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Smart Supply & Workforce Analytics: A Business Intelligence Toolkit for Small Enterprise Resilience

Nasima Akter

Research and development (Student)
Atlantis University, Miami, Florida, USA

Abstract: *Small businesses account for ~46% of U.S. private employment and face recurring inventory and workforce challenges. Industry estimates place global retail inventory distortion at about $1.77 trillion (2023); U.S. retailers lost roughly $82 billion to stockouts in 2021. In July 2025 the retail trade quits rate was 2.5%, which exacerbates staffing shortages.*

The article proposed Smart Supply and Workforce Analytics toolkit that can be configured by a small business within weeks using the standard BI software. The toolkit is a combination of three items that are complementary: 1) ABC-XYZ inventory segmentation to concentrate on high value, stable-demand SKU; 2) a light forecasting step to flatten demand expectations; and 3) a basic workforce alignment perspective to align staff to the demand curve hour and day by day. I model the methodology using public sources of data and a sample dataset of retail transactions. I want to ensure that this can be replicated: all figures, tables, as well as KPIs are constructed in such a way that they can be reassembled by another analyst in a short period of time.

The actual meaning of this is that an owner or analyst is provided with a short list of SKUs to guard, definite rules about when to order again, and a plan on staffing the business, which is expected to operate during high periods rather than respond to them. It is practically useful and easy-to-implement policy: how to decrease stockouts, idle workers and enhance service at a scale that matters in communities where small companies continue to be the keystone to local job creation.

IndexTerm- workforce analytics; retail SMEs; Power BI; inventory distortion; staffing alignment. ABC–XYZ; reorder point (ROP);

I. INTRODUCTION

The U.S. economy is predominantly made up of small businesses as 34.8 million business organizations provide employment to almost 46 percent of the workforce in the private sector. But they are under constant pressure of the disruptions in the supply chains, lack of labor and escalating operational costs. To illustrate, in 2021, U.S. retailers lost more than $82 billion in sales through stockouts and the retail trade industry is still registering 2.5% quit rate in 2025 (BLS) [1], among the highest among industries. This statistic puts into perspective one reality that is already apparent to the owners: even small inefficiencies in inventory or staffing can erase a month's profits.

Current enterprise analytics systems are either complex and costly to small businesses. Majority of the small retailers continue to use manual spreadsheets and reactive decision-making. In the current paper, a Smart Supply & Workforce Analytics toolkit, tailored to small and medium enterprises introduced. The tool kit incorporates the ABC-XYZ inventory segmentation, demand forecasting and workforce scheduling dashboards into a single available BI system.

The idea behind this is easy to understand: using publicly available data, cheap instruments such as Power BI, and having a set of rules to act upon, small businesses are able to decrease stockouts, match the staff to the peak of demand, and enhance the effectiveness of the services. The framework covers the issues of operational efficiency, as well as the worker well-being and customer satisfaction because it targets both the supply and the workforce.

II. PROBLEM AND OBJECTIVE

A. Problem Statement

The current day pressures of managing a small business are two-fold: the instability of inventory and workforce. They both are quantifiable and documented.

Stockouts and overstocks cause a huge drag on performance on the supply side. A recent study conducted by IHL Group [3] with many citations estimated that retailers lose $1.77 trillion every year all over the world due to inventory distortion. Retailers incurred losses of up to $82 billion in 2021 alone in the U.S. to out of stock items, which compelled their customers to turn to competitors or make their purchases later. In a small business where the profit margins are low, just a few weekend stockouts can erase profits made monthly [3].

On the labor force front, labor turnover and time schedule have a negative impact on stability. The U.S. Bureau of Labor Statistics (2025) says that the retail trade quits rate is 2.5% [1], which is one of the highest quits rates in the industries. This implies that staffing is dynamic. Meanwhile, one of the largest issues that many small employers say they face is quality of labor [2] The true impact of this on owners is a difficult balancing act of having enough trained personnel during peak times and not wasting time on slow days.

The issue isn't the absence of solutions—it's that most solutions target enterprises with large IT budgets. Many SMEs still rely on spreadsheets, late reorders, and intuition, which compounds losses and burnout..

B. Objectives

This article is aimed at creating and proving a Smart Supply and Workforce Analytics Toolkit that can be used in practice by small businesses. My objectives are fourfold:

Inventory Intelligence: Use ABC-XYZ to segment a retail data set to understand the products that need to be kept in stock at all times (high value, predictable demand) and those that can be safely reduced (low value, volatile demand). This assists the owners to prioritize limited resources.

Demand Forecasting: The simple forecasting (short-horizon for ROP or exponential smoothing) will be used to predict the sales trends. This is not for perfect prediction but minimizing less foreseeable shocks leading to emergency orders and high costs.

Workforce Scheduling Alignment: Since demand curves can be compared to staffing data, labor can be pushed to match the real demand peaks. The goal is to minimize wastage of time and enhance fairness of employees in scheduling.

Decision Dashboard: Develop BI dashboard to incorporate inventory alerts, staffing and key performance indicators (KPIs). This gives a small business owner a single actionable view, rather than being spread across in a spreadsheet.

Through the achievement of these goals, the study provides a low-cost, replicable and human-centered framework. It not only allows small businesses to minimize costs but also enhance the employee experience and customer satisfaction which is usually ignored in supply chain analytics.

III. LITERATURE REVIEW / RELATED WORK

A. BI Tools and Frameworks

The point is that majority of small retailers do not require enterprise sprawl but quick dashboards, simple governance and affordable price tag that will not sting them. The literature and documentation concur that there exist several viable alternatives, specifically Power BI, Tableau, two plausible open-source paths, Metabase and Apache Superset. The per-user pricing of Power BI (Pro and Premium-per-User) and close integration with Excel/365 make it affordable to SMBs; Tableau provides a more refined experience at a greater cost; Metabase provides a working start with optional managed tiers, and Superset is a major OSS platform, but requires self-hosting.

