Business Requirements Document (BRD)

Project: Identify underperforming segments (AOV & revenue contribution) and recommend solutions

Executive Summary

The retail enterprise operates multiple store formats (Department, Warehouse, Pharmacy, Specialty) across major cities. The business suspected that some segments underperform in Average Order Value (AOV) and overall sales contribution.

Based on systematic analysis of the transaction-level dataset, the underperforming segment was identified, the behavioural drivers were validated through user interviews, and actionable solutions were outlined to increase transaction value.

Key outcome: AOV is statistically uniform across store types, cities, customer categories, promotions, and seasons.

The primary differentiator is **basket-size behaviour:** AOV and price-per-item decrease sharply as basket size increases. Therefore, the underperforming segment is defined by shopping behaviour (multi-item buyers), not by demographic or store type.

1. Business Context

The company operates several store formats and reports high transaction volume, yet management perceives underperformance in certain segments. The core question: *Which segment(s) show low AOV and low contribution to revenue, and why?* Success metric chosen for this project: **AOV and revenue uplift** in the identified underperforming segment (target: measurable % increase in AOV over a defined period).

2. Objective

- Identify segments with lower AOV and low revenue contribution using the Retail_Transactions_Dataset.
- Validate quantitative findings with user research (interviews) to understand drivers of behavior.
- Propose 2–3 prioritized, measurable solutions and define KPIs to track impact

3. Data & Preparation

Dataset: Retail_Transactions_Dataset.csv (transaction-level)

Key fields used: Transaction_ID, Date, Customer_Name, Product (list), Total_Items, Total_Cost, Payment_Method, City, Store_Type, Discount_Applied, Customer_Category, Season, Promotion.

Preparation steps: - Imported into Excel as a Table (Table1).

Calculated derived columns:-

AOV (Average Order Value) = Average of Total_Cost across all transactions. (AOV = SUM(Total_Cost) / COUNT(Transaction_ID))

Price_Per_Item = Total_Cost / Total_Items (used to analyze per-item value behavior; not the same as AOV).

Validated for missing values and obvious anomalies; noted product–items mismatches as data quality observations.

Note on data quality: Some records showed mismatches between the textual Product list and Total_Items values. There were a few inconsistencies in how item counts were recorded, so Total_Items was used as the reliable measure of how many products were bought in each transaction. The analysis therefore focuses on overall buying patterns rather than exact product-level details.

Total_Cost values remain within a narrow range across different basket sizes, meaning they do not scale proportionally with item count.

Throughout this BRD, AOV-related insights refer to a proxy metric — **price per item (Total_Cost ÷ Total_Items)** — which is used consistently as the value indicator across segments. Wherever "AOV" or "value per basket" is mentioned, it reflects this per-item proxy unless otherwise specified.

4. Methodology

Analytical approach:

1. **Descriptive analysis of AOV and revenue across key dimensions**
   Examined how AOV varies across Store Type, City, Customer Category, Season, Promotion, and Discount Applied.
   Example: comparing average transaction value between Department vs. Warehouse stores, or between City A vs. City B.

2. **Multi-dimensional (two-way) analysis to identify interactions**
   Checked how two factors behave together to uncover hidden patterns.
   Example: Store_Type × City to see if a specific store type underperforms in certain cities.

3. **Derived-metric analysis for deeper behavioral insights**

Calculated supporting metrics such as Price_per_Item and variability measures to understand consistency in spending.
Example: comparing Price_per_Item for customers buying 1 item vs. 3 items to see how spend per product changes.

4. **Product-type impact check to confirm whether item categories influenced AOV**

   Performed a product-level scan to see whether certain items (commonly considered higher-value in retail, such as appliances) influenced transaction value. Due to the absence of SKU prices, this was a qualitative check only. The analysis showed that the product category did not meaningfully change AOV patterns; basket size behavior was the primary driver.

   Example: Transactions with the same number of items showed similar AOV even when one included a high-value product (e.g., a vacuum cleaner) and the other contained only daily-need items.

5. **Behavioral validation through user interviews**
   Used interview insights to understand motivations behind the observed data patterns.
   Example: identifying why multi-item shoppers tend to choose lower-priced items.

