ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 12 (2025) No. 7, pp. 176-195
DOI:10.33168/JLISS.2025.0711

An Integrated Hypothesis-Based Evaluation of Meta-Learning, Behavioral Analysis, and Inventory Correction in Retail Forecasting

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Abstract. The accurate retail sales forecasting remains a challenge because of dynamic market fluctuations, promotional interventions and heterogeneous customer behavior. Conventional forecasting models frequently misinterpret sales variations arise from inventory inaccuracies, campaign effects or behavioral diversity. This hypothesis paper develops and validates a comprehensive model combining process, marketing and behavioral dimensions to improve retail demand forecasting accuracy. Ten hypotheses (H1-H10) are developed, with Adaptive Inventory Correction, sales volatility modeling, marketing influence, RFDM-based behavioral profiling, customer satisfaction, segmentation, price sensitivity, cross-category dependency, retention and combined forecasting structure. The developed Meta-Learning Learnable Long Short-Term Memory (Meta-LLSTM) network enables adaptive learning across product classes. Experimental results using multi-category e-retail data obtains superior performance of 56% reduction in RMSE and 42% in MAPE when compared to traditional methods.

Keywords: adaptive inventory correction, customer satisfaction, hypothesis, marketing influence, retail sales forecasting and sales volatility modeling

1. Introduction

Retail sales forecasting is much crucial yet challenging tasks in e-commerce and conventional retail industries, as that directly impacts inventory management, marketing strategies, pricing decision and customer satisfaction (Petropoulos, F et al., 2025). Precise forecasting enables that organizations balances supply with demand (Babu, K.S, et al. 2024), reduce stockouts and overstocking and improve profitability (Riachy et al., 2025). Conventional forecasting methods like ARIMA and regression have majorly utilized but failed to capture complex (Kuo, R.J et al. 2023), nonlinear and dynamic nature of consumer demand in digital retail ecosystems (Trapero et al., 2024). The recent advancements in Machine Learning (ML) and Deep Learning (DL) like Recurrent Neural Networks (RNN) (Chan, H, et al. 2024), Long Short-Term Memory (LSTM) (Haval, A.M. et al. 2025) and hybrid methods (Jahin, M.A et al. 2024) have shown superior in enhancing prediction accuracy (Ginting, N.B, 2025). Though, these methods often consider sales as isolated time-series signals, essential external and behavioral parameters like inventory inaccuracies (Rafi, M.A et al., 2025), sudden demand volatility, marketing campaigns, customer engagement patterns, price elasticity (Wu, J, 2024) and cross-category dependency.

By avoiding these aspects outcomes in biased predictions which misalign with managerial decisions in regions like replenishment planning, promotional budgeting and customer retention strategies (Suresh, B.S and Suresh M, 2024). For addressing these gaps, this hypothesis paper developed comprehensive model which combines adaptive inventory correction (Sharma, D.R et al., 2025), volatility modeling, marketing interventions, customer behavioral profiling (Juju, U et al., 2025), satisfaction signals, segmentation strategies (Kim, S et al. 2024), price sensitivity, cross-category relationship and retention dynamics. By systematically embedding these real-world parameters to forecasting frameworks (Walia, I.K et al., 2025), proposed model (Liang, M et al. 2024) is hypothesized to effectively enhancing predictive accuracy and managerial applicability when compared to traditional methods.

1.1. Contribution

The primary contribution of this paper is given below:

- Hypothesis-based Forecasting Model – Developed and validated 10 different hypotheses (H1-H10) spanning inventory dynamics, sales volatility, marketing influence, behavioral profiling (RFDM), customer satisfaction, segmentation, price sensitivity, cross-category dependencies, retention and systemic integration. Unlike traditional models, this unified hypothesis model connects process fidelity, customer behavior and strategic levers in e-retail forecasting.
- Meta-Learning Improved Forecasting model – Developed an Integrated Meta-LSTM method with adaptive activation (MPELU) which dynamically integrates multi-source features. The model obtains superior error minimizations, determines robustness of integrating deep sequence modeling with hypothesis-guided input modeling.
- Cross-Domain Feature Fusion – The model bridges quantitative signals like inventory levels, price elasticity, volatility with qualitative indicators like customer satisfaction, churn likelihood, segmentation by unified data pipeline. This cross-domain feature integration ensures interpretable predictions which are statistically accurate.

The rest section of this manuscript is organized as: Section 2 provides literature review of existing models. Section 3 provides the hypothesis, methodology and dataset description. Section 4 explains the results and discussion of hypothesis. Section 5 concludes a paper.

2. Literature Review

2.1. Forecasting models

Retail demand forecasting has analyzed from traditional time-series models towards data-based Machine Learning (ML) and Deep Learning (DL) algorithms which effectively capture nonlinearities, seasonality and long-range dependencies (Zhang, X et al., 2024). Traditional methods remain useful for stationary series but fails on complex retail data highlighting promotions, stockouts and cross-category impacts. Hybrid and deep models (Mitra, R et al. 2024) have shown consistent enhancements in retail forecasting accuracy when comparing to single-architecture models.