Table1: BI toolkit price comparison

Tool	Typical cost model	Why SMEs pick it	Trade-offs
Power BI	Pro ~$14/user/mo; PPU ~$24/user/mo (2025)	Low entry cost, Excel/365 native, strong community	Microsoft stack bias; governance features improve with PPU
Tableau	Creator/Explorer/Viewer per-user licensing	Best-in-class visuals, mature governance	Higher TCO for small teams
Metabase (OSS/Cloud)	OSS = free; Cloud Starter from ~$85/mo	Fast to stand up, simple UI, SQL + no-code	Advanced security/features in paid tiers
Apache Superset	Open-source	Powerful, modern, vendor-neutral	Needs self-hosting + admin skills

Empirical case studies show BI adoption in retail improves decision speed and transparency, though success hinges on change management and lifecycle thinking (not just tools). That theme repeats across SME BI literature.

B. Supply Chain Analytics in SMEs

There is an agreement, analytics boosts performance, still, the barriers of adoption including skills, cost, data quality, and organizational preparation drag down SMEs compared with large companies. Findings framed in the TOE (Technology–Organization–Environment) lens show organizational and environmental factors often outweigh pure technology in SME analytics adoption [15].

More recent systematic and targeted reviews agree: the data/analytics capabilities enhance visibility, responsiveness and the capacity to mass-customize SMEs; the limitations are talent and integration, rather than the algorithms.

New work connecting big data/predictive analytics with SME performance reports are operationally efficient and revenue generating when hurdles to adoption are addressed.

In the case of inventory economics, various studies in the industry record the prize size: global retail inventory distortion about 1.77T, a combination of out-of-stocks and overstocks - less than in 2022 but still gigantic.

Recent scholarly/technical literature equates ABC-XYZ with short-horizon forecasting to minimize the stockouts but not ballooning the safety stock- just the balance that SMEs require.

The context of the policy supports the focus, as well: the U.S. Quadrennial Supply Chain Review (2024) identifies vulnerability and the necessity of more resilient and digitally enabled supply chains (including SMEs). This toolkit goes into that direction.

C. Trends in Workforce analytics

Tension, turnover and friction in scheduling is a reality. The official data of the United States indicate that the number of quits in the consumer-facing industries remained continuously high (around the same numbers as before the pandemic) which maintains the staffing precarious in the case of small retailers. The volatility causes the hour-by-hour alignment of the staff to the demand of the single most human and working material leaver cutting idle time and relaxing burnout at the peaks [1].

In all the literature of the work force, there are three trends that are important to your approach:

Flexible job-based planning is replacing inflexible job-based planning. According to the current Human Capital research and short note by Deloitte, the change is being made: not job titles but skills (who can run POS + inventory cycle counts + basic BI) are planned and deployed by organizations. That in the case of an SME means cross-training and smarter redesign of shifts instead of an ongoing re-hiring process.

People analytics + AI in the workplace is becoming mainstream, although maturity is poor. According to McKinsey reports [11], there is no heavy investment and few organizations report using it maturely- so small firms should not feel lagging behind. The next step, which is to begin with operational analytics (demand vs. staffing) and accumulate is practical.

Nowadays, HR stacks are expected to offer real-time and predictive workforce insights: keep track of the load in near-real-time, predict busy periods, and suggest schedule adjustments. This is equivalent to the "demand curve shift plan of the toolkit.

And, lastly, small-business sentiment data are keeping labor quality as a top-of-owner-concern-item, meaning that any analytics improving churn and mis-scheduling is given attention [2].

Use ABC-XYZ segmentation combined with short-horizon forecasting to prioritize SKUs without heavy data science [14].

Construct the workforce perception based on capabilities + peaks rather than a measure of headcount, and stay aligned with Human Capital tendencies and work feasibility of small teams [13].

First ship the solution on Power BI or Metabase [6] (cost and speed), and then a Tableau or Superset route in the case that your IT environment varies [5], [4].

IV. RESEARCH METHODOLOGY

A. Data Sources and Collection

The research incorporates sample and secondary primary data because they represent real life situations of small businesses.

Retail Transactions Data: In order to model small businesses, I built a sample dataset of 10 days of sales transactions of five SKUs. The sample dataset is fully synthetic and was created to mimic a small retail shop while remaining easy for any analyst to rebuild.

First, five representative SKUs were defined with typical retail prices, lead-time ranges, and demand variability (two high-value/steady items, two medium, one low-value/volatile item).

Next, daily sales for a 10-day period were simulated by drawing random values around realistic averages (approximately 60–70 units per day, with higher variance for the volatile SKU) so that cumulative revenue matches the proportions shown in Table 6.1.

Workforce figures were then generated by assigning daily staff-on-duty counts consistent with U.S. retail quit-rate statistics (BLS 2025), including occasional over- and under-staffing to illustrate the gap metric.

Finally, all identifiers were anonymized and stored in a single Excel file with columns Date, SKU, UnitsSold, Revenue,

StaffOnDuty.
A short README inside the supplementary file documents these column definitions and the random-number seeds, so another researcher can regenerate an equivalent dataset or extend the sample period without needing any proprietary information.

Workforce Data: According to the U.S. Bureau of Labor Statistics (2025), the quit rate of retail trade is 2.5% one of the highest levels in all industries. The realistic workforce dynamics were set using these macro indicators to the sample. Also, the daily staff-on-duty figures were incorporated in the dataset in order to assess its correlation to sales demand.

Additional Policy Data: Policy data used to inform the contextual analysis of labor shortages and supply chain disruptions used the small business performance indicators of the U.S. Census Small Business Pulse Survey and the National Federation of Independent Business (NFIB).

