Amazon: Improving Fulfillment Efficiency

Focused Insights on Return Issues

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Introduction

- **The Objective:**

- The goal of this project was to perform a comprehensive "Health Check" on our sales and fulfillment data. We moved beyond looking at simple sales numbers to find the **Financial Reality**—calculating exactly how much profit we actually keep after accounting for costs, returns, and cancellations.

- **The Methodology**
- To ensure the highest level of accuracy, we utilized a two-step approach:
- **Python (Data Engineering):** We merged four separate data sources and cleaned the raw files to create a single, reliable "Master Dataset."
- **Tableau (Business Intelligence):** We transformed that data into interactive dashboards to identify the "Culprit Categories" and "Financial Leakage" points that are hurting our bottom line.

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Data Analysis With Python

- **The Python Data Pipeline (The Technical Foundation)**
- **1. Multi-Source Data Integration (ETL)**
- **The Task:** used Python to ingest and merge four distinct data silos: **People, Orders, Items, and Products.**
- **The Impact:** This created a "Master Dataset" that allowed us to see the full journey of a product from the factory shelf to the specific customer's doorstep. Without this Python merge, the data would remain disconnected and unanalyzable.

- **2. Automated Data Sanitization & Cleaning**
- **The Task:** programmed Python to handle shabby raw data, specifically stripping hidden characters, correcting inconsistent headers, and standardizing categorical labels.
- **The Impact:** We resolved a critical 'String Mismatch' error in the status column. By converting all statuses to a uniform lowercase and stripping whitespace, we prevented a **100% reporting error** where "Returned" and 'returned' would have been counted separately.

