

From Data to Insight: A Machine Learning Approach for Quantifying and Visualizing the Pink Tax Disparity.

Team_No: 11

| Sl. No. | Reg. No. | Name of the student |
|---------|------------------|---------------------|
| 1 | BL.EN.U4CSE22202 | Yasasree Lasya |
| 2 | BL.EN.U4CSE22203 | Archana Reddy P |
| 3 | BL.EN.U4CSE22204 | Asi Kuushalie |
| 4 | BL.EN.U4CSE22221 | Divya Jyothi G |

Project Advisor: Dr Sajitha Krishnan

Introduction

- Gender-based pricing discrimination persists across global retail markets.
- Pink Tax charges women more for similar products.
- Indian e-commerce remains largely unstudied for this issue.
- Dynamic pricing may unintentionally worsen gender price gaps.
- No large-scale Indian dataset exists to measure Pink Tax.
- Research gap limits consumer protection and policymaking.

Problem Statement

- Women pay higher prices for functionally identical items.
- Indian platforms lack transparency in gendered pricing.
- Algorithmic pricing may reinforce hidden discriminatory patterns.
- No standardized system tracks pricing disparities in India.
- Policymakers lack evidence for regulating price inequality.
- Consumers remain unaware of systematic gender-based overpricing.

Research Gaps

1. Limited Use of Advanced Machine Learning for Pink Tax Analysis
2. Heavy Reliance on Descriptive or Self-Reported Data
3. Lack of Dynamic Pricing Systems
4. Geographical and Dataset Limitations
5. BI and Visualization Papers Lack Predictive Depth
6. Lack of context based justification

Dataset

Dataset Source:

- Data collected through automated web scraping from major Indian e-commerce platforms: Amazon, Flipkart, Nykaa, Myntra.
- Scrapers handled dynamic layouts, JS-loaded data, product variations, and ensured multiple time-interval scrapes to reduce price fluctuations.
- Only publicly available product details were collected—no login, no policy violations.

Dataset Size & Structure

- Total scraped: 3,621 product entries.
- Final cleaned dataset: 2,000 entries → forming 1,000 male–female matched product pairs.
- Each record has 13 variables, including: productid, pairid, brand, category, subcategory, gendertarget, price, size, sizeunit, retailer, description, ingredients

Dataset

Category Distribution

- Personal Care – 45%
- Hygiene Products – 20%
- Shaving Products – 15%
- Health Products – 10%
- Clothing/Footwear – 10%

Target Variable

- Pink Tax (absolute): $\text{womenprice} - \text{menprice}$
- Pink Tax %: percentage difference relative to men's price
- Preliminary Insight:
 - Women's products cost more in 68.7% of pairs
 - Avg absolute markup: ₹110.79
 - Avg percentage markup: 33.6%

Data Preprocessing and Exploration

1. Data Cleaning

- Normalized price formats from different sites into consistent numerical values.
- Standardized brand names and corrected spelling variations.
- Converted sizes into uniform units (ml, g, count, clothing sizes).
- Removed duplicate listings and cross-platform repetitions.

2. Gender Filtering & Pair Matching

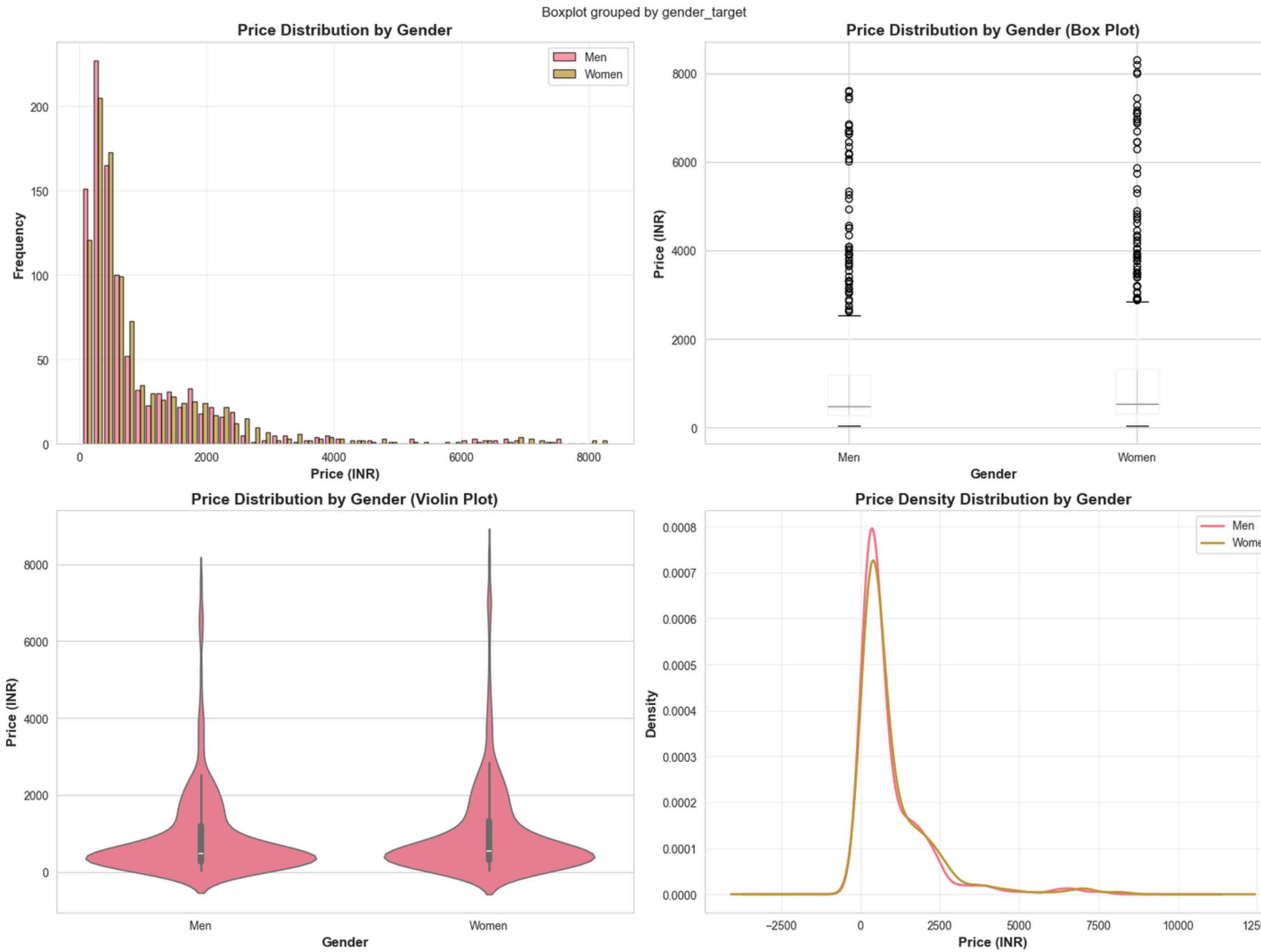
- Removed unisex items to keep only clearly gender-targeted products.
- Implemented a matching algorithm based on: **brand, category & subcategory, size similarity, name similarity**.