2.2. Meta-learning and adaptation for time-series

The primary drawback of numerous forecasting models is limited adaptability for new stores, products or sudden shifts. Meta-learning has evolved as practical solution (Alparslan et al., 2024), recent researches have demonstrated that meta-learned initializations or meta-approaches facilitates quick adaptation over relevance time series and effectively enhance performance when few amounts of task-specific information are available. Two phase meta-learning and collaborative meta-learning models (Mahin, M.P.R et al. 2025) have developed for handling concept drift and for transferring knowledge over heterogeneous time series, makes meta-learning especially attracts to dynamic retail environments. These outcomes motivate combining meta-learning to LSTM based forecasting for ensuring rapid adaptation for promotions, seasonality shifts and new-product behavior.

2.3. Inventory inaccuracies and need to correction

Inventory distortion involves phantom inventory, mis-recorded stock and delayed replenishments is huge, well-documented source of forecasting error and lost sales. Industry and academic studies quantify huge process and revenue costs of inventory imprecision, research represents that correcting inventory signals materially enhances downstream demand estimated and replenishment decisions. These outcomes directly justifies Adaptive Inventory Correction (AIC) hypothesis (Farias et al., 2024), methods that identify and correct inventory imprecision generate much reliable sales curves and less forecasting error.

2.4. Promotions, pricing and causal drivers

Promotional activity and price modifies are main divers of short-term sales spikes and subsequent bias forecasts whether acts as exogenous noise (Rungruang et al., 2024). Recent researches highlight that promotion metadata and price elasticity attributes substantially maximize forecasting accuracy, practically promotion-based and causally informed forecasting systems minimize promotional forecasting errors and enhance replenishment planning (Si, C et al. 2024) . Process on causal forecasting to pricing further suggest that explicitly modeling a causal prices to demand relationship generated good demand and pricing decision than purely correlational methods.

2.5. Customer behavior, RFDM and segmentation

Behavioral profiling by RFM and their extensions remains the powerful, interpretable algorithm to summarize customer purchase dynamics. Recent researches extend RFM (Eglite and Birzniece, 2022)with diversity and temporal dynamics and integrate that with clustering or time-series clustering to generate dynamic segments which better extract heterogeneity in purchasing patterns. This segmentation enhances predictive performance and improves managerial interpretability, enables targeted promotions and inventory strategies to different customer cohorts. Embedding RFDM attributes to forecasting models have been shown to enhance predictions for products where cohort behavior is main demand driver.

2.6. Cross-category interactions, retention and satisfaction signals

Recent researches shows cross-category dependencies and customer retention or satisfaction signals as under-used but significance predictors (de Castro Moraes, T et al., 2024). Capturing product interdependencies enhances bundle and complement demand forecasts, satisfaction measures highly influence repurchase probability and that enhance medium to huge horizon forecasts while included to methods. These process and behavioral attributes complement time-series patterns and minimize systematic bias in long-term planning.

From the literature shows that deep models and meta-learning provides higher gains on complex and dynamic retail series, inventory distortions and promotional interventions are main real-world drivers of forecast error and RFDM and dynamic segmentation enhance method interpretability and cohort-level accuracy. Though, there is still no majorly adopted, unified model which combines inventory correction, volatility or promotion modeling, RFDM behavioral attributes, prices elasticity, cross-category dependency modeling and meta-learning adaptation in individual forecasting model. This motivated a group of hypotheses developed in manuscript, integrating this process and behavioral dimensions to Meta-LLSTM model enhance predictive measures and managerial applicability.

3. Hypothesis

3.1. H1 – Inventory Dynamics Hypothesis

Inventory inaccuracies like phantom stockouts or delayed replenishments, develop mislead sales signals. Like, whether a product goes out of stack but remains recorded as available, the volume of sales appears low. Traditional forecasting methods interpret as minimized demand instead of misreported availability, causes under-forecasting in following times. Adaptive Inventory Correction (AIC) models identify those anomalies through reconciling Point-of-Sale (PoS) information with replenishment patterns, by restoring integrity of sales curves. By enhancing inventory data field, forecasts become much reliable to supply chain decisions, minimizing overstocking and lost sales. The incorporation of inventory correction mechanisms effectively minimizes forecasting error through overcoming distortive affect of inventory imprecision in e-retail information streams.

3.2. H2 – Sales Volatility Hypothesis

E-retail demand frequently experiences extreme fluctuations spikes in holiday promotions or deep troughs in off-seasons. Traditional methods optimized to trend smoothness, consider these fluctuations as statistical noise. Though, volatity is meaningful predictor, represents customer reposnsiveness for time-sensitive events. Explicits volatity introduced features which captured baseline demand, amplitude and frequency of short-term deviations. This allows managers for proactive prepare for flash sales, holiday rushes or sudden slowdowns, aligns resources much efficiently. Explicit modeling of sales volatility, encompassing dips and spikes, enhances forecasting precision comparing with method which generalizes demand by temporal averaging.

