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# PRODUCT OPTIMIZATI AND REVENUE CONTRIBUTION ANALYSIS: A DATA-DRIVEN FRAMEWORK FOR THE SPECIALTY COFFEE RETAIL INDUSTRY AFFICIONADO COFFEE ROASTERS -- MULTI-STORE PRODUCT PORTFOLIO STUDY

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GitHub: [https://github.com/ganapathi-ai/Product\\_Optimization\\_-\\_Revenue\\_Contribution\\_Analysis](https://github.com/ganapathi-ai/Product_Optimization_-_Revenue_Contribution_Analysis)

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## Abstract

This study addresses three explicit research objectives: (RO1) to identify which products and categories are primary revenue and volume drivers in a specialty coffee retail environment; (RO2) to quantify revenue concentration using Pareto analysis and identify portfolio rationalization candidates; and (RO3) to evaluate geographic performance variation across store locations and derive actionable recommendations. The study context is Afficionado Coffee Roasters, a three-store specialty coffee chain operating in New York City across Astoria, Hell's Kitchen, and Lower Manhattan. Using a transactional POS dataset of 149,116 customer transactions across 80 products and 9 categories, a multi-dimensional analytical framework was developed and operationalized through an interactive Streamlit dashboard. The framework integrates: (i) a composite product Efficiency Score combining normalized revenue and normalized sales volume; (ii) Pareto concentration analysis; (iii) median-based quadrant segmentation; and (iv) store-level comparative benchmarking. Key findings: total portfolio revenue is \$698,812.33 at an average transaction value of \$4.69. Coffee dominates at 38.63% (\$269,952.45), followed by Tea (28.11%) and Bakery (11.78%). Pareto analysis shows 42 products (52.5%) account for 79.25% of revenue. Nine Hero-tier products -- led by Sustainably Grown Organic Lg (\$21,151.75, 3.03%) -- achieve efficiency scores above 0.80. Store revenues are near-equal (gap < 2.8%). A strong positive Pearson correlation ( $r = 0.8468$ ,  $p < 0.001$ ,  $n = 80$ ) between units sold and revenue validates volume-first optimization strategy.

**Keywords:** product portfolio optimization, revenue contribution analysis, pareto principle, composite efficiency scoring, specialty coffee retail, streamlit dashboard, multi-store analytics, data-driven menu engineering, pos transaction analysis

## 1. Introduction

The global specialty coffee market was valued at USD 47.9 billion in 2023 and is projected to grow at a CAGR of 10.6% through 2030 [1]. Within this expanding landscape, multi-location specialty coffee operators face a fundamental and under-researched challenge: how to optimally manage broad product portfolios across stores with heterogeneous customer segments, while maintaining operational efficiency and financial sustainability. Unlike large-format Quick Service Restaurants (QSR), specialty coffee operators rarely possess the analytical infrastructure to conduct systematic product performance diagnostics from their point-of-sale (POS) transaction data [2].

This research is motivated by three empirically grounded gaps in the existing literature. First, while the Pareto principle (80/20 rule) is widely cited in product management, its empirical validation in specialty coffee retail -- where product counts are moderate (50-100 SKUs) and unit prices are low -- remains sparse [3]. Second, composite efficiency scoring models that integrate revenue, volume, and transaction frequency into a single normalized metric are underutilized in food-service analytics, despite their demonstrated utility in broader retail contexts [4]. Third, intra-chain geographic performance benchmarking for coffee retailers operating in dense urban markets has not been systematically examined [5].

This paper presents a replicable, data-driven analytical framework applied to Afficionado Coffee Roasters' POS dataset, covering 80 products, 9 categories, 3 NYC store locations, 149,116 transactions, and \$698,812.33 in total revenue. The three explicit research objectives are:

1. RO1: Identify the primary revenue and volume drivers across the product portfolio and product categories.
2. RO2: Quantify revenue concentration via Pareto analysis and identify rationalization candidates.
3. RO3: Compare store-level performance and derive specific, data-grounded strategic recommendations.

The findings are operationalized through a 7-tab interactive Streamlit web dashboard supporting real-time filtering by category, product type, store, performance tier, Top-N, revenue range, volume range, and efficiency score. All code, data, and the dashboard are publicly available on GitHub for full reproducibility.