Result: 1,000 reliable male–female matched product pairs.

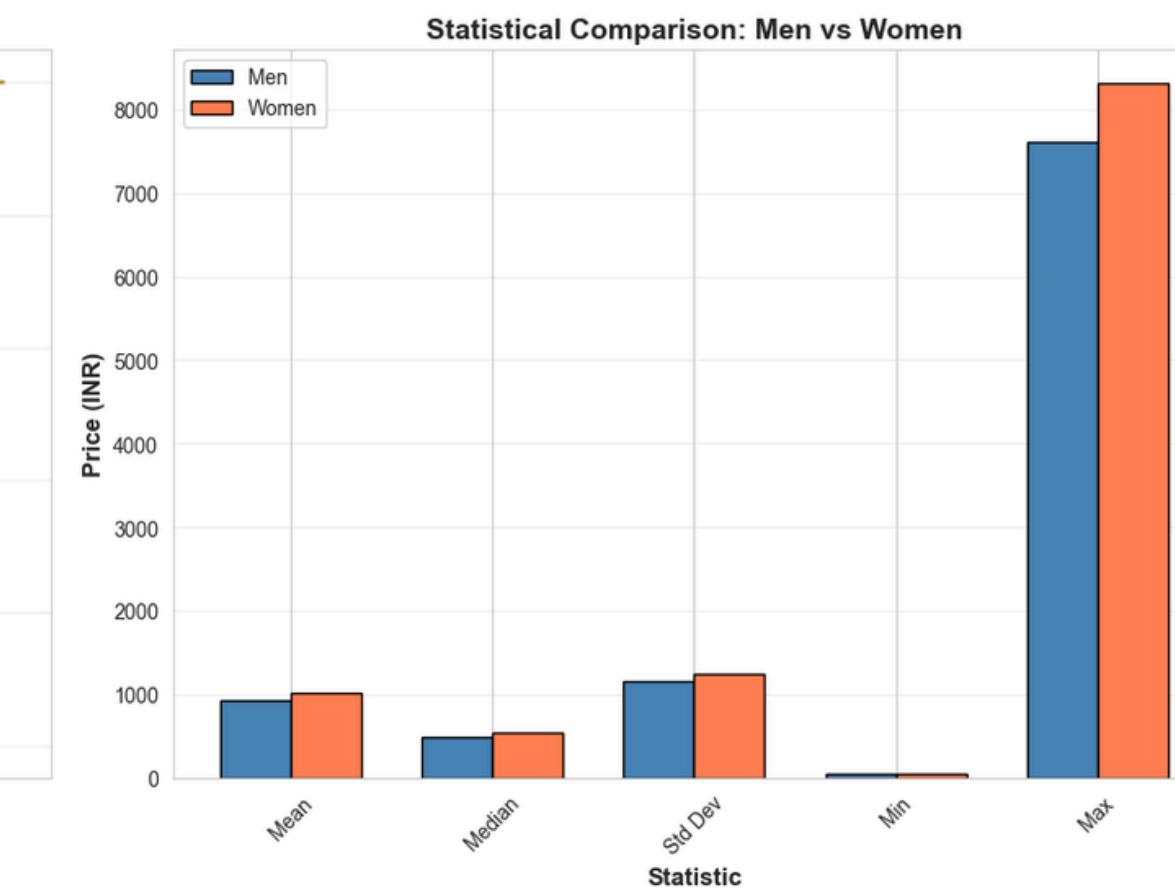
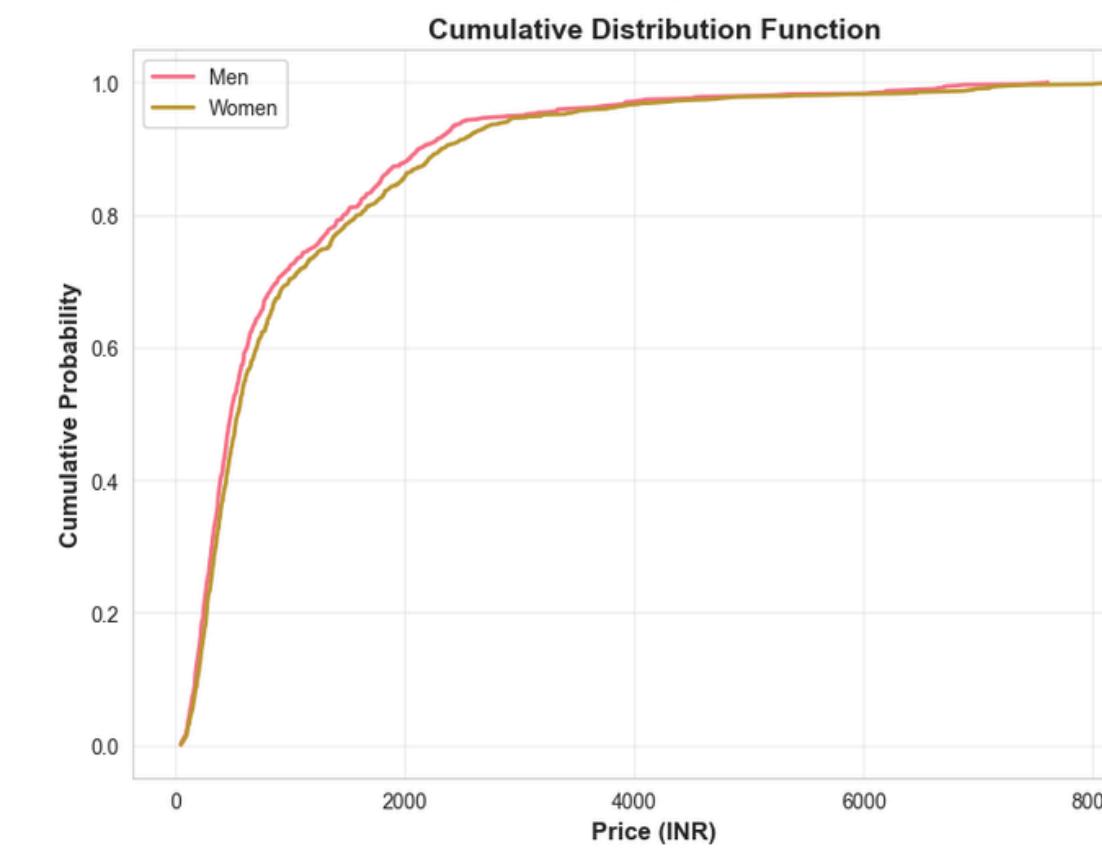