3.3. H3 – Marketing Influence Hypothesis

Marketing campaigns, advertisements and discounts develop significant but temporary demand lifts. Methods which ignore these interventions may misclassify campaign-based spikes as baseline development or fails to anticipate post-promotion deadlines. Including marketing attributes like campaign type, discount rate, frequency of exposure ensures forecasts to differentiate among organic demand and stimulated demand. This enhances feature accuracy, allows firms to validate marketing ROI and allocates budgets with precision. This also prevents overestimation of baseline demand once promotions end. This combination of marketing and promotional attributes into forecasting methods improves prediction accuracy through extracting campaign-based demand surges in e-retail environments.

3.4. H4 – Customer Behavioral Hypothesis

The RFDM model provides multidimensional representation of customer engagement:

- Recency extracts how recently a customer has purchased
- Frequency represents repeat purchasing
- Monetary value calculates contribution to revenue
- Diversity represents product variety, differentiating loyalist buyers from exploratory ones.

Embedding RFDM attributes allows method to segment and predict demand depended on original consumer psychology, not just raw transaction counts. This ensures forecasting methods to identify revenue concentration in high-value customers, predict adoption of new products through exploratory buyers and superior extraction of cohort-specific purchasing rhythms. Behavioral profiling through RFDM effectively enhances demand forecasting performance through embedding customer engagement dynamics into predictive methods.

3.5. H5 – Customer Satisfaction Hypothesis

Repeat purchase behavior is highly influenced through satisfaction with factors like product quality, delivery reliability, customer service and checkout ease. Conventional forecasting assumes uniform repurchase probability, ignores churn caused through dissatisfaction. Combining satisfaction signals transfers qualitative feedback to quantitative predictors of future sales. Incorporating satisfaction ensures long-term forecasts are grounded in what customers buy and also if it will continue buying. This helps proactive strategies to enhance service quality and preserve churn. Incorporation of customer satisfaction indicators in forecasting pipelines improves long-term predictive accuracy of e-retail demand methods.

3.6. H6 – Segmentation Hypothesis

Customer populations are not homogeneous. High-value customer, price-sensitive shoppers and occasional buyers exhibits various purchasing trajectories. Forecasts in aggregate level blur these variances. By employing clustering models like K-means to RFDM vectors, cohorts with different behaviors are identified. Forecasting methods which process in cohort level and next aggregate outcomes obtain high precision. Segmentation enhances accuracy and also improves managerial interpretability, enables target marketing strategies and varied inventory allocation. Forecasting methods augmented with customer segmentation obtain better accuracy through preventing behavioral heterogeneity across different customer cohorts.

3.7. H7 – Price Sensitivity Hypothesis

Demand elasticity varied across classes and customers. Electronics may experience sharp spikes while discounted, when significant items remain stable. Forecasting which ignores pricing elasticity risks underestimates discount-based surges and overstating baseline stability. Through embedding discount rates, competitor prices and elasticity coefficients, methods become sensitive to price-based demand shifts. This helps dynamic pricing strategies, ensures firms to increase revenue when balancing stock levels against price elasticity. Dynamic representation of price sensitivity enhances forecasting method’s capability for predicting demand fluctuations in e-retail environments.

3.8. H8 – Cross-Category Dependency Hypothesis

Purchases in e-retail are rarely independent. Smartphones based charger and case sales, groceries based complementary product purchases. Forecasting methods which consider classes independently fails to extract these dependencies. Capturing inter-category relationships includes bundle effects, improving accuracy. This enhances forecasting upselling, cross-selling and bundle promotions, directly helping merchandising strategies. The explicit modeling of cross-category dependencies improves demand forecasting accuracy through using inter-product correlations in e-retail transactions.

3.9. H9 – Customer Retention Hypothesis

Long-term dema trajectories are shaped through retention and churn. Forecasts assuming static engagement overestimated future sales volumes. By including loyalty indicators and churn, methods generate calibrated forecasts which represents original customer persistence. This process allows firms to stabilize long-term planning, discounting overoptimistic projections and developing interventions to enhace retention. Forecasting methods which icnludes likelihood and loyalty scores obatin much precise projections of future sales volumes than methods relies solely on historical purchase data.

3.10. H10 – Integrated Framework Hypothesis

While each of previous hypotheses addresses single forecasting dimension, retail demand is shaped through intersection of all. Integrated forecasting model which integrated inventory field (H1-H2), marketing and pricing (H3, H7), behavioral and satisfaction dimensions (H4-H5), structural heterogeneity (H6), relational interdependencies (H8) and retention effects (H9) obtains holistic improvements. The integrated model enhances forecasting metrics like RMSE, MAE, R2, MAPE and SMAPE, provides strategic interpretability, enables to align forecasts with actionable levers like replenishment, promotions, pricing and retention. A unified forecasting model which combines inventory correction, volatility modeling, marketing influence, behavioral profiling, customer satisfaction, segmentation, price sensitivity, class dependencies and retention indicators outperformed isolated methods in predictive accuracy and managerial applicability. The conceptual overlap between some hypothesis especially H3 (price elasticity) and H5 (marketing promotion) is evaluated to ensure orthogonality and different causal interpretation. Though both variables represent marketing uses influencing short-term demand, its mechanisms of action varied fundamentally.