## 2. Literature review

Product portfolio optimization has a rich theoretical and empirical foundation. The foundational Pareto principle -- that approximately 80% of outcomes arise from 20% of causes -- was formalized by Juran (1951) [6] and subsequently operationalized in inventory management as the ABC analysis framework. In food service, Kasavana and Smith (1982) pioneered Menu Engineering, classifying dishes by profitability and popularity into stars, plowhorses, puzzles, and dogs [7]. Miller (1980) further established the theoretical basis for restaurant menu analysis as a revenue optimization tool [8].

Kimes and Chase (1998) extended menu engineering to yield management contexts, demonstrating that systematic product-level analysis could increase per-cover revenue by 15-25% [3]. Taylor and Brown (2007) showed that selective menu rationalization in foodservice chains increased operational efficiency by 15-22% without adverse customer satisfaction effects [9]. These foundational works underpin the quadrant-based popularity-revenue analysis adopted in this study.

More recent literature has examined data-driven approaches enabled by the proliferation of POS systems. Raab, Mayer, Shoemaker, and Ng (2009) proposed composite scoring systems combining revenue, transaction frequency, and pricing efficiency for objective menu item ranking [4]. Kwon and Jang (2012) applied demand-side analytics to identify pricing elasticity variations across product categories in casual dining [10]. Ottenbacher and Harrington (2013) examined menu innovation as a competitive strategy in the specialty coffee sector, noting the tension between portfolio breadth and operational complexity [11].

In multi-location retail, Ailawadi and Keller (2004) documented significant intra-chain heterogeneity in SKU-level sales even within proximate store locations, driven by local demographics and footfall patterns [12]. Zhang, Agarwal, and Lucas (2011) demonstrated that granular store-level product analytics could improve inventory allocation accuracy by 18% in multi-unit food-service operations [13].

Recent work has leveraged machine learning and advanced analytics for retail product optimization. Dzyabura and Jagabathula (2018) applied machine learning models to optimize assortment planning under customer preference uncertainty [14]. Ferreira, Lee, and Simchi-Levi (2022) demonstrated that data-driven markdown optimization using transaction-level data could increase revenue by 5-10% in fashion retail -- a methodology transferable to beverage menu pricing [15]. Huang, Chen, and Wang (2023) applied XGBoost-based product demand forecasting to coffee retail, achieving RMSE improvements of 22% over ARIMA baselines [16]. Liu, Zhang, and Peng (2024) employed natural language processing on customer review data to augment product performance scoring with sentiment signals [17]. Nakagawa and Tanaka (2023) applied graph neural networks to cross-product affinity analysis in beverage retail, revealing complementary product clusters informative for bundling strategies [18].

In the domain of business intelligence and dashboard design, Few (2012) established best practices for operational dashboards emphasizing multi-view integration with interactive filtering [19]. The emergence of Streamlit has democratized real-time analytical dashboards for domain experts without front-end development expertise [20]. Chen, Chiang, and Storey (2012) demonstrated the utility of Pearson correlation analysis in uncovering demand patterns

from transactional retail data [21]. Virtanen et al. (2020) provided the foundational SciPy computational infrastructure used for statistical analysis in this study [22].

### 3. Dataset And Methodology

#### 3.1 Dataset Description and Provenance

The Afficionado Coffee Roasters POS dataset was sourced from the company's point-of-sale records. The raw transactional data was pre-processed and aggregated into a product-level consolidated analytical file. The raw dataset comprises individual transaction records within the year 2025, spanning three New York City retail locations. Table 1 summarises the dataset characteristics.

**Table 1. Dataset Characteristics Summary (Source: Afficionado Coffee Roasters POS System, 2025)**

Characteristic	Value
Total Products (SKUs)	80
Product Categories	9
Store Locations	3 (Astoria, Hell's Kitchen, Lower Manhattan, NYC)
Total Customer Transactions	149,116
Total Portfolio Revenue	\$698,812.33
Average Transaction Value	\$4.69 (computed: \$4.6864)
Analysis Period	2025 (transactional POS records)
Analytical Columns (derived)	25 per product
Performance Tiers	Hero (ES >= 0.80), High (0.50-0.79), Medium (0.20-0.49), Low (<0.20)
Pareto Classes	Top_80% (42 products), Long_Tail (38 products)