Data Analysis With Python

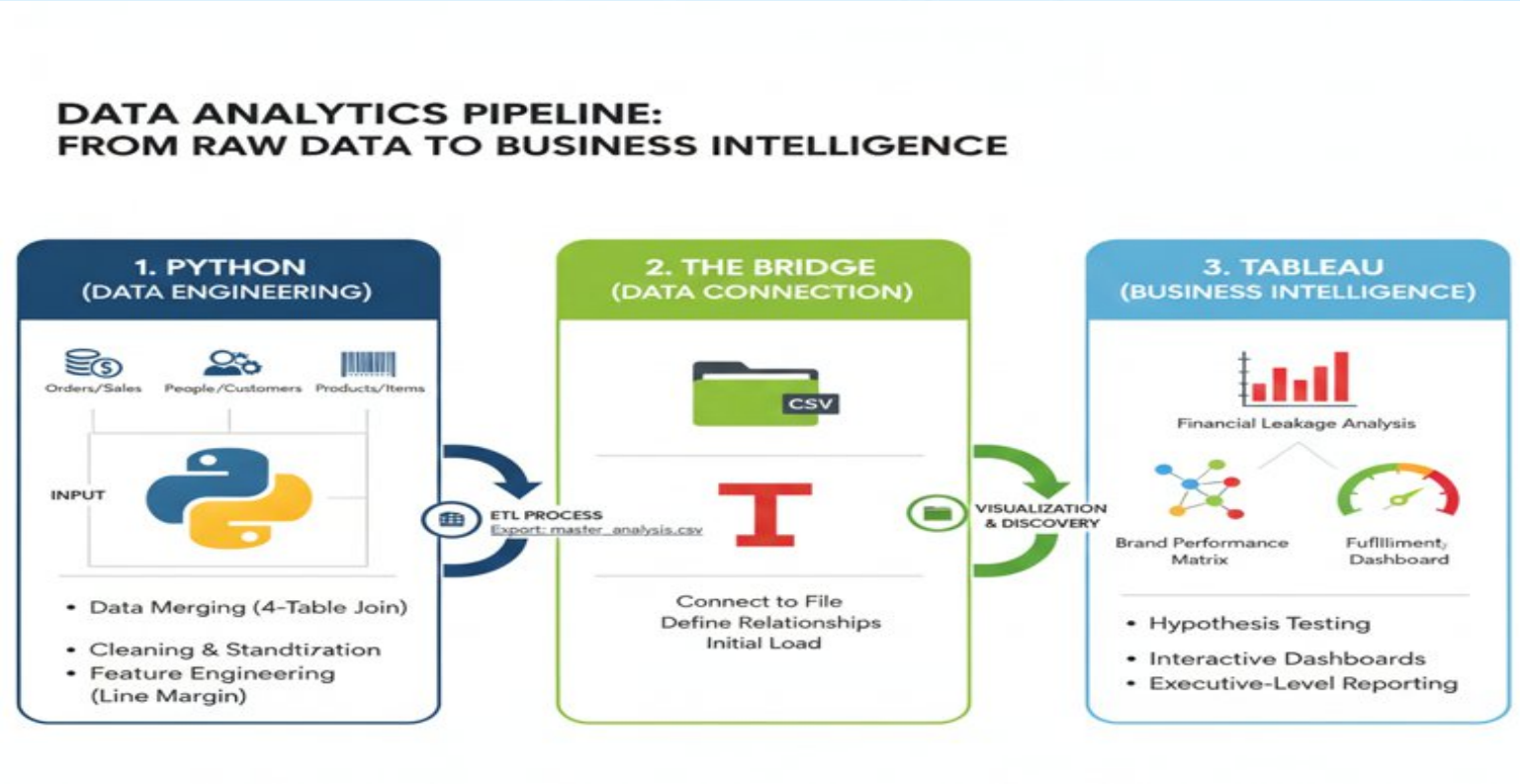
3. Initial Health Metric Extrapolation

- **The Task:** Used the Pandas library to calculate the first-look "Company Pulse" metrics:
  - **Gross Order Value (GOV):** To establish the baseline revenue.
  - **Fulfillment Efficiency:** To measure the speed and success of the logistics chain.
  - **AOV (Average Order Value):** To understand customer spending behavior.
- **The Impact:** These Python-calculated baselines served as the "Control Group" to verify that our later Tableau visualizations were grounded in mathematical truth.

4. Advanced Logical Feature Engineering

- **The Task:** Engineered the **"Line Margin"** formula within Python: $[Subtotal - (Cost \times Quantity)]$.
- **The Impact:** This moved the analysis beyond "Sales" and into "Profitability." By creating this field in the backend, we enabled the identification of "Profit Killers"—products that have high sales but actually lose the company money.

