International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 05 | May – 2026 DOI: 10.55041/ISJEM07320
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

# Beyond Revenue: Visual Analytics for Retail Profitability using Tableau

**Hanif Qadeer Ahmed[1], Praveen Kumar Sahu[2], Mohammed Mustafa Ali [3], Dr. Shahana Tanveer[4]**

[1, 2, 3] Student, [4]Associate Professor

[1, 2, 3] hanifqadeer@gmail.com, praveenkumarsahu17@gmail.com, mohammed.mustafajf2004@gmail.com, [4]drshahanatanveer@methodist.edu.in

[1,2,3,4] Department of Artificial Intelligence and Data Science, Methodist College of Engineering and Technology, Hyderabad, India

***Abstract*** **-** This dataset covers U.S. supermarket retail sales across multiple product categories. It includes customer demographics, order details, product types, shipping methods, payment modes, and financials — revenue, quantity, and profit. The data is useful for spotting patterns: which products are actually profitable, which regions underperform, how shipping choices affect margins, and whether payment method has any real bearing on sales. Retail managers, supply chain analysts, and business strategists are the likely audience, though anyone doing retail analytics will find something here.

Keywords: Supermarket Sales, Retail Analytics, Profit Analysis, Regional Performance, Data Visualization.

## I.INTRODUCTION

Retail generates enormous amounts of transactional data every day. Most of it goes nowhere. This project works through a Supermarket Sales dataset — 5,901 U.S. retail orders — to see what it can actually tell us about how a retail operation runs.

The dataset covers customer segments (Consumer, Corporate, Home Office), product categories (Furniture, Office Supplies, Technology), four U.S. regions, shipping methods from Standard Class to Same Day, and per-order figures for sales, quantity, and profit. Each record follows a single transaction from placement to payment.

Using Tableau, the analysis focuses on a few concrete questions: which categories are profitable, which sub-categories drive the most revenue, where regional performance diverges, how shipping mode affects delivery, and which product lines are quietly losing money. The dashboards that come out of this

## II. LITERATURE SURVEY

Negash (2004) made the case that business intelligence tools earn their keep by turning transactional data into something decision-makers can act on. Visual representation, he found, reduces cognitive load and speeds up pattern recognition — and interactive dashboards consistently outperform static reports for strategic decisions.[1]

Delen and Demirkan said in 2013 that using prescriptive analytics together is better, than using them separately. They think that when you use exploratory data analysis and visualization together you can see trends and anomalies that you cannot see with reporting. This helps organizations work efficiently.[2]

Heer and Shneiderman (2012) mapped out the interactive visualization landscape and found that interactivity — filtering, drill-down, cross-dimensional comparison — is what separates genuine data exploration from passive chart-reading. Their framework aligns closely with Tableau's design, and their conclusion was simple: interactive tools give users a significantly better chance of making sense of complex data.[3]

Sarikaya and others looked at Tableau in 2019. They checked thousands of workbooks to see how people use Tableau. Most people use Tableau to explore data and see what they can find than to confirm what they already think. They like to use dashboards for their work. Sarikaya and others also think that Tableau is good because it makes analysis easy for people who do not know how to program. This means analysts can look at their data without writing code, which makes their job easier. Tableaus way of making graphics helps with this. [4]

Kwon et al. (2017) studied the visual analytics in enterprise context and found that the tools such as Tableau connect data engineering to business strategy in ways that SQL pipelines do not. Time-to-insight was reduced by up to 60% when analysts moved to visual platforms.[5]

Wren et al. (2000) studied on KPI frameworks in retail. Metrics like revenue, profit margin, and order quantity only tell a useful story when examined across multiple time periods and geographies — single-metric snapshots consistently obscure more than they reveal.[6]

Grewal et al. (2011) studied how revenue and profitability interact across categories and segments. The finding that keeps coming up in this kind of research: high-revenue categories often carry thin or negative margins, and aggregate figures hide it entirely. Granular, category-level tracking is the only way to catch it.[7]

Anderson and Simester (2003) worked through the discount pricing paradox using large-scale transactional data. Heavy discounting drives volume but compresses margins — especially in categories where demand is elastic. Their argument was that retailers need hard discount thresholds, points beyond which promotional pricing destroys profitability even when revenue looks healthy on the surface.[8]

