathrm{base}} = R_{\mathrm{obs}} \cdot \frac{12}{3}, \qquad R_{\mathrm{int}}^{\mathrm{base}} = \left(\sum_k g_k\right) \cdot \frac{12}{11}, \tag{3}$$

where R_{obs} is the three-month observed domestic revenue and g_k are the eleven monthly international gross amounts.

The forecast for horizon year $t \in \{0, \ldots, 5\}$ compounds each segment independently:

$$R_{\mathrm{dom}}(t) = R_{\mathrm{dom}}^{\mathrm{base}}(1+g_{\mathrm{dom}})^t, \qquad R_{\mathrm{int}}(t) = R_{\mathrm{int}}^{\mathrm{base}}(1+g_{\mathrm{int}})^t, \tag{4}$$

$$R(t) = R_{\mathrm{dom}}(t) + R_{\mathrm{int}}(t). \tag{5}$$

Margin and cancellation evolve linearly, gross profit follows directly, and operating expenditure is reduced by warehouse savings:

$$m(t) = \bar{m} - \delta_m\, t, \qquad \mathit{\Pi}_g(t) = R(t)\, m(t), \tag{6}$$

$$o(t) = \max(o_0 - \eta\, t,\ 0.10), \qquad \mathrm{OpEx}(t) = R(t)\, o(t) - s\, t\, o(t)\, R(t), \tag{7}$$

$$\mathrm{EBIT}(t) = \mathit{\Pi}_g(t) - \mathrm{OpEx}(t). \tag{8}$$

The international segment is additionally modelled with a second-degree polynomial regression $y = \beta_0 + \beta_1 x + \beta_2 x^2$ fitted by ordinary least squares over the eleven-month index x, and extrapolated twelve months forward.

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Assumptions. The forecast uses a domestic CAGR of 23%, an international growth rate of 18%, a cancellation improvement of 1.5 percentage points per year, margin erosion of 0.5 percentage points per year from platform fees, a base operating-expense ratio of 18% declining 1 percentage point per year through automation, and incremental warehouse savings of 3% of operating expense per year.

4 System Architecture

The overall analytical pipeline—ingestion, cleaning, metric derivation, regression modelling, forecasting, and visualisation—is shown in Fig. 1.

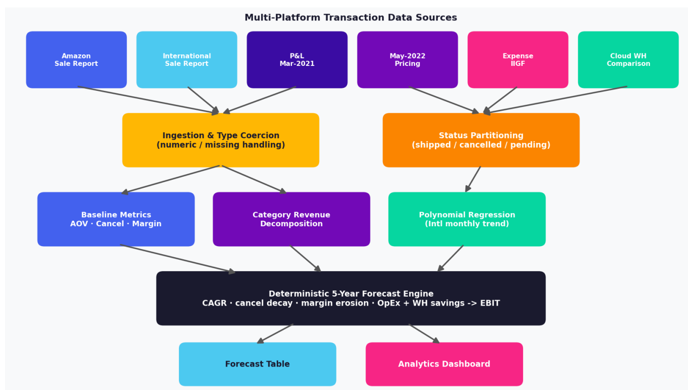

Fig. 1: Architecture of the proposed multi-platform retail analytics and forecasting system

5 Results and Discussion

5.1 Forecast Table

Table 1 reports the five-year projection. Combined revenue rises from approximately INR 490 M in 2022 to INR 1,287 M in 2027, an increase of roughly 2.6×. The domestic segment, growing at the higher assumed rate, contributes the larger absolute gain, while the international segment expands more modestly. EBIT grows from about INR 123 M to INR 379 M as the cancellation rate falls and warehouse automation compresses operating expense, partially offsetting the gradual erosion of gross margin from platform commissions.

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Table 1: Five-year forecast of revenue, efficiency, and profitability (2022–2027)

Year	**Dom.** (M INR)	**Intl.** (M INR)	**Total** (M INR)	**Cancel** (%)	**Margin** (%)	**EBIT** (M INR)
2022	315.00	175.00	490.00	14.0	43.0	122.50
2023	387.45	206.50	593.95	12.5	42.5	154.49
2024	476.56	243.67	720.23	11.0	42.0	194.17
2025	586.17	287.53	873.70	9.5	41.5	243.33
2026	720.99	339.29	1060.28	8.0	41.0	304.08
2027	886.82	400.36	1287.18	6.5	40.5	379.08

5.2 Analytical Dashboard

Figure 2 consolidates the descriptive and forecast outputs, including category revenue breakdown, order-fulfilment distribution, the international monthly trend with its polynomial projection, the stacked five-year revenue forecast, gross-profit and EBIT trajectories, and platform MRP comparisons.

