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Smart Demand Sensing Cloud AI for Retail Inventory Optimization

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Abstract

Demand sensing is the practice of using real-time or near-real-time information to understand customer demand variations and to take action commensurate with the temporal nature of those changes. The objective is to be responsive to real-time demand signals and address the variations within the overall demand trend. Demand sensing can bring significant benefits to the supply chain and support key processes such as inventory management and planning. In the context of retail, it is particularly useful for managing perishables and fashion goods.

Although demand sensing and forecasting are distinct, they are complementary. Forecasting is typically focused on the longer-term view, while demand sensing emphasizes real-time signals. Demand sensing is limited by the availability of real-time signals, and their freshness, quality and relevance also need to be considered. A fresh real-time signal is imperative to make reliable, short-term adjustments.However, a signal with a high volume and frequency can result in noise and unnecessary response. High-velocity data arrives at high speed into Data Lakes. Time-sensitive decisions must be based on these transient signals.

Keywords: Demand Sensing, Real Time, Demand Forecasting, Supply Chain, Inventory Management, Retail Analytics, Perishables, Fashion Retail, Data Signals, Data Freshness, Data Quality, Data Relevance, Signal Processing, Noise Reduction, High Velocity, Data Lakes, Short Term, Decision Making, Demand Variations, Supply Planning.

1. Introduction

Demand Sensing is a new paradigm in supply chain management. Real-time demand data improve inventory control and reduce stockouts. Cloud platforms provide AI tools to analyze demand signals and optimize inventory levels. Demand Sensing and AI-based inventory management cut stockouts, excess inventories, and costs.

Demand Sensing is a new approach to inventory management that uses real-time demand signals and AI to improve inventory optimization. Retail stores tend to have fast-moving goods

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with short lifecycles. Any demand deviation, whether actual or forecasted, must be monitored and managed continuously to avoid stockouts, excess inventories, or wastage. Such deviations are best managed by accessing, analyzing, and utilizing real-time signals such as footfall in the store, weather, local events, promotions, and customers' online activities. The integration of cloud computing and artificial intelligence provides a cost-effective solution by allowing access to various data streams, such as historic store and product performance, social media, macroeconomic indicators, and suppliers, to continuously sense demand and optimize inventory levels.

Demand Sensing, however, is not the same as demand forecasting. While demand forecasting predicts future demand based on historic demand patterns, demand sensing continuously monitors demand signals and adjusts inventory levels for product categories with short lifecycles in order to optimize stock and minimize potential wastage. Making the distinction clearer requires an understanding of a few key concepts: real-time signals, data freshness, signal quality, aggregation, delay, and latency.

2. Fundamentals of Demand Sensing

Demand sensing is a data-driven approach that uses real-time information to detect and interpret actual consumption patterns. Properly applied, demand sensing minimizes forecasting errors and improves merchandising effectiveness, especially for fresh products and promotional items. Demand sensing differs from demand forecasting. Demand forecasting estimates future customer demand based on historical data, whereas demand sensing uses timely input signals from various sources to determine current demand. A demand sensing model is a collection of algorithms that process signals from internal and external input sources to produce a set of

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demand signals.

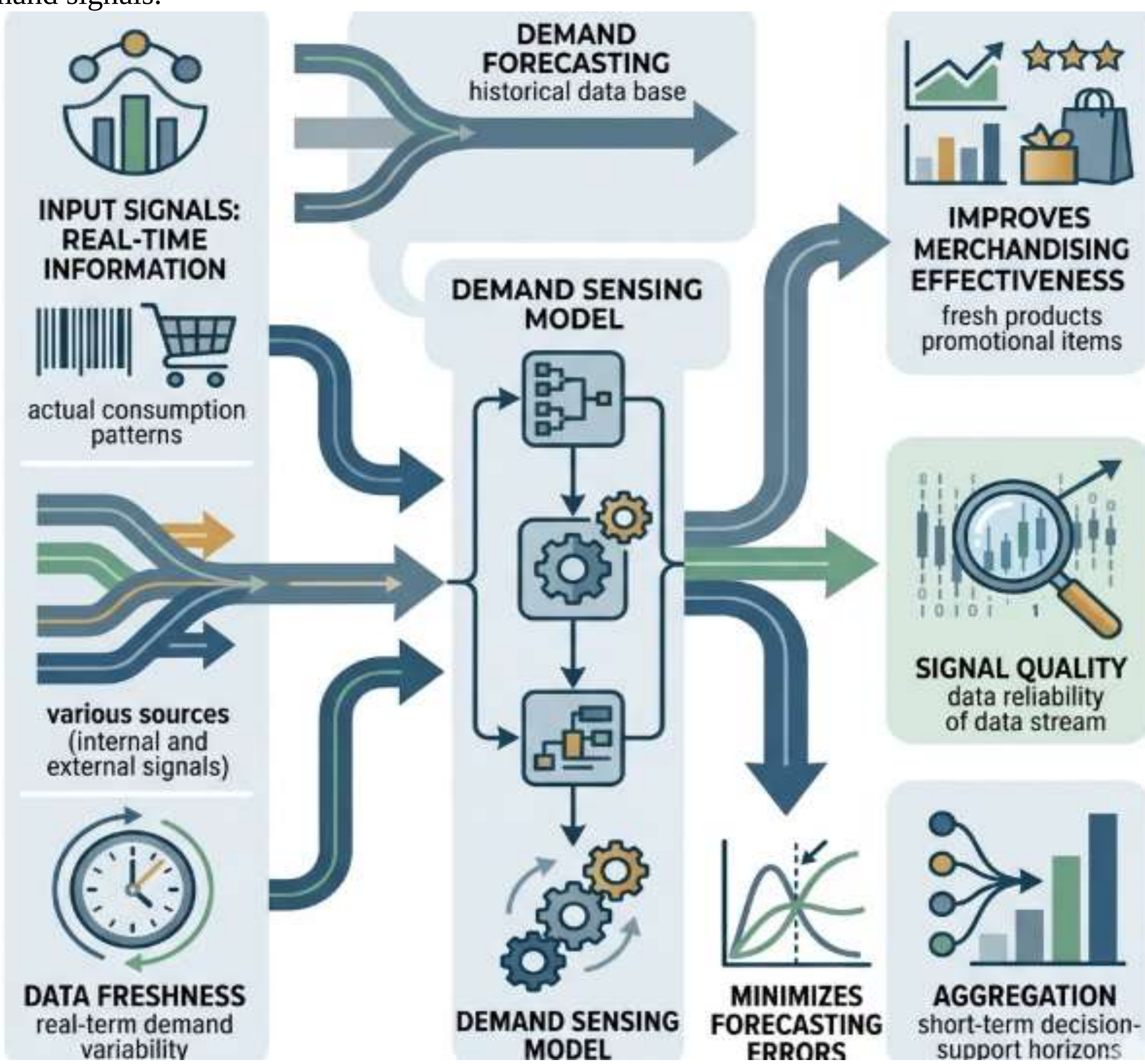

Fig 1: Dynamic Demand Sensing: Algorithmic Fusion of Fresh Signals for Near-Term Precision

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Demand-sensing decisions are guided by several properties of input signals. The first is data freshness. Demand-sensing detects near-term demand variability, which requires short-latency data acquisition and processing. The second property is signal quality. Demand-sensing algorithms exploit a variety of data sources, but not all sources are equally reliable. Data quality directly affects the performance of demand-sensing models. Aggregation is critical because demand-sensing decision horizons are generally short, ranging from one to two weeks or less. Therefore, the need for signal aggregation increases as the distance from the decision-support horizon increases.

