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TACKLING POST-HARVEST LOSS WITH TECHNOLOGY

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Post-Harvest Losses Problem: Reducing Post-Harvest Losses to Build Youth-Led Agri-Businesses

Investigating Strategies to Mitigate PHL

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Organizers: Data Community Africa, AgriConnect, Dicey Tech, REDtech Africa

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Abstract

In Nigeria, millions of tons of food go to waste every year; not because of poor harvests, but because they never make it from farms to markets. To tackle these losses, we present Okra — a data-driven digital marketplace and logistics platform built to seamlessly connect farmers, buyers, and logistics providers in real time. Its stand-out feature is an AI-powered tool for predicting freshness and quantity of produce using image recognition, and helping buyers make faster, more informed decisions. Okra also uses data such as rainfall forecasts and harvest schedules to predict high-risk post-harvest loss periods, enabling early interventions like dispatching logistics or alerting farmers.

Keywords: Post Harvest Loss, Digital Marketplace, AI.

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1 Introduction

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AdventureWorks operates as a global manufacturing entity, distributing products through a dual-channel strategy comprising an online direct-to-consumer interface and a robust reseller network. This report presents a comprehensive analysis of business performance, customer behavior, and product trends based on the provided dataset. The primary objective is to identify high-quality insights with actionable business relevance, supported by quantitative evidence.

> **Tip**
>
> *AdventureWorks has generated a total revenue of $109.85M with a net profit of $9.37M. The business relies heavily on its Reseller channel, which accounts for approximately 73% of total revenue.*

1.1 Business Performance Overview

The analysis of the dataset reveals a business with a substantial market footprint. The aggregate financial and operational metrics indicate a mature operation with a significant customer base. As detailed in Table 1.1, the company has processed sales amounting to nearly $110 million, serving over 19,000 customers with a high Average Order Value (AOV).

Table 1.1: *Key Performance Indicators (KPIs)*

Metric	Value
Total Revenue	$109.85 M
Total Profit	$9.37 M
Total Customers	19.12 K
Average Order Value (AOV)	$3.49 K

1.2 Channel Distribution Analysis

A critical component of the AdventureWorks business model is its channel diversification. The revenue stream is bifurcated into Reseller and Online channels. The data demonstrates a clear dominance of the Reseller channel, which contributes the vast majority of gross revenue.

As presented in Table 1.2, the Reseller channel generated approximately $80.5 million, while the Online channel contributed $29.4 million. This distribution suggests a B2B-centric business model where bulk purchasing or wholesale agreements drive the core financial performance.

Table 1.2: *Total Revenue by Sales Channel*

Channel	Total Revenue ($)	Share of Total (%)
Reseller	80,487,704.18	73.27%
Online	29,358,677.22	26.73%
Total	**109,846,381.40**	**100.00%**

1.3 Temporal Revenue Trends

The temporal analysis of revenue from 2011 through 2014 highlights distinct growth trajectories for both channels.

1.3.1 Growth Phase (2011–2013)

The fiscal period beginning in Q2 2011 marked the initial intake of revenue, with the Reseller channel quickly outpacing Online sales.

- **2011:** The Reseller channel demonstrated aggressive growth, expanding from $489k in Q2 to $4.74M by Q4. Online sales showed steady but more modest growth, ending the year at $1.9M in Q4.
- **2012:** Both channels stabilized, with Reseller revenues consistently ranging between $5.8M and $7.7M per quarter.
- **2013:** This year represented the peak performance period. Reseller revenue surged, hitting a high of $9.82M in Q3 2013. Online revenue also saw its highest values, reaching $4.3M in Q4 2013.

1.3.2 Consolidation and Decline (2014)

The first half of 2014 shows a shift in momentum. While Q1 2014 maintained strong figures (Reseller: $8.27M; Online: $4.58M), Q2 2014 indicates a significant contraction, particularly in the Reseller market, which dropped to $3.42M. Data for Q3 and Q4 2014 is currently absent, suggesting either a reporting lag or a cessation of the analyzed period.

This trend analysis suggests that while the Reseller channel is the primary revenue engine, it is also subject to higher volatility compared to the relatively stable Online channel.

2

Channel Performance Analysis

2.1 Overview of Sales Channels

AdventureWorks distributes its products through two channels: the **Online** channel (Direct-to-Consumer) and the **Reseller** channel (Business-to-Business). These channels handle money and profit very differently. The Reseller channel is responsible for the highest sales volume, but the Online channel is the most stable source of profit.

2.2 Financial Performance and The Profitability Paradox

A key finding from the longitudinal data (2011–2014) is that channels with higher revenue volume generally had lower profit margins.

As illustrated in Table 2.1, the Reseller channel consistently generates the majority of revenue, peaking at $32.89 million in 2013. However, this volume appears to come at a cost. The Reseller channel has operated at a negative profit margin since 2012, recording a loss of -2.85% in 2013. Conversely, the Online channel, while smaller in scale, maintains a profit margin of about 40%.