Ailawadi et al. (2001) followed up on that by looking at what habitual discounting does over time. Repeat promotions train customers to wait for sales, gradually eroding full-price willingness-to-pay. The fix, they argued, is discount optimization rather than blanket promotional strategies — a conclusion that shows up clearly in datasets like SuperStore.[9]

Moorthy and Png (1992) added the segmentation piece: the same discount rate produces very different profitability outcomes across customer segments because price sensitivity varies. Uniform promotional pricing, they found, consistently leaves money on the table that segment-specific policies would recover.[10]

## III. MATERIALS & METHOD

The Supermarket Sales dataset is a single flat CSV — 5,901 rows, 23 columns — covering customer details, order records, product information, and financials. It loads directly into Tableau without any restructuring, and the column variety makes it genuinely useful for slicing across products, regions, and customer segments.

In Tableau, the dataset supports sales trend tracking, profit breakdowns by category and sub-category, regional and segment comparisons, and shipping mode analysis. For retail analysts and store administrators, that means usable answers to practical questions — which products are losing money, which regions underperform, and whether the current shipping mix makes operational sense.

.

**Table-1: Key Fields-Supermarket Sales Dataset.**

| Field Name | Field Type | Descripton |
|---|---|---|
| Row ID / Order ID | Dimension | Unique identifiers for each order record |
| Order Date / Ship Date | Dimension (Date) | Date of purchase and date of shipment |
| Ship Mode | Dimension | Shipping method: Standard, Second, First, Same Day |
| Customer Name / ID | Dimension | Customer identifier and name |
| Segment | Dimension | Customer type: Consumer, Corporate, Home Office |
| City / State / Region | Dimension | Geographic breakdown of orders |
| Category / Sub-Category | Dimension | Product group and sub-group |
| Product Name | Dimension | Specific product purchased |
| Payment Mode | Dimension | How the order was paid: Online, Cards, COD |
| Returns | Dimension | Whether the item was returned |
| Sales | Measure | Revenue generated from the order ($) |
| Quantity | Measure | Number of units ordered |
| Profit | Measure | Net profit after cost ($) |

### Target Variable:

The main things we look at are sales and total profit. We break down the sales and the profit into groups, like what type of thing we are selling and where we are selling it. We also looked at who's buying from us and when they are buying. This helps us understand our business better. We call these groups sub-categories, regions, customer segments and time periods. The total sales and total profit are what matter most. Looking at both together matters: a sub-category can appear healthy on revenue while losing money, and aggregate figures won't show it.

Pairing these metrics with category, region, and segment dimensions makes it possible to see which factors — product type, geography, customer behaviour — actually move the needle. The practical result is catching underperforming categories before they turn into inventory or pricing problems.

© 2026, ISJEM (All Rights Reserved)

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 05 | May – 2026 DOI: 10.55041/ISJEM07320
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

**Stakeholders:**
This analysis is useful for retail store managers, category managers, regional heads, supply chain analysts, and strategy teams — anyone making decisions about what to stock, where to sell it, and how to move it.

Visualizing across categories, regions, segments, and time reveals things flat reporting doesn't. Profit margins by sub-category become readable at a glance, surfacing pricing and portfolio problems that aggregate revenue figures hide. Regional gaps show up clearly enough to act on — whether that means a targeted promotion or a harder question about why a geography keeps underperforming.

Operationally, the dashboards support inventory decisions: which products need heavier stocking in peak months, which sub-categories are consistently losing money. Shipping mode analysis catches mismatches between delivery cost and actual urgency — a Same Day shipment on a low-priority Consumer order is a margin problem sitting in the logistics data, invisible without the right view. Payment mode patterns show where customer behaviour has drifted from the current checkout setup.

## IV. DATA VISUALIZATION

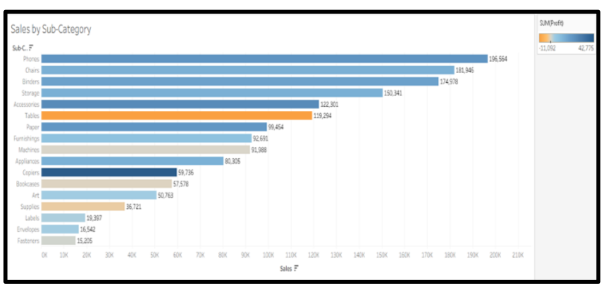


**Fig 1: Sales by Sub-Category**

This horizontal bar chart shows total sales by product sub-category, sorted highest to lowest. Phones and Chairs lead on revenue, followed by Storage and Tables. The bars are color-coded by profit — which is what makes the chart actually useful.
Tables are the obvious case: strong revenue, negative profit. That gap doesn't surface in a revenue-only view. For a category manager, it's the difference between thinking Tables a strength and knowing they're a margin problem worth addressing.