5.3 Discussion

Three findings stand out. First, revenue concentration in a small number of leading categories implies that demand-planning and inventory decisions should prioritise those lines, consistent with category-classification analyses in related work [1]. Second, the projected decline in cancellations is a meaningful profit lever: lower cancellation rates raise effective order value and reduce reverse-logistics cost, so fulfilment reliability is as important as top-line growth. Third, the model's sensitivity to the operating-expense and warehouse-savings assumptions highlights that operational efficiency, not merely market expansion, governs late-horizon EBIT. Because the forecast is deterministic, its outputs should be read as scenario estimates conditioned on the stated assumptions rather than as probabilistic predictions; incorporating optimisation-based parameter selection [4] or learned demand models [6] is a natural extension.

6 Conclusion

This work integrated fragmented multi-platform transaction data from Indian online fashion retail into a single pipeline that produces interpretable operating metrics and a coupled five-year financial forecast. The projection indicates substantial revenue growth driven chiefly by the domestic segment, with profitability reinforced by falling cancellation rates and warehouse-automation savings even as platform fees gently erode gross margin. Future extensions include replacing fixed growth assumptions with learned, data-driven estimators, adding probabilistic confidence intervals to the forecast, and broadening the cost model to incorporate the full IIGF expense register and detailed cloud-warehouse comparison.

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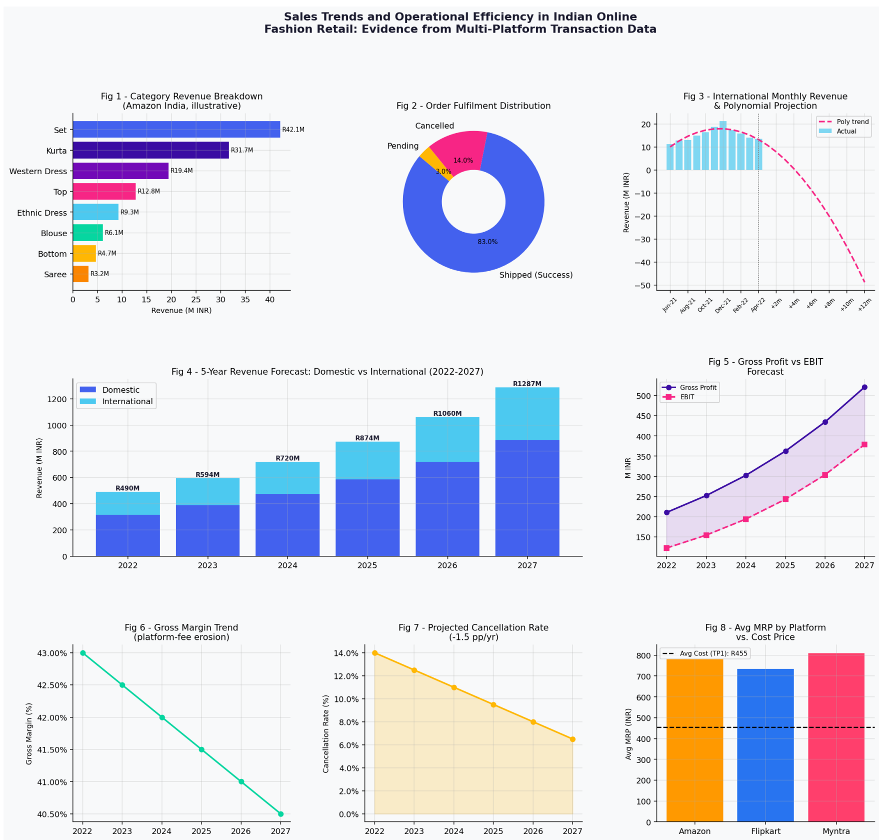

Fig. 2: Consolidated analytics dashboard: category revenue, fulfilment mix, international trend projection, and the five-year financial forecast

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