Table 2.1: *Yearly Revenue and Profit Margin Comparison*

Year	Channel	Total Revenue ($)	Total Profit ($)	Margin (%)
2011	Online	3.86 M	1.54 M	39.91%
	Reseller	8.78 M	0.08 M	0.97%
2012	Online	6.39 M	2.38 M	37.28%
	Reseller	27.13 M	(1.43 M)	-5.29%
2013	Online	10.73 M	4.29 M	40.00%
	Reseller	32.89 M	(0.94 M)	-2.85%
2014*	Online	8.37 M	3.47 M	41.45%
	Reseller	11.69 M	(0.03 M)	-0.24%

**2014 data represents a partial fiscal year.*

This discrepancy suggests that the pricing strategy for Resellers—likely involving deep volume discounts—may be eroding the bottom line, whereas the Online channel benefits from premium pricing power.

2.3 Operational Metrics: Volume vs. Value

Average Order Value (AOV) tells you how much money, on average, each customer spends per transaction.

- **Reseller Channel:** High AOV of **$21,147.58** and an average of **16 items per order**. This indicates complex, large-scale logistical requirements.
- **Online Channel:** Lower AOV of **$1,061.45** and an average of **2.18 items per order**, reflecting a transactional, high-frequency retail model.

This confirms that the Reseller channel functions as a bulk-wholesale mechanism, while the Online channel serves individual consumer needs.

2.4 Geographic & Personnel Performance

2.4.1 Territorial Growth

The North American market remains the stronghold for AdventureWorks. The **Southwest** territory, for instance, is a dominant performer, generating over $7.19 million in 2013 alone as seen in Figure 2.2. However, international markets are showing promise. The **United Kingdom** and **France** showed positive year-over-year growth in 2013 (1.23% and 1.61% respectively), identifying them as key expansion targets. On the other hand, established markets like Central North America have shown signs of saturation or decline (-0.68% growth in 2014).