2.1. Key Concepts in Demand Sensing

In the context of demand sensing, several important concepts deserve attention. Real-time signals are data streams that provide insights into near-term demand. Freshness refers to the timeliness of data as it relates to its value for demand discovery. Signal quality encompasses the appropriateness of content, accuracy, and utility for demand detection. The ability to aggregate data in a hierarchy and according to predictor importance enhances the richness of demand-sensing information. Delay is the point at which data become available and sensitive to demand. Latency is the average duration until data are reflected in sales.

A demand-management item is an entity viewed in the context of production and distribution operations and includes a product description, a location in the system, and other logistics information. Demand-sensing evaluation is the procedure that determines the extent to which demand sensing has succeeded. Sensitivity quantifies the observable change in demand detected within the supply chain response time to a demand signal. Sensitivity goes hand-in-hand with signal availability: a very sensitive model may not provide useful information if the supporting signals are sporadic. Sensitivity also translates to cost and benefit implications: the more information is used, the higher costs become; conversely, costs can be reduced by being more selective in using information.

3. Methodology

The study focuses on integrating cloud-based AI technologies in retail demand-sensing and inventory-optimization processes. The demand-sensing part identifies real-time demand signals for short-term use. The capability to process these signals is vital, so the study delineates key data characteristics that define sensor effectiveness. Consequently, data sources and

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machine-learning methods capable of capturing the time-variant relationships necessary for demand-sensing are specified. A proof of concept assesses the entire process chain leading to inventory recommendations. An integrated cloud setup connects data collection, storage in a data lake, governance, preparation, and readiness for consumption by demand-sensing and subsequent inventory-optimization models.

Demand-sensing models require three types of data: streaming and batch data supporting demand signals and historical demand data. Streaming data drives closer-to-real-time signals, while batch data—delivered at regular intervals—fills gaps and improves the quality of the detected signals. The primary focus is to identify ML- and deep-learning-based methods for short-term inventory management in the retail sector. In retailing, the inventory-control task involves determining replenishment needs at different locations. Considering that the decision environment is close to real time, demand forecasts typically cover the very short term, spanning the next few hours to the next few days.

4. Objectives of the Study

The two-fold objective is to demonstrate the potential of smart retail concepts for AI analytics in demand sensing and inventory optimization, and to deliver the proof of concept. The first goal is to enhance demand sensing performance in selected pilot sites using prospective data streams from the data management framework to provide accurate signals of even short peaks in demand, such as flash sales for online stores—thus enabling timely replenishment—and to achieve superior prediction of product-shelf gaps for brick-and-mortar stores. The second goal is to enhance performance for perishable products. It targets freshness and shelf loss with timely distribution, lowering spoilage while minimizing the risk of stockouts. For other categories, it seeks to meet normal demand volume but reduce variability to enable stable inventory levels with longer replenishment cycles, thereby lowering logistical costs and mitigating carbon emissions with greener operations.

Success will be gauged through consumption patterns and operational metrics in pilot stores, focusing on freshness for items like yogurt, fruit juice, and bakery products, and on inventory turnover for non-perishable goods. In addition, resource needs for scaling up the planned analytics to additional product categories and pilot sites will be evaluated.

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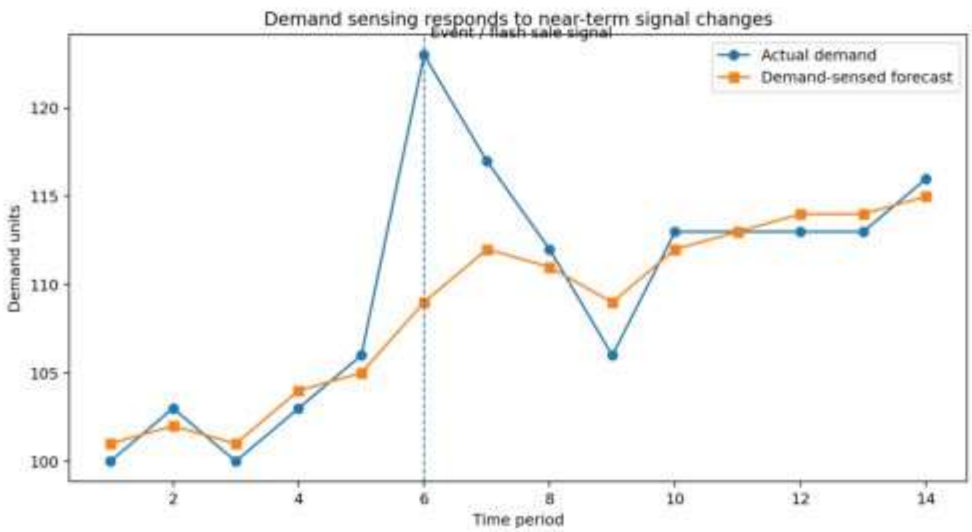

Equation 1: Forecast Error

$$e_t = A_t - F_t$$

Steps:

1. Start with actual demand A_t
2. Subtract predicted demand F_t
3. Result = error

4.1. Data Management Framework

Data management is critical for demand sensing. It must encompass data collection, storage, quality checks, governance, security, and access. For the testbed, a demand-sensing data management framework has been implemented.

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Over the years, the Latino Community Credit Union in North Carolina has accumulated large amounts of retail-data. Most of these data is stored in a cloud data warehouse. Data freshness, noise and gaps can however hinder effective demand sensing. To create reliable real-time demand signals, demand-sensing data streams are therefore prepared with care. Several operating principles guide this preparation.

Data is therefore carefully collected and checked for quality. The data is then cleaned for gaps and noise and, once set, the cleaned data is no longer altered. Data stewards ensure data quality. Data governance policies, including documentation of data sources and meaning, are established in advance. Access to data assets is defined and governed with care. Security and privacy are further ensured by appropriate access-and-authentication systems.

5. Research Summary

This research identifies the potential of real-time retail demand sensing as a key enabler of inventory optimization and proposes the development of a set of cloud-based AI models that integrate many different real-time data signals. It provides a sound process for implementation, a data governance framework, and detailed recommendations for monitoring model quality. Successful deployment enables smart retailers to create efficiencies in their product replenishment processes with significant benefits for both physical stores and their e-commerce offerings.

Real-time demand-sensing models, directly tied to the sales processes of physical stores, allow for more timely, targeted, and challenging inventory management of perishable goods. They contribute to stock policies that increase the selling window, minimize the spoilage of less-fresh products, and reduce the risk of out-of-stock situations. They also serve as early-warning systems for online e-commerce offerings, alerting the product supply team when inventories need to be replenished in response to an accumulation of online orders, a function that becomes even more critical in peak-demand phases such as festive seasons. Similar models for high-demand, low-availability seasonal items help remove products from a website once demand has come to an end.