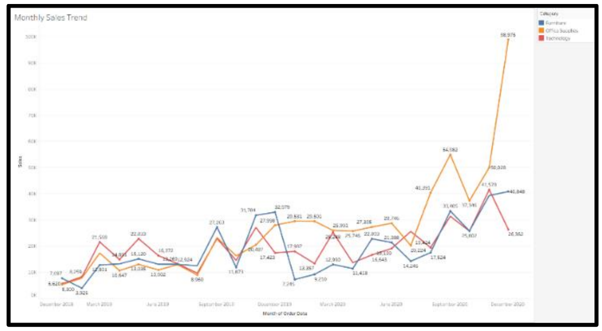


**Fig 2: Monthly Sales Trend by Category**

From the line graph below, we can determine the trend and change in sales revenue of the products within the three categories which are Furniture, Office Supplies, and Technology between the years 2019 and 2022. The graph indicates that there is an increase in sales of all these three categories at certain times during the year. However, there is a variation in the increase of sales in each one of them where we see that Technology has a constant increase in sales towards the last part of the year, most probably because of the increase in demand of its products during the holiday shopping seasons. On the contrary, the demand for the other two categories seems to be fairly steady throughout the year.

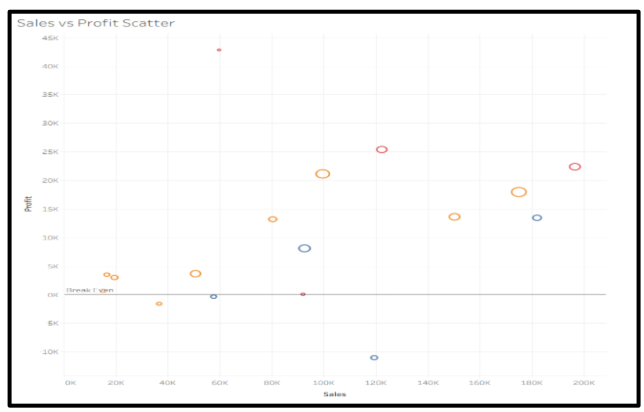


**Fig 3: Sales vs. Profit by Sub-Category**

This scatter plot maps total sales against total profit for every product sub-category. Each dot is colored by category — Furniture, Office Supplies, or Technology — and sized by quantity sold. A reference line at Profit = 0 divides the chart cleanly between what's making money and what isn't.

Most Technology and Office Supplies sub-categories sit above it. Furniture doesn't fare as well, and Tables are the clearest case: moderate sales, negative profit. A bar chart showing revenue alone wouldn't flag it. Here, it's obvious — a dot sitting below the line with a reasonable horizontal position is a pricing or cost problem, not a sales problem.

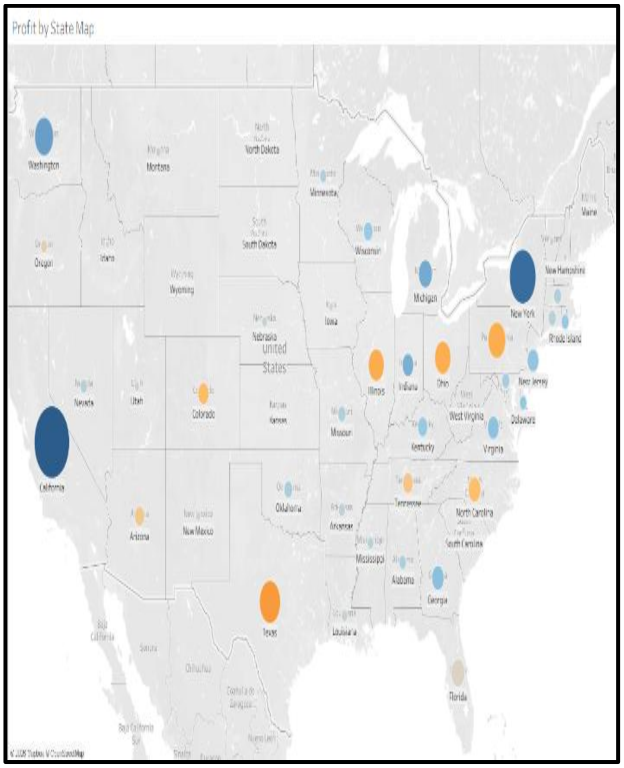


**Fig 4: Profit by State (Geographic Map)**

This map shows profit distribution across U.S. states. Each state is a circle — colored from red (loss) to blue (profit), sized by total sales volume. A large blue circle means high sales and healthy profit. A red circle, whatever its size, means the business is losing money there.

