

FINAL REPORT

An End-to-End Data Analytics Pipeline MySQL · Python (Jupyter) · Power BI

\$441.41M	\$307.34M	\$134.07M	38.72%	\$2.71M
Total Sales	Total Purchase	Gross Profit	Profit Margin	Unsold Capital

Tool / Technology	Role in Project
MySQL 8.0	Database design, CSV import (LOAD DATA INFILE), date normalisation, summary table creation
Python — pandas / NumPy	Data cleaning, aggregation, statistical calculations
Python — Matplotlib / Seaborn	Distribution plots, box plots, correlation heatmap, bar charts
Python — SciPy	Two-sample t-test for hypothesis testing
SQLAlchemy / PyMySQL	Live Python-to-MySQL connection in Jupyter Notebook
Power BI Desktop (.pbix)	Interactive executive dashboard from vendor_sales_summary.csv

1. Project Overview & Business Impact

This project analyzes a **1.5 GB dataset** containing over **15.6 million rows** of liquor sales and inventory to optimise supply chain efficiency and capital management. By engineering a complete end-to-end pipeline across MySQL, Python, and Power BI, critical bottlenecks were identified where **\$2.71M in capital is currently trapped** in stagnant inventory and underperforming vendors.

The central analytical output is the **vendor_sales_summary** table: a consolidated 10,692-row dataset of per-vendor, per-brand KPIs covering purchases, sales, freight, pricing, gross profit, profit margin, and stock turnover.

Key Business Insights

- Unsold Capital:** Identified \$2.71M in capital currently trapped in stagnant inventory.
- Vendor Turnover:** Isolated 5 high-risk vendors (including Altamar Brands and Caledonia Spirits) with turnover rates as low as 0.035, indicating significant overstocking.
- Profit Leaders:** Verified that while Diageo North America leads in total sales (\$68M), smaller "Hidden Gem" brands offer higher profit margins but require better marketing visibility.
- Target Brands:** Developed logic to flag brands with high profit margins (>85th percentile) but low sales volume (<15th percentile) as primary growth opportunities.

Technical Workflow Highlights

- Data Engineering (MySQL):** Managed user privileges (GRANT) and utilised LOAD DATA INFILE for high-performance ingestion of 15.6M rows.
- Exploratory Data Analysis (Python):** Connected via SQLAlchemy to calculate stock turnover and perform statistical hypothesis testing.
- Business Intelligence (Power BI):** Developed a comprehensive dashboard using custom DAX measures (PERCENTILEX.INC) to automate brand identification.

Project Architecture & Data Pipeline

The end-to-end pipeline flows from raw CSV ingestion through MySQL, into Python for transformation and analysis, and finally into Power BI for executive reporting.

Stage	From	To	Method	Output
Ingest	6 CSV Files (1.5 GB)	MySQL Database	LOAD DATA INFILE	15.6M rows loaded
Extract	MySQL Database	Jupyter / pandas	SQLAlchemy	Raw dataframes
Transform	Raw dataframes	vendor_sales_summary	pandas merge + KPI calc	10,692-row summary
Load	vendor_sales_summary	MySQL (persisted)	to_sql	Central source of truth
Analyse	vendor_sales_summary	Statistical findings	SciPy t-test	$p < 0.0001$
Visualise	MySQL / CSV export	Power BI Dashboard	Direct query / import	Executive dashboard

2. Project Objectives

#	Objective
1	Design and populate a MySQL relational database from six large-scale CSV files (up to 1.5 GB).
2	Establish a live Python–MySQL connection via SQLAlchemy for iterative Exploratory Data Analysis.
3	Build a consolidated vendor_sales_summary table using CTE-based multi-table SQL joins.
4	Conduct in-depth vendor and brand performance analysis including distribution, correlation, segmentation, and statistical hypothesis testing.
5	Deliver an interactive Power BI dashboard for executive stakeholder reporting.

3. Data Sources & Database Schema

Six CSV files were loaded into the `inventory` MySQL database using `LOAD DATA INFILE`. All date columns were imported as `VARCHAR` and converted to native `DATE` types via `STR_TO_DATE()` and `ALTER TABLE`.