6. Cloud-Integrated AI Models

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Cloud-enabled AI supports better demand sensing and inventory optimization in smart retail.

Demand sensing relates to the monitoring and understanding of real-time signals of demand across the supply chain. In addition to indication of demand, these signals can also be leveraged to dynamically adjust inventory levels, thereby more closely aligning supply with real demand for specific products over time and minimizing the risk of stockouts. Integrating real-time demand signals from the supply side as well as from sales on the demand side into inventory management processes enables more responsive retail operations that use resources more efficiently. Such demand sensing capability is particularly applicable to products with a limited

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shelf life, making fresh food and beverage products in retailers' inventory a prime target.

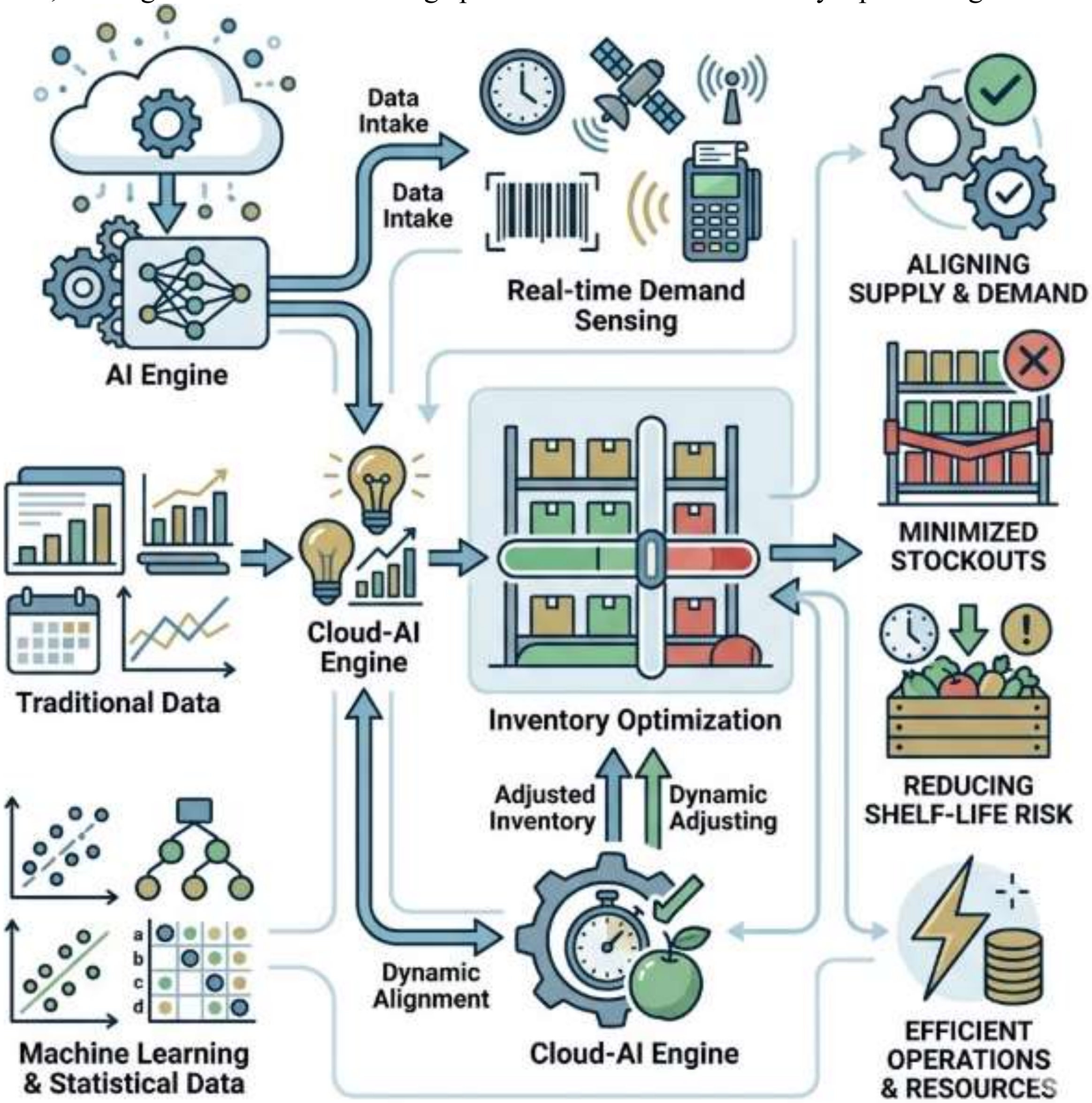

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Fig 2: Leveraging Cloud-Enabled AI for Predictive Demand Sensing and Dynamic Inventory Optimization in Smart Retail: A Focus on Fresh Produce

The combination of multiple data sources and streams provides a more complete and, therefore, clearer picture of expected demand for specific items across sales and stock, and multiple technologies are suited to the task. More traditional time-series analysis methods capture long-term trends in consumption patterns. Machine-learning methods, including both statistical and neural-network-based approaches, take advantage of relationships with other variables to model demand over time. Time-series and machine-learning methods focus predominantly on understanding and predicting demand at various levels of granularity, such as store, store category, product, and store-product combinations.

6.1. Data Streams and Integration

Demand-sensing models leverage streaming data in real time, as well as data available in batch mode for training, testing, and enhancement. At its core is signal management: capturing real-time data, assessing freshness, quality and freshness, accounting for delay and latency. Real-time demand signals can come from many sources, and typically a large set of non-confidential, non-personal data can be collected from these various signals (e.g., online events, consumer behaviour) to help reduce or better anticipate demand. Although most of the signals are available in real time, the incorporation of batch data—for training, recalibration and evaluation purposes; especially for validation tasks requiring a long look-back period; and to fill missing or erroneous patches—cannot be neglected. Therefore, a key element of real-time data signal management involves data freshness: up-to-dateness is a must in real-time demand detection and should be guaranteed for all real-time data sources. Apart from data freshness, the quality of the signal is vital for correct demand detection, as decision-making relies on it—data monitoring is crucial to check that the signals are functioning properly. In this context, additional processes may be activated (e.g., cleansing, replacement) if needed.

A key differentiator of real-time demand sensing is its capability to leverage data streaming in real time and with minimal look-ahead time, better satisfying SC time frames. Thus, a sudden surge or a negative shock on a product’s demand pattern has a greater chance to be captured and acted upon (e.g., making stock available for −1 day to avoid stockouts or −x days monitoring for demand-pattern trend). These properties also make real-time demand sensing especially useful for managing perishable products whose freshness status tilts. Delay and

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latency are important issues. Delay refers mainly to an information-action gap. A neglected but often critical feature of delay in SCs is that different SC members—wholesalers, retailers, suppliers, etc.—geo-temporally amplify demand deviations, so the increased volume and pattern variability requires closer SC synthesis. Latency relates to the start time of model operation: a model can hardly be determined in T-1 for execution in T if development needs several months of historical data.