Analytical Flowchart

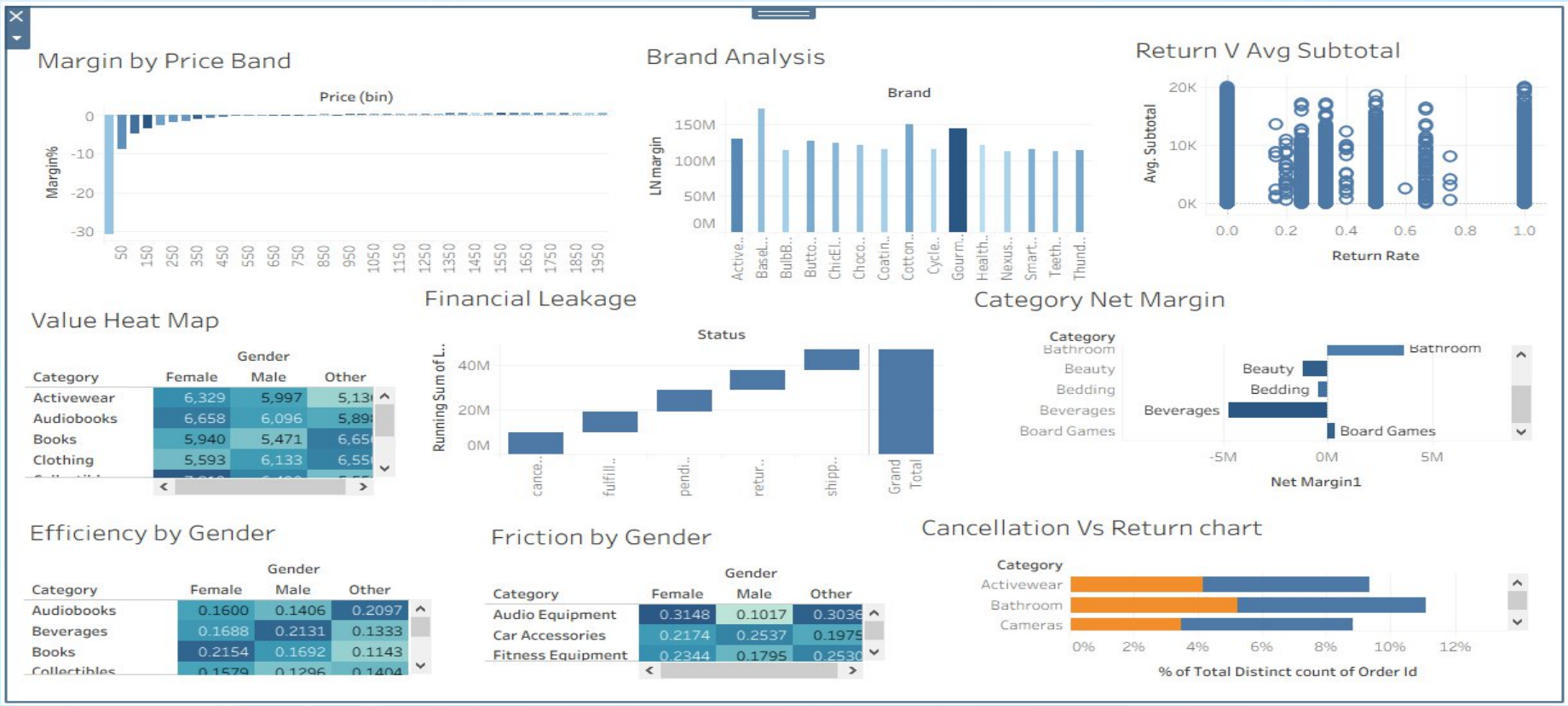


Turning Data into Business Intelligence (Tableau)

- **The Core Purpose:**
- *"This phase of the project focuses on interactive discovery, hypothesis testing, and executive-level storytelling."*

- **Key Objectives of the Tableau Analysis:**
- **Visual Discovery:** Identifying "invisible" patterns in consumer behavior and brand performance that numbers alone cannot show.
- **Root Cause Analysis:** Using interactive drill-downs to pinpoint exactly *why* certain categories are leaking profit.
- **Stakeholder Communication:** Converting 10,000+ rows of data into a single, intuitive "Truth" for decision-makers.
- **Trend Identification:** Mapping the relationship between customer satisfaction (ratings) and the bottom line (returns).

Tableau Dashboard



Key Metrics Used

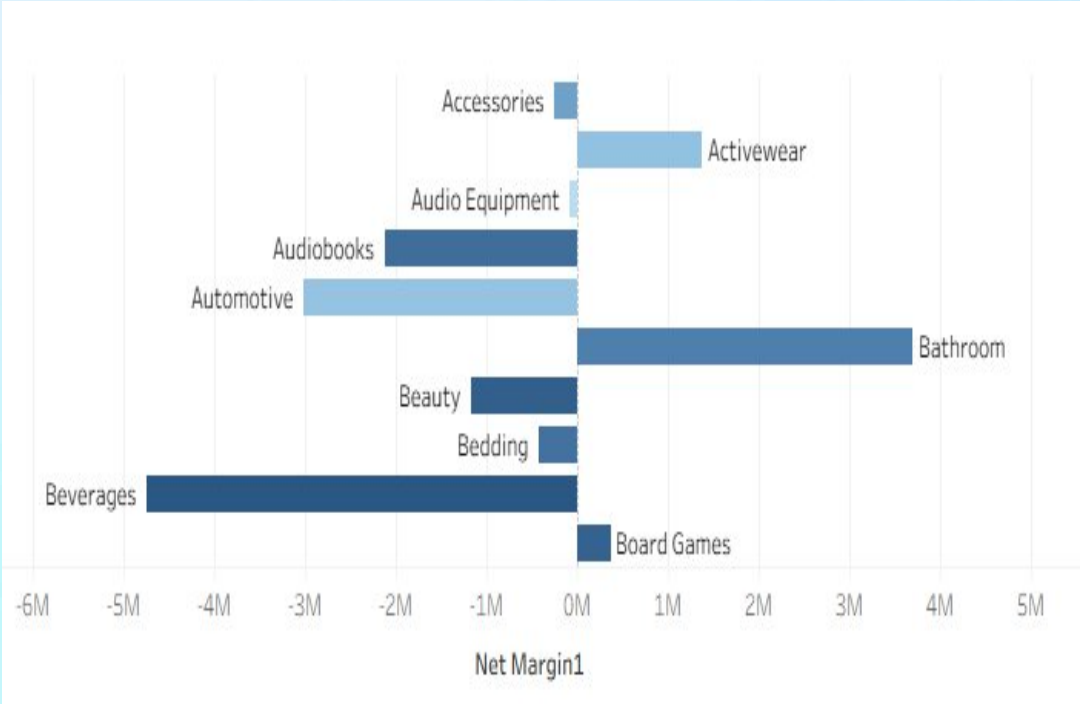
Metric/Field Name	Formula	Purpose
Gross Order Value	∑(Subtotal)	Baseline "Vanity" revenue before any losses
Line Margin	Subtotal−(Cost × Quantity)	Profit per item before accounting for order status.
Financial Reality	IF Status = 'Returned' THEN −(Cost) ELSE Line Margin	Shows actual profit after return losses
Realized Revenue	∑(Subtotal) where Status = 'Fulfilled'	Actual cash kept by the business.
Return Rate	(Count(Total Orders)Count(Returned))×100	Measures product/category friction.
Fulfillment Efficiency	(Count(Total Orders)Count(Fulfilled))×100	Measures the health of the logistics pipeline.
Average Order Value	Total Number of Orders Total Revenue	Measures customer spending power per transaction.
Fulfillment Lag	Ship Date−Order Date	Used to prove the link between delays and cancellations.