Table	Row Count	Key Columns	Purpose
begin_inventory	206,529	InventoryId, Store, Brand, onHand, Price	Opening stock position at period start
end_inventory	224,489	InventoryId, City, Brand, onHand, endDate	Closing stock; used for turnover calculation
purchase_price	12,261	Brand, Price, PurchasePrice, VendorNumber	Reference pricing per brand/vendor
purchases	2,372,474	VendorNumber, Brand, PurchasePrice, Quantity, Dollars	Procurement transactions — core spend data
sales	12,825,363	VendorNo, Brand, SalesQuantity, SalesDollars, SalesPrice	Revenue & volume data (1.5 GB source file)
vendor_invoice	5,543	VendorNumber, Quantity, Dollars, Freight	Aggregated invoicing; freight cost source

The analytical output table `vendor_sales_summary` (10,692 rows) was engineered in Python using pandas to merge multi-table SQL data and compute derived KPIs: GrossProfit, ProfitMargin, StockTurnover, FreightCost, and SalesToPurchaseRate. This processed table was then written back to MySQL via `to_sql` for centralised reporting.

4. Workflow & Methodology

Step	Phase	Tool	Action & Output
1	Ingest	MySQL	High-speed ingestion of 15.6M rows using LOAD DATA INFILE; normalised date schema via STR_TO_DATE.
2	Connect	SQLAlchemy	Established a live Python-to-MySQL bridge to extract raw dataframes into Jupyter Notebook.
3	Explore	Python / Jupyter	Row count verification across all tables; column inspection; vendor drill-downs (e.g. Vendor 4466).
4	Transform	Python (pandas)	Engineered vendor_sales_summary by merging 6 datasets; data cleaning and KPI calculation.
5	Load	MySQL (to_sql)	Pushed the engineered summary table back into MySQL for centralised storage and persistence.
6	Analyse	Python (SciPy)	EDA, distribution plots, correlation heatmap, brand segmentation, Pareto, bulk pricing, t-test ($p < 0.0001$).
7	Visualise	Power BI	Interactive executive dashboard built by connecting directly to the processed MySQL summary table.

5. Exploratory Data Analysis

5.1 Dataset Verification

After ingestion, row counts were verified programmatically via Python. All **15.6 million rows** loaded successfully. The vendor_sales_summary table was subsequently created with **10,692 rows**; a filtered version retaining only positive-profit, positive-margin, and non-zero-sales records yielded **8,564 rows** (80.1% of total), with 19.9% flagged as dead stock or loss-making.

5.2 Summary Statistics Highlights

KPI Column	Key Value	Interpretation
GrossProfit (min)	-\$52,002.78	Some SKUs are being sold below cost; urgent pricing review needed.
ProfitMargin (min)	-Infinity	Zero-revenue records exist — purchased but never sold inventory.
TotalSalesQuantity (min)	0	Dead stock: products purchased but with zero units sold.
FreightCost (range)	\$0 — \$250K	Bimodal: many vendors pay near-zero; a cluster pays \$100K–\$150K.
StockTurnover (max)	350+	A few SKUs turn over very rapidly; most cluster near 0–10.
PurchasePrice (max)	>\$5,000	Premium specialty products drive extreme outliers in small orders.

5.3 Correlation Analysis

The Pearson correlation matrix across all 15 KPI columns reveals the structural relationships within the dataset.