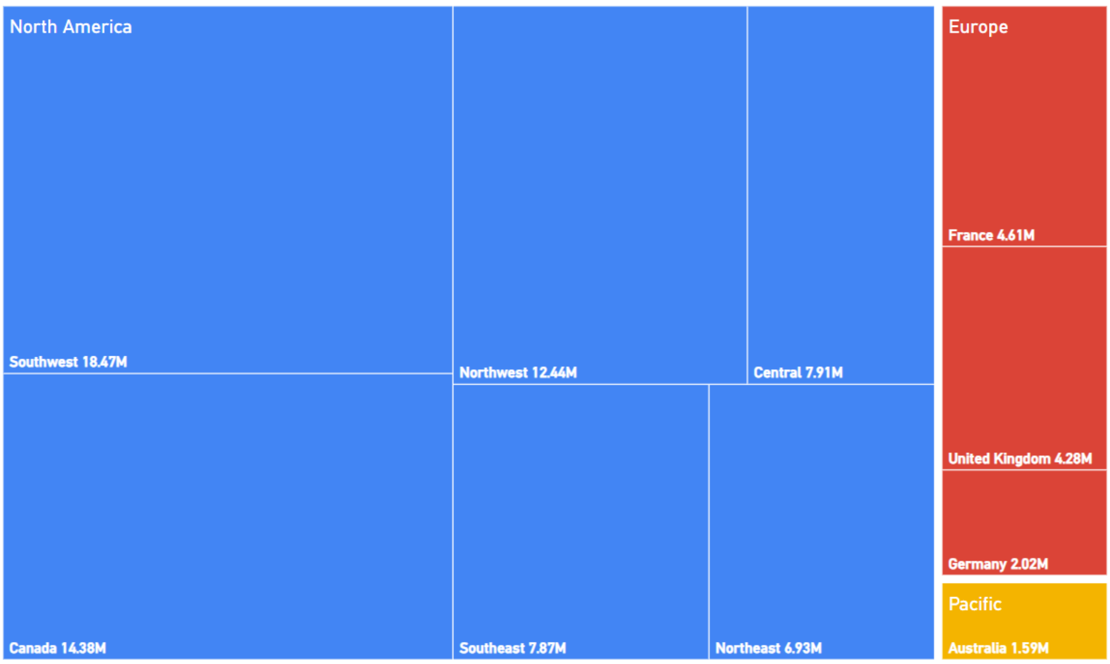

Figure 2.1: *Regional revenue distribution across territories (all years).*

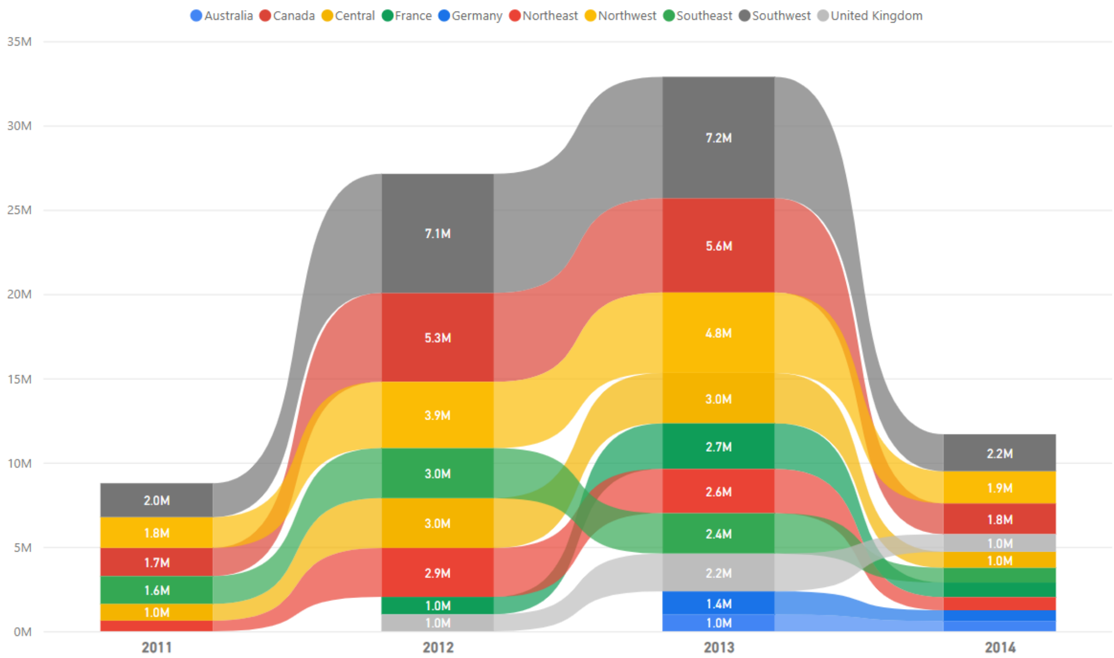

Figure 2.2: *Trend of revenue growth by territory.*

2.4.2 Salesforce Efficiency

An analysis of the top salespeople within the Reseller channel reiterates the concern regarding profitability noted earlier. Table 2.2 lists the top five performers by revenue. Notably, **all top five salespeople generated negative profit margins**.

Table 2.2: *Top 5 Salespeople by Revenue (Reseller Channel)*

Salesperson	Total Revenue	Total Profit	Profit Margin
Michael Blythe	$9,293,903	($281,662)	-3.03%
Jae Pak	$8,503,338	($142,034)	-1.67%
Tsvi Reiter	$7,171,012	($147,095)	-2.05%
Shu Ito	$6,427,005	($396,323)	-6.17%
Amy Alberts	$732,759	($24,279)	-3.31%

For example, Michael Blythe generated the highest revenue ($9.29M) but incurred a loss of over $281k. This suggests that sales commissions or targets may be aligned solely with gross revenue rather than net profitability, incentivizing aggressive discounting to close deals.

3
Customer Segmentation Analysis

3.1 Introduction

Following the analysis of channel performance, this chapter attempts to understand the customer base through segmentation. By grouping customers with similar purchasing behaviors, AdventureWorks can tailor marketing strategies, optimize resource allocation, and enhance customer lifetime value (CLV).

3.2 Data and Preprocessing

The segmentation analysis uses sales transaction data filtered for the **Online** channel, combined with customer demographic and geographic data. The primary dataset is derived from `Analytics.Fact_Sales`, joined with `Sales.Customer` and `Person.Person` to attribute transactions to unique individuals.

Data sources (views):

- `v_RFM_Online.csv`: Transactional data aggregated to the customer level for RFM scoring.
- `vTopCustomerGeography.csv`: Geographic distribution of top-tier customers.
- `v_AvgDaysToSecondPurchase.csv`: Metrics on purchase latency.
- `vMonthlyCustomerTypeTrend.csv`: Time-series data distinguishing new versus repeat customer activity.

Preprocessing Steps:

1. **Filtering**: Analysis was restricted to customers where `Channel = 'Online'` to focus on digital consumer behavior.

2. **Aggregation**: Transaction data was grouped by `CustomerID`. Key metrics (Last Order Date, Order Count, Total Spend) were calculated.
3. **Handling Nulls**: Customer names were constructed by concatenating First and Last names; nulls or missing person records were coalesced into "Company/Unknown".
4. **Derived Features**: `Recency` was calculated as the number of days elapsed since the last purchase relative to the current date (`GETDATE()`).

Table 3.1: *Fields used for segmentation*

Field Name	Type	Purpose
CustomerID	Identifier	Unique key for customer aggregation.
Recency	Computed (Int)	Days since last purchase; measures engagement retention.
Frequency	Computed (Int)	Number of distinct sales orders; measures loyalty.
Monetary	Computed (Money)	Sum of LineTotal; measures revenue contribution.
R/F/M_Score	Rank (1–4)	Quartile scoring for segmentation logic.