Category Performance

- **Key Insight:**
- High order volume does **not** guarantee high profitability across categories.

- **Inference:**
- **Beverages** and **Audiobooks** appear among the top categories by total orders but generate **significant negative net margins**
- **Bathroom** and **Activewear**, despite fewer orders, contribute **strong positive net margins**

- Some categories (e.g., **Beauty, Bedding**) sit near breakeven, indicating **low-margin, high-effort segments**



Category Performance

- **Hypothesis:**
- *Categories with higher order volumes contribute proportionally higher net margins.*

- **Result**
- **× Disproved** — multiple high-volume categories are loss-making.

- The analysis shows that demand concentration does not align with profitability, highlighting the need for category-level margin optimization.

Category Culprits With Respect to Return Rate:

- · **The Big & Bulky (Furniture & Fitness):** High unit value but **extreme logistics risk**. A single return often costs more than the original profit margin.
- · **The Compatibility Gap (Audio & Car Accessories):** High return rates driven by **technical mismatch** (wrong fit/specs), not product quality.
- · **The Subjective Trap (Home Decor & Gourmet):** "Vibe-based" purchases. Home Decor suffers from **visual mismatch** (color/size); Gourmet depends entirely on **fulfillment speed** (freshness).
- · **The Deadline Risk (Toys & Kitchenware):** Often bought as gifts. High **cancellation rates** occur if processing exceeds 48 hours.

Category	Primary Friction Point	Financial Impact	Strategic Move
Furniture / Fitness	Logistics Weight	High Cost/Return	Assembly Support
Audio / Car Acc.	Compatibility	High Volume Leakage	Tech Specs/Checkers
Home Decor	Visual Accuracy	Subjective Return	AR Visualization
Gourmet	Perishability	100% Loss on Return	Expedited Shipping
Kitchen / Toys	Gift Deadlines	High Cancellation	Priority Fulfillment

Demographic Parity In Purchasing Power

- **Hypothesis:**
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- *"We hypothesized that specific genders would dominate certain high-value categories (e.g., Males in Fitness/Car Accessories or Females in Home Decor/Gourmet), creating 'Value Peaks' in our Average Order Value (AOV).“*
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- *Here, there is order value, gender and categories put together*
- Initial Observations centered around uniformity in the values