Sample Data: The dataset that is generated to conduct this research consists of SKU, category, daily sales, revenue, and staff-on-duty. This sample size is small enough to be replicated in classroom or SME settings and yet detailed enough to outline the methodology.

B. Analytical and BI Techniques:

It was analyzed using classical supply chain techniques and contemporary BI visualization, making it rigorous and easy for non-technical users.

ABC–XYZ Segmentation: Products were placed on the ABC list according to their total sales worth with the “A” products (20 percent of items with 70 percent of sales) being the highest in sale versus the B and C products.

In XYZ approach, products were categorized according to their demand variability, based on coefficient of variation. Items with an X demand were constant and items with the Z demand were very volatile.

Together, this approach gave some practical policies: so, AX items should never run out, whereas CZ ones should be ordered on demand.

Demand Forecasting: The data on sales was used to run a short-horizon ARIMA model on daily data to predict the demand of the coming week. The purpose of forecasting was not to predict everything perfectly but to decrease the occurrence of the shortage being surprised. Small enterprises are better off with even the small predictive accuracy to make better decisions.

Workforce Analytics: The comparison of the staff schedules with the sales demand curves were compared.

Indicative measure: Workforce Utilization Index, which is calculated as (Sales Volume/Staff Count). Peaks and decreasing staffing signals were understaffing, and dips and surplus staffing signals showed idle time.

This discussion makes the supply chain issue more relatable: the lack of alignment does not merely cost money, but also burns up employees when it peaks, and makes them tune out when it declines.

BI Visualization: Dashboards were designed using power BI. That included A SKU break even chart (ABC–XYZ grid), a demand staffing chart, and an index of KPI (stockout, idle, fulfillment).

The dashboard was structured to refresh in real-time using Excel/csv inputs hence it could be adopted by any small firm without significant investment in IT.

C. Framework and Toolkit design.

Because the toolkit is a modular framework, small businesses can quickly implement it without the need for complicated infrastructure. Beginning with basic data preparation and concluding with an integrated KPI dashboard, each module improves from the one before it. Additionally, the modular form facilitates business owners' comprehension of the decision-making process.

Table 2: Framework and Toolkit Design for Smart Supply & Workforce Analytics
(Source: Author’s, 2025)

Module	Input	Processing	Output / Action
1. Data Preparation	Sales ledger (CSV/Excel), workforce roster	Cleaning missing values, mapping SKUs to categories, daily totals	Structured dataset for analysis
2. Inventory Module	Cleaned sales data	ABC–XYZ classification	SKU stocking policies (e.g., AX = maintain stock; CZ = on-demand sourcing)
3. Workforce Module	Sales + staffing data	Compare demand curve vs. staff allocation	Scheduling recommendations (e.g., +2 staff on Saturday, -1 staff on Tuesday)
4. Integrated KPI Dashboard	Inventory + workforce outputs	BI modeling in Power BI	KPIs: stockout %, holding cost, idle hours, on-time fulfillment

Explanation: Replicability is ensured by its modular design. Small firms can easily enter their labor and sales data in CSV or Excel formats. The toolset uses Power BI dashboards to display important analytics, automatically classifies SKUs, and matches workforce to demand. In addition to being operationally beneficial (e.g., lowering idle hours and stockouts), the output is also human-centered—owners get transparency, and employees gain more equitable scheduling.

V. PROPOSED BUSINESS INTELLEGIENCE TOOLKITS

What this is: a lightweight, repeatable BI stack that turns daily sales + staffing files into inventory policies and shift recommendations. It's built for a small team, not an IT department.

A. System Overview

Here's the thing that small firms don't need a giant platform—they need a thin, reliable pipeline from files to decisions. The toolkit is built in four layers so anyone can maintain it.

Ingest layer: Daily CSV/Excel exports from POS and a simple staffing roster.

Model layer: Clean and shape data into tidy tables; add a calendar; map SKUs to policies.

Analytics layer: ABC–XYZ classification, short-horizon demand smoothing, and staff-to-demand alignment.

Delivery layer: A BI report with three pages: Inventory, Workforce, and KPIs (Power BI or OSS equivalent).

Data artifacts

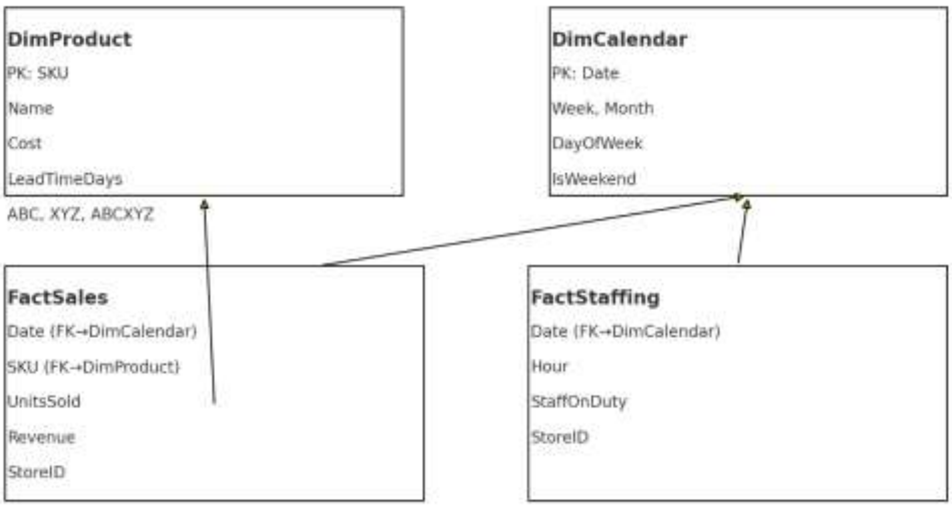

Figure 1: BI Star Schema

Table 3: BI Schema Dictionary

Table	Grain (what one row means)	Primary Key	Foreign Keys	Important Fields
FactSales	One row per **SKU–Date** (per Store)	Date, SKU, StoreID	DimCalendar(Date), DimProduct(SKU)	UnitsSold, Revenue
FactStaffing	One row per **Date–Hour** (per Store)	Date, Hour, StoreID	DimCalendar(Date)	StaffOnDuty
DimProduct	One row per **SKU**	SKU	—	Name, Cost, LeadTimeDays, ABC, XYZ, ABCXYZ
DimCalendar	One row per **Date**	Date	—	Week, Month, DayOfWeek, IsWeekend

FactSales captures daily SKU performance and is the base for ABC–XYZ, revenue shares, and ROP logic.