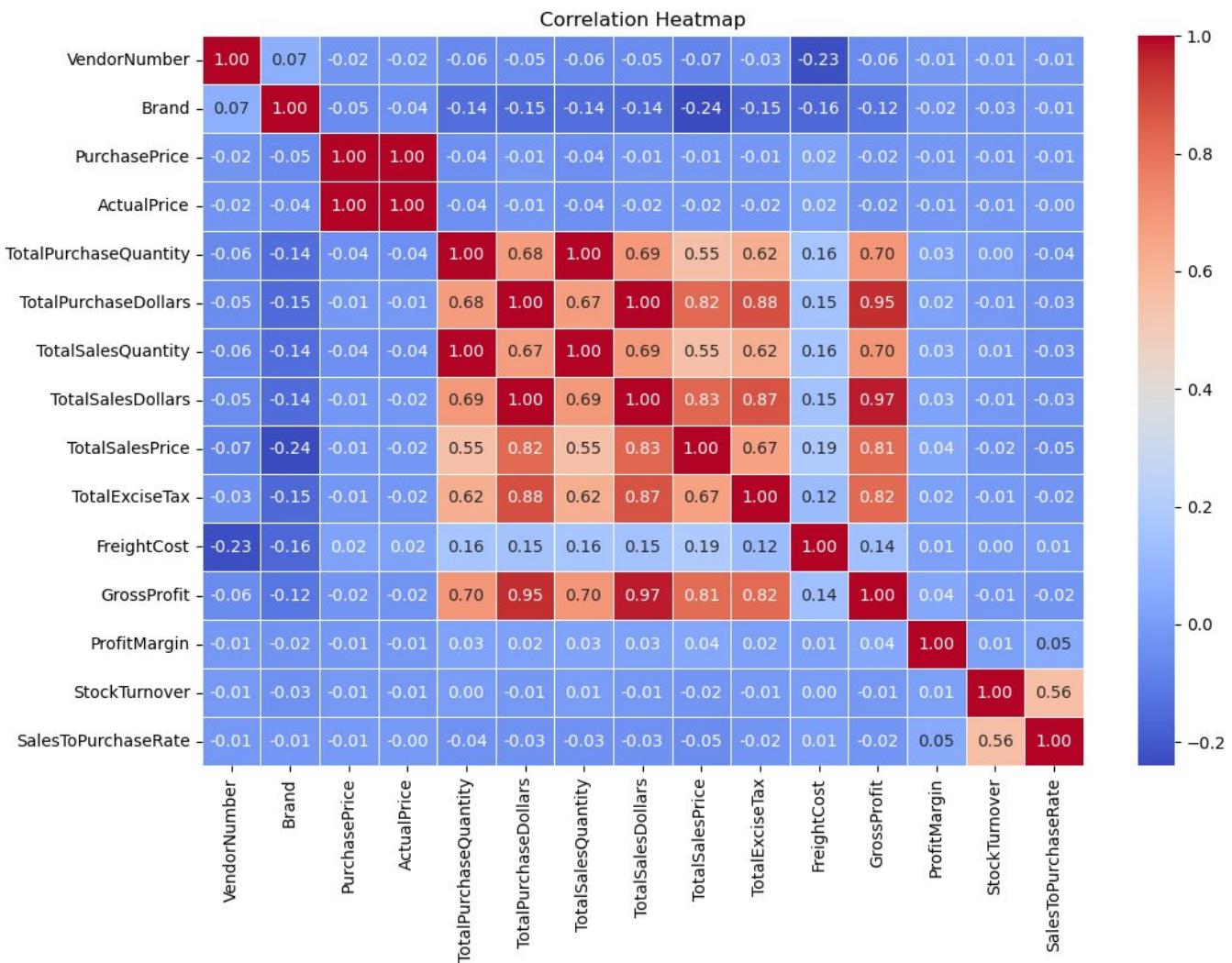


Figure 1: Pearson Correlation Heatmap — red = strong positive, blue = strong negative

Key correlation findings:

- **TotalPurchaseQty ↔ TotalSalesQty: 1.00** — Near-perfect correlation confirms inventory purchased is being sold with minimal aggregate waste.
- **TotalPurchaseDollars ↔ GrossProfit: 0.95** — Higher-spend vendors generate more absolute gross profit.
- **TotalSalesDollars ↔ GrossProfit: 0.97** — Revenue and profitability are tightly coupled.
- **TotalSalesDollars ↔ TotalExciseTax: 0.87** — Excise tax scales proportionally with alcohol sales revenue.
- **PurchasePrice ↔ Revenue / Profit: ~0.00** — Price variations have no meaningful bearing on volume or margin; demand is price-inelastic for most SKUs.
- **StockTurnover ↔ SalesToPurchaseRate: 0.56** — Faster-turning SKUs also convert a higher share of purchases into sales.