#### 3.2 Data Pre-Processing Pipeline

The raw transactional data underwent the following processing steps prior to analysis: (Step 1) Transaction-level records were aggregated by product SKU to compute total units sold, total revenue, and transaction frequency per product. (Step 2) Store-level revenue was disaggregated by joining on store\_location, yielding three store-specific revenue columns (revenue\_Astoria, revenue\_Hell's\_Kitchen, revenue\_Lower\_Manhattan). (Step 3) Average unit price (avg\_unit\_price) was sourced from the raw transactional unit\_price field per product. Products may have variable unit pricing across size variants. (Step 4) Revenue rank and volume rank were assigned using the minimum (competition) ranking method in descending order -- tied products receive the lowest rank value of the tie group. (Step 5) Cumulative revenue and cumulative revenue percentage were computed by summing ranked revenue in order, enabling Pareto classification. (Step 6) Pareto class was assigned as 'Top\_80%' for the first 42 products (cumulative revenue reaching 79.25% of portfolio total) and 'Long\_Tail' for the remaining 38. (Step 7) Category-level and type-level aggregates were computed by grouping product-level data. The final consolidated CSV contains 80 product records, 25 analytical columns, and was cross-checked against the raw transaction totals and derived summary tables.

#### 3.3 Composite Efficiency Score (ES) Model

The Efficiency Score (ES) is a pre-computed metric provided in the consolidated dataset and independently reproducible from the transaction-level raw data. The formula, documented in the project's Transformation Logic specification, combines revenue performance (weighted 60%) and volume performance (weighted 40%), both normalised relative to the portfolio maximum:

$$ES = 0.6 \times (\text{Product\_Revenue} / \text{Max\_Revenue}) + 0.4 \times (\text{Product\_Units} / \text{Max\_Units})$$

Where Max\_Revenue = \$21,151.75 (highest product revenue) and Max\_Units = 4,708 (highest product unit volume in the portfolio). This normalisation yields ES values in [0,1] that are directly interpretable as weighted proportional performance relative to the portfolio leader. Verification confirms the formula replicates all 80 CSV efficiency\_score values within a tolerance of 0.001 (max deviation = 0.0005). ES range: 0.031 (lowest, rank-80) to 0.992 (highest, Dark chocolate Lg). Performance tier boundaries: Hero (ES >= 0.80) -- 9 products; High (0.50 <= ES < 0.80) -- 33 products; Medium (0.20 <= ES < 0.50) -- 15 products; Low (ES < 0.20) -- 23 products.

#### 3.4 Pareto Revenue Concentration Analysis

Products were sorted in descending order of total\_revenue and assigned cumulative revenue percentages. Products were classified as 'Top\_80%' if their cumulative revenue fell within the first 79.25% of portfolio revenue (the point at which the 42nd product was added), and 'Long\_Tail' for all subsequent products. Separately, the SUMMARY\_STATISTICS report identifies 22 products with individual revenue shares below 0.5% -- a stricter threshold identifying the most marginal long-tail contributors within the broader 38-product Long\_Tail classification.

### 3.5 Quadrant Analysis Methodology

Popularity-revenue quadrants were constructed using dataset median values as boundaries: median units sold = 3,629.5, median revenue = \$9,225.00. Products above both medians were assigned to Q1 (Hero Zone); below volume but above revenue median to Q2 (Premium); below both to Q3 (Rationalization); and above volume but below revenue median to Q4 (Volume Drivers). Quadrant counts: Q1=38, Q2=2, Q3=38, Q4=2.

### 3.6 Statistical Analysis

Pearson product-moment correlation was used to quantify the linear relationship between total units sold and total revenue across the 80-product portfolio. The SciPy library (v1.11+) was used for computation. All statistical tests used alpha = 0.05 as significance threshold. Descriptive statistics (mean, median, range, standard deviation) were computed for all continuous analytical variables using pandas (v2.0+).

### 3.7 Dashboard Implementation

The analytical framework was operationalized in a Streamlit (v1.28+) web application structured across 7 interactive tabs: (1) Product Rankings, (2) Revenue Contribution, (3) Popularity vs Revenue Scatter, (4) Pareto Analysis, (5) Store Performance, (6) Product Drill-Down, and (7) Data Export. The sidebar implements 8 real-time filters: product category (multi-select), product type (multi-select), store location (multi-select), performance tier (multi-select), Top-N slider (5-50), revenue range slider, volume range slider, and efficiency score range slider. Visualizations were built using Plotly (v5.17+) with 10 interactive chart types. Data caching was implemented via Streamlit's @st.cache\_data decorator.

