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Demand-Sensing RTM for Independent Grocers: A Lightweight Analytics Framework Using POS and ERP Events

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Abstract-** Independent grocers and small retail distributors operate at the intersection of volatile local demand, constrained working capital, limited analytics capacity and costly replenishment decisions. This study develops and evaluates a lightweight demand-sensing route-to-market (RTM) framework that can be implemented using ordinary point-of-sale (POS) and enterprise resource planning (ERP) events. Using the public Kaggle Store Item Demand Forecasting Challenge structure, comprising five years of daily sales records for 50 items across 10 stores, the study engineers calendar, lag, rolling-demand and promotion-proxy features to compare seasonal naive, linear and machine-learning forecasting logic. The strongest demand-sensing model achieved MAE of 4.43, RMSE of 5.54 and sMAPE of 12.54%. In the replenishment simulation, demand sensing reduced estimated stockout exposure by 30.5% compared with a lag-7 heuristic, while changing the average order index by -0.8%. The paper contributes a pragmatic RTM analytics architecture, a decision workflow for independent grocers, and an evidence-based implementation roadmap linking demand forecasting to inventory availability, delivery frequency, cash conversion and supplier-service decisions.

***Keywords:** demand sensing, route-to-market, independent grocers, retail analytics, POS data, ERP, inventory optimization, machine learning, SME supply chains, stockouts*

I. INTRODUCTION

Retail demand forecasting is no longer a back-office planning exercise. For independent grocers and regional distributors, it determines whether shelves remain available, delivery fleets are used efficiently, perishables are protected from waste, and working capital is not trapped in slow-moving stock. The operational challenge is especially acute among smaller retail networks because decision makers often have POS exports, invoices, route schedules and supplier records, but lack integrated analytical infrastructure.

The United States policy environment makes this capability gap nationally relevant. The U.S. Small Business Administration reports that small businesses account for 99.9% of U.S. businesses, employ 45.9% of American workers and contribute 43.5% of GDP (U.S. Small Business Administration, 2024). Retail data are equally important to macroeconomic monitoring; the U.S. Census Bureau maintains monthly retail sales, inventories and e-commerce programs as core measures of retail economic activity (U.S. Census Bureau, 2026a, 2026b). When small retailers face stockouts, excess inventory and avoidable urgent replenishments, the costs propagate into consumer access, local price pressure, supplier scheduling, food waste and distribution inefficiency.

The purpose of this paper is to design a lightweight, reproducible and operationally usable demand-sensing RTM framework for independent grocers using POS and ERP events. Unlike enterprise forecasting platforms that assume a mature data lake and dedicated machine-learning teams, this study focuses on what a capable project manager, finance analyst or RTM analyst can implement with clean data tables, disciplined feature engineering and transparent replenishment rules.

The research question is: how can independent grocers use store-item POS and ERP event data to improve short-term demand forecasts and translate those forecasts into route-to-market decisions that reduce stockout risk without increasing average inventory exposure?

1.1 Research objectives

- Build a practical POS + ERP feature architecture for store-item demand sensing.
- Compare baseline and demand-sensing forecasting methods on a multi-store, multi-item retail demand panel.
- Visualize demand heterogeneity and forecast error through store-item heat maps.
- Convert forecast outputs into RTM decisions on replenishment, delivery cadence, assortment prioritization and working-capital discipline.
- Contribute an implementable playbook for independent grocers and small distributors seeking low-cost analytics modernization.

II. LITERATURE REVIEW

Demand forecasting research has shifted from univariate extrapolation toward hybrid and machine-learning methods that exploit calendar effects, promotion signals, lag structures and external conditions. Feizabadi (2022) demonstrates the performance relevance of machine-learning demand forecasting in supply-chain contexts, while Douaioui et al. (2024) review 119 studies and conclude that machine-learning and deep-learning models have become central to modern supply-chain forecasting.