6. Vendor Performance Analysis

\$441.41M	\$307.34M	\$134.07M	38.72%	\$2.71M
Total Sales	Total Purchase	Gross Profit	Profit Margin	Unsold Capital

6.1 Top Vendors & Brands by Sales Revenue

Diageo North America dominates with **\$68.74M** in sales — 68% more than the second-ranked vendor. At brand level, premium spirits occupy all top positions.

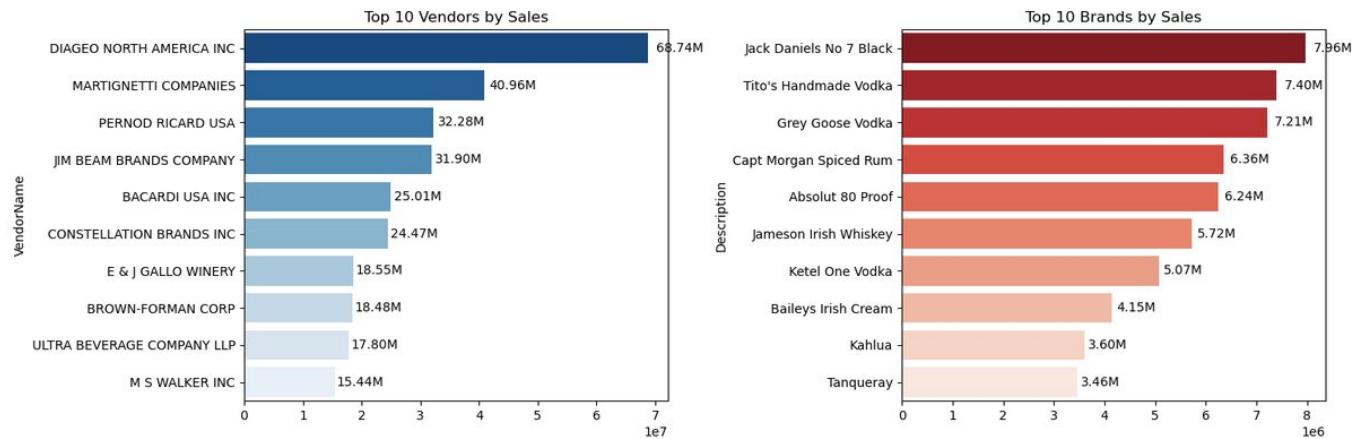


Figure 2: Top 10 Vendors (left) and Top 10 Brands (right) by Total Sales Dollars

Vendor Name	Purchase \$	Gross Profit	Sales \$	Buy %
DIAGEO NORTH AMERICA INC	\$50.96M	\$17.78M	\$68.74M	15.83%
MARTIGNETTI COMPANIES	\$27.86M	\$13.10M	\$40.96M	8.66%
JIM BEAM BRANDS COMPANY	\$24.21M	\$7.69M	\$31.90M	7.52%
PERNOD RICARD USA	\$24.13M	\$8.15M	\$32.28M	7.49%
BACARDI USA INC	\$17.65M	\$7.36M	\$25.01M	5.48%
CONSTELLATION BRANDS INC	\$15.60M	\$8.87M	\$24.47M	4.84%
BROWN-FORMAN CORP	\$13.54M	\$4.94M	\$18.48M	4.20%
ULTRA BEVERAGE COMPANY LLP	\$13.21M	\$4.59M	\$17.80M	4.10%
E & J GALLO WINERY	\$12.31M	\$6.24M	\$18.55M	3.82%
M S WALKER INC	\$10.96M	\$4.48M	\$15.44M	3.40%

6.2 Vendor Procurement Concentration — Pareto Analysis

The top 10 vendors collectively represent **65.34%** of all procurement dollars — a significant concentration risk.