## 4. Results And Analysis

### 4.1 Portfolio-Level Descriptive Statistics

The Afficionado Coffee Roasters portfolio generates \$698,812.33 in total revenue across 149,116 transactions at 3 store locations. The mean transaction value is \$4.69 (SD not available at transaction level in the consolidated dataset). Product-level revenue ranges from \$21,151.75 (Sustainably Grown Organic Lg, rank=1) to \$755.20 (Dark chocolate, rank=80), a 28.0x range demonstrating substantial portfolio heterogeneity. Mean product revenue is \$8,735.15. Median product revenue is \$9,225.00, substantially below the mean, confirming a right-skewed revenue distribution characteristic of long-tail portfolios.

### 4.2 Performance Tier Distribution

The composite Efficiency Score model classifies 80 products as: 9 Hero (11.25%), 33 High (41.25%), 15 Medium (18.75%), and 23 Low (28.75%). Hero products collectively generate \$162,265.75 (23.22% of total portfolio revenue), confirming their outsized commercial importance relative to their small portfolio share (11.25%). Low-tier products (n=23) are concentrated in Loose Tea, Coffee Beans, Packaged Chocolate, Branded merchandise, and Flavour syrup categories.

### 4.3 Category Revenue Distribution

Table 2 presents category-level revenue statistics sorted by total revenue contribution. Coffee and Tea together account for 66.74% of total portfolio revenue, confirming their strategic centrality. Drinking Chocolate achieves the highest average revenue per product (\$18,104.00) despite only 4 SKUs, driven by premium unit pricing (\$3.50-\$4.75 per unit). Flavours and Packaged Chocolate represent the lowest revenue categories despite high transaction volumes for Flavours (10,511 units), reflecting unit prices of approximately \$0.80 per syrup addition.

**Table 2. Revenue Distribution by Product Category -- Sorted by Total Revenue (Source: CATEGORY\_SUMMARY.csv; n=80 products, 9 categories)**

Category	Revenue (\$)	Share (%)	Units Sold	Products	Avg Rev/Product (\$)
Coffee	\$269,952.45	38.63%	89,250	21	\$12,854.88
Tea	\$196,405.95	28.11%	69,737	16	\$12,275.37
Bakery	\$82,315.64	11.78%	23,214	11	\$7,483.24
Drinking Chocolate	\$72,416.00	10.36%	17,457	4	\$18,104.00
Coffee beans	\$40,085.25	5.74%	1,828	10	\$4,008.52
Branded	\$13,607.00	1.95%	776	3	\$4,535.67
Loose Tea	\$11,213.60	1.60%	1,210	8	\$1,401.70
Flavours	\$8,408.80	1.20%	10,511	4	\$2,102.20
Packaged Chocolate	\$4,407.64	0.63%	487	3	\$1,469.21

#### 4.4 Top Product Performance

Table 3 presents the top 5 products by total revenue. The top-ranked product, Sustainably Grown Organic Lg, generates \$21,151.75 (3.03% revenue share) with 4,453 units sold and an efficiency score of 0.978 -- the second-highest composite score in the portfolio. Dark chocolate Lg achieves the highest efficiency score (0.992) due to its #2 revenue rank combined with the second-highest sales volume (4,668 units; volume rank #2). The top 10 products collectively account for 25.38% of total portfolio revenue, with all top-5 products classified as Hero-tier (ES > 0.85).

**Table 3. Top 5 Products by Total Revenue (Source: CONSOLIDATED\_ANALYSIS.csv; Rank=1 is highest revenue product)**

Rank	Product	Category	Revenue (\$)	Share (%)	Units Sold	Tier	ES
1	Sustainably Grown Organic Lg	Drinking Chocolate	\$21,151.75	3.03%	4,453	Hero	0.978
2	Dark chocolate Lg	Drinking Chocolate	\$21,006.00	3.01%	4,668	Hero	0.992
3	Latte Rg	Coffee	\$19,112.25	2.73%	4,497	Hero	0.924
4	Cappuccino Lg	Coffee	\$17,641.75	2.52%	4,151	Hero	0.853
5	Morning Sunrise Chai Lg	Tea	\$17,384.00	2.49%	4,346	Hero	0.862

#### 4.5 Pareto Revenue Concentration Analysis

Pareto analysis reveals that 42 products (52.5% of the portfolio) generate \$553,791.63 (79.25%) of total revenue, while the remaining 38 Long\_Tail products (47.5%) generate \$145,020.70 (20.75%). Within the Long\_Tail classification, 22 products each hold an individual revenue share below 0.5%, representing the most marginal contributors. This split (52.5% of products driving 79.25% of revenue) represents a modified Pareto pattern: wider than a strict 20/80 split, indicating moderate-to-high revenue dispersion rather than extreme hyper-concentration. Table 4 summarises Pareto metrics.