3.3 Methods

The primary method employed was **RFM Analysis (Recency, Frequency, Monetary)**. This rule-based segmentation approach was chosen for its interpretability and direct application to marketing action. Unlike black-box clustering algorithms, RFM provides actionable levers tailored to engagement, purchasing frequency, and value.

Feature Creation & Scoring Logic: Customers were scored on a scale of 1 to 4 for each dimension using the SQL `NTILE(4)` window function:

- **Recency (R)**: Ordered ascending (Lower days = Higher Score). A score of 4 represents the most active, recent customers.
- **Frequency (F)**: Ordered descending (Higher order count = Higher Score).
- **Monetary (M)**: Ordered descending (Higher spend = Higher Score).

An aggregate `RFM_Score` was calculated by summing R + F + M, resulting in a range from 3 to 12. Segments were defined using the following thresholds:

- **Champions**: Score ≥ 11
- **Loyal Customers**: Score ≥ 9
- **Potential Loyalists**: Score ≥ 6
- **At-Risk Customers**: Score ≥ 4
- **Lost Customers**: Score < 4

3.4 Results

3.4.1 Segment Distribution and Scale

The analysis identified 18,484 unique online customers distributed across five RFM segments as shown in Table 3.2. The **Champions** and **Loyal Customers** drive a disproportionate share of revenue, characterized by frequent purchases and high average order values. Champions comprise only 5.5% of the total customer base, yet they are responsible for most of the profit. On the other hand, the **Lost** and **At-Risk** segments represent a combined 21.5% of customers — a substantial population of disengaged or inactive accounts warranting recovery strategies.

Table 3.2: *Customer Segmentation Distribution*

Segment	Customer Count	% of Base	Business Implication
Champions	1,007	5.5%	High-value core; maximize retention.
Loyal Customers	6,257	33.8%	Stable revenue base; nurture loyalty.
Potential Loyalists	7,319	39.6%	Largest segment; prime growth target.
At-Risk Customers	2,907	15.7%	Require win-back; high recovery value.
Lost Customers	994	5.4%	Low-touch or reactivation pilots only.
Total	**18,484**	**100%**	—

Cluster Summaries:

- **Champions**: High purchase frequency (4+ orders), high monetary value (> $10k), very recent buyers.
- **At-Risk**: Moderate monetary value but poor recency trends; customers who have "gone quiet."
- **Lost Customers**: Single low-value purchases made long ago; Recency often > 4000 days.

Figure 3.1 provides a visual breakdown of customer counts across all five segments.

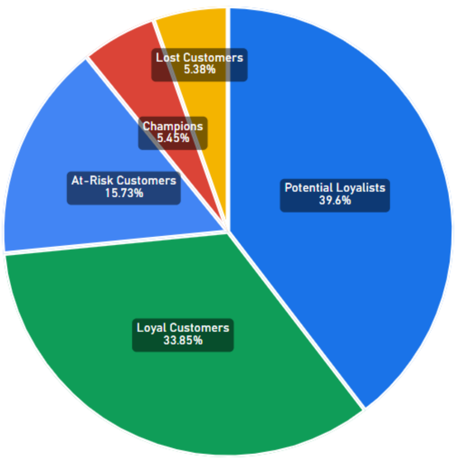

Figure 3.1: *Customer count distribution across RFM segments.*

3.4.2 New vs. Repeat Customer AOV Dynamics

An interesting observation was noted: repeat customers exhibit Average Order Values (**AOV**) that are **8–20x higher** than new customer AOVs. From the acquisition and retention data, new customers in peak acquisition months (July 2013) averaged ~$1,602 AOV, while repeat customers in the same period averaged ~$6,268 — a 3.9x difference. In earlier cohorts (2011–2012), the spread widened significantly: repeat customers achieved AOVs of $\$18,000$–\$37,000+, while new cohorts remained in the $\$3,000$–\$8,000 range.

Strategic Implication: This suggests that new customer acquisition may be driven by lower-priced entry-level products (e.g., accessories or promotional bundles). Success metrics should prioritize repeat purchase rate and customer lifetime value over initial transaction size.

Figure 3.2 illustrates the stark AOV difference between new and repeat customers across the observation period.