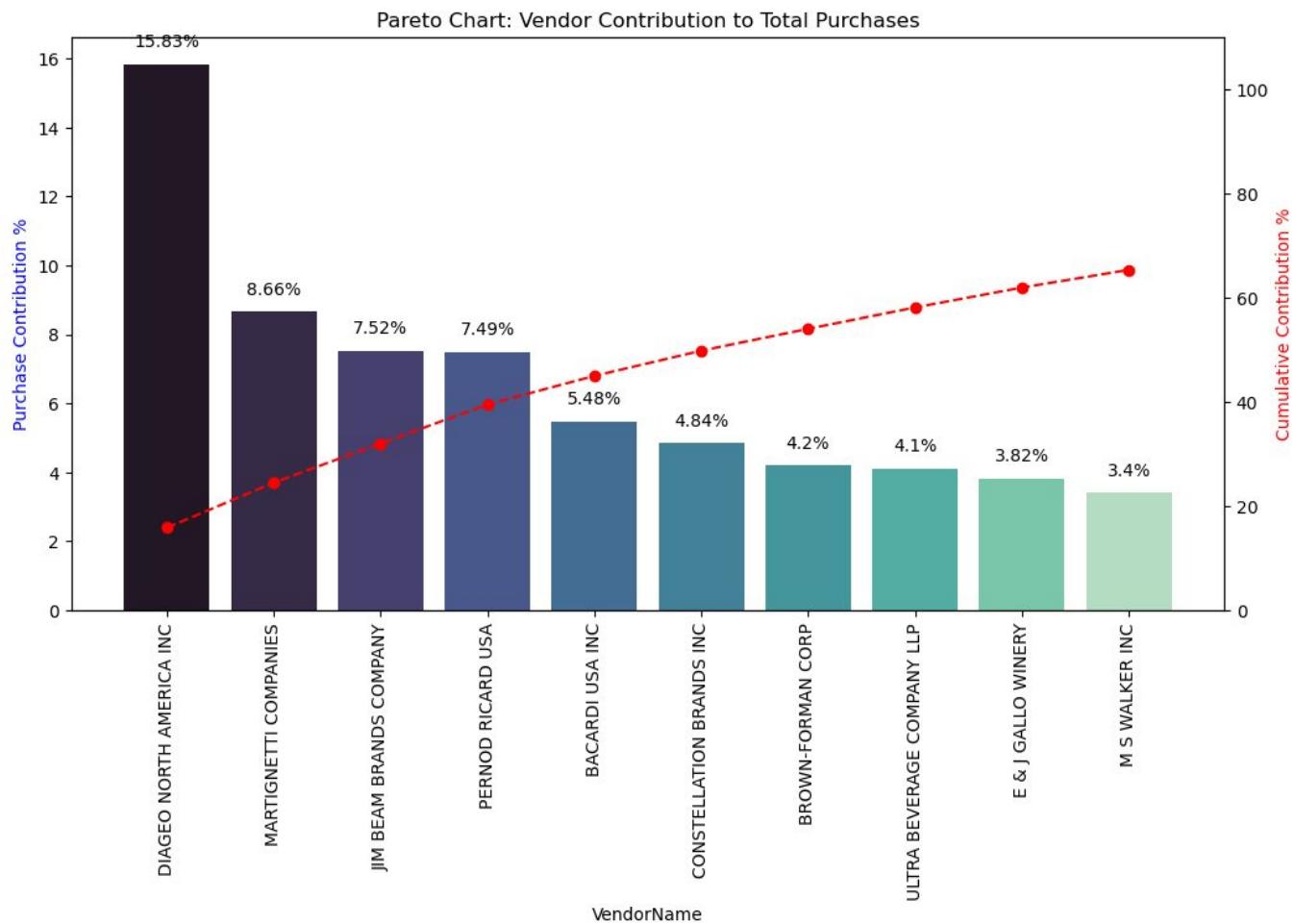


Figure 3: Pareto Chart — Individual & Cumulative Vendor Purchase Contribution (%)

6.3 Procurement Dependency

The donut chart confirms that 65.34% of all purchase dollars flow to just 10 vendors, with Diageo North America alone accounting for **15.8%**. This level of supplier dependency creates meaningful supply-chain vulnerability.