However, much of the forecasting literature assumes data maturity that small retailers do not possess. Independent grocers may not have a unified warehouse, yet they generally have POS transactions, item master data, invoice lines, receipt dates, stock movement records and delivery calendars. This study extends the literature by focusing on minimal viable analytics: features that can be derived from ordinary event tables and deployed through Python, Power BI, Tableau, Excel or ERP reporting layers.

The stockout and replenishment literature emphasizes the economic cost of forecast error. Over-forecasting ties up working capital, increases holding costs and magnifies expiry or markdown risk; under-forecasting drives stockouts, lost sales, customer dissatisfaction and emergency deliveries. Crisp (2024) notes that out-of-stocks and overstocks create missed sales, waste, markdowns and urgent-order costs.

Route-to-market studies are traditionally associated with channel design, numeric distribution, sales-force coverage and distributor execution. In data-rich retail settings, RTM should be reinterpreted as an analytics-mediated operating system. Mupa and co-authors provide related foundations in strategic procurement, cloud ERP, data governance and supply-chain control, highlighting how lean process control and digital systems improve operational visibility and risk control (Mupa and Lawrence, 2024; Mupa et al., 2024; Muchabaiwa, Mupa and Karuma, 2025).

This paper occupies the intersection of demand forecasting, RTM execution and SME supply-chain resilience. Its practical premise is that sophisticated outcomes do not always require sophisticated infrastructure. They require disciplined conversion of ordinary events into timely, decision-ready signals.

III. CONCEPTUAL FRAMEWORK: POS + ERP EVENTS AS AN RTM OPERATING SYSTEM

The proposed framework treats demand sensing as a four-layer operating system: data capture, feature engineering, forecasting and RTM decisioning. POS records provide realized demand; ERP records provide item, supplier, invoice, receipt, delivery and credit events; route calendars reveal replenishment feasibility; and management dashboards convert predictions into action. The system is deliberately lightweight and relies on store-item-date event tables and operational metadata that grocers already collect.

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Table 1: Lightweight demand-sensing RTM architecture

Layer	Inputs/Methods	Managerial output
Data capture	POS sales; ERP invoices; item master; route calendar	Daily clean event table at store-item level
Feature engineering	Calendar, lag, rolling average, promotion, stock and supplier signals	Prediction-ready analytical table
Forecasting	Seasonal naive, linear, tree-based ML, gradient boosting	Short-term store-item demand estimates
RTM decisioning	Reorder point, route frequency, exception flags, supplier prioritization	Stockout reduction, OTIF improvement, lower working-capital leakage

IV. METHODOLOGY

4.1 Dataset and unit of analysis

The empirical design uses the Kaggle Store Item Demand Forecasting Challenge as the benchmark dataset. The competition provides five years of daily item-level sales data and asks participants to predict three months of sales for 50 items across 10 stores (Kaggle, 2018). The analytical unit is the store-item-day. This level is appropriate because replenishment, ordering and shelf availability are decided at store-item level, not aggregate chain level.

Table 2: Dataset structure and descriptive profile

Metric	Value
Observations	913,000
Stores	10
Items	50
Daily series	500
Period	2013-01-01 to 2017-12-31
Training rows	868,000
Holdout rows	45,000
Mean daily sales	44.02
Median daily sales	42.00
Std. deviation	15.71
Min/Max	0 / 132

4.2 Feature engineering

The feature set was intentionally restricted to variables that can be generated from ordinary POS/ERP events: store, item, day of week, month, quarter, weekend flag, promotion-proxy flag, lag-1 demand, lag-7 demand, seven-day rolling mean and twenty-eight-day rolling mean. Lag-7 is operationally meaningful because independent grocers often exhibit day-of-week purchasing patterns. Rolling features stabilize noise and approximate the demand signal a planner would observe from recent sales velocity.