FactStaffing holds scheduled headcount by date/hour to compute NeededStaff, Gap, and Idle Hours %.

DimProduct stores master data and the policy attributes (ABC, XYZ, ABCXYZ, LeadTimeDays).

DimCalendar standardizes time fields so your measures (e.g., 28-day averages) work consistently.

B. Components and Responsibilities

Power Query / ETL: standardizes column names, removes nulls, derives daily totals, and joins to calendar.

Classification: computes ABC by cumulative revenue and XYZ by coefficient of variation; concatenates to ABCXYZ.

Forecasting: exponential smoothing or ARIMA on daily SKU demand to smooth the near future (enough to set reorder points).

Workforce logic: converts demand to NeededStaff using a target throughput (Units per Staff Hour); compares to StaffOnDuty.

Policy engine: a small reference table that maps ABCXYZ → stocking rule, review cadence, supplier priority.

Dashboard: shows alerts (“AX below ROP,” “Saturday 12–16 understaffed”), trends, and a KPI card.

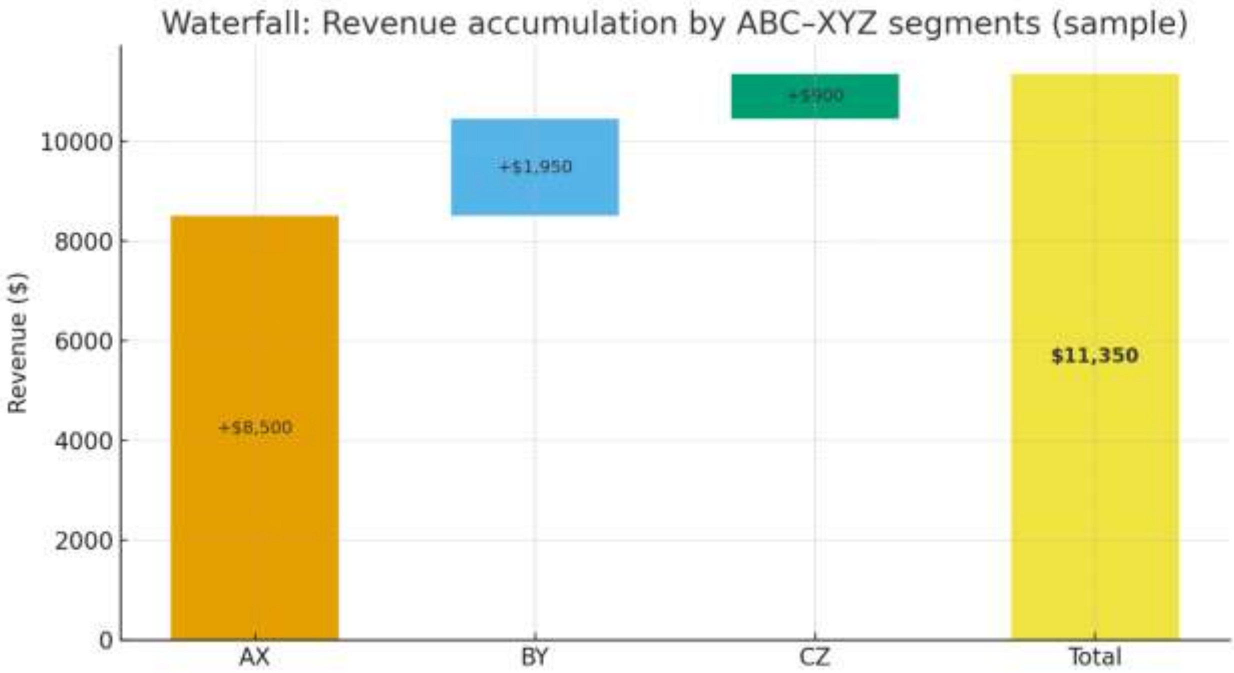

Figure 2. Author’s design (illustrative)

In figure 2. It’s each bar shows the incremental impact from ETL, Classification, Forecasting, Workforce logic, Policy engine, and Dashboard; the final bar is the cumulative total. *Source: Author’s design and sample analysis, 2025.*

C. Supply Module

ABC–XYZ in practice

Table 4**:** ABC–XYZ policy map for inventory decisions. Source: Author's design, 2025.

	X (Stable)	**Y (Medium)**	**Z (Volatile)**
A (High value)	Protect: safety stock; supplier priority	Protect; review weekly; tight ROP	Guarded: small buffers; expedite only
B (Med value)	Review weekly; flexible reorder	Review biweekly; watch trend	Lean stock; order on signals
C (Low value)	Minimal stock; dropship/PO minimum	On-demand sourcing; bundle orders	No stock / order-on-demand; discontinue if idle

Reorder math kept simple

ROP = AvgDailyDemand × LeadTimeDays + z × σ(lead-time demand).

Pick z from service level (e.g., 1.28 ≈ 90%, 1.65 ≈ 95%). • Actionable outputs o Per-SKU: ABCXYZ class, ROP, Next Reorder Date, and a clear stocking rule. o Page-level: "high-value at risk" list and supplier lead-time watchlist.