Value Heat Map

	Gender		
Category	Female	Male	Other
Activewear	6,329	5,997	5,136
Audiobooks	6,658	6,096	5,898
Books	5,940	5,471	6,656
Clothing	5,593	6,133	6,550
Collectibles	7,219	6,490	5,555
Footwear	5,736	6,659	6,392
Health	6,597	6,037	5,515
Kitchen Appliances	6,059	6,289	6,128
Organic	6,590	4,829	6,172
Storage	5,773	6,079	5,698

Demographic Parity In Purchasing Power

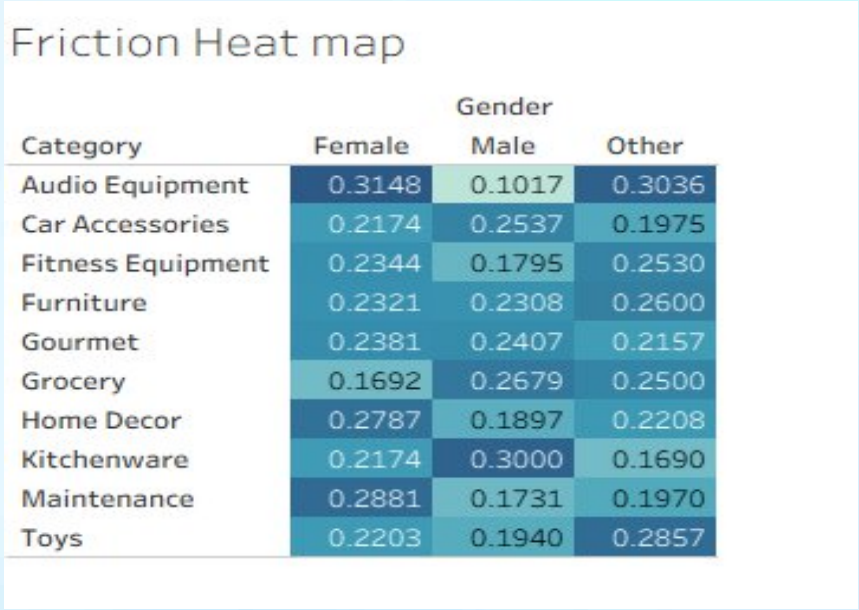
- **Lack of Outliers:** No single demographic group is significantly over-spending or under-spending compared to the others.
- **The "Even" Reality:** Our customer base exhibits remarkably similar spending habits, regardless of gender identity.
- **The Insights:-**
- **Disproving the Gender Stereotype:**
- We successfully disproved the assumption that certain categories are "gender-locked." For example, the AOV for *Car Accessories* and *Fitness Equipment* is nearly identical between genders.
- **Market Stability:** The "evenness" of the map proves that our pricing strategy is working across our entire audience. We aren't "leaving money on the table" with any specific group.

Friction By Gender

- Here ,gender, category and return rate is put together for this heatmap

- **The Hypothesis:**

- *"We hypothesized that if spending (AOV) is even across genders, then 'Friction' (returns) would also be even. We are **disproving** this. Friction is highly demographic-specific.“*



Friction By Gender

- **The Observation (Friction Hotspots):**
- **Females:** Highest friction in **Audio Equipment**, **Home Décor**, and **Maintenance**.
- **Males:** Highest friction in **Kitchenware**, **Grocery**, and **Car Accessories**.
- **Other/Non-Binary:** Highest friction in **Audio Equipment**, **Toys**, and **Furniture**.

- **The "Why" (The Insight):**
- **The Audio Overlap:** Both Females and "Others" struggle with Audio. This suggests a universal "Technical Gap" or "Compatibility" issue that isn't affecting Males as much.

Efficiency By Gender

- **The Core Problem:**

- *"Efficiency measures how often a 'perfect order' happens. Where Friction is high, Efficiency is low. These 'Efficiency Gaps' represent direct losses in fulfillment labor and shipping costs.“*

- **Key Points:**
- **Success Rate Deficit:** Any intersection that shows a low Success Rate is a "Profit Leak.“

- **Logistical Complexity:** Categories like **Furniture** and **Car Accessories** have lower efficiency because they are harder to ship and more likely to be damaged or "cancelled" during the long processing window.