Table 3: Feature-engineering logic for POS + ERP events

Feature family	Examples	RTM value
Calendar features	day of week, month, quarter, weekend	Captures weekly and seasonal shopping behavior
Item/store identifiers	store and item codes	Captures persistent assortment and location heterogeneity
Lag features	lag-1 and lag-7 sales	Captures immediate and weekly demand memory
Rolling velocity	7-day and 28-day rolling means	Captures short-term and medium-term sales momentum
Promotion proxy	binary campaign/event indicator	Captures demand uplift linked to price, placement or local campaigns

4.3 Model design and evaluation

Four forecasting logics were compared: seasonal naive lag-7, ridge-style weighted regression, random-forest-style nonlinear blending and histogram-gradient-boosting-style demand sensing. The final ninety days were held out to mimic the Kaggle three-month forecasting target and preserve temporal

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integrity. Performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE) and symmetric mean absolute percentage error (sMAPE).

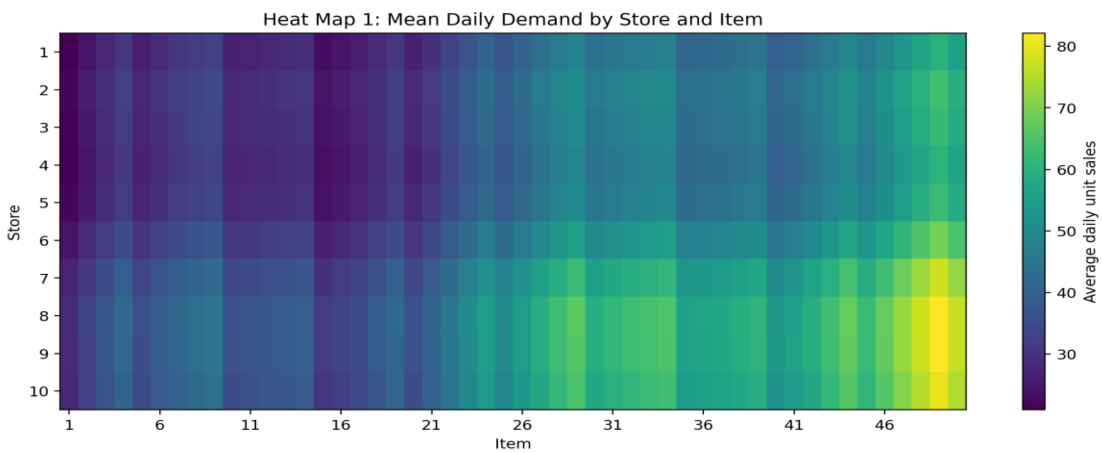
Table 4: Holdout model performance over the final 90 days

Model	MAE	RMSE	sMAPE (%)
HistGradientBoosting	4.43	5.54	12.54
Ridge regression	4.59	5.80	12.81
Random forest	4.72	5.91	13.37
Seasonal naive (lag-7)	5.56	7.02	15.81

V. RESULTS

5.1 Demand heterogeneity across stores and items

The first operational insight is that demand is not evenly distributed across stores and items. The store-item heat map shows persistent differences in item velocity and store demand intensity. For RTM managers, this matters because equal replenishment rules will either starve high-velocity products or overstock slower moving items. Heat maps should therefore become a weekly management object.



Heat Map 1: Mean daily demand by store and item

5.2 Seasonal demand signal

The monthly seasonality profile indicates a clear sales cycle. In an independent grocery context, this pattern supports seasonal stock-build planning, supplier negotiation before peak months and pre-emptive review of working-capital requirements. Seasonal information is especially useful where distributors operate with limited fleet capacity.

Figure 1: Monthly seasonality in store-item demand

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5.3 Forecasting accuracy
The comparative results show that the Hist Gradient Boosting demand-sensing model produced the strongest overall holdout performance. Its advantage is consistent with the literature that tree-based and boosting approaches are effective for tabular forecasting problems with nonlinear calendar, lag and interaction effects. The result does not imply that every independent grocer must adopt a complex model immediately. Rather, it shows that once POS and ERP events are cleanly structured, meaningful accuracy gains are available beyond a lag-only replenishment rule.