5. Key Analytical Findings

5.1 AOV across primary segments

AOV is *uniform* (15.3–15.5) across Store_Type, City, Customer_Category, Season, Payment_Method, and Promotion types. Single-level and multi-level pivot tables did not reveal meaningful AOV differences.

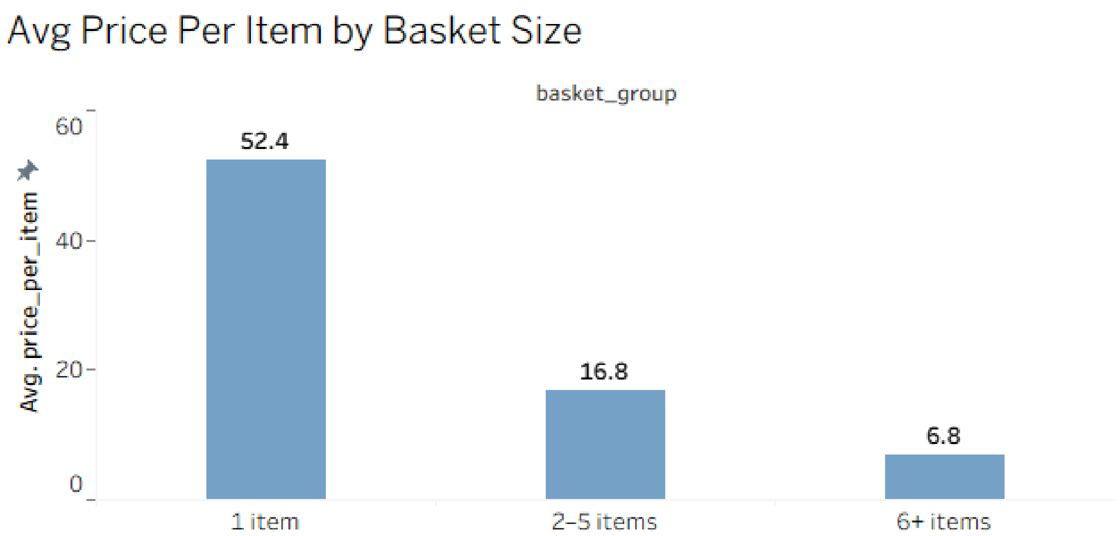
5.2 Price_Per_Item decomposition

Price_Per_Item was used to check whether certain store types sell consistently higher- or lower-priced products. The analysis showed that both average item price and average item count per transaction were similar across store types, indicating that AOV differences are not driven by product pricing patterns.

5.3 Critical discovery — Basket Size effect

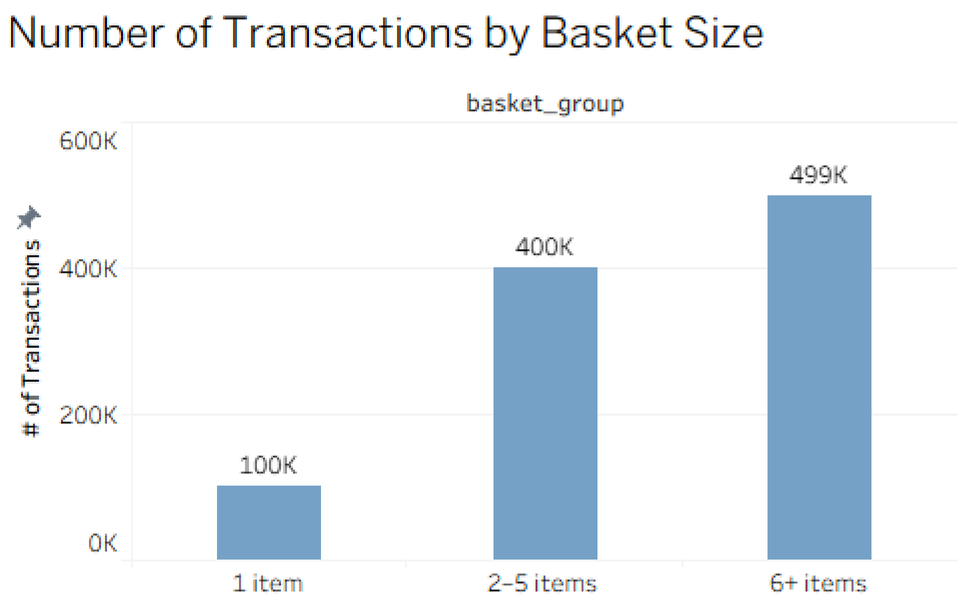
Bucketing transactions by number of items revealed a clear pattern:

- 1-item transactions: avg price_per_item ≈ 52 (higher per-item value)
- 2–5 items: avg price_per_item ≈ 16
- 6+ items: avg price_per_item ≈ 6–7



Additional observations:

- Standard deviation of *Price_Per_Item* drops from ~27 → ~11 → ~3 as basket size increases.This indicates that the price per item becomes more stable as basket size grows, and Total_Cost does not increase proportionally with the number of items.
- Pearson correlation between Total_Items and Price_Per_Item is strongly negative (r ≈ –0.6), confirming the inverse per-item value relationship.



Based on the distribution:

- **1-item transactions:** ~10%
- **2–5 items:** ~40%
- **6+ items: ~50% (largest segment)**

The 6+ items segment contributes nearly half of all transactions.

Even though this group has the **lowest price per item**, it represents the **highest transaction volume**.

Business Implication:
Small improvements in PPI for the 6+ basket segment can drive large revenue impact, because of its high transaction share.

5.4 Promotions/Discounts

Discount_Applied and Promotion types (BOGO, % off, None) do not materially change the AOV trend. Promotions increase item counts but not per-item value.

5.5 Product-level concentration

A high-level review of product occurrences showed that certain items appeared more frequently in transactions, but inconsistencies between the Product List and Total_Items fields prevented reliable SKU-level or category-level insights. Due to these data quality limitations, the analysis focused on transaction-level behavioral patterns instead of product-specific recommendations.

Conclusion from analysis: The dataset does not indicate meaningful AOV differences across store types, cities, or customer categories. Instead, the primary underperformance emerges from basket-size behavior: multi-item transactions show a significantly lower price per item because Total_Cost does not scale with the number of items. This identifies the underperforming segment as a behavioral group (large-basket shoppers) rather than a demographic or store-type segment.

6. User Research Summary

Approach: Interviews conducted with shoppers exhibiting different basket behaviors; responses synthesized into four personas. The research specifically explored motivations for basket size, price sensitivity, and response to promotions.

Personas (concise)

- **Young Professional (Ashok)**
  Buys 3–6 items; convenience-oriented; brand-aware; responds to promotions tied to quantity thresholds.
- **Homemaker (Lakshmi)**
  Buys 15–20 items; monthly stock-up behavior; highly price-sensitive; focuses on essentials.
- **Student Shopper (Prem)**
  Buys 1–3 items; shops for immediate needs; prefers specific brands;

higher per-item spend.

- **Mid-Age Bulk Buyer (Raj)**
  Buys 8–12 items; shops at warehouse/hypermarket formats; purchases predictable low-value items in bulk.

Persona	Shopping Pattern	Behavioral Traits	User Quote
Young Professional (Ashok)	Buys 3-6 items; quick, convenience-driven trips.	Brand-aware; responds to relevant quantity-linked promotions.	*"I grab what I know and leave quickly. If reminded of a better deal, I might add it."*
Homemaker (Lakshmi)	Buys 15-20 items; planned monthly/bi-weekly stock-ups.	Highly price-sensitive; explores upgrades only with clear value.	*"I stick to essentials and look for savings. I try better only if it is worth it."*
Student Shopper (Prem)	Buys 1-3 items; immediate needs and impulse purchases.	Higher per-item spend; prefers specific or trending brands.	*"I pick up what I need now. If it looks good, I don't mind spending more."*
Mid-Age Bulk Buyer (Raj)	Buys 8-12 bulk staples; predictable household purchases.	Seeks long-term savings; prefers value packs and bundles.	*"I buy the same things in bulk. I upgrade only if it saves long-term."*

Behavioural Themes

1. Large baskets are dominated by essential, low-value purchases.
2. Price sensitivity increases as basket size grows.
3. Promotions encourage higher item counts but do not increase value per item.
4. Small baskets often contain preference-driven or higher-value items.