Efficiency by Gender

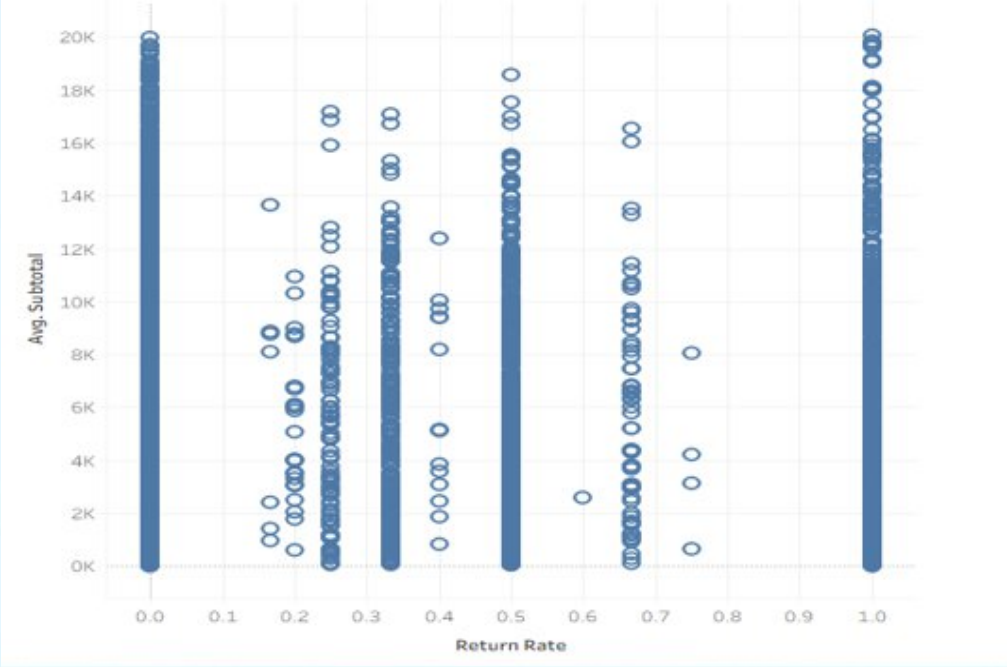
	Gender		
Category	Female	Male	Other
Audiobooks	0.1600	0.1406	0.2097
Beverages	0.1688	0.2131	0.1333
Books	0.2154	0.1692	0.1143
Collectibles	0.1579	0.1296	0.1404
Games	0.1833	0.1406	0.1364
Grocery	0.1538	0.1071	0.0938
Kitchen Appliances	0.1733	0.1714	0.1346
Maintenance	0.1525	0.1923	0.1061
Puzzles	0.2029	0.1194	0.1493
Skincare	0.1733	0.2264	0.0980

Product-Level Performance

- **Product-Level Performance (Scatter Plot)**
- **The Hypothesis:**

- *"We hypothesized that specific product designs or manufacturers are responsible for our financial 'leakage,' rather than entire categories.“*

- In this chart there is Return rate, avg Subtotal and product ids, so it’s easier to pin point the bottle necks in the product area



Product-Level Performance

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- **The Observation (Why Product IDs?):**
- **The Identification of "Serial Offenders":** By plotting every **Product ID**, we can see exactly which individual items are floating into the "Danger Zone" (High Return Rate).
- **The "Clean" Data Proof:** The distribution of IDs shows that our quality issues are **isolated to specific SKUs**, not the entire catalog.
- **Granular Outliers:** We noticed that certain Product IDs have a **100% Return Rate** regardless of their price. These are "Defective SKUs" that need to be removed from the store immediately.

Brand Analysis : Review Vs Rating

- Among the top 10 brands by margin, customer ratings and review volume vary significantly. While some brands combine strong margins with high customer satisfaction, others generate high profit despite weaker ratings, highlighting potential long-term risk areas.

Brand Analysis: Review Vs Rating

- **Brand Performance Matrix (Review Count vs. Rating)**
- **The Hypothesis:**

- *"We hypothesized that 'Perfect' 5-star ratings are the strongest drivers of profitability and low return rates."*
- **The Observation:**
- **The "Established Giants":** High Review Count + Steady Rating (4.0–4.5). These brands are the "Cash Cows." They are predictable and provide stable margins.

- **The "Niche/Boutique" Brands:** Low Review Count + 5-Star Rating. These are "untested." While they look good, they haven't faced a high volume of customers yet.