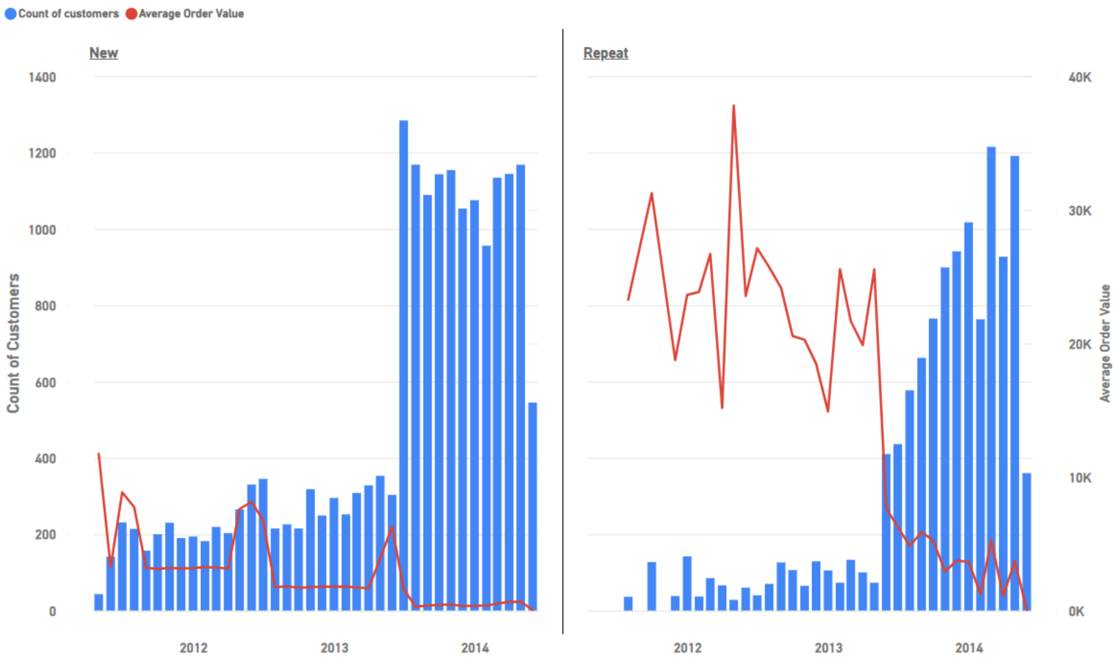

Figure 3.2: *Average order value comparison: new versus repeat customers by month.*

3.4.3 The Repeat Purchase Cycle and Retention Insights

The average days to a second purchase is **161 days** (approximately 5.3 months). This metric is important for campaign timing:

- **Nurture Window**: A 90–120 day post-purchase nurture sequence can intercept customers during their consideration phase before they drift to competitors.
- **Cohort Retention**: Cohorts acquired in 2011–2012 (earlier) show proportionally higher repeat purchase rates; newer cohorts (2013–2014) display lower repeat penetration, suggesting either shorter observation windows or changing customer behavior.
- **Repeat Volume Trends**: The total repeat customer volume in 2014-03 (1,215 customers) surpassed new customer acquisitions (1,134) for the first time, indicating maturing customer base maturation.

3.4.4 Geographic Concentration and Regional Targeting

Top-tier customers (top 10%) show extreme geographic concentration:

Table 3.3: *Top 5 Geographic Clusters (Top 10% Customers)*

Region/State	Top Customers	Concentration Rank
England	66	1st (9.0% of top tier)
Seine (Paris), France	33	2nd (4.5% of top tier)
Queensland, Australia	29	3rd (4.0% of top tier)
California, USA	15	4th (2.0% of top tier)
New South Wales, AUS	23	5th (3.1% of top tier)

Key Insight: England has the most top-tier customers with 66, followed by Paris with 33. The Australian states (Queensland and NSW) represent a significant regional base, with 52 top customers. This concentration represents an opportunity to efficiently scale operations in high-density regions, and a risk of significant disruption from supply chain or regulatory issues in a limited number of areas.

3.5 Interpretation and Business Insights

3.5.1 The Retention Gap and Purchase-to-Purchase Timing

Data from the repeat purchase analysis indicates that the average time to a second purchase is approximately **161 days (5.3 months)**. Based on this insight, the following actions are recommended:

Timeline-Based Actions:

- **Days 0–30 (Onboarding Phase)**: Confirm receipt, upsell complementary products, begin loyalty program enrollment.
- **Days 60–90 (Consideration Window)**: Deploy targeted email nurture (personalized product recommendations, exclusive discounts, social proof testimonials).
- **Days 100–120 (Critical Intervention Point)**: First engagement drop-off risk; deploy SMS or retargeting ads to prevent churn.
- **Days 130–161 (Conversion Goal)**: Win-back campaigns with time-limited incentives to trigger repeat purchase.
- **Days 162+ (At-Risk Zone)**: Customer transitions to "Inactive" status; move to quarterly win-back or low-touch reactivation.

Recommendation: Implement an automated drip campaign series with three touchpoints at day 60, day 100, and day 140 to maximize repeat purchase likelihood before the 161-day threshold is exceeded.

3.5.2 Segment-Specific Acquisition and Retention Strategy

Based on segment distribution and behavioral patterns:
Champions & Loyalists (39.3% combined):

- **Retention Focus**: Quarterly business reviews, VIP customer councils, exclusive new product previews.
- **Expansion**: Cross-sell higher-margin product lines; upsell service contracts (e.g., extended warranty, priority support).
- **Referral Programs**: Offer $500–$1,000 incentives for Champions to refer new customers (high-trust referrals convert faster).