Metric	Formula	Purpose	Advantage	Limitation
MAPE	(\frac{1}{n}\sum \left	\frac{A_t-F_t}{A_t}\right	\times100)	% error
WMAPE	(\frac{\sum	A_t-F_t	}{\sum	A_t
SMAPE	(\frac{100}{n}\sum \frac{	A_t-F_t	}{(	A_t
IMAPE	Trimmed MAPE	Robust error	Removes outliers	Requires quantile choice
Hit Rate	$\frac{n_{correct}}{n_{total}}$	Direction accuracy	Business-friendly	Ignores magnitude

6.2. AI Methods for Demand Sensing

A variety of methods fit within the demand sensing category of traffic lights for a smart store or smart marketplace demand sensing inventory optimization full system. When residual demand variation downstream the supply chain is visible on otherwise clean continuous-time signals, recursive time series regression can be used. Alternatively, transparent machine learning can create generalized models to predict inbound demand for stores or sub-store network zones within stores based on real-time rotating signals. If high-quantity data is available in a single time zone, demand sensing is typically done by applying deep learning to that region, allowing time to construct synthetic data sets to retrain deeper models for other regions. If historical signals close to the decisional horizon clearly depend on others, then a better approach is to apply Time-Delayed Neural Networks.

This general hierarchy allows appropriate methods to be resourced effectively in terms of data freshness, size, and other quality issues. Critical is to remember that any method or model

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can work badly. When demand sensing fails, it is likely due to using a method at the wrong point in the external factors) model. Distortions on any of the input signals make it impossible for residual variation to be seen by the applied method. Bad, noise-dominated, or incorrect data become more critical, and method selection processes can be modified accordingly.

7. System Architecture

The architecture enables the execution of the business use cases defined in the previous section. With data from various sources, cloud-integrated AI models—comprising time series techniques, machine learning models, deep learning algorithms, and rules-based approaches—deliver demand signals for different categories of products. Business stakeholders at different levels of the retailer, supplier, and distributor organizations can leverage these signals to take timely and data-driven decisions, resulting in improved inventory management, lower stockout levels, and reduced wastage during the product life span. Other business use cases go beyond AI-enabled demand signals but are crucial prerequisites for successful demand sensing in the retail space.

A specialized data infrastructure within the cloud environment collects data from online and offline sources. Test data using the rudimentary demand signal processing has been provided. Over time, as the quantity and quality of off-line data improve, the freshness of the real-time displayed demand feed and accuracy of the signals will get further enhanced. An integrated process monitors common components and procedures associated with AI model training and deployment. Storage usage is tracked, model health is verified, and quality corners and metrics are monitored for detection of drift. These, in turn, act as triggers for combination with monitoring dashboards for early detection of retraining requirements.

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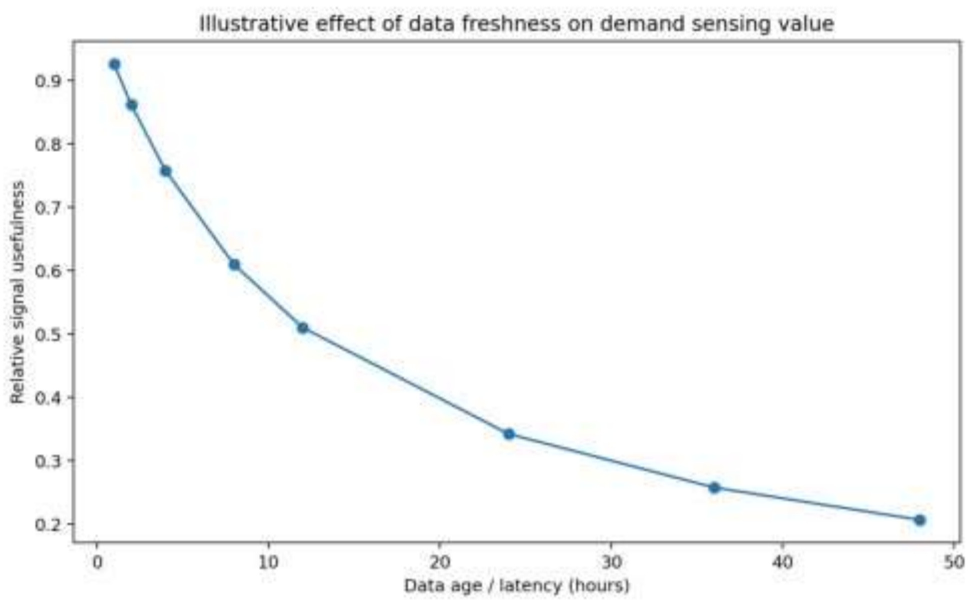

Equation 2: Absolute Percentage Error

$$APE_t = \left|\frac{A_t - F_t}{A_t}\right| \times 100$$

Steps:

1. Compute error: $A_t - F_t$
2. Take absolute value
3. Divide by actual demand
4. Multiply by 100

7.1. Data Infrastructure

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Cloud services provide the necessary tools for data storage, processing, and analytics. Candidate data is gathered from the various online and offline sources identified, then stored within the cloud. Data quality is constantly monitored during the data ingestion phase, and flagged records are promptly cleansed by the data maintenance team. Data records are encrypted during the storage phase to ensure that sensitive data are adequately protected. Sensitive personally identifiable information is automatically removed at source or abstracted by data masking techniques before being written to the cloud. Data governance frameworks ensure that proper access controls are enforced whenever sensitive information is involved. External data source connections are compliant with the latest industry regulations, and privacy statements are respected at all times to eliminate any reputation risks. Moreover, connections to critical internal services are also subject to strict role-based access for both administrative and service accounts.

Cloud services also facilitate the appropriate training of AI demand sensing models. Both data freshness and available historical records are leveraged when preparing the training set. Dummy forecast signals are created during the staging phase to prevent total silence when the demand-sensing system goes online. The model training process is continuously monitored through state-of-the-art hyperparameter optimization libraries and instrumentation dashboards that track different stages of execution. Validation metrics are reviewed at the end of each training job using dedicated slicing and dicing notebooks. When sufficient clean data are available in the candidate data store, the AI service level manager triggers the model edge deployment process through a dedicated monitoring dashboard. The demand-sensing pipeline is also monitored for drift. Whenever the gap between forecast signal and actual sales signal exceeds predefined thresholds, the model is automatically retrained from scratch or the last recommended checkpoints using the entire training set. An intuitive business dashboard seeks to communicate this information to the proper business users and service level managers.

7.2. Model Training and Deployment

Data preparation precedes training for demand sensing models. Cloud-based tools offer a robust yet flexible framework. Depending on the source model and method for demand signals and inventory levels, data is cleaned, transformed, aggregated, and stored in the Data Management Framework. Users supply variables. Prediction windows determine test sizes. After a real-time online batch, compartmentalized training begins. Transparent methodology supports monitoring and regulation.

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Freshness of inventory or supply is vital. Time series models use historical data exclusively. External time series models requiring batch data span training periods. Machine learning techniques divide data into training, testing, and validation sets. Artificial neural networks are set up using KNIME. Reinforcement learning setups depend on library availability. Pyspark and Spark cloud Deep Learning pipelines require monitoring. Monitoring optimizes performance of production and testing phases. Dashboards point out anomalous outliers needing attention. Results depend strongly on training, validation, and testing processes.