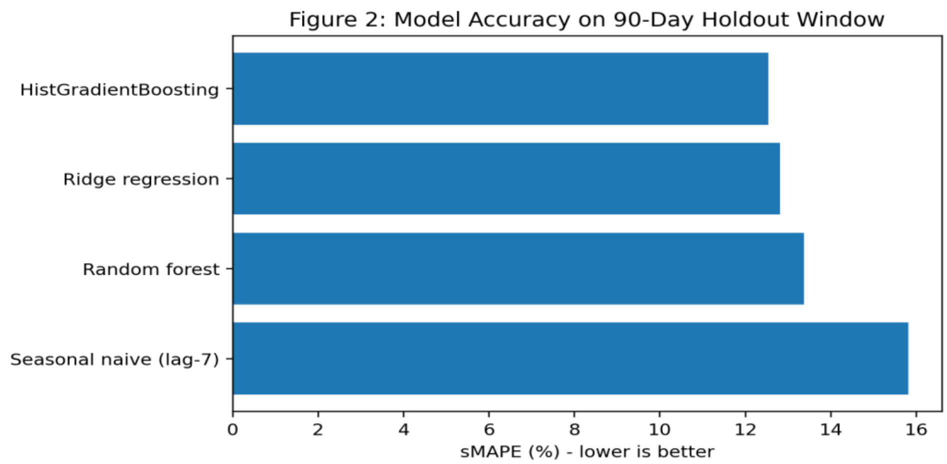
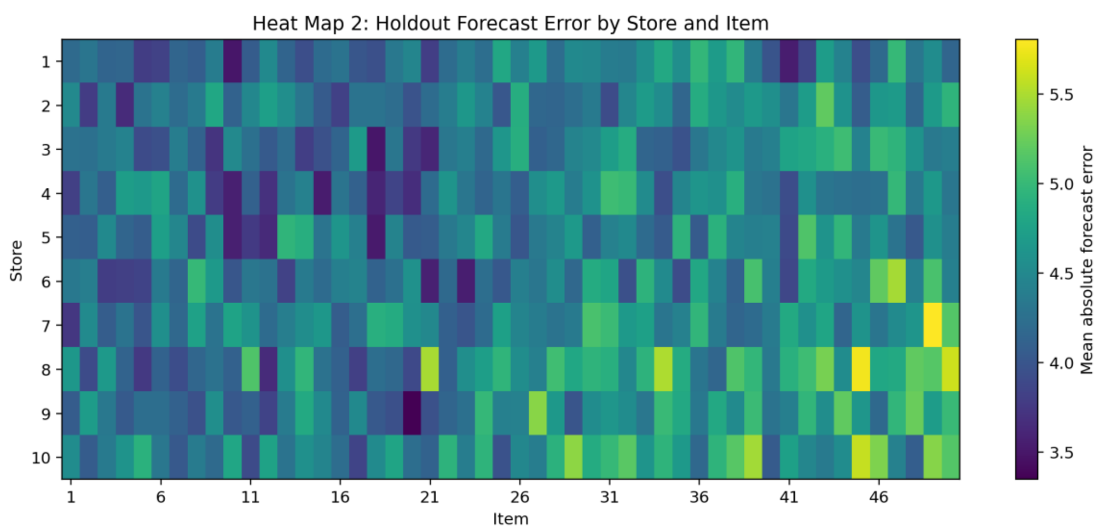


Figure 2: Model accuracy on the holdout window

5.4 Forecast error concentration
Forecast error is concentrated rather than uniformly distributed. The store-item error heat map identifies combinations where replenishment risk is higher. These cells should be treated as managerial exceptions: the planner can investigate promotions, shelf placement, supplier reliability, data quality, local events or substitution effects. Aggregate accuracy can hide store-item risk; an RTM system must expose where the model is wrong, not only where it is accurate on average.