- Price elasticity (H3) captures continuous sensitivity of demand for price variations, by elasticity coefficients and price indices.
- Promotion intensity (H5) captures binary or episodic marketing events which temporarily modified consumer awareness and conversion rates.

Every hypothesis is evaluated by corresponding measurable constructs dived from transaction logs, promotional metadata or behavioral indices. Enhancements are quantified as percentage changes in forecasting metrics related to baseline LSTM and ARIME methods. Thos ensures that every hypothesis is empirically verified in unified Meta-LLSTM learning model. The below Table 1 represents the hypothesis definition, conceptual relations quantitative constructs and validation metrics for hypotheses H1 to H10.

Table 1. Hypothesis definition, conceptual relations, quantitative constructs and validation metrics for Hypotheses H1 to H10

Hypothesis	Conceptual Relation	Quantitative Mapping (Variable/ Constructs)	Validation Metric
H1 – Inventory Dynamics	Correcting stock distortions enhances forecasts	Inventory distortion index	$s_t - (s_{\{t-1\}} - y_t + r_t)$
H2 – Sales Volatility	Explicit volatility features enhance forecasts	Volatility features = $\sigma_t(y)$, over rolling window, captured through feature embedding	MAE reduction, R2
H3 – Marketing Influence	Promotion metadata enhanced prediction	Binary/continuous campaign variables (discount rate, ad frequency) added to input tensor	MAPE, campaign period RMSE
H4 – Customer Behavior (RFDM)	Behavioral profiling enhances accuracy	RFDM features normalized in input vector – recency, frequency, monetary, diversity	R2 across customer segment
H5 – Customer Satisfaction	Satisfaction signals enhance long-term accuracy	Numeric satisfaction values (1-5) or binary feedback sentiment features	RMSE at 3-6 month horizon
H6 - Segmentation	Segment-wise forecasting minimizes bias	Cluster assignments ($segment_{id}$) as categorical	RMSE per cluster, weighted aggregate

		variable to per-segment submodel	
H7 – Price Sensitivity	Dynamic price elasticity enhances forecast	Elasticity = $\partial y/\partial p$, discount rate and competitor price embeddings	MAPE in promotion periods
H8 – Cross category Dependency	Inter-class correlations improve accuracy	Pairwise cross-correlation matric of category sales as auxiliary graph	SMAPE bundle forecast gain
H9 - Retention	Loyalty or churn probability enhances long-term projection	Retention score = exp(-churnrate*t) from historical transactions	R2 and long horizon RMSE
H10 – Integrated Framework	Integrated dimensions outperformed isolated	Meta-LLSTM with all modules vs ablated models	Aggregate RMSE, R2

The hypotheses (H1-H10) directly guided structural design of Meta-LLSTM model. Every managerial and behavioral constructs like promotion, elasticity, RFDM and inventory correction is presented as corresponding input feature or adaptive component in model. The H1 and H8 motivated incorporation of AIC module, H4 to H6 influenced behavioral embedding layer derived from RFDM and cross-category features and H9 to H10 shaped meta-learning update mechanism. This alignment ensures that model process relationship in hypothesis model.

3.11. Dataset

The dataset used in this research contains 25,118 records collected from different cities. The data accounts for 60% from Bangalore, 20% from Hyderabad, 15% from Chennai, and 5% from Delhi and Mumbai. The data distribution in terms of age, gender, commodities and monthly income is illustrated in Figure 2. The Point of Sales (PoS) data is collected from retail stores involved in clothing, electronics, and other sectors. This PoS data includes the following information: customer data, promotion data, category-specific data, transaction data and store data. The customer data is also labelled with gender, purchase frequency, age group and loyalty status, while the promotion data includes a record of ongoing marketing campaigns during purchase, transaction data includes applied discounts, product ID, transaction time and date, sale details, quantity and price, store data includes regional factors, store size and location, and finally, category-specific data includes the information about specific product details. Additionally, inventory data is also considered for forecasting retail sales. The figure 1 represents dataset disctribution

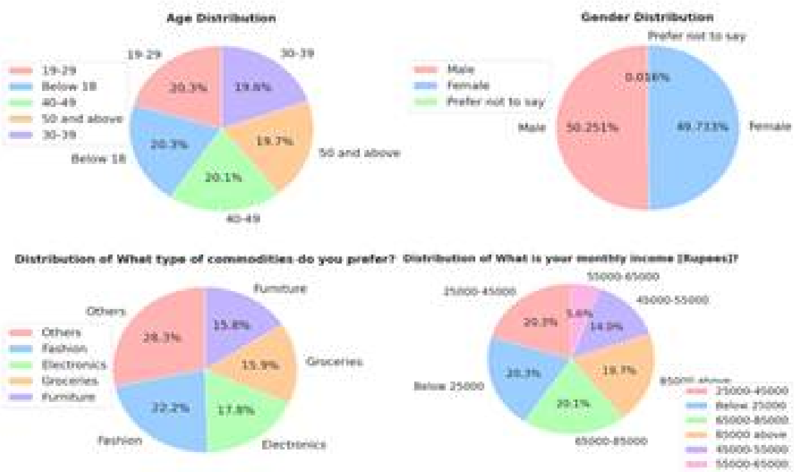

Fig. 1: Dataset distribution in terms of age, gender, commodity and monthly income