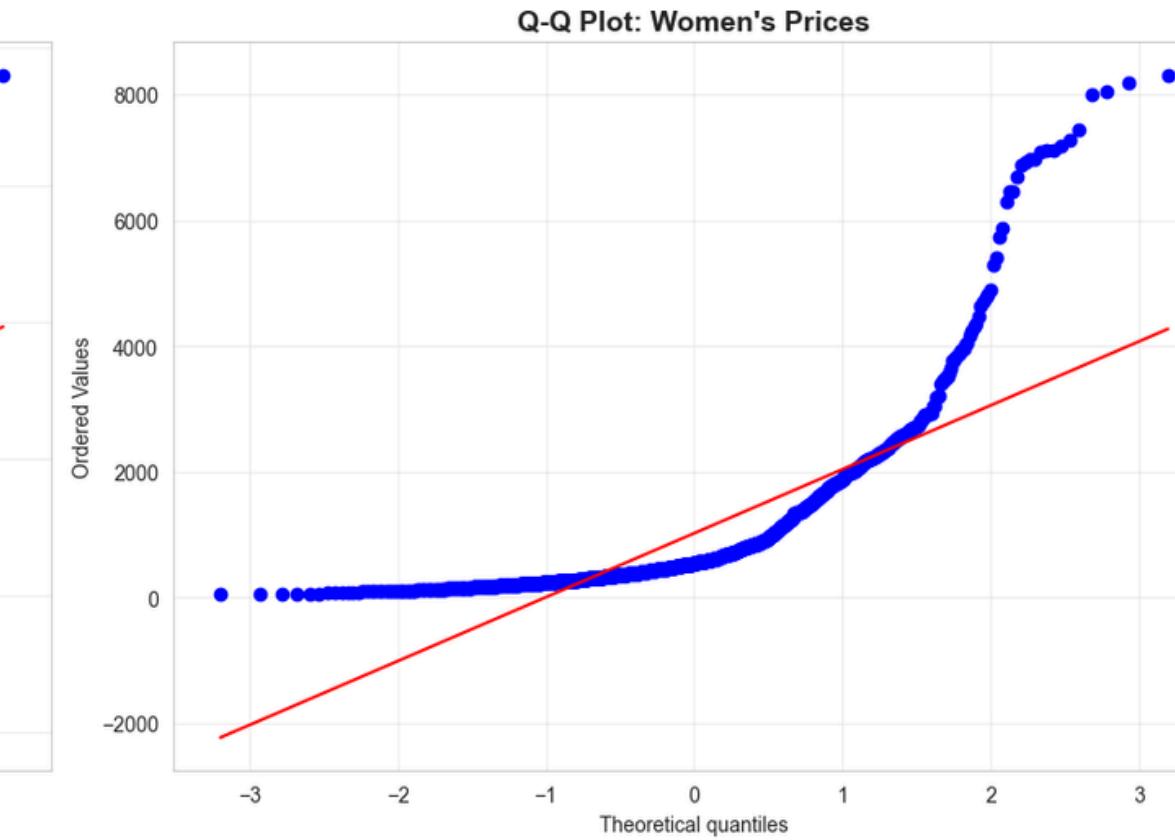
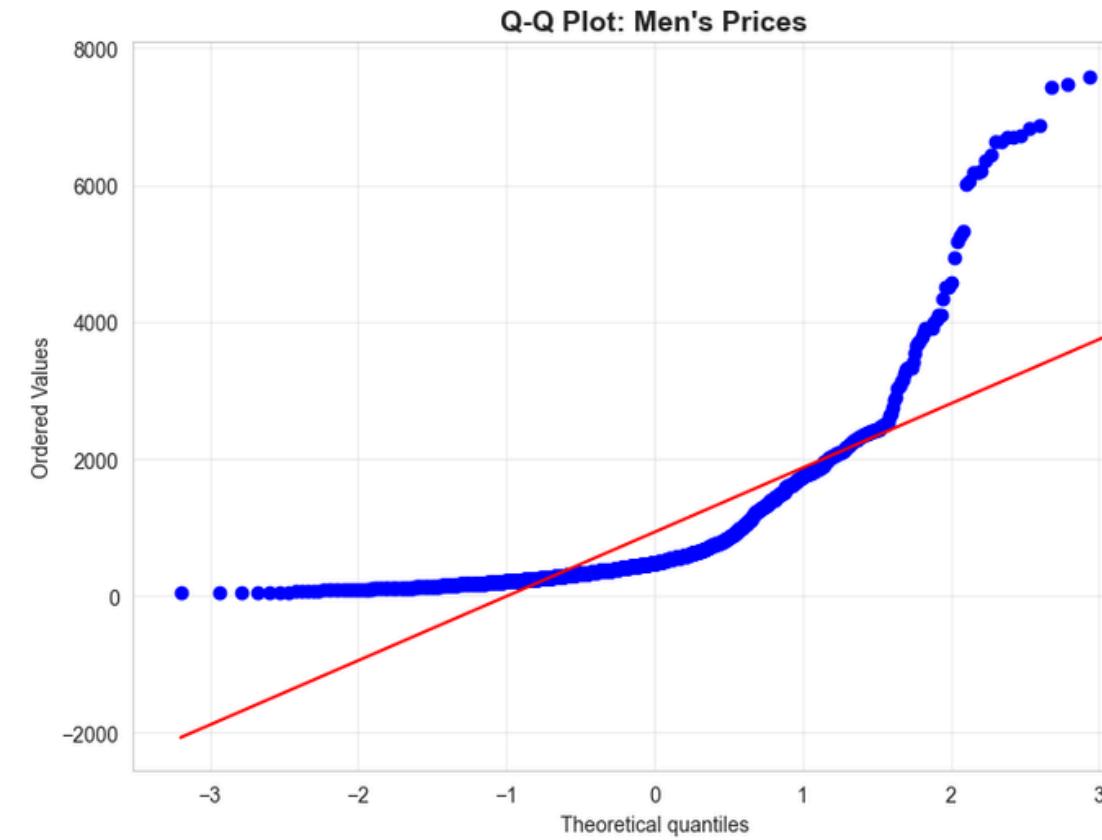
3. Exploratory Analysis