8. Use Cases in Retail

Practical examples illustrate how the smart retail solution benefits physical stores and e-commerce. For perishables, the focus is on freshness, stockouts, spoilage risk, and shelf life; for non-perishables, the emphasis shifts to inventory levels, replenishment needs, and demand variability.

In physical stores, models help address supply and demand issues for perishable goods. Demand spikes are often caused by factors like holidays, weather, and sports events; however, these events are not automatically flagged by systems that capture visual cues and ease-of-use factors for delivery apps (e.g., a day without rain). While traditional models mainly react to past conditions, augmented forecasts reduce stockouts and spoilage. They can also suggest appropriate and easy-to-provide replacements for delivery customers.

For non-perishables, the interest lies in improving inventory turnover ratio (ITR) and reducing ITR variability. Levels are often higher than necessary, and the bot needs to suggest when to replenish different products. ITR should also remain stable because demand for some products closely follows seasonality or calendar effects. Unusual patterns can be further investigated, with season tickets and studies of festivals and shows being common practices that may fulfil this need for particular goods.

Signal Type	Example	Impact
POS Data	Sales transactions	High accuracy
Weather	Rain, temperature	Seasonal demand
Social Media	Trends, hype	Sudden spikes

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Signal Type	Example	Impact
Promotions	Discounts	Artificial demand lift
Supply Signals	Stock levels	Constraint-based demand

8.1. Perishable Goods Management

Freshness and an appealing presentation are vital for food, but managing these qualities can be costly and complex. Stockouts are frustrating for customers; spoilage is expensive for sellers. Some retailers game the system, keeping stock low to maximize margins, and rely on data science for reliable inventory. A strong demand-sensing capability helps businesses anticipate future stock levels more accurately. Improved shelf-management techniques (like better placement and handling of products) can also help minimize spoilage, while accurately forecasting shifts in freshness can cut financial losses due to unavoidable bad stock.

Demand-sensing models for perishable groceries typically focus on real-time signals. For products with a limited shelf life, such signals can include weather and events, social media chatter, website visits, deliveries, and e-commerce purchases. Integrating these external data sources tends to improve quality without the latency that often plagues sensing efforts. Early planning signals and social-media analyses can also deliver fresher information.

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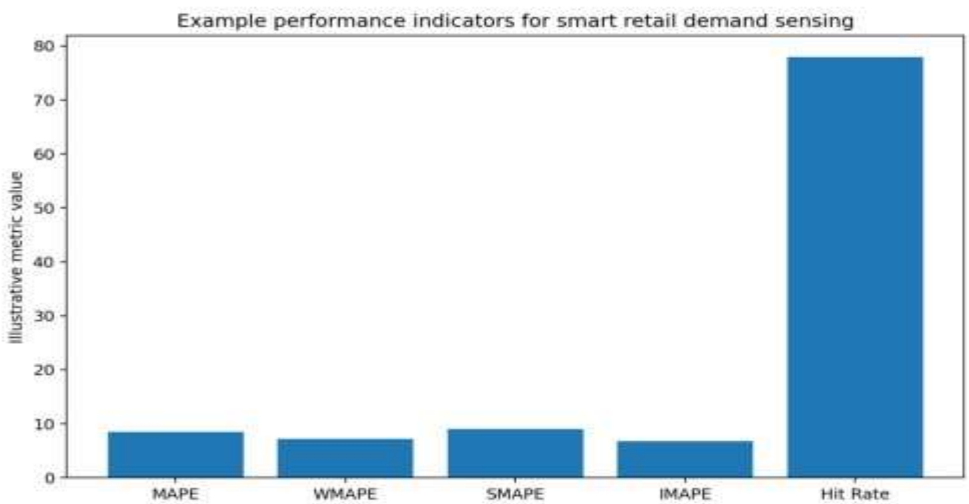

Equation 3: MAPE

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100$$

Steps:

1. Compute APE for each time step
2. Sum all APE values
3. Divide by total observations n

8.2. Non-Perishable Goods

The demand signals for non-perishable categories act over longer time horizons than those of perishables, presenting different yet equally demanding challenges. Non-demand-related factors can alter demand levels, such as promotions and seasonal sales peaks, which could be an

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addition to the non-periodic signal. Furthermore, demand variability can be pronounced and even misleading even at larger temporal windows.

Hyper demand velocity can also be critical, often leading to stockouts. Such anomalies may be present at shorter time frames than the business considers for replenishment. Stock-level signals should thus be leveraged, especially when approaching an out-of-stock situation. In that case, replenishment prior to a possible stockout may be demand-focused, yet not on replenishment quantity. The recommended method for demand temporal aggregation will depend on the product, availability level, and expected signal quality. A data-driven approach could therefore help optimize calibration, validate preliminary results, and consolidate learnings. Demand cross-impact effects may also be pronounced, where a supply chain node being almost out of stock may trigger a volume demand signal on a linked child node in the product hierarchy.

9. Performance Metrics

Research success requires careful definition of objectives and useful ways to gauge achievement. Relevant measures indicate the degree to which desired outcomes are attained. For the smart retail demand-sensing study, standard metrics of forecast accuracy, in-stock levels, shelf days, and inventory turnover provide insight into performance across distinct yet related model areas.

To assess the quality of demand signals for order preparation and stock replenishment, accuracy is the principal focus. Traditional measures include mean absolute error, mean absolute percentage error, and symmetric mean absolute percentage error, where smaller numbers indicate better prediction. For non-perishable products and overall demand signals, an accuracy target threshold has been set at ≤10%. Greater demand variability, as measured by coefficient of variation, usually leads to higher errors. Despite potential shortcomings, accuracy remains a primary metric for demand-signal quality.