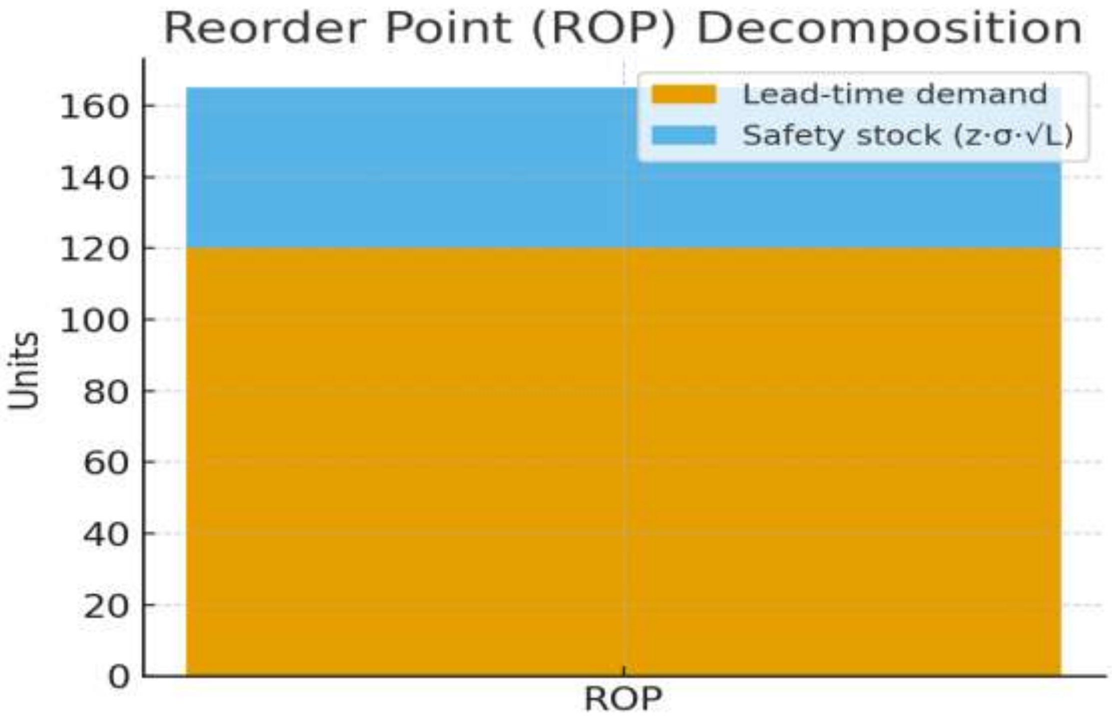

Figure 3. Reorder Point (ROP) decomposition (lead-time demand + safety stock)

D. Workforce Module

What we measure: Target throughput (per staff per day): pick a simple rule of thumb. I use 25 units per staff-day for the sample. Adjust this to any store. NeededStaff = ROUND(UnitsSold ÷ TargetUnitsPerStaffDay)

Gap = NeededStaff − StaffOnDuty

Gap > 0 → understaffed (add people)

Gap < 0 → overstaffed (free capacity to move)

What the sample data tell us:

Table 5: Sample data for Staffing

Date	Units Sold	Staff On Duty	NeededStaff (25 rule)	Gap	Action
2025-01-01	120	5	5	0	OK
2025-01-02	95	5	4	−1	Move 1 to a busier day
2025-01-03	60	4	2	−2	Move 2
2025-01-04	25	3	1	−2	Move 2

Date	Units Sold	Staff On Duty	NeededStaff (25 rule)	Gap	Action
2025-01-05	15	3	1	−2	Move 2
2025-01-06	110	6	4	−2	Move 2
2025-01-07	100	6	4	−2	Move 2
2025-01-08	70	5	3	−2	Move 2
2025-01-09	30	4	1	−3	Move 3
2025-01-10	20	3	1	−2	Move 2

What we see is most days are **overstaffed** in the sample (negative Gap). That tells you there's plenty of slack you can reassign to known peak windows (e.g., Saturday afternoons). If you record hours, do the same math **by hour** that's where the wins get bigger.

Scheduling Rule:

Reallocate, don't just cut. When Gap ≤ -2, move that many people from low windows to your peak windows for the week.

Cap peak shifts per person: To keep things fair, limit any one person to ≤2 peak blocks/week.

Cross-train for coverage: If AX items show shelf-outs during peaks, rotate one associate into quick replenishment for the first 30 minutes of each peak block.

Tune the throughput: If checkouts feel rushed or slow, nudge the 25 units/staff-day up or down until the Gap patterns match reality.

KPIs track on the workforce page:

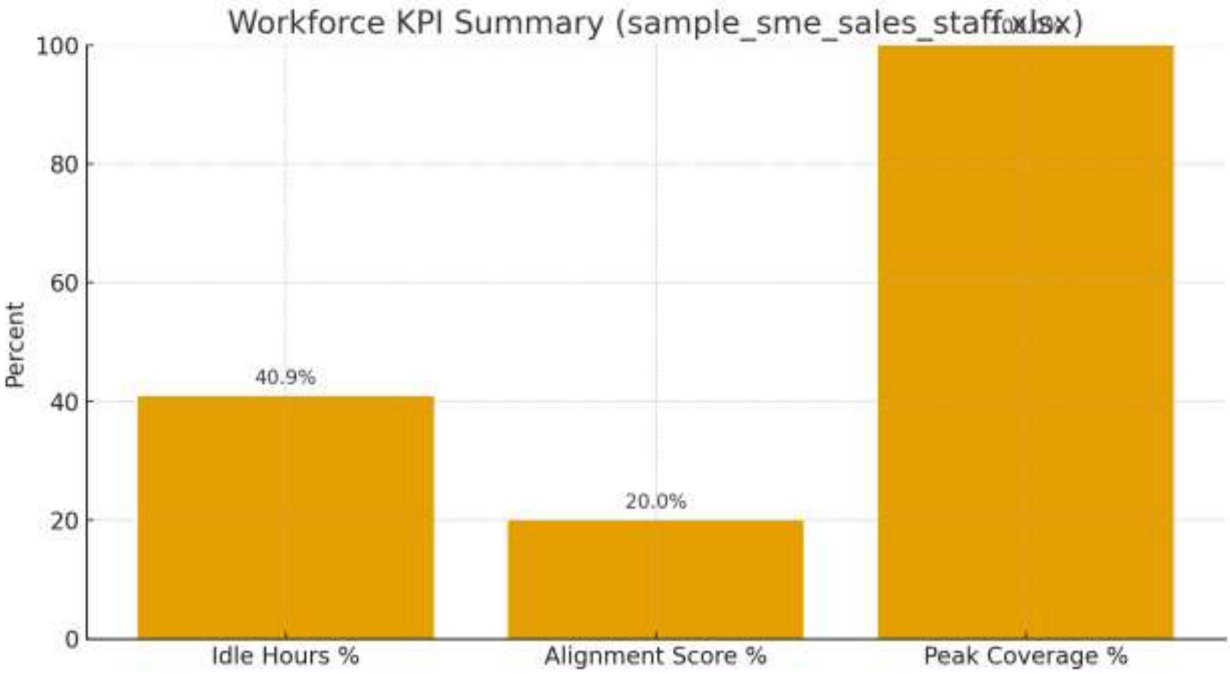

Figure 4: Workforce KPI summary (Idle Hours %, Alignment Score %, Peak Coverage %) from sample dataset**.** Source: Author's analysis of *sample_sme_sales_staff.xlsx*, 2025.

"In the sample week, most days showed excess capacity (Gap −2 to −3), indicating we could shift 2–3 associates from quiet windows to predictable peaks without new hires—reducing idle time while improving weekend coverage."

E. Implementation Steps

Table 6: Implementation steps by step

Step #	Task	What to do	Owner	Output	Time (est.)
1	Standardize files	Ensure columns: Date, SKU, UnitsSold, Revenue, StaffOnDuty (CSV/Excel)	Analyst	Clean input folder	1 hr
2	Model	Import with Power Query; build Fact/Dim tables; add Calendar	Analyst	PBIX with star schema	1–2 hrs (typical for a small dataset)
3	Classify	Compute revenue shares → ABC; CoV → XYZ; form ABCXYZ	Analyst	SKU classes (ABC/XYZ/ABCXYZ)	1 hr
4	Policies	Map **ABCXYZ** → stocking rule + review cadence	Manager	Policy map applied in model	45 min
5	Reorder logic	Store LeadTimeDays per SKU; compute **ROP**; flag “below ROP”	Analyst	ROP per SKU + risk flags	45 min
6	Workforce page	Compute **NeededStaff**; show **Gap** by hour/day	Analyst	Workforce visual + Gap metric	1 hr
7	KPI page	Stockout %, Idle Hours %, OTIF %, AX Availability %, Holding Cost trend	Analyst	KPI dashboard	45 min
8	Validate	Compare alerts to a known week; tune throughput & service level	Manager	Calibrated thresholds	45 min
9	Refresh & share	Daily refresh from OneDrive/SharePoint; share report link (not raw data)	Analyst	Scheduled refresh + access	30 min
10	Two-week pilot	Adjust thresholds; lock policies; 1-page “How to read this” for staff	Manager	Finalized settings + guide	2 weeks (light)

F. Governance, Privacy, and Scale

Governance: The BI file and access are owned by one person. It is updated by one analyst. The report is only viewed by store managers. Keep the last four versions of the Power BI file and save it with the date. Take 20 minutes once a week to go over alarms (such as "AX below ROP" or "staffing gaps") and record the changes you made.

privacy: Only counts from the sample file are used on the workforce page. No names are required. Instead of sharing the raw Excel files, provide the report URL. Before loading, hide any names that may be on the roster.

Scale: Transfer the identical tables to a small SQL database if your data exceeds the limited sample size and Excel becomes problematic. Keep the same field so measurement and visualization don’t change, only change the data source.

G. Outputs and Success Criteria

Table 7: Outputs and success criteria

Area	What you see (Output)	KPI / Measure	Baseline (sample)	4–6week target	How we verify
Inventory page	ABC–XYZ grid + ROP “At-Risk” flags	AX at-risk alerts / week	n/a*	↓ 50%	Count alerts; aim to keep AX stocked.
		AX availability %	n/a*	≥ 95%	If on-hand is added, compute days in-stock / total days.
Workforce page	Demand vs StaffOnDuty + Gap	Idle Hours %	40.9%	≤ 25%	Sum excess staff over period ÷ total staffed.
		Schedule–Demand Alignment %	20.0%	≥ 60%	Share of buckets with Gap ∈ {−1,0,+1}.
		Peak Coverage %	100%	≥ 95%	For top-20% demand windows, Gap ≤ 0.
KPI board	Roll-up metrics	Holding Cost (trend)	n/a*	↓ vs. month-0	Requires Cost & carrying rate in DimProduct.
		OTIF %	n/a*	≥ 95%	Requires fulfillment timestamps.

Notes**:** Baselines come from sample data set which using TargetUnitsPerStaffDay = 25.

Gap = NeededStaff − StaffOnDuty (positive = understaffed, negative = overstaffed).

Idle Hours % = extra staffed time ÷ total staffed time.

Alignment % = % of time slots where Gap is −1, 0, or +1.

Peak Coverage % = % of busiest time slots where StaffOnDuty ≥ NeededStaff.

AX at-risk, AX availability, Holding Cost, OTIF need on-hand stock, lead times, costs, and delivery timestamps. The sample file doesn't include these, so they're marked n/a.