- Price distribution found to be right-skewed.
- Identified clear pricing differences across: categories, brands, retailers
- Verified consistency of product sizes and prices before statistical modelling.

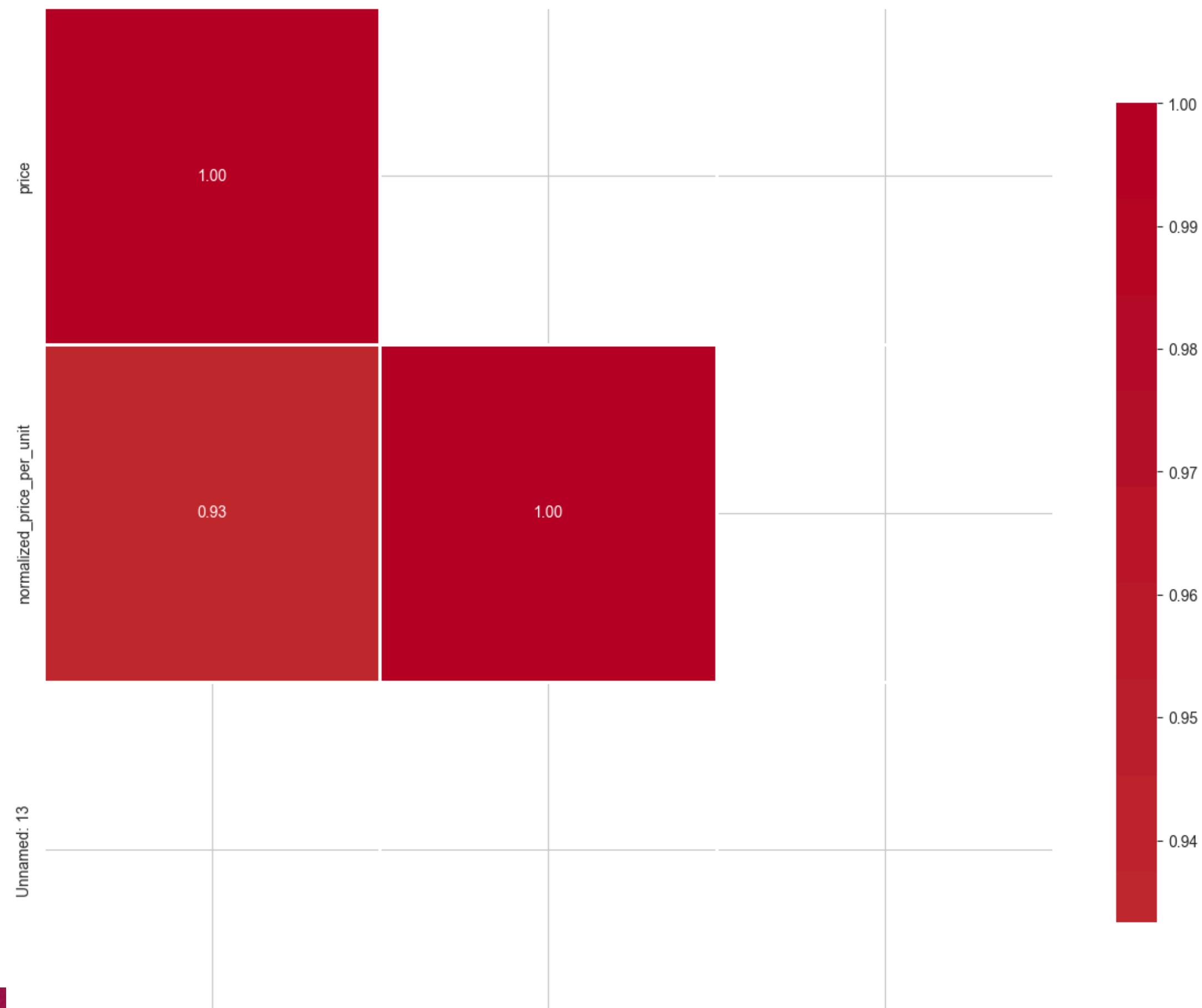
Data Exploration: Price Distribution by Gender



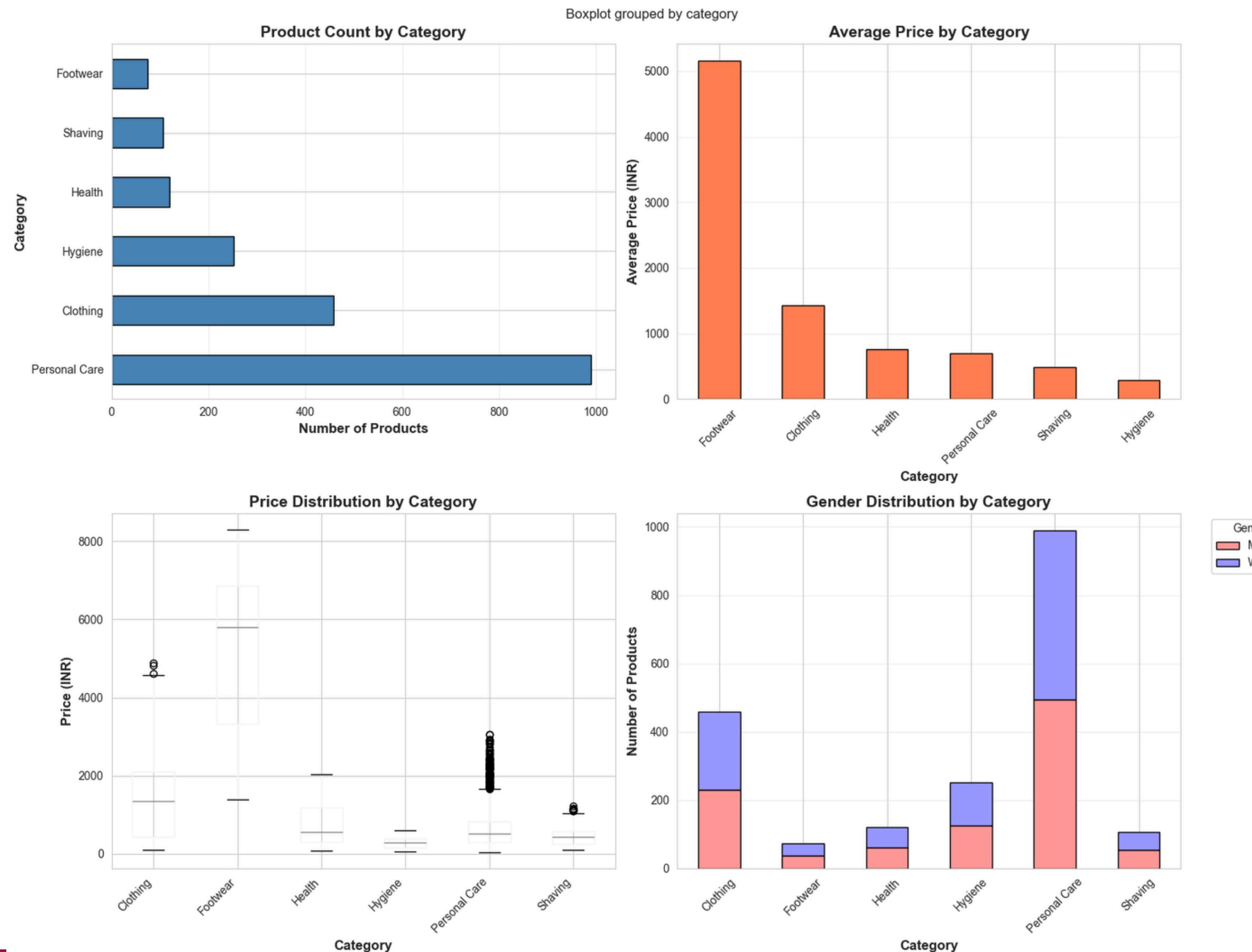
Data Exploration: Statistical Comparison