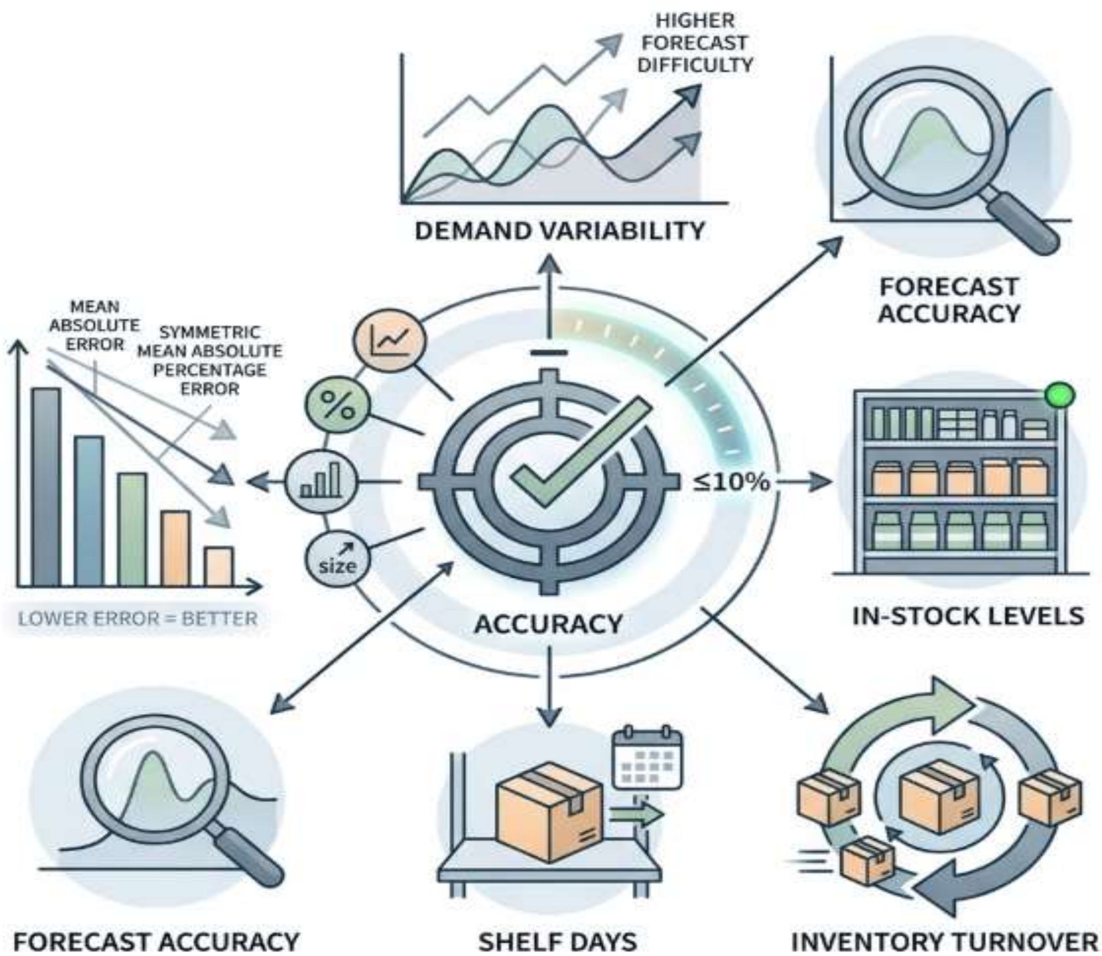

Fig 3: A Multi-Dimensional Metric Framework for Smart Retail Demand Sensing: Balancing Accuracy, Stockout, and Turnover

9.1. Forecast Accuracy

Five forecasting accuracy metrics help measure the effectiveness of demand sensing and inventory optimization. The Mean Absolute Percentage Error (MAPE) assesses a forecast's

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accuracy as a percentage of the forecasted value. A MAPE within a channel of about 10% is considered good, 10–20% is acceptable, and above 20% should be improved. The Weighted Mean of Absolute Percentage Errors (WMAPE) calculates the absolute percentage errors, weighted by the volume of sales associated with each product, allowing for easy interpretation. A WMAPE lower than 10% is excellent, 10–20% is acceptable, and above 20% should be improved.

The Symmetric Mean Absolute Percentage Error (SMAPE) compares forecast errors to the average of actual and forecasted values, restricting MAPE to between 0% and 200% and avoiding large errors producing extremely high MAPE values. However, SMAPE can over- and under-emphasize errors at either extreme, particularly when actual values are close to zero. The Interquantile Mean Absolute Percentage Error (IMAPE) mitigates these deficiencies by limiting the calculation to quantiles specified by the user. Finally, the Hit Rate (HR) indicates success in matching direction: HR = n(matching forecasts)/n(total forecasts). A practical target is for at least 70% of forecasts to match.

9.2. Inventory Turnover

The inventory turnover ratio indicates how often the stock is replenished over a given period. A higher ratio implies that a retailer is stocking and selling goods in sufficient quantity relative to the turnover of the overall store. The industry average varies from segment to segment, but a rate of six times or more is typically regarded as healthy because it indicates quick stock replenishment, reducing spoilage and obsolescence while generating sales.

A declining inventory turnover ratio is therefore a cause for concern. Inadequate movement of merchandise can lead to increased holding and carrying costs and reduced product freshness. Other costly problems such as expired use-by dates may also occur. If suppliers have agreed to longer lead times, it may create a high and inflexible stock level that does not correlate with actual demand. A low turnover may indicate the need for reconsideration of prices or promotional efforts, or even an assessment of the appropriateness of the product in the store.

Equation 4: WMAPE

$$WMAPE = \frac{\sum|A_t - F_t|}{\sum|A_t|} \times 100$$

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Steps:

1. Add all absolute errors
2. Add all actual demand values
3. Divide error sum by demand sum
4. Convert to percentage

10. Challenges and Risks

In Smart Retail Demand Sensing and Inventory Optimization Using Cloud-Integrated AI Models with Data Streams from Multiple Sources, the main challenges include ensuring sufficient quantity and quality of data for demand sensing and inventory optimization, providing appropriate security measures for stored and processed data, and applying best practices for efficient implementation and operation. Each challenge and its associated risk mitigation strategy is outlined clearly here.

Quality and quantity of data, two of the key enablers of demand sensing and inventory optimization models, are typically not under the control of the model developers but rather are determined by third parties. Various types of noise and pattern inconsistencies may need to be filtered out. For data streams coming from external sources, suitable cleansing approaches should be developed and applied. Quality gates should be established for input data to avoid unexpected behavior of the trained models caused by data outside the expected range or containing spurious distortions. AQA should be employed to close gaps created by missings in quickly aging signals. Data freshness is taken into account by introducing data latency and aggregation considerations.

Data privacy and security are of critical importance for any demand-sensing solution. Best practices in this area should be followed to safeguard personally identifiable information about customers stored in the customer data platform database, noise in credit and debit card data coming from the acquirer and processing partner that could give competitors advance visibility about campaign-driven demand, and transaction data and panel data from the loyalty app. Consequently, only legally stored and required data should be retained, and suitable access rights should be granted to partners in compliance with local legislation such as the General Data Protection Regulation (GDPR) in the European Union.

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Measure	Formula	Meaning
Inventory Turnover	$\frac{COGS}{Avg\ Inventory}$	Speed of stock movement
Coefficient of Variation	$\frac{\sigma}{\mu}$	Demand variability
Freshness	Function(delay, latency)	Data usefulness
Sensitivity	$\frac{\Delta D}{\Delta S}$	Model responsiveness

10.1. Data Quality

Real-time demand-sensing models rely on many signals. Gaps or noise in key streams (e.g., past sales, media activities, or competitive prices) will hurt forecast results. As a first step, missing values need to be identified and filled to avoid model breaks. Next, a series of noise-reduction techniques—such as regression-based or clustering-based outlier detection—should be used to clean the data. When developing the sales-forecasting models, statistical tests should determine whether the cleaned signals remain significant. If they do not, then signal cleansing must be repeated.

Real-time demand-sensing models combine together a wide range of signals; therefore, the quality of the integrated data sets must be continuously monitored. Filters and alerts can help spot problems early. For instance, if the h-index drops below a given threshold, it may signal a data-cleaning issue or high noise levels in key sources. When necessary, remedial action may involve re-running the signal-cleansing routines or changing integration procedures to improve quality.