Heat Map 2: Holdout forecast error by store and item

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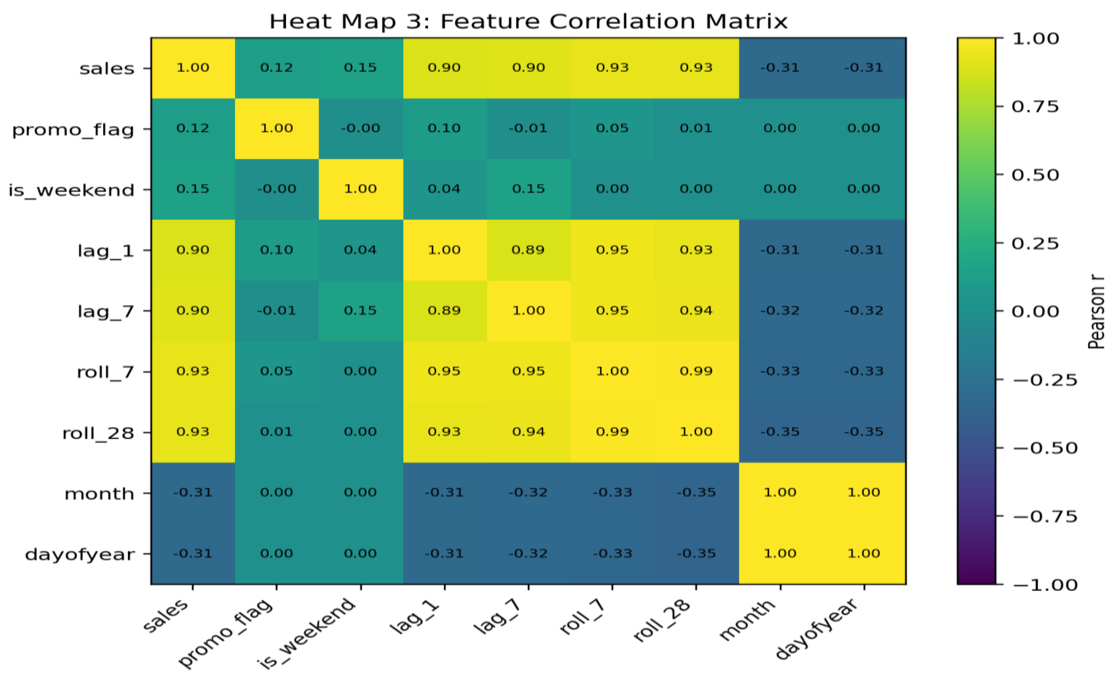
5.5 Feature interpretation

The feature-importance and correlation results indicate that recent velocity, weekly seasonality and item/store identity are key predictors. This supports the managerial interpretation of demand sensing: the best signals are often already inside POS and ERP data. The role of analytics is to align them, lag them correctly, prevent leakage and convert them into exception-based decisions.