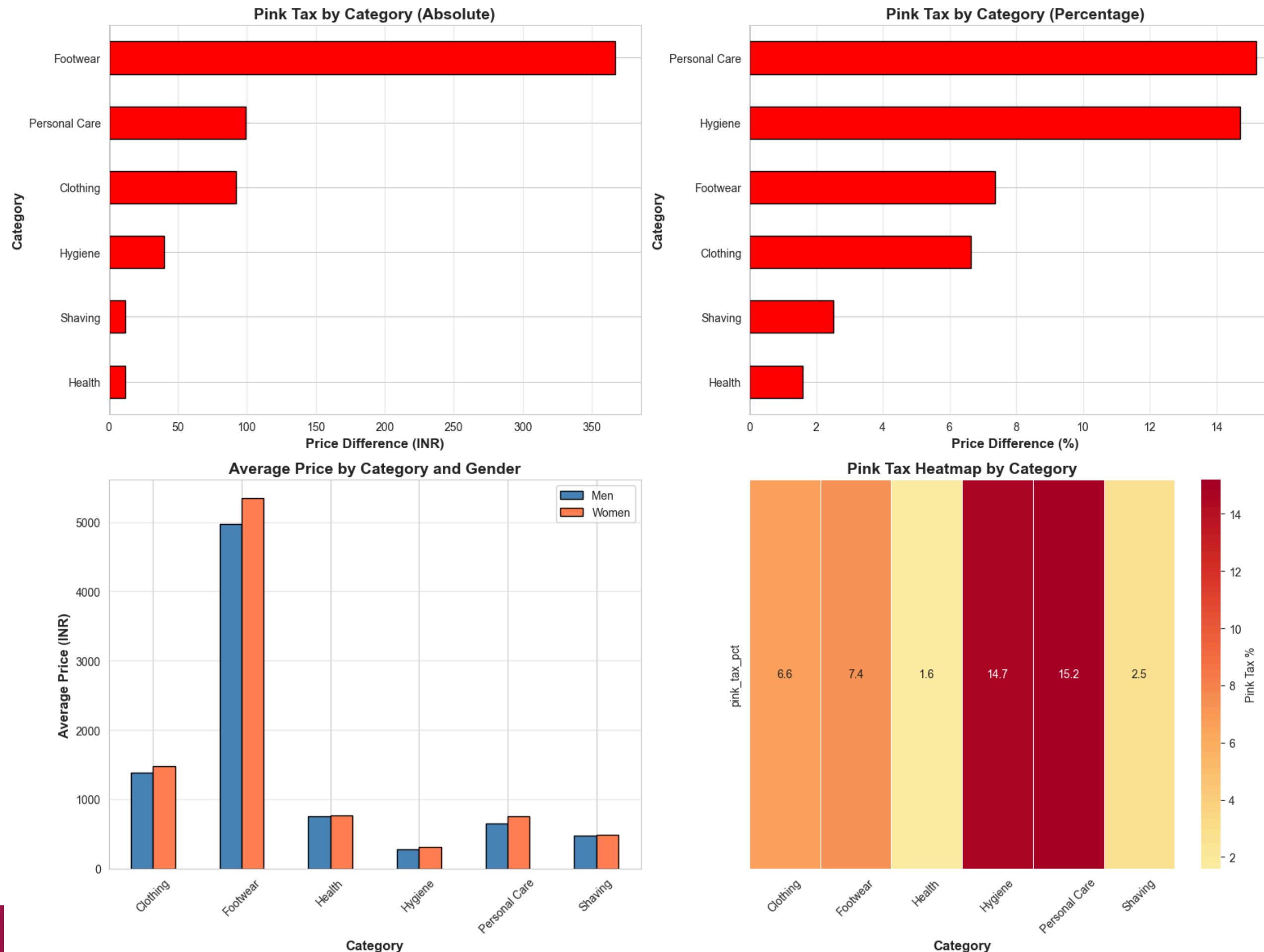
Data Exploration: Correlation Heatmap



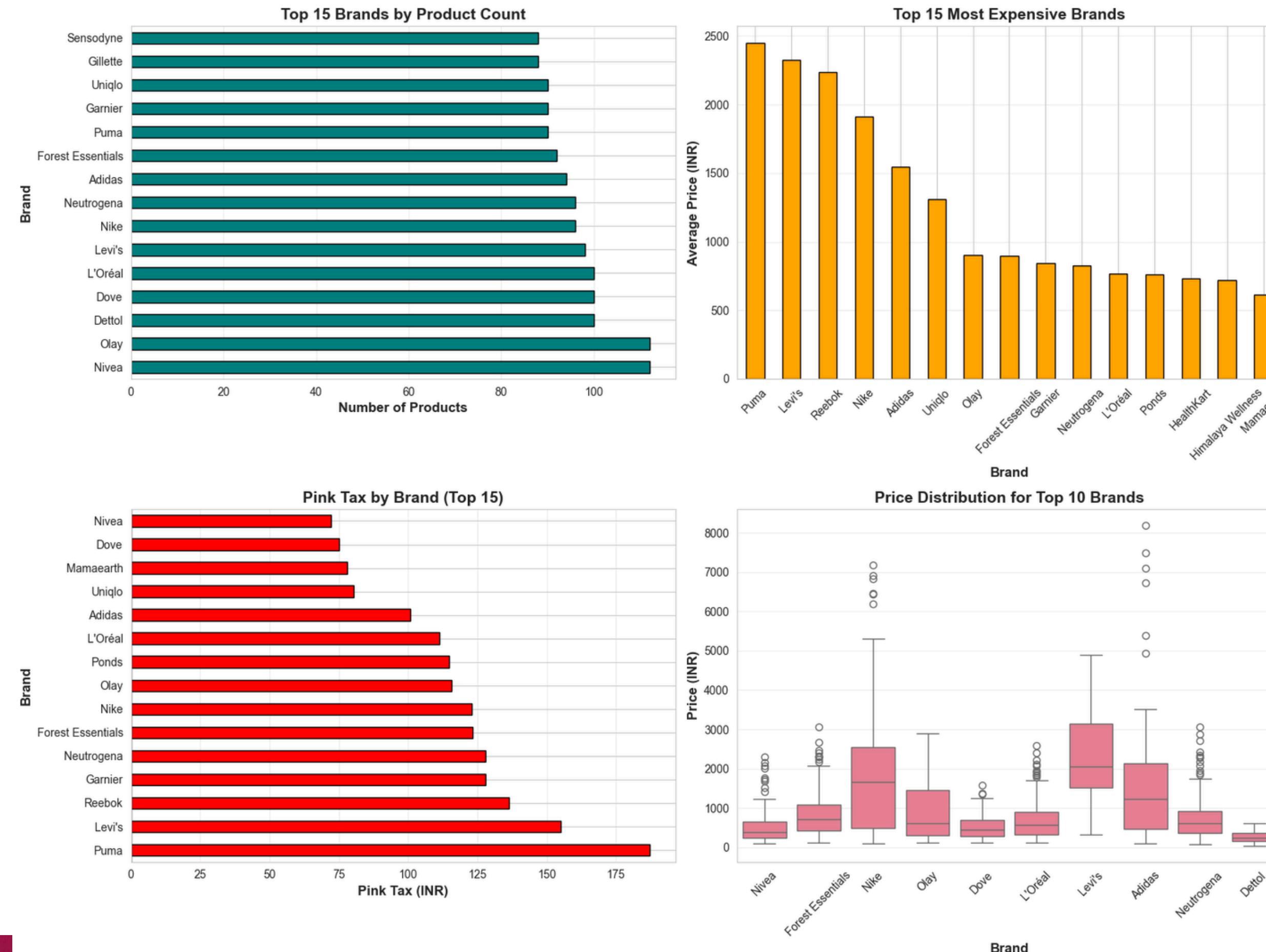