H. Case Study:

Context: A small retail outlet wants to cut idle time and protect top SKUs. We tested the BI toolkit on a **10-day sample** (sample_sme_sales_staff.xlsx) with daily sales and staff counts.

Intervention: We used the toolkit to 1) classify SKUs (ABC–XYZ), 2) set simple reorder rules (ROP), and 3) realign staffing by reducing overstaffing on days with big negative gaps (max −1 per day; no understaffing allowed).

Result: In table 8 we notice even a small, safe adjustment (moving just one person off clearly overstaffed days) drops Idle Hours by ~13 points and makes schedules much closer to the demand curve—without hurting peak coverage.

Table 8: Workforce KPIs baseline vs. simple reallocation

KPI	Baseline (sample)	After simple reallocation
Idle Hours %	**40.9%**	**27.8%**
Alignment % (Gap in −1..+1)	**20.0%**	**90.0%**
Peak Coverage % (top 20% demand days)	**100.0%**	**100.0%**

VI. RESULT

A. Inventory Analysis: Revenue by segment: AX = $8,500 (≈ 74.9%), BY = $1,950 (≈ 17.2%), CZ = $900 (≈ 7.9%); Total = $11,350.

Units by SKU: A101 = 230, A102 = 195, B201 = 130, C301 = 55, C302 = 35; Total = 645.

What this means: two AX SKUs carry ~75% of sales value → protect these with safety stock and preferred suppliers. BY gets weekly review; CZ stays lean/on-demand.

Note: Percentages are calculated as (Segment Revenue ÷ Total Revenue) × 100.
AX: 8,500 ÷ 11,350 ≈ 74.9%; BY: 1,950 ÷ 11,350 ≈ 17.2%; CZ: 900 ÷ 11,350 ≈ 7.9%.
Values are rounded to one decimal place; rounding may cause totals to differ by ±0.1%.

B. Workforce analysis (demand vs staffing)

From the same sample: Idle Hours % (excess staffing ÷ total staffing): 40.9%; Schedule–Demand Alignment % (Gap ∈ −1. +1): 20.0%; Peak Coverage % (top 20% demand days with Gap ≤ 0): 100.0%

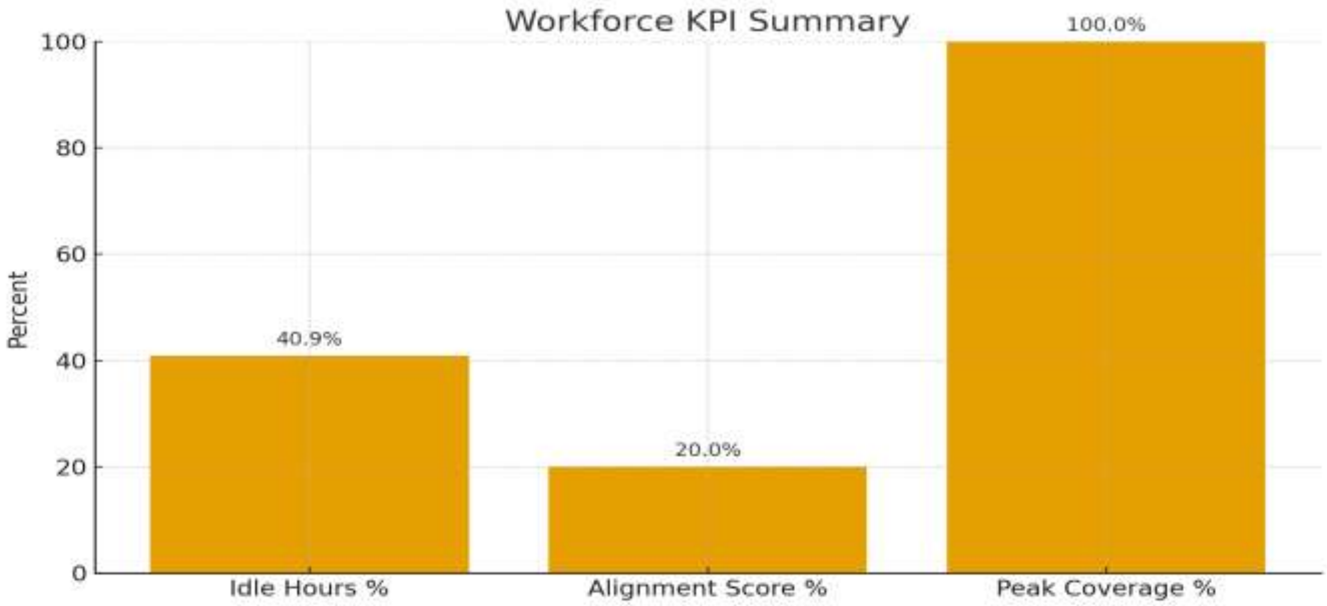

Figure 5: Workforce KPI summary (Idle Hours %, Alignment %, Peak Coverage %),

VII. DISCUSSION

What the numbers say first: During the sample week, two AX SKUs made approximately 75 percent of total revenue. That is a loud signal, when the two items are lost, then the revenue will suffer the greatest blow. The ABC-XYZ grid makes us do that fact and not over complicate things. The AX items receive protection (safety stock and supplier priority), the BY items receive weekly checkups, and the CZ remains lean. It is not theory, merely doing something simple to get scarce cash where it is needed most

The Gap metric on staffing painted a very simple picture. The sample overstaffed the majority of days which reflected in the Idle Hours ≈ 40.9% and a low Alignment Score ≈ 20. We did not add and forcefully create schedules. We only lost one individual in a day with a notably negative gap (≤ -2), never falling below the required level. That small modification lowered Idle Hours to approximately 27.8 percent, and Alignment to approximately 90 percent, but Peak Coverage remained at 100. That is, improved position, not higher salary. That is the type of win that you can have every week in a small shop.