**Table 4. Pareto Revenue Concentration Summary (Source: CONSOLIDATED\_ANALYSIS.csv; pareto\_class column; n=80)**

Class	Products	% of Portfolio	Revenue (\$)	Revenue Share (%)
Top_80%	42	52.5%	\$553,791.63	79.25%
Long_Tail	38	47.5%	\$145,020.70	20.75%
TOTAL	80	100%	\$698,812.33	100%

#### 4.6 Popularity-Revenue Quadrant Analysis and Correlation

Using median boundaries (volume = 3,629.5 units; revenue = \$9,225.00), 80 products were distributed across four quadrants: Q1 Hero Zone (high volume, high revenue) = 38 products; Q2 Premium (low volume, high revenue) = 2 products; Q3 Rationalization (low volume, low revenue) = 38 products; Q4 Volume Drivers (high volume, low revenue) = 2 products. The strong bimodal distribution (Q1+Q3 dominating, Q2+Q4 = 4 products) indicates the portfolio is well-segmented into clearly high-performing and clearly underperforming tiers with minimal ambiguous mid-tier products. Pearson product-moment correlation analysis (n = 80) reveals a strong positive relationship between total units sold and total revenue:  $r = 0.8468$ ,  $p < 0.001$ . The coefficient of determination  $R^2 = 0.7171$  (71.71%), indicating that units sold volume explains approximately 71.7% of the variance in product-level revenue. This strong correlation validates the joint optimization approach of simultaneously maximizing volume and revenue, and confirms that products deviating significantly from this pattern (Premium quadrant: high revenue, low volume) represent a distinct minority (n=2) warranting individual pricing analysis.

#### 4.7 Store-Level Performance Analysis

Table 5 presents store-level performance metrics. Revenue distribution across three NYC locations is remarkably balanced, with an inter-store revenue range of only \$6,453.92 (2.81% gap relative to the lowest-revenue store). Hell's Kitchen leads marginally at \$236,511.17 (33.84%), followed by Astoria \$232,243.91 (33.23%), and Lower Manhattan \$230,057.25 (32.92%). Transaction volume differences (Hell's Kitchen: 50,735; Astoria: 50,599; Lower Manhattan: 47,782) suggest Lower Manhattan achieves a higher revenue per transaction, consistent with its average revenue per transaction of \$4.81 versus Hell's Kitchen (\$4.66) and Astoria (\$4.59).

**Table 5. Store-Level Revenue and Transaction Summary (Source: STORE\_SUMMARY.csv; 3 NYC locations)**

Store	Revenue (\$)	Share (%)	Transactions	Avg Rev/Txn (\$)
Hell's Kitchen	\$236,511.17	33.84%	50,735	\$4.662
Astoria	\$232,243.91	33.23%	50,599	\$4.590
Lower Manhattan	\$230,057.25	32.92%	47,782	\$4.815

## 5. Discussion

### 5.1 RO1: Revenue and Volume Drivers -- Strategic Implications

RO1 is substantially addressed by Sections 4.2-4.4. The 9 Hero-tier products -- concentrated in Drinking Chocolate (2 products), Barista Espresso Coffee (3 products), and Brewed Chai Tea (1 product) -- represent the core of Afficionado's revenue engine. Specific actionable recommendations: (R1.1) The 9 Hero products should be designated 'Anchor SKUs' with guaranteed year-round availability, preferential shelf positioning, and inclusion in all promotional offers. (R1.2) Sustainably Grown Organic Lg (ES=0.978) and Dark chocolate Lg (ES=0.992) should anchor combo meal deals given their top revenue and volume ranks. (R1.3) The 33 High-tier products represent a growth tier -- targeted upselling scripts for baristas (e.g., 'Would you like to upgrade to our Large?') should be tested as a structured upselling intervention for this group.

### 5.2 RO2: Pareto Rationalization Recommendations

RO2 is addressed by Section 4.5. The 38 Long\_Tail products generating \$145,020.70 (20.75% of revenue) warrant stratified review. (R2.1) Immediate review candidates include the 23 Low-tier products (ES < 0.20). Recommended pilot: review the bottom 5 products by efficiency score (Dark chocolate, Spicy Eye Opener Chai, Earl Grey, Guatemalan Sustainably Grown, and Lemon Grass) over a 3-month trial and monitor revenue and customer satisfaction impact. (R2.2) Flavours category (\$8,408.80, 1.20% share) generates high transaction volumes (10,511 units) at \$0.80/unit. These are add-on items; their value lies in revenue uplift for beverages (cross-sell), not standalone revenue. They should NOT be rationalized. (R2.3) Branded items (3 SKUs, \$13,607.00, ES=0.10-0.19) serve brand equity functions beyond revenue. Maintained as per brand strategy, but not prioritized for promotion.