Data Exploration: Category



Data Exploration: Subcategory



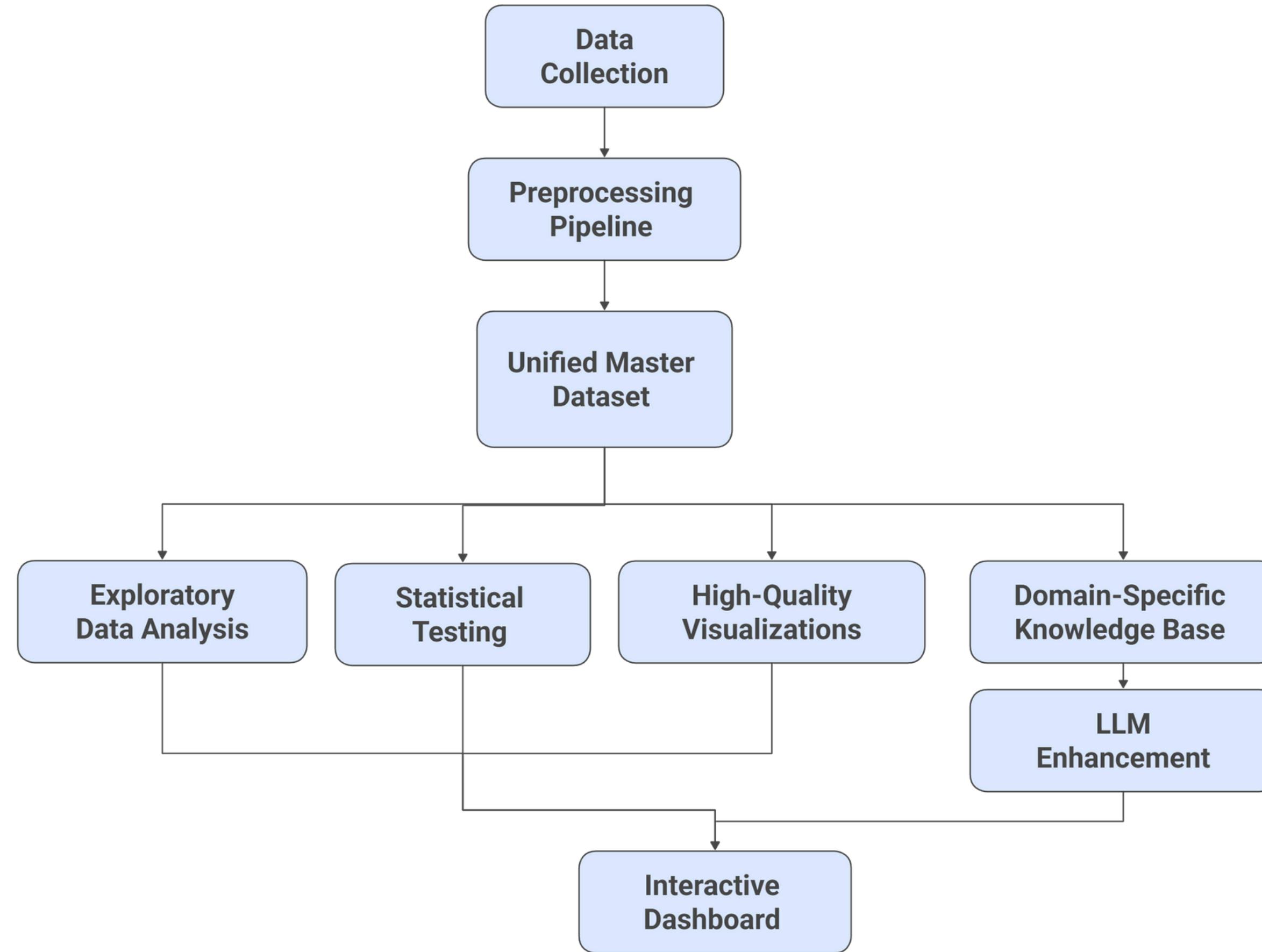
Data Exploration: Brand Based Classification