Potential Loyalists (39.6%):

- **Growth Target**: This cohort represents 39.6% of the customer base but lower monetary value; moving even 10% into Loyal status would add 731 high-value customers.
- **Accelerated Repeat**: Implement a 60-day post-purchase incentive (e.g., "Buy again within 60 days, get 15% off") to compress the natural 161-day repeat cycle.
- **Bundle Offers**: Create starter bundles to increase basket size and trigger higher-tier RFM scores.

At-Risk Customers (15.7%):

- **Value Salvage**: Many possess strong historical monetary values (often $\$5,000$–$15,000 lifetime spend). Prioritize recovery.
- **Win-Back Campaigns**: Deploy segmented email sequences: "We miss you" offer (10% discount), followed by "Last chance" urgency messaging, then a final "Say goodbye" sentiment message.
- **Root Cause Analysis**: Survey a sample ($n = 50$) of At-Risk customers to understand churn drivers (product dissatisfaction, price sensitivity, switching to competitor, etc.).

Lost Customers (5.4%):

- **Reactivation Pilot**: Test a limited reactivation campaign (e.g., 50 customers) with a dramatic offer (e.g., "Come back with 25% off your next order").
- **Cost-Benefit Check**: If AOV for Lost customers was $< \$500$, focus marketing budget on Potential Loyalists instead.

3.6 Limitations

- **Rank-Based Scoring**: The NTILE quartile system may mask true variance in skewed distributions; e.g., a customer with $50k lifetime spend scores the same as one with $5k if both fall in the top quartile.
- **Data Recency**: Recency calculations depend on the reference date (`GETDATE()`); results are valid only for analysis runs performed on or near the original report generation date.

- **Temporal Bias**: Cohorts acquired in 2011–2012 have longer observation windows; newer 2013–2014 cohorts may appear to have lower repeat rates simply because insufficient time has passed.
- **Geographic Data Granularity**: Top customer data is provided at state/province level; city-level clustering (e.g., within California or England) is not available for deeper micro-targeting.
- **External Factors**: Competitive dynamics, product launches, and promotional calendars are not accounted for in the RFM scoring; a customer in the "Lost" segment may return if triggered by a seasonal sale or new product launch.

4
Product Optimization

4.1 Objectives

The objective of this chapter is to evaluate product performance with the aim of optimizing the AdventureWorks product portfolio, improving profitability, and identifying opportunities for bundling and cross-selling. Based on the datasets provided, the analysis focuses on four strategic goals:

1. **Identify Product Profitability Extremes:** Determine the top-performing "hero" products and the underperforming "laggard" products using revenue and profit margin metrics.
2. **Analyze Cross-Selling Patterns:** Conduct Market Basket Analysis to find frequently co-purchased product pairs that can inform bundling strategies.
3. **Evaluate Channel-Specific Trends:** Compare product category performance between Online and Reseller channels.
4. **Assess Discount Sensitivity:** Examine the relationship between discount depth, sales volume, and profitability to guide pricing decisions.

4.2 Data and Preprocessing

The analysis relies on `Fact_Sales` and `Dim_Product`. These tables provide product identifiers, transactional revenue, cost-derived profit, discount information, and descriptive product metadata.

Data Preparation

- **Cleaning:** Sales records were aggregated by product ID, category, and subcategory.
- **Feature Engineering:**
  - **Profit Margin:** $\frac{\text{Total Profit}}{\text{Total Revenue}}$

- **Discount Buckets:** Discount values segmented into four buckets (0–5%, 5–15%, 15–30%, >30%).
- **Pair Frequency:** Self-join across sales orders generated co-occurring product pairs.

Table 4.1: *Key Data Fields and Definitions*

Field Name	Type	Source	Purpose
ProductID	Integer	Dim_Product	Unique product identifier.
LineTotal	Decimal	Fact_Sales	Total revenue (Quantity × Unit Price).
LineProfit	Decimal	Fact_Sales	Derived profit metric (Revenue – Standard Cost).
Channel	String	Fact_Sales	Distinguishes Online vs. Reseller sales.
UnitPriceDiscount	Decimal	Fact_Sales	Discount percentage applied.
OrderQty	Integer	Fact_Sales	Number of units sold.

4.3 Methods

Profitability and Pareto Analysis

High and low performers were identified through revenue-based ranking using CTEs. Products were sorted in descending order to capture the top performers and ascending order to determine laggards. Profit margin was then calculated.[1]

Market Basket Analysis

A self-join on `Fact_Sales` grouped products purchased within the same `SalesOrderID`. Only pairs where `ProductA < ProductB` were retained to prevent duplicates such as A–B and B–A. Pair frequencies were aggregated to reveal dominant co-purchase patterns.[2]

Discount Impact Analysis

Discount rates were categorized using SQL `CASE` logic, and `OrderQty` and `LineProfit` were aggregated at the Subcategory × Discount-Bucket level. This enabled identification of categories where discounts either supported volume or eroded value.[3]

4.4 Results

Hero vs. Laggard Products

A clear performance variance exists across the product portfolio. The *Mountain-200* series dominates the top revenue and profitability lists, with margins between 15–20%. Conversely, the *Road-250 Black* series appears in the revenue top 10 but shows negative profitability, indicating it may be a loss-making product.