### 5.3 RO3: Store-Level Strategy Recommendations

RO3 is addressed by Section 4.7. The near-equal store revenues suggest strong portfolio-level calibration, but hide actionable micro-level variations: (R3.1) Lower Manhattan achieves the highest avg\_rev/transaction (\$4.81 vs. \$4.66 HK). This suggests Lower Manhattan's customer base exhibits higher willingness to pay. Pilot premium-priced seasonal specials (e.g., Single-Origin Pour Over at \$6.50) in Lower Manhattan first, before chain-wide rollout. (R3.2) Hell's Kitchen leads in transactions (50,735) suggesting highest footfall. Focus operational efficiency initiatives (queue reduction, mobile ordering) in Hell's Kitchen to convert higher footfall into revenue gains. (R3.3) Astoria leads in no dimension, suggesting potential for targeted marketing campaigns aligned with its residential neighborhood demographic.

### 5.4 Methodological Reflection

The composite Efficiency Score (ES) used in this study employs a weighted normalisation formula:  $ES = 0.6 \times (\text{Revenue}/\text{Max\_Revenue}) + 0.4 \times (\text{Volume}/\text{Max\_Volume})$ , as documented in Section 3.3. These weights reflect a revenue-first prioritisation philosophy embedded in the consolidated analytical dataset. Note: an alternative rank-based weighting scheme (0.50 revenue, 0.30 volume, 0.20 transactions) has been discussed in some formulations of similar models; this study does not employ that variant. Sensitivity analysis across alternative weight configurations was not conducted. Future work should examine whether equal weighting (0.50/0.50 revenue/volume) or a three-factor model including transaction frequency materially affects tier classification for the 8-12 borderline products near the Hero/High and Medium/Low boundaries. The strong Pearson r (0.8468) suggests that a simpler volume-first ranking may approximate the composite ES model for most products.

### 5.5 Limitations

Five limitations should be acknowledged: (L1) Single-year (2025) dataset precludes multi-year trend detection and seasonality decomposition. (L2) Customer-level data (loyalty membership, demographics) is unavailable, precluding customer lifetime value (CLV) or RFM segmentation analysis. (L3) Cost data (COGS, labour) is unavailable; profitability cannot be computed -- revenue is used as a proxy for contribution. (L4) The Pareto classification boundary is sensitive to the choice of threshold; the 79.25% cumulative revenue point (not exactly 80.00%) results from discrete product boundaries in a finite portfolio. (L5) The dataset represents a single coffee chain operating in one city; results may not generalize directly to other geographies, retail formats, or product portfolios.

## 6. Conclusion

This study successfully addressed all three research objectives. RO1: Coffee (38.63%) and Tea (28.11%) are the primary revenue drivers; 9 Hero-tier products with  $ES \geq 0.80$  constitute the revenue engine. RO2: 42 products (52.5%) drive 79.25% of revenue (modified Pareto pattern); 38 Long\_Tail products are rationalization candidates, prioritized by ES score. RO3: Store revenues are balanced (gap = 6453.92, <3%) but Lower Manhattan shows superior avg revenue per transaction (\$4.81), informing differentiated premium pricing strategy.

Key scientific contributions include: (1) Empirical validation of a modified Pareto pattern in specialty coffee retail (52.5%/79.25% vs. the theoretical 20/80); (2) a statistically validated strong positive correlation between units sold and revenue ( $r = 0.8468$ ,  $R^2 = 0.7171$ ,  $p < 0.001$ ); (3) a replicable composite Efficiency Score methodology deployable on any multi-product POS dataset; and (4) a production-ready 7-tab Streamlit analytics dashboard.

Future work should: (i) incorporate customer-level CLV and RFM analysis; (ii) add seasonal time-series decomposition using at least 3 years of data; (iii) apply unsupervised clustering (k-means, DBSCAN) to product segmentation as an alternative to rule-based tier classification; (iv) integrate COGS data for true profitability analysis; and (v) extend the dashboard with demand forecasting (Prophet, LSTM) functionality.

## 7. Acknowledgments

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