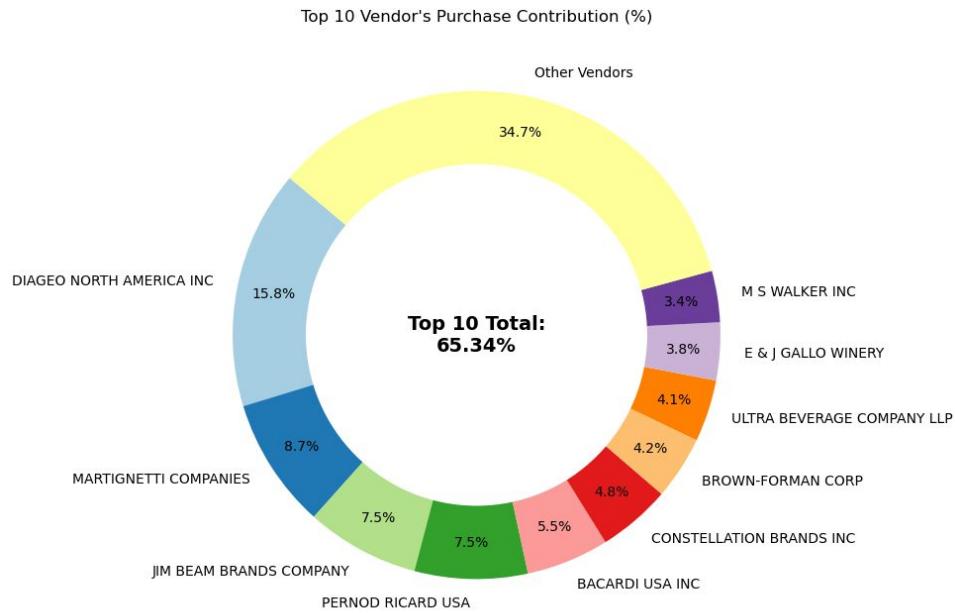


Figure 4: Top 10 Vendors hold 65.34% of total purchase spend

6.4 Brand Opportunity Segmentation

Brands were segmented using two thresholds: **15th percentile of TotalSalesDollars (\$286.18)** as the low-sales cut-off and **85th percentile of ProfitMargin (56.20%)** as the high-margin cut-off. Brands in the low-sales / high-margin quadrant are prime promotional candidates — strong per-unit margins but not yet reaching scale.

Brand Description	Total Sales (\$)	Profit Margin (%)
Santa Rita Organic Sauvignon Blanc	\$9.99	66.47%
Debauchery Pinot Noir	\$11.58	65.98%
Acrobat Pinot Noir	\$15.24	64.21%
Dreaming Tree Cabernet Sauvignon	\$22.10	63.89%
Rock Steady Chardonnay	\$31.50	62.54%
Sycamore Lane Cabernet	\$45.00	61.30%
Wente Morning Fog Chardonnay	\$58.00	59.88%
Alamos Malbec	\$72.00	58.74%

6.5 Bulk Purchasing & Unit Price Effect

Orders were categorised into Small / Medium / Large tiers. Larger orders achieve dramatically lower unit costs, confirming a strong bulk-discount effect from vendors.

Order Size Tier	Avg Unit Price	vs Small Orders	Implication
Small	\$43.78	—	High price variance; includes specialty/premium products.
Medium	\$17.89	-59% cheaper	Moderate bulk savings realised.
Large	\$11.31	-74% cheaper	Best unit economics; maximum bulk discount captured.

6.6 Unsold Inventory & Stock Turnover

Total unsold inventory value: **\$2.71 million**. Stock turnover (SalesQty / PurchaseQty) was computed per vendor; several vendors recorded 0.000 — meaning none of their purchased stock has been sold.

Vendor (Unsold Inventory)	Unsold \$	Vendor (Stock Turnover)	Turnover
DIAGEO NORTH AMERICA INC	\$980K	AAPER ALCOHOL & CHEM. CO	0.000
MARTIGNETTI COMPANIES	\$929K	LAUREATE IMPORTS CO	0.000
JIM BEAM BRANDS COMPANY	\$850K	TRUETT HURST	0.020
PERNOD RICARD USA	\$710K	COUNTRY VINTNER LLC	0.050
BACARDI USA INC	\$590K	TOTAL BEVERAGE SOLUTION	0.080

Left: Top 5 vendors by unsold inventory value. Right: Vendors with lowest stock turnover.

7. Statistical Hypothesis Testing

A two-sample independent t-test (SciPy) was used to determine whether top-performing and low-performing vendors have statistically different profit margins. **Null hypothesis (H_0):** There is no significant difference in profit margins between top and low-performing vendors.