[1] See citation 4.
[2] See citations 7 and 10.
[3] See citation 1973.

Table 4.2: *Top 5 Best-Selling Products by Revenue and Profitability*

Product A	Product B	Pair Frequency
Water Bottle - 30 oz.	Mountain Bottle Cage	1692
Water Bottle - 30 oz.	Road Bottle Cage	1521
AWC Logo Cap	Long-Sleeve Logo Jersey, L	1172
AWC Logo Cap	Water Bottle - 30 oz.	1019
Sport-100 Helmet, Blue	AWC Logo Cap	1011

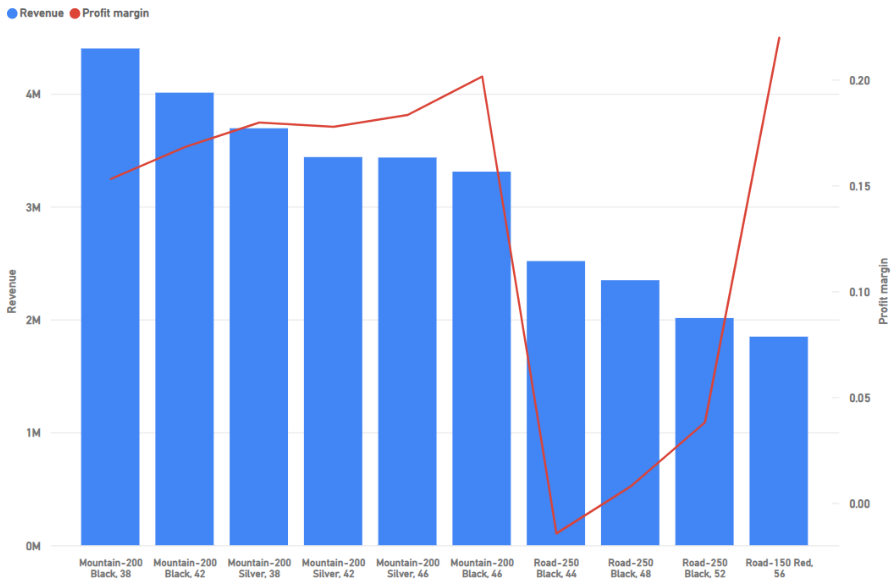

Figure 4.1: *Revenue vs. Profit Margin for Top 10 Product.*

Market Basket Opportunities

The basket analysis revealed strong cross-selling patterns. Frequent pairs include frame-and-fork combinations (common in reseller assembly orders) and accessory bundles often purchased by individual Online customers.

Table 4.3: *Top 5 Frequently Purchased Product Pairs*

Product A	Product B	Frequency	Insight
LL Road Frame - Red, 48	Road-650 Black, 58	225	High-volume component pairing.
Road-650 Black, 58	Road-650 Black, 60	319	Bulk reseller stocking.
Sport-100 Helmet, Red	Patch Kit/8 Patches	132	Strong accessory add-on.
Mountain-200 Silver, 38	Mountain-300 Black, 40	193	Cross-model buyer overlap.
Hitch Rack - 4-Bike	Touring-3000 Yellow, 54	71	High-value accessory attachment.

Channel Performance Analysis

Table 4.4: *Product Category Revenue by Sales Channel*

Category	Online Revenue	Reseller Revenue	Total Revenue	Online %
Bikes	$28.3M	$66.3M	$94.7M	29.9%
Components	$0.0M	$11.8M	$11.8M	0.0%
Accessories	$0.7M	$0.6M	$1.3M	55.1%
Clothing	$0.3M	$1.8M	$2.1M	16.0%

From this data, it can be observed that **Components are exclusively reseller products** (0% online penetration), while Accessories show strong online adoption (55% online revenue). Bikes split 30%–70% favoring resellers. This channel segmentation suggests different customer personas and distribution strategies.

Discount Impact on Profitability

Discount sensitivity varies by subcategory. Road Bikes at minimal discounts (0–5%) generate $2.93M profit on 46,837 units ($62.48 profit per unit), but aggressive discounting (15–30%) on just 304 units yields losses exceeding $97K. Mountain Bikes at deep discounts (>30%) are very unprofitable: 838 units sold at a loss of $709K total, or $846 loss per unit.[4]

On the other hand, Helmets and Jerseys show resilience to moderate discounting (5–15%), maintaining positive margins even at discount rates. This suggests that discount sensitivity is category-dependent and requires tailored strategies. The data on discount impact across product categories and discount bands is presented in Table 4.5.