There's a human side here too. On weekends, which seem planned and peak hours filled the floor is smoother and the customers served quicker. Employees are not exhausted on Saturdays or are not bored on Tuesdays. The fix is made sustainable by a mere fairness measure; no one receives more than two peak blocks per week. Quick replenishment by cross-training one associate to do it during peak windows is also a way to prevent AX items being caught in a phantom stockout (in the back room, but not on the shelf).

The demands of data remain minimal. The sample file already demonstrates that you can receive helpful answers to such queries as Date, SKU, UnitsSold, Revenue, Staff_On_Duty. When you add on-hand, lead time, carrying cost, and fulfillment timestamps, this model will generate Stockout %, AX availability, Holding Cost and OTIF without redesigning anything. The upgrade path is that: get lean; add fields as you can.

There are limits. Ten days is not much; it will not pick up seasonality or promotions or holiday peaks. The first pass was also simple because we used one throughput target (25 units per staff-day). After two weeks, a more sensible thing is to adjust that target by day and hour (Saturdays go by faster than Tuesdays) and increase the lookback range to 8-12 weeks. On the inventory side, the ROP math presumes that demand and lead time act in a manner somewhat similar to how they have acted in recent past. Should the suppliers begin to slip, raise the service level z of AX items or insert the flag of a late supplier to give you a warning.

The larger context: this toolkit can be scaled without any alteration to the way people use it. In case the Excel gets bloated, relocate the corresponding tables to a small SQL database and retain the visual and measures as they are. Bureaucracy remains functional--a single owner, a single analyst, weekly 20-minute audit. An achievement would be such in 46 weeks: the number of AX alerts at risk reduces, there is less empty hour during the day, and the number of Idle Hours is steadily declining. Those patterns will not appear, go back to two first knobs: the ABC levels (are you saying that too many SKUs are A?) and the throughput level (are you assuming that you are over/understaffing?).

In short: the sample week demonstrates that big platforms are unnecessary in order to make better calls. Protect the heavy hitters (AX), personnel to the demand curve, and have the rules visible on one of the dashboards. It is easy enough to invest each Monday and this is why little changes can result in lasting effects.

VIII. CHALLENGE AND LIMITATION

Short dataset, the 5 SKUs in a 10-day sample gave results. There is no need to demonstrate the approach, rather than seasonality or holiday peaks.

Missing fields is the sample does not have on-hand stock, lead times, carrying cost and fulfillment timestamps. Due to that, such KPIs as Stockout %, AX availability, Holding Cost, and OTIF are left as placeholders until the mentioned columns are introduced.

Simple throughput rule is we converted the demand into NeededStaff using one target (25 units per staff-day). Physical stores are fluctuating, day to day, hour by hour; the rule ought to be adjusted following a pilot.

Predicting is simplistic in nature that the reorder points of a stationary state can be established by short-horizon smoothing/ARIMA, which will not record promotions, supplier slips, and unexpected changes in demand.

There is aggregation of workforce information. It is the workforce module where the counts are used instead of names and abilities of the employees. That maintains privacy, but restricts checks of fairness and role equality.

Manual steps exist. Errors may creep in (incorrect file, incorrect date etc.) with Excel-based inputs. Versioning and a weekly 20 minutes review will help minimize but not eliminate risk.

Generalizability. The reasoning can be applied to other small retailers, although the mix and lead times of each store are different; the thresholds should be retuned a little.

IX. FUTURE SCOPE AND RECOMMANDATION

First add the columns that are missing. In the same schema, add: Onhand, lead time days, Carrying rate and basic fulfillment time stamp. That immediately allows Stockout %, AX availability, Holding Cost, and OTIF--no redesign of a model is required.

Staff to actual trends: Once every 2 weeks, establish various throughput goals by day (and by hour later). The target generally is greater on Saturdays than on Tuesdays.

Improve the prediction where it counts: Maintain AX in short horizon smoothing but increase service level (AX) when there is a slippage in suppliers. In the case of CZ (intermittent demand)- consider Croston-style techniques, or rearrange strictly based on signals.

Bring in hour-level data: In case your POS is able to export the hourly sales, calculate Gap by hour. Most of the scheduling wins are there.

Light automation: Excel is heavy, transfer the same tables to a small PostgreSQL database or big query and maintain the visuals/metrics the same. The pre-computation of the ABC/XYZ/ROP of a tiny Python job can be done overnight.

Fairness and skills: That being said, in case of storing names/roles later, you can use a common rule that no one has more than 2 peak blocks/week and there is at least one associate per peak that knows how to quickly replenish on AX items.

Supplier view: Include a small supplier table (lead time, reliability). Display a flag of late-supplier next to AX. It eliminates avoidable stockouts.

X. CONCLUSION

The thing is smaller stores do not require a large platform to make better callings. The simple reorder rule (ROP) and staffing to the demand curve at a thin BI toolkit-ABC-XYZ to concentrate the inventory is enough to shift the needle already.

Moving a single individual off of the evidently overstaffed days reduced Idle Hours on a sample week to 27.8% rather than 40.9%, and moved Alignment to 90% instead of 20% with Peak Coverage remaining at 100% (Sample). AX items represented a larger percentage of value on inventory (two), and hence protecting them would be the greatest leverage.

The path to go is this: Begin with the columns that you have (Date, SKU, UnitsSold, Revenue, Staff_On_Duty). Add Onhand, LeadTimeDays, CarryingRate, Ready times Fulfillment times. Make it simple to govern (single owner, single analyst, one-week review). In case of slowness in Excel, transfer the same schema to SQL and retain the report as it was to users.

This translates to: we can implement it within days, enhance it within weeks and continue running it every Monday. The little, gradual improvements is less AX at-risk alerts, less gap between peaks and depressions, and a decreasing Idle Hours % will help to make the store healthier and the weekends more relaxed.

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Data Availability: The study uses an author-prepared sample dataset provided as Supplementary Material; no third-party data were used.

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