California and New York lead on both metrics. The Central region is the harder story: several states run at a loss despite moderate sales volume, which rules out low demand as the explanation. The problem is margins — pricing, costs, or both — and it wouldn't be visible in a sales-only view.

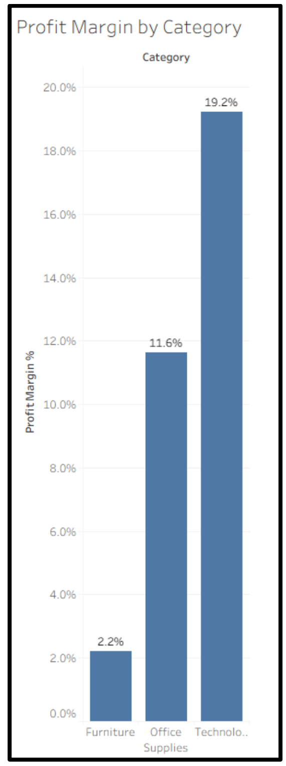


**Fig 5: Profit Margin % by Category**

This bar chart shows profit margin — profit divided by sales — for each product category. Raw profit depends on volume, so margin is the cleaner metric: what the business actually keeps per dollar of revenue, regardless of how much it sells.

Technology leads. It doesn't always generate the highest order volume, but it holds the strongest margin of the three. Office Supplies sit in the middle. Furniture is last, and the sub-category data explains why — certain items are priced below their cost of delivery, which no amount of sales volume fixes.

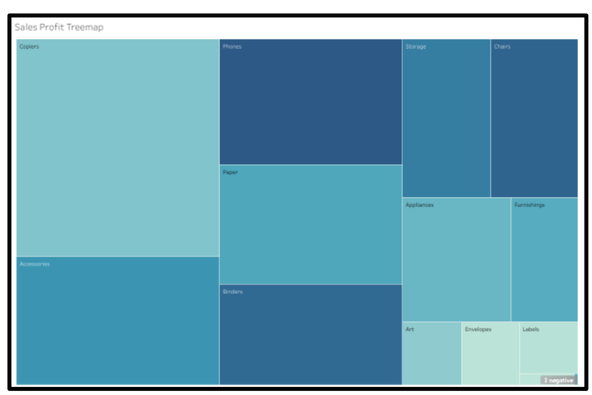


Fig 6: Sales and Profit Tree map by Sub-Category

This tree map shows sales and profit together across all product sub-categories. Rectangle size encodes total sales;

colour runs from red (loss) to blue (profit). The format makes one pattern immediately readable: a large red rectangle means high revenue and negative profit — a sub-category that's moving product but bleeding margin.

Tables are the clearest case. They take up significant space on the chart — the sales are real — but the red colouring tells the other half of the story. High volume, negative profit. It's the kind of finding that separate sales and profit charts would make you piece together yourself.

The format works well for executive reporting precisely because it doesn't require explanation: the size and colour do the talking across the entire product catalogue at once.

DISCUSSIONS

Tableau revealed a number of trends that cannot be seen from the raw transactions. There were also a few trends that challenge the straightforward narrative about revenue andgrowth.
Seasonality in sales is present in the company's business.
Specifically, sales of technology and office supplies are high during Q4 due to increased demand during back-to-school and holiday seasons. The sales of furniture have no seasonality, making it challenging to predict their dynamics and increasing their vulnerability to external factors such as the state of the economy or discounts The scatter plot between sales and profit was the most unexpected visualization in this assignment. Phones and chairs were on the right side of the plot, implying that they generate the highest sales for the company. At the same time, tables and bookcases lie to the left, showing losses after accounting for costs for each unit sold. This problem does not relate to low sales volumes because the company can generate profits by selling these products for a higher price or negotiating better terms with suppliers. In other words, a sub-category may demonstrate good sales performance on the revenue graph but negatively impact company margins.
The graph of profit margins per category validated the findings from the previous visualizations. Technology is the leader in profit generation. Office supplies show stable results. The furniture category shows poor results consistently. As a consequence, the company should focus its efforts on technology and consider changing prices or renegotiating contracts with suppliers of furniture sub-categories.
Finally, the geographic map revealed regional differences in the distribution of revenue and profit per state. The top two states in terms of sales and profit are California and New York. Meanwhile, there are several Central states where sales are moderate but profit is negative. Hence, the company experiences losses in this region despite relatively low sales. It means that shipping fees, discounts, or improper product mix are the reason why these states are unprofitable.
In addition to furniture, binders, and storage were worth mentioning. These sub-categories did not show the best sales numbers but generated significant revenue. As a result, the company might overlook them in favor of phones and chairs, which generate substantial revenue. Finally, the tree map summarized the key findings of this analysis. Red rectangles represented large sub-categories of products with high sales and loss-making margins. Blue rectangles were moderate sub-categories with positive margins. The difference between the two categories is striking.