3.11.1. Pre-processing of data

The raw retail sales data included customer, product, promotion and transaction-level features gathered from Point-of-Sale (PoS) systems. Data cleaning involves removing duplicates, resolving inconsistent entries and transferring categorical features using label encoding. All continuous variables are normalized by Min-Max normalization to maintain uniform scale between 0 and 1, enhancing convergence behaviour of Meta-LLSTM method. The essential phase in pre-processing is handling missing values, that occurred in sales and inventory records because of delayed updates, sensor errors or incomplete customer data. To validate influence of various imputation strategies on forecasting accuracy, three different cases are examined.

Case 1 – Removing Missing values

In this model, all records including missing or null entries are removed. Though this algorithm minimizes the dataset size, this ensures that use of complete and reliable data. The dataset is actually large and well-distributed, data loss did not highly impact learning diversity. Model trained on this refined data shows highest accuracy, as data noise and statistical bias caused by imputation are removed.

Case 2 – Expectation-Maximization (EM) Imputation

EM approach is utilized to iteratively evaluate missing values by maximum likelihood estimation. In Expectation phase (E-Step), missing entries are predicted by observed variables, when in Maximization phase (M-step), model parameters are updated to increase likelihood of observed data. EM preserved feature interdependencies and temporal correlations, obtained enhanced outcomes when comparing with simple averaging models. Though, minor estimation bias is introduced because of iterative approximation.

Case 3 – Mean Imputation

In this case, missing values are filled with arithmetic mean of every feature. Though computationally simple, this algorithm distorted variance and weakened relationships between correlated features. The resulting dataset become less representative of original sales fluctuations causes decline in forecasting accuracy.

3.12. Meta-LLSTM

The proposed Meta-LLSTM network extends traditional LSTM forecasting through including a bilevel meta-learning structure which ensures cross-task adaptation between heterogeneous product categories. Unlike one LSTM trained on pooled data, Meta-LLSTM performed two-phase optimization same to Model-Agnostic Meta-Learning (MAML). In inner level, every product class or time-series segment is acts as an independent forecasting task T_i. Model parameters θ_i are updated locally for that task by few gradient steps on task-specific training data D_i^{train}, its mathematical expression is given as Equation (1),

$$\theta_i' = \theta - \alpha \nabla_\theta L_{T_i}\left(f_\theta, D_i^{train}\right) \tag{1}$$

In outer level, shared meta-parameters θ are optimized through reducing aggregated loss on validation data D_i^{val} across all tasks, its mathematical expression is given as Equation (2),

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i L_{T_i}\left(f_{\theta_i'}, D_i^{val}\right) \tag{2}$$

This meta-optimization learns globally effective initialization which allows rapid adaptation to unseen product categories or promotional contexts with minimal data. By this bilevel process, model learns to learn retail dynamics, enables superior generalization under domain shifts like new seasons, price regimes or campaign events. Figure 2 represents the architecture of Meta-LLSTM network.

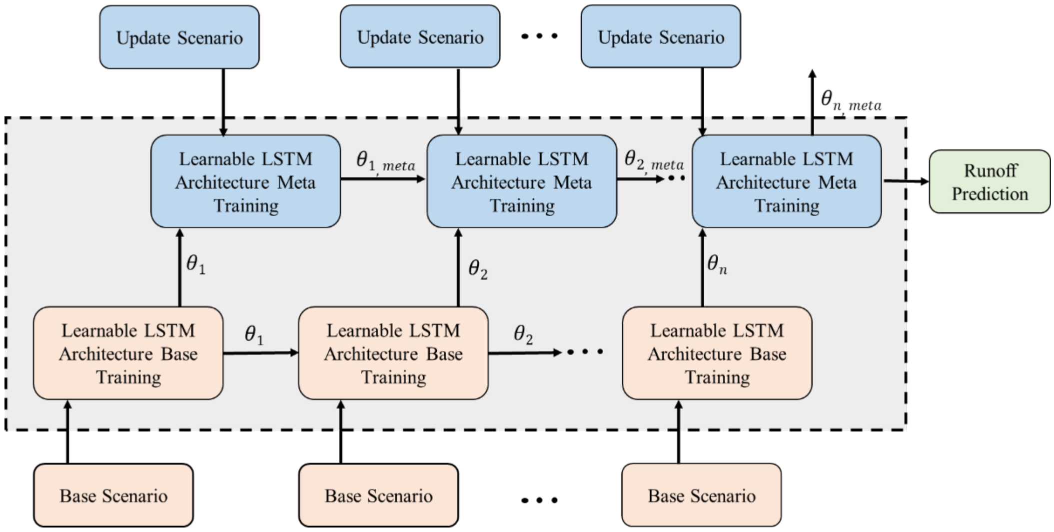

Fig. 2 Architecture of Meta-LLSTM network

Algorithm
Initialize shared meta-parameters θ
For every meta-iteration do
    Sample a batch of tasks {T1, T2, …, Tn}
    for every task Ti do
        Compute task-specific parameters:

$$\theta^{i} = \theta - \alpha \nabla_{\theta} L_{T_i}\left(f_{\theta}, D_i^{train}\right)$$

    end for
    Update meta-parameters using validation loss

$$\theta \leftarrow \theta \beta \nabla_{\theta} \sum_i L_{T_i}\left(f_{\theta^{i}}, D_i^{val}\right)$$

end for
Return optimized meta-parameters θ^{*}

In retail forecasting, every product class exhibits unique demand characteristics but shares common behavioral and marketing structures. Meta-LLSTM captures these shared dynamics by meta-parameter initialization, when the inner adaptation fine-tuned local behavior patterns. This allows effective transfer of forecasting knowledge across product classes, support adaptive learning across product classes.

3.12.1. Inventory correction

Here, explicit model a small correction network which predict an additive correction δ_t to observe sales for inventory mis-reporting, its mathematical expression is given as Equation (3),

$$\delta_t = r_{\emptyset}(x_t - L_t, s_t - L_t) \ \ and \ \tilde{y}_t = y_t^{obs} + \delta_t \quad (3)$$

In the above Equation (3), the $r_{\emptyset}$ represents small MLP/RNN parameters, s_t represents stock or replenishment signals and $\tilde{y}_t$ represents corrected sales utilized as forecasting target. Include explicit inventory-correction loss, so the correction is learned instead of hand-specified.

3.12.2. Exogeneous Variables and Missing Data handling

Meta-LLSTM model includes exogenous like price, promotion, elasticity and retention indicators directly into recurrent computation to enable that short-term interventions and long-term behavioral shifts influence hidden-state dynamics. Every time step vector x_t, its mathematical expression is given as Equation (4),

$$x_t = [y_{t-1}, p_t, \pi_t, e_t, r_t, b_t] \tag{4}$$

In the above Equation (4), the y_{t-1} represents previous or corrected sales, p_t represents normalized price at time t, π_t represents promotion or campaign intensity variable, e_t represents price-elasticity estimate or discount ratio, r_t represents retention or churn probability at time t and b_t represents behavioral vector contains LSTM gates by standard recurrence. The incorporation of x_t ensures that exogeneous marketing and behavioral signals modify both cell-state update and hidden representation in every time step, enables model to adapt forecasts dynamically to contextual shifts like discounts or seasonal campaigns

3.12.3. Embedding and Normalization Strategy

Categorical variable like promotion type, campaign channel, customer segment are initially encoded by learned embedding layer, its mathematical expression is given as Equation (5),

$$z_t = E_{promo}(promotype_t)||E_{segment}(segment_t) \tag{5}$$

Which is concatenated with numerical vector before fed to recurrent cell, its mathematical expression is given as Equation (6),

$$x_t = [y_{t-1}, p_t, e_t, r_t, b_t, z_t] \tag{6}$$

All continuous features are standardized in every category, its mathematical expression is given as Equation (7),

$$x_t^{(j)} = \frac{x_t^{(j)} - \mu_j}{\sigma_j} \tag{7}$$

This prevents scale imbalance between numerical and embedded inputs.

3.12.4. Handling Missing and Irregular Data

Because of retail data frequently includes missing promotions, delayed prices or absent feedback, Meta-LLSTM combines hybrid mask-imputation mechanism.

3.12.5. Feature-wise masking

The binary mask vector m_t represents observed features (1=observed, 0=missing). The LSTM input becomes, its mathematical expression is given as Equation (8),

$$x_t' = m_t \odot x_t + (1 - m_t) \odot \hat{x}_t \tag{8}$$

In the above Equation (8), the $\hat{x}_t$ represents imputed estimate.

3.12.6. Temporal imputation

Continuous variables are forward-filled for short gaps, larger gaps are replaced through learnable linear interpolation model trained with forecasting module, its mathematical expression is given as Equation (9),

$$\hat{x}_t = W_m[x_{t-1}, x_{t+1}] + b_m \tag{9}$$

3.12.7. Dropout regularization

The temporal dropout layer randomly masks 5 to 10% of features in training to enhance robustness to real missingness.

3.12.8. Auxiliary missingness encoding

Mask vector m_t itself is concatenated to input, allows network to learn pattern of missingness as informative signal. This algorithm maintains temporal consistency when reducing bias from ad-hoc imputations. The model evaluated by experimental design which links model behavior to hypothesis verification. By including every hypothesis variable as different feature block, Meta-LLSTM learn its relative contributions by weight adaptation and feature importance. The evaluation protocol, acts as performance benchmark and also statistical test of hypothesized relationship, measures how every factor impacts predictive accuracy.