Tools Used

- Python for data processing and automation
- Pandas & NumPy for cleaning and analysis
- Matplotlib & Seaborn for visualizations
- BeautifulSoup / Requests for data collection
- Flask for chatbot backend API
- Ollama / LLM for AI-driven explanations
- HTML, CSS, JavaScript, Chart.js for the dashboard
- JSON & CSV for data storage

Architecture Diagram



Methodology

1. Data Acquisition

- Collect raw product data from major e-commerce websites.
- Use website scraping to extract product names, prices, categories, and gender labels.
- Ensure enough volume and variation for accurate analysis.
- Use simple Python tools for scraping and creating sample data.

2. Data Cleaning And Normalization

- Clean messy raw data and convert it into a standard format.
- Fix inconsistent price formats and convert them into numeric values.
- Standardize size units (e.g., L → mL, g → kg).
- Remove unwanted characters and correct brand/product names.
- Ensure all data columns follow the same structure.

Methodology

3. Product Matching & Pink Tax Calculation

- Match similar men's and women's products using a common product key.
- Remove gender-specific words to find equivalent items.
- Pair comparable products based on brand, size, and features.
- Calculate the price difference between men's and women's versions.
- Compute the pink tax percentage and absolute difference.

4. Product Matching & Pink Tax Calculation

- Study overall price trends and distributions in men's vs women's products.
- Use statistical tests to check if price differences are significant.
- Identify which categories show the highest pink tax.
- Detect unusual price values or outliers.
- Confirm that results are real and not due to random chance.

Methodology

5. Visualization & Reporting

- Convert findings into simple, clear charts and graphs.
- Show comparisons using bar charts, pie charts, box plots, and histograms.
- Build an interactive dashboard for easy exploration.
- Allow users to filter products and see real-time comparisons.
- Present insights visually for better understanding.

6. AI-Driven Analysis & Interaction

- Add a smart chatbot that explains pink tax findings.
- Use NLP to understand user questions about pricing differences.
- Build a knowledge base from the cleaned dataset.
- Use an LLM (Llama3 via Ollama) to generate clear insights and suggestions.
- Provide personalized explanations through a Flask-powered API.

Results

| Accuracy Metrics | Value |
|------------------|--------|
| Accuracy | 98.65% |
| Precision | 95.90% |
| Recall | 95.90% |
| F1 Score | 92.81% |

| Confusion Matrix Metrics | Value |
|--------------------------|--------|
| False Positive Rate | 5.30% |
| False Negative Rate | 5.30% |
| True Positive Rate | 95.90% |
| True Negative Rate | 89.23% |

Results

| Justification Quality Metrics | Value |
|--------------------------------------|--------------|
| Justified Price MAE | ₹10 |
| Justified Price Median AE | ₹10 |
| Upgrade Completeness | 85.60% |
| Upgrade Precision | 77.80% |
| Upgrade F1 Score | 87.20% |

| Consistency Metrics | Value |
|----------------------------|--------------|
| Verdict Consistency | 98% |
| Verdict Flip Rate | 4.50% |
| Justified Price Std Dev | ₹10 |
| Brand Consistency | 100% |
| Overall Consistency | 98.50% |

Results

| Response Quality Metrics | Value |
|----------------------------|----------|
| Average Explanation Length | 24 words |
| Clarity Score | 4.6 |
| Evidence Citation Rate | 73% |
| High Confidence Accuracy | 85% |
| Confidence Calibration | 92.80% |

Conclusion and Future Scope

- The project collected, cleaned, and analyzed product data to identify price gaps between men's and women's products.
- Results showed clear and significant Pink Tax across several categories, supported by visual and statistical evidence.
- An interactive dashboard with AI insights made the findings easy to explore and understand.
- Future work includes expanding the dataset, improving matching with ML methods, adding real-time pricing APIs, and deploying the dashboard online with a stronger LLM.

THANK YOU