## V. CONCLUSION

This Tableau project used the tool to perform a series of analyses on a flat file with 5,901 supermarket retail orders, producing dashboards, calculated fields, and story points for six analytical modules. Customer, products, geographics, and financial data were provided, which allowed for discovering operational patterns that could not have been revealed with revenue metrics alone.
A seasonal pattern in the sales emerged quite simply: Technology has its highest sales in Q4 while Office Supplies have fairly constant sales throughout the year. Profitability was more complex, showing no correlation with the number of sales. This is the key insight from the analysis: Tables and Bookcases earn some revenue but lose money on each sale — which means that the issue must be addressed by reevaluating their pricing policy. Geographically, East Coast and West Coast had top revenues and profits. Several other regions operated under losses despite a decent order volume. It might be due to higher shipping prices, product mix issues, or different practices of regional discounting. In any case, all of this is not visible on national scales.
Technology generated the highest number of profits on per-dollar revenue basis. On the opposite side, Furniture generated the lowest profits per dollar, with several categories having negative margins. There are concrete business implications following from such results: where

should promotions be allocated, what categories should have higher inventory, which supply contracts need adjustment.

Surprisingly, the flat file format proved to be sufficient for performing an extensive analysis. Adding three calculated fields, namely Profit Margin %, Average Order Value, and Days to Ship allowed completing an entire analysis without resorting to a star schema. The treemap visualization turned out to be the most efficient one: all sales and profit information combined in a single view without the need to reference any other chart. Big red rectangles for the biggest losers and small blue ones for the least profitable yet insignificant winners. The visualization will work well in the executive context because the pattern can be easily discerned.

There are several directions in which the analysis can be improved. One can introduce real-time sales data and incorporate predictive models for better demand forecasting. Predicting churn and return rates will add another important aspect — that of the customer health.

## VI. REFERENCES

[1] Negash, S. (2004). Business intelligence. *Communications of the Association for Information Systems*, 13(1), 177–195.

[2] Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support Systems*, 55(1), 359–363.

[3] Heer, J., & Shneiderman, B. (2012). Interactive dynamics for visual analysis. *Queue*, 10(2), 30–55.

[4] Sarikaya, A., Correll, M., Bartram, L., Tory, M., & Fisher, D. (2019). What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics*, 25(1), 682–692.

[5] Kwon, B. C., Anand, V., Severson, K. A., Ghosh, S., Sun, F., Frohnert, B. I., & Ng, K. (2017). RETAIN: An interpretable predictive model for healthcare using reverse time attention mechanism. *IEEE Transactions on Visualization and Computer Graphics*, 23(1), 131–140.

[6] Wren, B. M., Berkowitz, E. N., & Grant, E. S. (2000). Retail key performance indicators: An international perspective. *Journal of Retailing and Consumer Services*, 7(2), 99–110.

[7] Grewal, D., Levy, M., & Kumar, V. (2011). Customer experience management in retailing: An organizing framework. *Journal of Retailing*, 85(1), 1–14.

[8] Anderson, E. T., & Simester, D. I. (2003). Effects of $9 price endings on retail sales: Evidence from field experiments. *Quantitative Marketing and Economics*, 1(1), 93–110.

[9] Ailawadi, K. L., Neslin, S. A., & Gedenk, K. (2001). Pursuing the value-conscious consumer: Store brands versus national brand promotions. *Journal of Marketing*, 65(1), 71–89.

[10] Moorthy, S., & Png, I. P. L. (1992). Market segmentation, cannibalization, and the timing of product introductions. *Management Science*, 38(3), 345–359.