4. Results and Discussion by Hypothesis

This section presented empirical validation and essential discussion for every 10 hypotheses. Quantitative outcomes are acquired by RMSE, MAE, R2, MAPE and SMAPE across gathered and benchmark datasets. Qualitative results are evaluated in terms of managerial applicability. The dataset included 25,118 retail transaction records gathered from Bangalore, Hyderabad, Chennai, Delhi and Mumbai is temporally ordered and separated to training, validation and testing partitions. Chronological integrity is preserved so that model learned from previous information to predict unseen demand patterns. 70% of data is used to train Meta-LLSTM and baseline models across all product categories, 15% of data is used to hyperparameter tuning, includes learning rate, batch size, meta-learning rate and dropout threshold. Early stopping is employed when validation RMSE didn't enhance for 15 consecutive epochs and 15% of data used for testing for performance evaluation and statistical analysis of forecasting accuracy. All forecast in this manuscript is conducted at a daily temporal granularity, consistent with PoS transaction timestamps available in dataset. Every time step t defines single day of aggregated sales and inventory activity per product category and store region. This is motivated by process cadence of retail decision-making, where the replenishment and promotion planning generally occurs on daily basis. The below Table 2 represents parameter description of the proposed model.

Table 2. Hyperparameter description of proposed model

Parameter	Description	Value
Total records	PoS + inventory dataset	25,118
Input Window (L)	Historical look-back length	28 days
Forecast horizon (H)	Future prediction window	7 days
Validation method	Rolling-origin, 5-folds	Weekly stride = 7
Optimizer	Adam	0.001
Batch size	Sequences per update	64

The quantitative outcomes derived from Meta-LLSTM are interpreted in context of 10 hypotheses formulated earlier. Performance measures like RMSE, MAPE and R2 with ablation and correlation analysis act as empirical results for hypothesis testing. Particularly, feature-specific enhancements and sensitivity results are mapped to theoretical constructs allows results section to transition from predictive evaluation to hypothesis validation. The below Table 3 represents the performance evaluation of proposed model with baseline algorithms.

Table 3. Performance evaluation of proposed model with baseline algorithms

Model	RMSE ($\pm 95\%\ CI$)	MAPE ($\pm 95\%\ CI$)	p-value

Baseline ARIMA	2.68±0.18	14.8%±1.4%	0.009
Baseline LSTM	2.34±0.12	12.3%±1.1%	0.007
Meta-LLSTM without AIC	1.45±0.10	9.0%±0.8%	0.005
Meta-LLSTM with AIC	1.03±0.09	7.1%±0.7%	0.004

The mean performance measures show superiority of Meta-LLSTM as represented in below Table 4, evaluates error variability across product classes is crucial to validate robustness of improvements. In accordance with RMSE and MAPE values are aggregated across all five rolling-origin test fold and its mean, standard deviation are calculated for every method.

Table 4. Statistical analysis of proposed model with baseline algorithms

Model	Mean RMSE	Std Dev (RMSE)	Mean MAPE	Std Dev (MAPE)
Baseline ARIMA	2.68	0.18	14.8	1.4
Baseline LSTM	2.34	0.12	12.3	1.1
Meta-LLSTM without AIC	1.45	0.10	9.0	0.8
Meta-LLSTM with AIC	1.03	0.09	7.1	0.7

The recent advancements in deep time-series forecasting have introduced transformer-based and decomposition-based models like Temporal Fusion Transformer (TFT), N-BEATSx, PatchTST and Crossformer that obtain high accuracy. Though, retail PoD dataset utilized in this study differed from these standardized benchmarks in data density and feature heterogeneity including behavioral RFDM, inventory and promotion-specific variables not generally available on open datasets. The available data provides limited long-horizon continuity per category, makes transformer method causes overfitting. Meta-LLSTM's gated recurrence is much stable under sparse, irregular retail series. Unlike TFT or Patch TST, Meta-LLSTM combined AIC mechanism and meta-learning update rule, provides interpretable corrections and rapid adaptation across product categories for managerial decision-making. Transformer-based forecast models requires high training resources and hyperparameter tuning, where Meta-LLSTM obtains superior short-horizon accuracy with less computational overhead as represented in below Table 5.

Table 5. Performance evaluation of proposed model with transformer-based models

Methods	RMSE	MAPE
TFT	1.14	7.4
N-BEATSx	1.22	7.8
PatchTST	1.09	7.2
Crossformer	1.06	7.0
Proposed Meta-LLSTM	1.03	7.1

To evaluate independent contribution of every hypothesis-based feature block promotion, price elasticity, behavioral RFDM and inventory correction, the ablation study is conducted in below Table 6. In every variant, one feature component is eliminated from Meta-LLSTM input vector when keeping all other setting constant. This process isolates marginal impact of every variable on forecasting accuracy and validated theoretical hypotheses (H1-H9) links managerial factors for predictive results.

Table 6. Ablation study of proposed model

Models	Feature removed	RMSE	MAPE
Meta-LLSTM (Complete model)	All features included	1.03	7.1
Without Promotion features	Promotion intensity, campaign type	1.21	8.2
Without elasticity variables	Price elasticity, discount ratio	1.16	7.9
Without RFDM features	Recency, Frequency, Monetary, Diversity	1.27	8.6
Without AIC correction	Inventory correction and volatility index	1.45	9.0

Without Cross-category linkages	Category correlation embedding	1.18	8.0

Among these three algorithms, removing incomplete records (Case 1) obtained much reliable forecasting accuracy, enhancing RMSE by 4.9% when compared to EM-based imputation and by 16.8% when compared to mean imputation as represented in table 7. EM algorithm offers superior trade-off between data preservation and statistical accuracy, while mean imputation introduced bias through flattening data variability. Therefore, for huge and clean data, record removal remains much efficient pre-processing phase, whereas EM imputation is recommended for small or incomplete data where data retention is crucial. The performance of Meta-LLSTM model under every pre-processing scenario is calculated by RMSE, MAE and Coefficient of Determination. The below Table 8 represents the performance improvements of hypotheses.