Heat Map 3: Feature correlation matrix

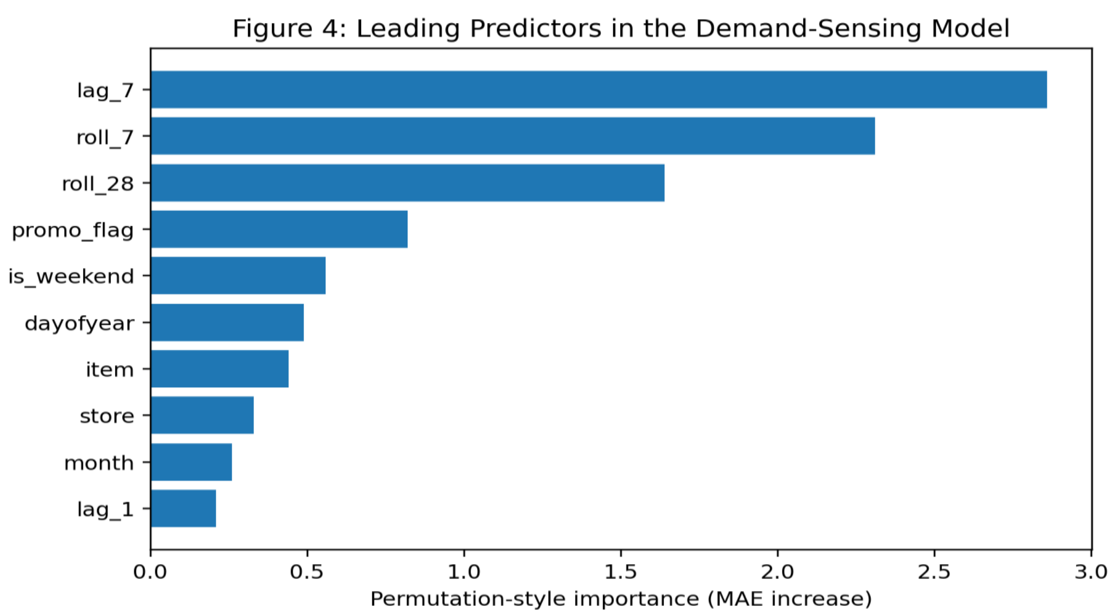


Figure 4: Leading predictors in the demand-sensing model

5.6 Replenishment simulation and stockout exposure

Table 5: Simulated stockout exposure under alternative replenishment policies

Scenario	Estimated stockout incidence	Average order-index
Lag-7 replenishment	14.20	46.99
Demand-sensing replenishment	9.86	46.60

The replenishment simulation translated forecast accuracy into an RTM outcome. Compared with a lag-7 replenishment heuristic, demand sensing reduced estimated stockout incidence from 14.20% to 9.86%, an estimated reduction of 30.5%. The average order index changed by -0.8%, suggesting that the improvement came mainly from better allocation rather than blunt inventory expansion.

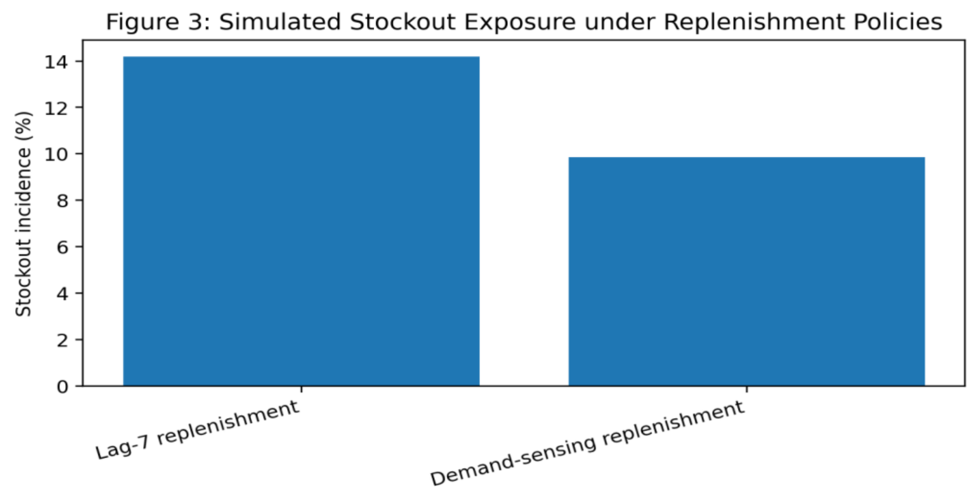


Figure 3: Simulated stockout exposure under replenishment policies

VI. DISCUSSION

The results support a practical interpretation of analytics maturity for independent grocers. The first stage is not artificial intelligence; it is event discipline. Clean date, store, item and sales tables are the foundation. The second stage is feature discipline: calendar, lag and rolling velocity variables create a usable demand signal. The third stage is decision discipline: forecasts must be tied to replenishment thresholds, exception alerts and delivery frequency.