Metric	Top Vendors	Low-Performing Vendors
Definition	Top 10 by total sales	StockTurnover = 0 (zero sales)
Mean Profit Margin	30.04%	-132.48%
95% CI Lower	29.53%	-165.39%
95% CI Upper	30.55%	-99.56%
T-Statistic	9.6799	—
P-Value	< 0.0001	—
Decision	Reject H_0	Significant difference confirmed

The p-value of **<0.0001** conclusively rejects the null hypothesis. The 162-percentage-point gap in mean profit margins between the two groups is not due to chance — vendor selection and management practices have a statistically significant impact on profitability.

8. Power BI Dashboard

The vendor_sales_summary table was exported to CSV and loaded into Power BI Desktop to build a single-page interactive dashboard. The .pbix file is available in the repository for local download and inspection of the DAX measures.

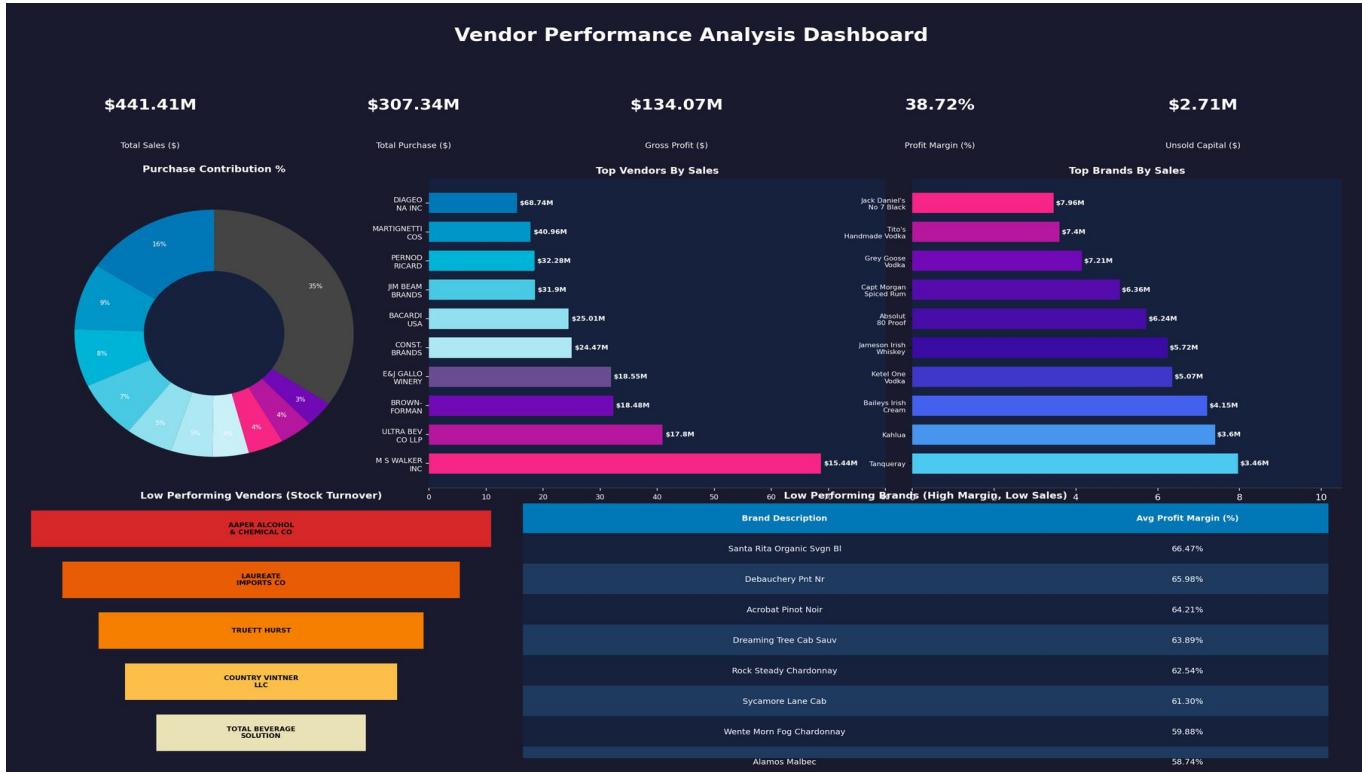


Figure 5: Vendor Performance Analysis Power BI Dashboard

Visual	Title	Fields Used	Insight Delivered
5 x Card	KPI Row	Total Sales, Purchases, Gross Profit, Profit Margin, Unsold Capital	Instant executive snapshot of key metrics
Donut Chart	Purchase Contribution %	VendorName x PurchaseContribution%	Visual of 65.34% spend concentration in top 10
Bar Chart	Top Vendors By Sales	VendorName x TotalSalesDollars	Revenue-ranked vendor leaderboard
Bar Chart	Top Brands By Sales	Description x TotalSalesDollars	Brand-level sales ranking across all SKUs
Funnel	Low Performing Vendors	VendorName x AvgStockTurnover	Suppliers with slowest stock movement
Table	Low Performing Brands	Description, AvgProfitMargin	High-margin, low-sales brands awaiting promotion

9. Key Findings

#	Finding	Detail
1	Inventory efficiency is strong	Near-perfect correlation (0.999) between purchase and sales quantity confirms stock is being sold with minimal aggregate waste.
2	Vendor concentration risk	Top 10 vendors hold 65.34% of all procurement spend. Diageo alone = 15.83%. A single vendor disruption could materially impact supply.
3	\$2.71M unsold inventory	Dead stock totalling \$2.71M is locked across all vendors; convertible via clearance pricing, bundling, or vendor return agreements.
4	19.9% of SKUs are loss-making or unsold	2,128 of 10,692 vendor-brand combinations generate zero or negative profit and require immediate pricing review or delisting.
5	Bulk orders cut unit costs by 74%	Large order tiers achieve \$11.31 avg unit cost vs \$43.78 for small orders. Consolidating orders is the single highest-leverage margin lever.