Validation statement: User interviews corroborate the analytical pattern: multi-item transactions are price-sensitive and dominated by essentials, explaining the AOV drop.

7. Root Causes (Synthesis)

Based on data patterns and user research insights:

1. Non-linear spend growth with basket size

Data shows that as item count increases, Total_Cost rises only slightly, causing the average value per item to drop sharply in larger baskets.
User signal: “I usually just pick all the basic things I need — nothing fancy.”

2. Promotion structures reinforce low-value baskets

Promotions increase item count but do not produce a proportional rise in AOV. Quantity-based offers prompt customers to add discounted units or switch to deal items.
User signal: *“I grabbed the offer pack — it felt like a better deal than my usual brand.”*

3. Limited value-led discovery during larger transactions

Higher-value alternatives, add-ons, or upgrades are not surfaced contextually during multi-item shopping. Customers stick to their planned list in the absence of helpful nudges.
User signal: *“I would've considered a better option if something caught my eye — but nothing did.”*

4. Task-oriented shopping mindset during large trips

Large baskets often reflect planned, functional shopping missions where the objective is completion and efficiency, not exploration. This reduces openness to premium or additional items.
User signal: *“When I’m doing the big shop, I’m focused on finishing the list, not browsing.”*

8. Connecting Insights to Recommendations

The data identifies multi-item shoppers as the key underperforming segment: as basket size increases, AOV decreases, showing that total spend does not scale proportionally with item count.

Insights from user interviews provide context for this pattern. Large baskets align with routine, task-driven shopping missions where customers focus on essentials, rely on familiar choices, and show limited engagement with higher-value options unless they are prompted or made visible.

Therefore, the recommendations focus on interventions that:

- Make **higher-value options more discoverable** during routine, essentials-heavy trips
- **Nudge value rather than quantity**, correcting the effects of quantity-driven promotions
- Introduce customers to **better alternatives they may adopt long-term**, strengthening repeat value
- Enhance the **effective value** of multi-item baskets — the key segment driving AOV underperformance

These actions directly link the behavioral drivers (from user research) with the AOV pattern (from data analysis), creating a coherent path from insight to intervention.

9. Recommendations

Each recommendation includes a description, why it addresses the root cause, and success metrics.

9.1 Recommendation — Value-Led Cross-Sell & Contextual Nudges

Description:

Deploy contextual cross-sell prompts that identify essentials-heavy baskets and surface one or two meaningful, mid-range add-ons during checkout (online or POS). These prompts should feel like helpful improvements, not upsell pressure.

Example:

“You’re picking up cleaning supplies — customers also added this concentrated floor cleaner (₹45 off today).”

Why this works:

- Counteracts **basket-value dilution** by offering relevant, low-friction value additions.
- Responds to user sentiment: *“I would’ve considered a better option if something caught my eye.”*
- Helps customers discover better-quality SKUs they may continue purchasing in the future, lifting **long-term category value**.
- Directly targets the underperforming segment: **large, essentials-heavy baskets**.

Success Metrics (KPIs):

- Cross-sell attach rate
- AOV uplift for >5-item baskets
- Conversion rate on suggested add-ons

Target:

+5–10% AOV lift in large baskets over 3 months.

9.2 Recommendation — Redesign Promotions into Value Bundles (Not Quantity-Only Deals)

Description:
Shift from purely quantity-driven promotions (BOGO, multi-pack discounts) to **value bundles** that combine essentials with a single higher-value or upgraded SKU. This maintains the perception of savings while lifting basket value.

Example:
"Family Essentials Pack + Premium Tea — Save ₹35."
vs.
"Buy 2 soaps, get 1 free."

Why this works:

- Addresses the issue that **promotions increase item count but not AOV**.
- Matches user behavior: *"I picked the offer pack because it felt like a better deal."*
- Introduces customers to upgraded SKUs via bundles, improving both immediate value and future repeat purchases.
- Retains the psychological benefit of "getting a deal" while guiding customers toward better-value choices.

Success Metrics (KPIs):

- Bundle conversion rate
- AOV uplift during promotional periods
- Margin change on bundled baskets

Target:
Increase value-bundle attach rate; achieve measurable AOV uplift in targeted categories.