10.2. Privacy and Security

Data privacy and security are essential to any cloud-integrated AI system. Sensitive data, whether related to individual transactions or people's activities, should only be kept as long as it is needed for valid and defined purposes. Access to critical data and any part of the system is strictly controlled and protected by common security measures such as active authentication and authorization, firewall policies, and intrusion detection and protection mechanisms. Data are

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stored and processed in compliance with the respective regional laws and regulations, such as the GDPR in the European Union.

11. Best Practices

By applying good practices, organizations can improve data-driven decision-making and system performance. First, data management policies should be developed and clearly documented. Second, it is essential to assign responsibility for data quality, covering aspects such as accessibility and protection. Data availability can be improved by preparing backup sources to limit service disruption when the primary data streams fail. Identification of blind spots can facilitate planning for future data collection, enabling any new sources to be operational before gaps in existing feeds appear. Data quality is essential for reliable outcomes. Noise reduction should be performed regularly. Delays in signal quality detection can be limited to hours, while masking excessive delays can improve usability.

Monitoring should be performed continuously. Signals drifting out of the range expected at deployment time should be flagged. When a signal changes over time, such as seasonality or parameter shifts, retraining should be performed. Dashboards customized to different audiences can also improve monitoring. For example, a visualization showing distribution for the last year and the rolling average can help data route owners identify possible drift and act accordingly.

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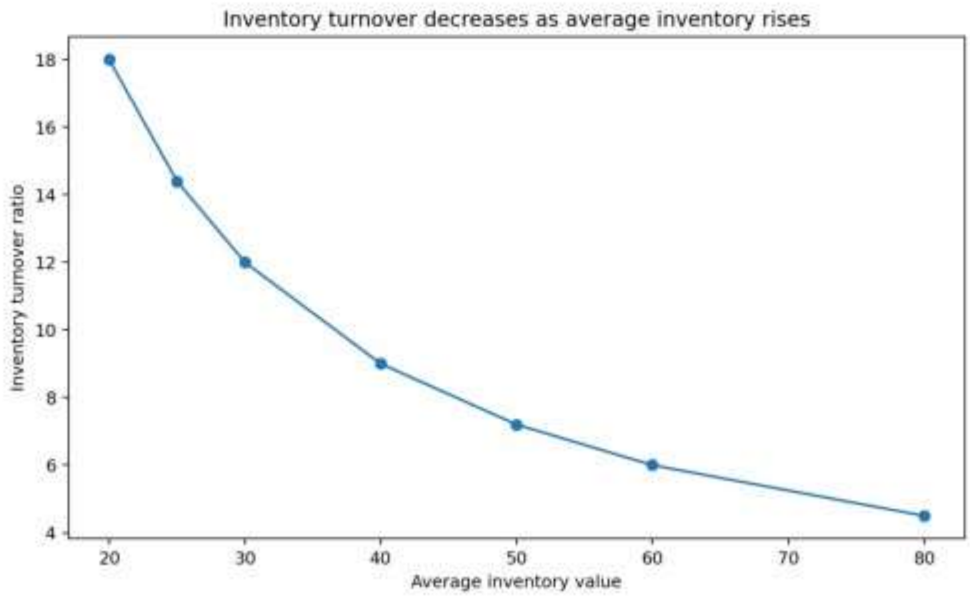

Equation 5: SMAPE

$$SMAPE = \frac{100}{n} \sum \frac{|A_t - F_t|}{(|A_t| + |F_t|)/2}$$

Steps:

1. Compute absolute error
2. Compute average of actual & forecast
3. Divide error by average
4. Average across all periods

11.1. Data Governance

The data governance framework defines who is responsible for the availability, usability, integrity, and security of the company data. It is an important element of the data management model and outlines the policies to establish roles and responsibilities for Data Management. The data governance framework assigns responsibilities at several levels, from execution to oversight and the hierarchies and interrelationships across these levels. Data governance supports all data activities.

Data governance identifies who can make decisions about the data. It ensures that the data used in analytics and machine learning is trustworthy, allowing the business to have confidence in the results of any analysis. Data governance also defines the policies and approach for data stewardship. Data stewards are responsible for ensuring that the data used across a business area meets quality and integrity standards. Data stewardship decides how data must be organized, where it resides, how accessible it is, and how security or compliance protections are applied.

For each of the governance elements, the data governance framework explains how decisions get made, who is accountable for those decisions, that such decisions are monitored and overseen, and how any required reviews are carried out. The framework also describes how the assignment of roles and responsibilities are documented, communicated, and enforced. Procedures for updating the framework are also defined.

11.2. Model Monitoring

Monitoring for model drift is essential for maintaining demand prediction accuracy. Retraining thresholds should be set, and a residual error dashboard made available to model users. A residual error dashboard enables the transparency demanded for emerging technologies. It shows how well the model continues to capture the data pattern. Residual error analysis provides model users with the necessary information for addressing delivery delays or stock decisions that are subsequently affected by model drift. If the model starts falling outside an acceptable error band, users should be alerted so that rescaling can be triggered. Actionable and usable dashboards demonstrate that—although not currently a major problem—the model can be sensitive to weather pattern changes. This potential sensitivity is what dashboard checks provide warning of and the needed justification for being prepared to update the model if warranted.

12. Results

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Demand sensing models were prepared and deployed using the cloud-integrated data management framework. Section 12.1 describes the data collection and preparation actions undertaken prior to building and deploying the models; and Section 12.2 discusses the services and the outcomes of Phase 1 of the implementation.

Planning

Eight demand sensing models were selected for initial deployment—the machine-learning regression and statistical time-series forecasting models—and related tools required to handle data quality and freshness. Demand sensing for perishable goods was prioritised, with whey drinks and fruit salads considered first as they had observations of stockouts along with sales. Planned actions included absorbing data into the cloud, assessing data freshness on a daily basis, running daily quality checks on batch data, and preparing the model-training datasets. The frequency for data collection was based on the needs of demand sensing (high freshness, low latency, high quality), while the period for model retraining was based on stability (low noise).

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Once model-training datasets were prepared, training and deployment would follow.