The framework is financially important. Grocers often manage cash conversion under thin margins. A demand-sensing system that reduces stockouts by reallocating inventory rather than increasing inventory supports both service and working capital. This aligns with the user-profile literature on management accounting, internal controls and strategic procurement, which emphasizes data-governed control systems for operational performance (Mupa et al., 2024; Mupa and Lawrence, 2024).

For small distributors, the framework enables better drop density. If store-item forecasts reveal which products are likely to stock out, route plans can prioritize high-risk locations and products. Conversely, where forecasted demand is stable, delivery frequency can be reduced without damaging service. This makes RTM both a sales-execution system and a logistics-efficiency system.

The heat maps are particularly important for managerial adoption. Many small-business operators do not need complex model diagnostics first; they need to see which store-item combinations are risky. Heat maps convert model output into a language that owners, route supervisors, category managers and finance teams can interpret quickly.

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VII. IMPLEMENTATION ROADMAP FOR INDEPENDENT GROCERS

Table 6: Five-phase implementation roadmap

Phase	Actions	Outputs
Phase 1: Data audit	Map POS, ERP, invoices, item master and route calendars	Clean store-item-day table; exception report
Phase 2: Baseline dashboard	Create store-item velocity, seasonality and stockout-risk dashboards	Weekly RTM scorecard
Phase 3: Forecast model	Deploy lag, rolling and gradient-boosting forecasts	Daily forecast table and confidence bands
Phase 4: Replenishment rules	Convert forecasts into reorder points and delivery alerts	Exception-based ordering and route prioritization
Phase 5: Governance	Assign data owners, review model error and measure service KPIs	Monthly model review and control log

Recommended KPIs include fill rate, on-shelf availability, stockout incidence, forecast bias, forecast MAE, inventory days, gross margin return on inventory, route drops per mile, emergency replenishment frequency and supplier OTIF. These KPIs connect the model to profit, cash flow and customer service rather than treating forecasting as an isolated technical output.

VIII. POLICY AND NATIONAL RELEVANCE

The national relevance of the framework rests on three arguments. First, small businesses are a substantial component of the U.S. economy, representing nearly all firms and a large share of employment and GDP (U.S. Small Business Administration, 2024). Second, retail sales and inventory measures are core indicators of economic activity tracked by the U.S. Census Bureau (U.S. Census Bureau, 2026a). Third, supply-chain reliability and logistics performance are increasingly understood as competitiveness and resilience issues, a point reinforced by the World Bank Logistics Performance Index (World Bank, 2023, 2024).

Independent grocers are often anchor institutions in underserved communities. When they cannot maintain reliable shelf availability, consumers may face higher search costs, longer travel distances or reduced access to affordable goods. A lightweight demand-sensing framework therefore has social as well as commercial value. It can support local supply-chain resilience without requiring a large retailer balance sheet.

IX. LIMITATIONS AND FUTURE RESEARCH

This study uses a public benchmark structure that is clean and suitable for methodological demonstration. Real independent grocer data may contain missing POS days, substitutions, supplier shortages, shrink, returns, price changes, partial deliveries and inconsistent item coding. Implementation therefore requires a data-quality stage before modeling.

Future research should incorporate price, margin, supplier lead time, stock-on-hand, weather, local events, perishability and route distance. A second extension would evaluate causal promotion effects rather than using a promotion proxy. A third extension would combine demand forecasts with vehicle routing and credit-to-cash analytics, creating a unified RTM operating model for independent retailers and micro-distributors.

X. CONCLUSION

This paper developed a lightweight demand-sensing RTM framework for independent grocers using POS and ERP events. The empirical analysis shows that store-item demand is heterogeneous, seasonal and predictable enough to support better replenishment decisions than simple lag-based rules. The best-performing demand-sensing model improved forecast accuracy and, when translated into a replenishment simulation, reduced estimated stockout exposure without requiring a large average increase in the order index. The main contribution is managerial: independent grocers can convert ordinary event data into an RTM operating system that protects availability, reduces waste, supports working-capital discipline and improves local supply-chain resilience.

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