9.3 Recommendation — Enhanced Visibility of Value-Add Options (In-store + Online)

Description:
Improve visibility of mid-range/premium alternatives and useful add-ons through aisle placement, highlighted shelf tags, and online recommendation banners. These integrations should support the natural flow of routine shopping without requiring additional effort from the customer.

Example:
Online: *"Customers who bought rice also upgraded to this premium oil."*
In-store: Shelf signage near staples showing a better alternative or complementary add-on.

Why this works:

- Addresses the visibility gap: users say they rarely see better options during large, routine trips.

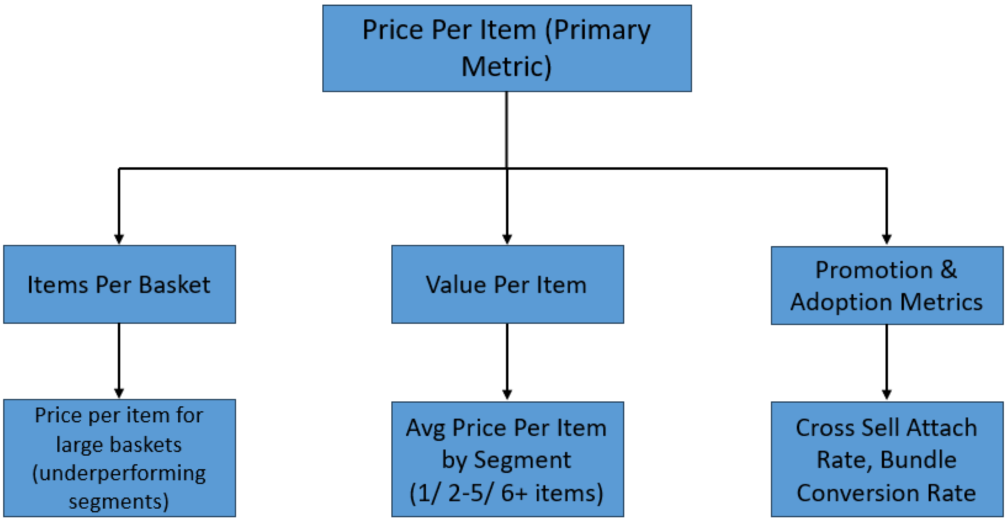
- Fits the **task-oriented mindset**: *"When I'm doing the big shop, I'm just finishing my list."*
- Surfaces value-led choices at the moment they are most relevant.
- Can gradually shift users toward better products, improving **long-term retention of higher-value SKUs**.

Success Metrics (KPIs):

- Click-through rate on recommendation placements
- Premium SKU share within categories
- AOV increases in stores/pages with enhanced merchandising

Target:
Lift premium SKU visibility and conversion within 8–12 weeks.

10. Measurements & Monitoring



Core KPIs

- **Price Per Item (overall and by basket-size segment)** — primary indicator
- **Cross-sell attach rate** (proportion of orders with at least one recommended or value-add item)
- **Value-bundle conversion rate** (for redesigned promotions)
- **AOV for >5-item baskets** (targeted underperforming segment)
- **Transaction volume** (to ensure no negative displacement from interventions)

Measurement cadence

- Monitor KPIs weekly
- Review and report impact monthly

11. Implementation Roadmap (High-level)

Phase 1 (0–4 weeks) — Validation & Quick-Win Pilot

- Finalize the business case and align stakeholders.
- Deploy a lightweight cross-sell nudge pilot (online/POS) in one city or store format.
- Establish baselines for AOV by basket-size segments.

Phase 2 (1–2 months) — Value Bundles & Recommendation Engine

- Introduce redesigned value bundles combining essentials + one value-add SKU.
- Implement contextual recommendation logic for essentials-heavy baskets.
- Track KPI movement (AOV uplift, attach rate, bundle conversion).

Phase 3 (2–3 months) — Scale-Up & Optimization

- Roll out successful interventions across additional cities/formats.
- Conduct structured A/B tests to optimize messaging, placement, and bundle design.
- Refine the model using observed behavioural response and performance data.