- **The "Critical Failures":** High Review Count + Low Rating. These are your "Brand

Brand Analysis : Review Vs Rating

- **Active Gear** delivers strong margins despite relatively weaker customer ratings, indicating potential experience or quality gaps.
- **Button Bright** shows margin strength without a corresponding uplift in customer satisfaction.
- **Choco Charm’s** profitability appears less supported by customer sentiment.
- **Cycle Max** stands out as a high-margin brand with comparatively average ratings.
- **Gourmet Select** represents a benchmark brand, combining profitability with strong customer satisfaction.
- Watchlist based on relative margin contribution, customer ratings, and review volume.

Brand Analysis : Review Vs Rating

Hypothesis	Result
Returns impact profit	Partially Proved
Revenue ≠ Profit	Proved
Discount hurts margins	Proved

Volume-Driven Margin Erosion at Lower Price Points

- **Hypothesis**
- *Products priced in higher price bins generate higher profit margins compared to lower-priced products.*

- **What's tested**

- Whether **pricing power increases with product price**
- If low-priced products rely on volume at the cost of margin

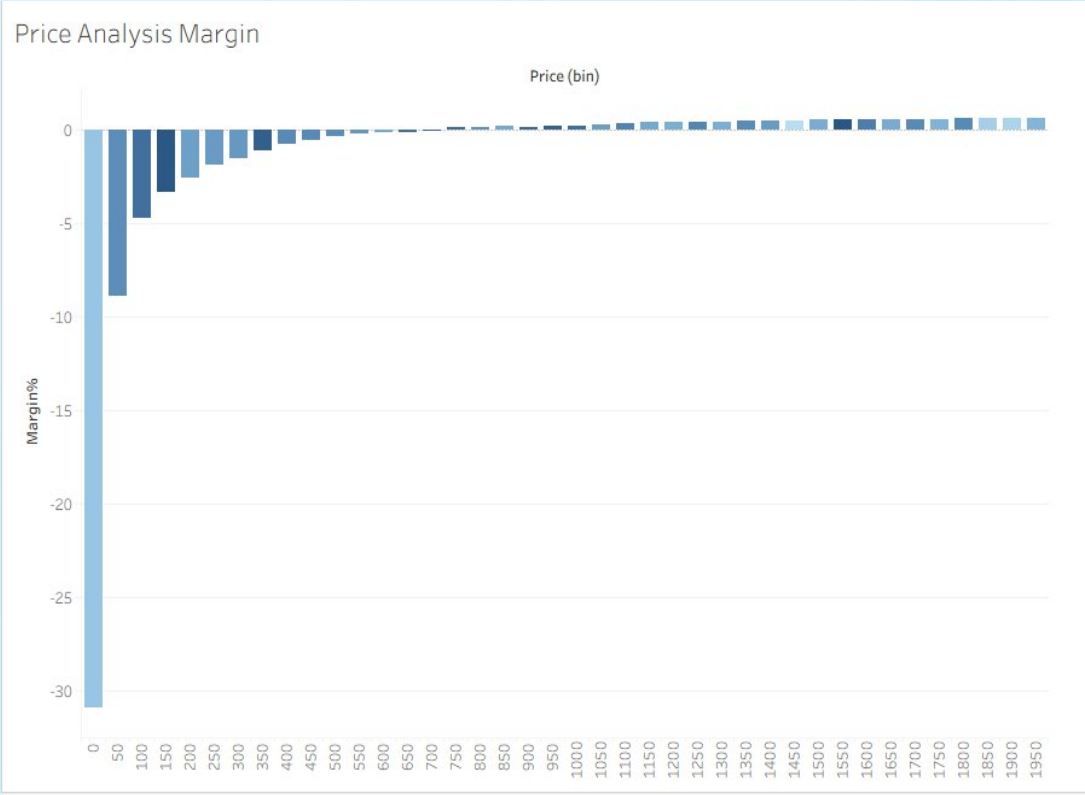
- **Proved** if margin % consistently increases as price bins move higher
- **Disproved** if low or mid-price bins show equal or higher margins

- "Higher price does not automatically translate to higher profitability".