6	High-margin / low-sales brand opportunity	Brands above the 85th margin percentile (>56.20%) but below the 15th sales percentile (<\$286) are untapped revenue with no price risk.
7	Statistically proven performance gap	T-test confirms: top vendors avg +30.04% margin vs low vendors avg -132.48% ($p<0.0001$). Vendor curation materially drives profitability.
8	Jack Daniel's No 7 Black is the revenue leader	\$7.96M in total sales — leads all 10,692 SKUs, followed by Tito's Handmade Vodka (\$7.40M) and Grey Goose Vodka (\$7.21M).

10. Recommendations

#	Area	Priority	Action
1	Pricing	High	Audit all 2,128 loss-making SKUs. Renegotiate purchase prices with vendors or raise retail prices to restore positive margins immediately.
2	Promotions	High	Launch targeted campaigns for high-margin / low-volume brands (margin >56%, sales <\$286). Shelf placement and digital promotion — no discounting required.
3	Supply Chain	High	Reduce dependency on the top-10 vendor cluster. Onboard 3–5 alternative suppliers for highest-spend categories to mitigate single-vendor disruption risk.
4	Dead Stock	Medium	Initiate clearance for \$2.71M in unsold inventory through discount bundling, time-limited promotions, or vendor return agreements.
5	Procurement	Medium	Consolidate small orders into large-order tiers to capture the 74% unit cost reduction. Prioritise top-spend brands first.
6	Automation	Low	Schedule the CTE SQL refresh query to run weekly so Power BI always reflects current data without manual re-export.

11. Conclusion

This project demonstrates a complete, production-quality analytics pipeline covering every stage from raw data ingestion to executive-ready reporting. The `vendor_sales_summary` table serves as a single source of truth — consolidating procurement, sales, freight, and pricing data into 10,692 actionable records — and the Power BI dashboard makes this intelligence accessible to non-technical stakeholders.

The analysis surfaces concrete, data-backed actions with measurable impact: \$2.71M in recoverable capital, 65.34% supplier concentration risk requiring diversification, high-margin brands awaiting promotional investment, and a statistically proven 162-point profitability gap between vendor tiers ($p<0.0001$). The modular stack — MySQL for storage, Python for analysis, Power BI for presentation — is maintainable, scalable, and ready for scheduled production refresh.

Built with MySQL · Python · Power BI