Table 4.5: *Comprehensive Profitability Impact Across Product Categories by Discount Band*

Product Category	Discount Band	Units Sold	Total Profit ($)	Profit per Unit ($)
Helmets	0–5%	18,369	227,117	12.36
Helmets	5–15%	1,172	1,213	1.03
Jerseys	0–5%	22,654	-148,916	-6.57
Jerseys	5–15%	57	-972	-17.04
Mountain Bikes	0–5%	27,483	5,617,396	204.40
Mountain Bikes	>30%	838	-709,354	-846.48
Road Bikes	0–5%	46,837	2,926,486	62.48
Road Bikes	5–15%	55	-17,439	-317.06
Road Bikes	15–30%	304	-97,973	-322.28

4.5 Interpretation and Operational Insights

Profitability Crisis in Road-250 Series

The Road-250 Black (44) represents a critical anomaly: $2.5M in revenue but negative $36K profit (–1.4% margin). This loss-making SKU, despite ranking in the top 10 by revenue, suggests either aggressive promotional pricing or uncontrolled cost inflation. Immediate investigation of COGS allocation is warranted.

Cross-Selling and Discount Insights

Market basket analysis reveals component pairing (LL Road Frame + Road-650 Black, 225 pairs), accessory add-ons (Sport-100 Helmet + Patch Kit, 132 pairs), and upsell opportunities (Mountain-200 to Mountain-300, 193 pairs). Additionally, discount sensitivity is category-dependent: Road Bikes at 0–5% discounts generate $62.48 profit per unit, while Mountain Bikes at >30% discounts lose $846 per unit.

[4] See citation 1975.

Channel Segmentation and Strategy

Components show zero online penetration yet generate $11.8M reseller revenue (pure B2B). Accessories show 55% online adoption, the highest of all categories. Bikes split 30%–70% online-to-reseller. This asymmetry requires tailored strategies:

1. **Profitability Crisis in Road-250 Series:** Despite strong revenue contribution, the *Road-250 Black* series incurs losses.[5] *Recommendation:* Review COGS allocation and consider price increases or discontinuation of unprofitable sizes.
2. **Optimized Bundling Strategy:** Strong bike–accessory relationships (e.g., Hitch Rack with Touring Bikes) indicate bundling potential.[6] *Recommendation:* Implement "Adventure Bundles" offering small discounts to increase average order value.
3. **Discount Discipline:** Losses in the Mountain Bike category correlate with excessive discounting.[7] *Recommendation:* Introduce a 15% discount floor except for discontinued models.
4. **Channel Segmentation:** Components show no Online sales.[8] *Recommendation:* Maintain reseller exclusivity while increasing Online promotion of high-margin categories.

4.6 Limitations

- **Cost Data Granularity:** Without manufacturing data (e.g., scrap, labor hours), the root cause of high COGS in laggard products cannot be fully diagnosed.
- **Temporal Blind Spots:** Aggregate lifetime performance obscures seasonality, product lifecycle (launch vs. decline), or promotional calendar effects.
- **Customer-Type Mixing:** Basket analysis combines Reseller bulk orders and Online impulse purchases, potentially masking distinct customer behavioral segments.
- **Missing Attribution:** Profit figures exclude distribution, marketing, and overhead allocation, so "true" product profitability may differ.
- **Competitive Context:** Without market pricing benchmarks, it is unclear whether Road-250 losses reflect competitive pressure or internal inefficiency.

4.7 Recommendations for Next Steps

1. **Urgent: Road-250 Profitability Audit** Conduct a detailed cost-to-serve analysis for Road-250 SKUs. Determine whether losses are driven by (a) aggressive promotional pricing, (b) manufacturing inefficiency, or (c) supply chain overhead. Quantify breakeven and decide: retain with margin targets, or exit the segment.

[5] See citation 6.
[6] See citations 13 and 14.
[7] See citation 1975.
[8] See citation 1970.

2. **Discount Cap Enforcement** Implement a pricing governance system preventing discounts >15% on Mountain Bikes and Road Bikes without VP approval. Expected savings: $400K annually based on reduced loss per unit.
3. **Reseller Assembly Program** Formalize a "Reseller Build Kits" program using top basket pairs (Road Frame + Road-650 Black; Touring Frames + Touring Bikes). Offer 2–3% bundled discounts to drive higher volumes without eroding unit margins.
4. **Online Accessory Growth Initiative** Launch a "Pack & Protect" ecommerce campaign bundling helmets, patch kits, and lights. Target 20% lift in online accessory revenue (from $0.7M to $0.84M) within 12 months through retargeting and email campaigns.
5. **Dashboard Development** Build a PowerBI "Product Margin Monitor" with:
   - Scatter plot of Revenue vs. Profit Margin per Product, colored by discount bucket
   - Channel Performance Heatmap (Category × Channel × Margin%)
   - Top 20 Product Pair Co-occurrence Network Graph
   - Discount Sensitivity Curve (Units Sold vs. Profit per Unit by Discount Level)
6. **Competitive Pricing Benchmark** Conduct quarterly market pricing analysis for top 20 SKUs against 3–5 key competitors. Quantify whether Road-250 and Mountain Bike margin pressure is market-driven or internal.

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