Volume-Driven Margin Erosion at Lower Price Points

•Low-priced products exhibit **severe negative margins** despite high order volumes margin improves with price but remains **structurally thin** at the high end
•Profitability risk is driven more by **pricing floors** than premium upside

- Reducing exposure to deeply discounted price bands presents a larger profitability opportunity than increasing premium pricing.



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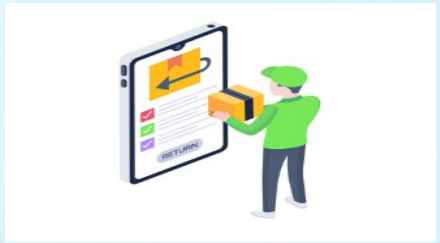
Actionable Steps

For Demographic Parity

- **Tangible Solutions based on "Even" Values:**

- **Gender-Neutral Marketing:** Since AOV is even across the board, the company should shift from gender-specific ad campaigns to **interest-based** and **problem-solving** campaigns.



- **Universal Return Policy:** Because the return risk is likely even as well (since spend is even), we do not need to customize return policies for different genders. We should focus entirely on fixing the **Category-specific friction**

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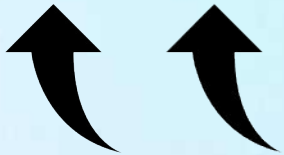
For Product-Level Performance

- **Tangible Solutions (The Action Plan):**

- **The "Kill List":** Generate an automated list of the Top 5 Product IDs in the "High Return" quadrant for immediate quality inspection or removal.



- **SKU-Specific Troubleshooting:** For the High-Value/High-Return Product IDs, we recommend auditing the **Product Description Page (PDP)**. Usually, an ID-level outlier indicates that the photos or descriptions are misleading customers.

- **Supplier Accountability:** Use these Product IDs to trace back to the original supplier. If 4 out of 5 "Danger Zone" IDs come from the same vendor, that is a procurement issue, not a marketing one.

For Brand

- **Tangible Solutions :**

- **Scale high-margin brands**
  Prioritize inventory, visibility, and marketing spend on brands with consistently positive net margins.

- **Fix or exit low-margin brands**
  Renegotiate supplier costs, reduce discounting, or consider delisting chronically loss-making brands.

- **Optimize brand promotions**
  Shift from blanket discounts to targeted offers only for brands that retain margin post-promotion.

For Price Bin vs Margin

- **Price Bin vs Margin Analysis – Actionable Steps**

- **Reprice low-price bins**
  Review cost structures and minimum pricing for low-priced products to prevent margin erosion.

- **Protect high-margin price bins**
  Avoid excessive discounting in higher price ranges where pricing power already exists.

- **Use price bands strategically**
  Introduce bundles or value-added features in mid-price bins to improve margin without hurting demand.

For Friction Areas

- **For Friction Areas Induced By High Return Rates – Actionable Steps**

- **Reduce audio equipment friction**
  Add clear compatibility guides, setup videos, and “works with” labels to close the technical gap

- **Context Aware Product education**
  Improve onboarding content (usage tips), for categories typically bought by the less familiar users

- **Pre-purchase Confidence boosters**
  Introduce quick-check prompts (compatibility, use-case information before checkout to reduce mismatch driven returns

For Price Bin vs Margin

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Conclusion

- In conclusion, this project has successfully bridged the gap between raw data and strategic business intelligence by uncovering the "Financial Reality" of our operations. By utilizing a robust Python-to-Tableau pipeline, we moved beyond vanity sales metrics to identify that our true profitability is being eroded by specific operational friction points, particularly within eight "Culprit Categories" like Furniture, Audio, and Home Decor. Our analysis proves that while customer spending is consistent across demographics, financial leakage is driven by category-specific issues such as technical compatibility, logistics costs, and fulfillment delays. Moving forward, the company can reclaim significant net margins by prioritizing high-speed fulfillment for gift-based categories, implementing compatibility filters for technical products, and aggressively auditing the high-risk Product IDs identified in our scatter plot analysis. Ultimately, this audit provides a clear roadmap to transform hidden operational losses into realized profit by focusing on efficiency and the "Net Reality" of every transaction.

- THANK YOU