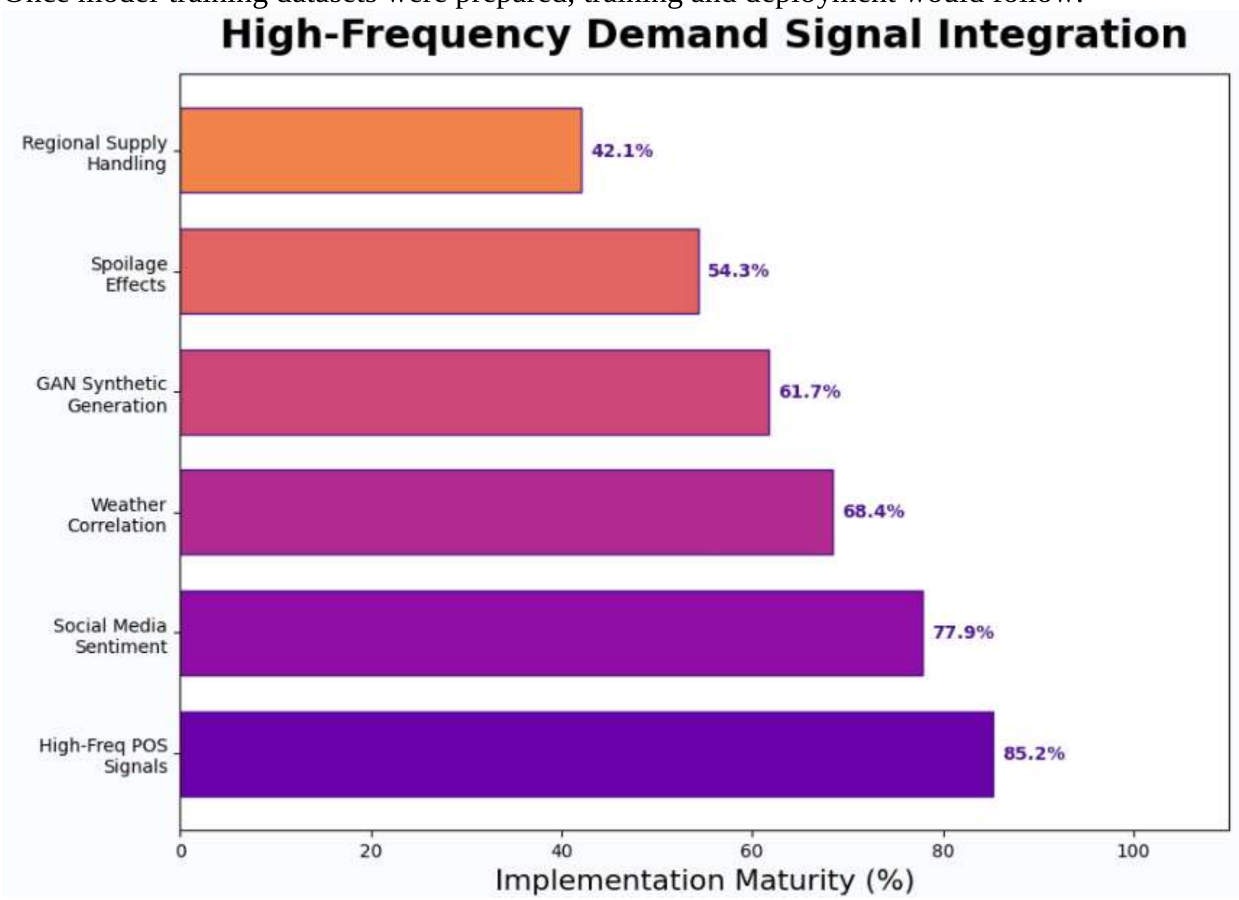

Fig 4: High-Frequency Demand Signal Integration

Implementation

During implementation, planned actions were adapted according to actual demand-data needs and the capacity of available data sources, tools, and models. Services were rolled out in phases, with completion and results shown in Tab. 12.2. Cloud storage was provisioned, consolidated feeds prepared, and perishable-demand models absorbed and tested. Cloud-processing services for demand-data quality checks were developed to ensure that data freshness,

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noise, and quality were within allowed thresholds. High-frequency demand signals (from POS, social media, and weather) were marked, and the synthetic-data-generating GAN models developed. Early demand-sensing capabilities for perishables were created for several stores, utilising flexibility in the pipelines and the detected demand-signal properties to incorporate freshness, stockout, and spoilage effects. The sensitivity of online-demand planning for perishables and the need for handling events and regional supply variations were also demonstrated.

12.1. Planning

Robust cloud-based AI/data architecture enables automatic demand sensing for multiple categories. A wide range of internal and external data feeds real-time demand signals. Demand models for large SKU volumes use time-series, ML, or deep-learning methods. Use cases improve stock levels and freshness for perishables and optimize reorders of non-perishables. Various quantifiable metrics assess success. Demand sensing is an essential component of an integrated demand-supply framework.

Demand sensing combines internal/external real-time signals—originating from control/sensor devices, store operations, marketing, customer behavior, and external events—to accurately detect current demand. In order to be effective, these signals should be timely (recently generated), possess high signal quality and low sensitivity to aggregation, and minimize delay and latency . Theory shows that utilizing high–real-time freshness signals has a greater impact on demand sensing than having lagging/low–signal freshness ones. Not all sources simplify demand sensing—those that can contain noise are handled last and in a cleansing stage. Recognizing the complexity of managing a large number of stores, categories, and SKUs, the demand-sensing process involves advanced AI.

12.2. Implementation

Planned actions in demand sensing followed one of the use cases: near-real-time signals (weather information predicting incoming storms) impacted a dry-grocery category (bread). Machine learning models that could adapt to changing relationships between inputs and outputs were explored using a sample grocery retailer's two-year data (2019 requested). Croissants stale-dated less than six hours prior exceeded stockouts by 3-k-/day (risk probability 15%). Additional signals decomposed the low-quality forecast (1421-PPH): events, seasonality, competing stores,

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cannibalization, holidays, and coupons. Near-real-time signals aiding dynamic availability and influenced replenishment decisions monitored through a dashboard contemplated. Workers highlighted loss minimization as a primary goal, alongside other secondary aims—demand forecast accuracy for stock level design tested through inventory turnover and spoilage level results. Winter holiday scans supported optimizing the carrousel for all categories throughout USA, while Germany-straight-order-refresh efforts reduced transit costs and restocking errors drove the use case pipeline overall.

Triggers returning the complete demand and sales schedule were the requested output, considered slightly delayed one day for practical purposes. Several sources presenting non-conditioned data streams required cleaning to remove noise, outliers, and spurious demand. New distribution centers with Blitzrot control and definition complemented the sensitivity panel, piloting probes adjusting Katrin parameters as needed. Golf stock continues to face delay latency issues despite integration testing. Christmas holidays present possible fresh-accuracy loss for some categories.

13. Conclusion

This work focused on the development and demonstration of cloud-implemented, AI-enabled, end-to-end solutions for improving demand sensing and inventory management—in stores and online—across goods with both a short and extended shelf life. Demand sensing combines using real-time signals from several sources (social media, search and sales data, local and larger events, and seasonality effects) with customer data to obtain a significant upper hand on demand forecasting. At the same time, turning to truly supply-chain-oriented non-proprietary AI methods for building forecasting models—such as time-series-based, machine learning, and deep-learning approaches—permits capitalising on months of work on signal generation, cleansing, and quality checks. Furthermore, the development of appropriate tools to gather, clean, and offer demand signals stored in a data-lake-type model paves the way for future performance enhancement.

Two use cases highlight the potential of applying the concept to demand sensing. In the realistic real-time planning phase, the demands are unknown; in the more ambitious planning phase, it is assumed that the shape of the demand is known (not the amplitude), and the objective is to set the optimal safety stock associated with a given service rate. The implemented inventory-control model helps achieve several targets, especially for perishable goods. Stockouts

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and spoilage are reduced, and on-shelf freshness is improved across the board. The services may not be very far from those possible with machine-learning-based approaches, but they are now available on data sources that are publicly accessible. For non-perishable goods, too, inventory levels for all items and replenishment orders are closer to the ideal, reducing the large variability that typically affects demand and supply planning.

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