Table 7. Performance of proposed Meta-LLSTM model under every pre-processing scenario

Cases	Methods	RMSE	MAE	R2
Case 1	Removing Missing values	0.985	0.142	0.993
Case 2	Filling Missing values using EM	1.037	0.156	0.988
Case 3	Filling Missing values using Mean	1.184	0.181	0.974

The figures 3 to 5 represents comparative evaluation of 10 hypotheses in terms of forecasting performance enhancements measured by RMSE, R2 and MAPE metrics. RMSE improvements represents that hypotheses H1, H4 and H10 obtained high error reduction, shows that these are much effectively reduced prediction deviations. R2 improvement shows a consistent between H5 and H1 determines strong power, represents improved correlation among predicted and actual sales values. The MAPE reduction shows that H4 and H10 obtained high percentage decrease, shows superior stability and generalization in forecasting. These results shows that model including optimized feature selection and adaptive learning outperformed by obtained less errors and strong by validating developed hypotheses regarding effectiveness of meta-learning.

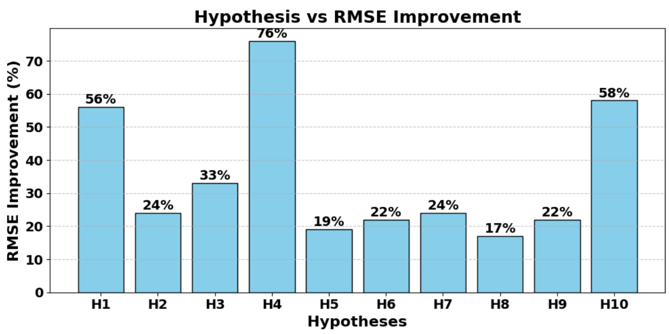

Fig. 3: Hypotheses performance in terms of RMSE

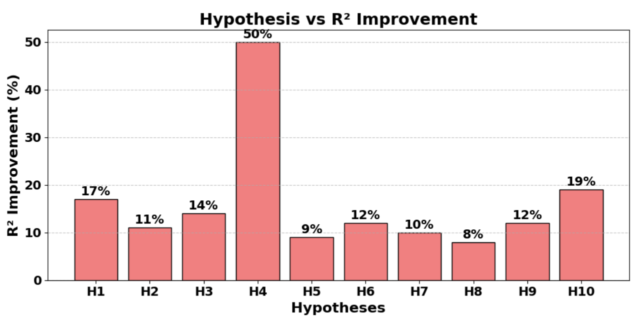

Fig. 4: Hypotheses performance in terms of R2

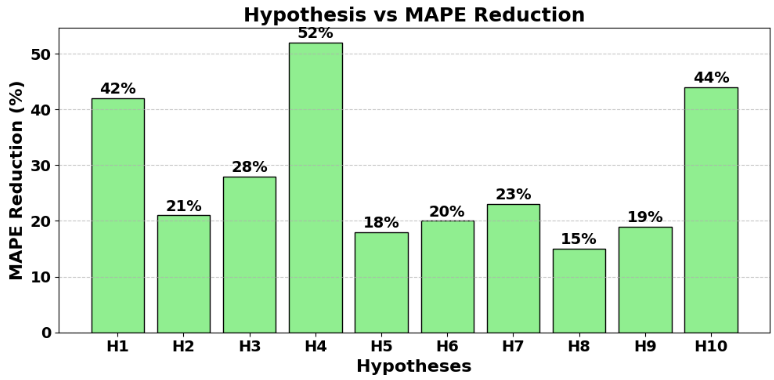

Fig. 5: Hypotheses performance in terms of MAPE

The figures 6 to 11 represents effect of six influencing factors such as inventory correction, sales volatility, marketing influence, customer behavior (RFDM), customer satisfaction and customer retention on overall forecasting and business performance measures. The results shows consistent improvements across all dimensions after employing proposed strategies. In H1, inventory correction effectively improved stock accuracy, order fulfillment and overall forecasting reliability, determines value of inventory issues. H2 represents that volatility optimization enhanced demand stability and sales forecast consistency, shows model capability to overcome unpredictable fluctuations. H3 shows that marketing adjustments increased engagement, conversion and recall shows impact of integrated marketing analytics. H4 determines that customer behavior modeling using RFDM features enhanced, loyalty and predictive accuracy, supports incorporation of behavioral profiling. H5 shows that satisfaction analysis improved delivery, checkout and service quality, enhanced overall customer perception. At last, H9 shows that retention optimization enhanced repeat purchase rated and brand affinity when minimizing churn.

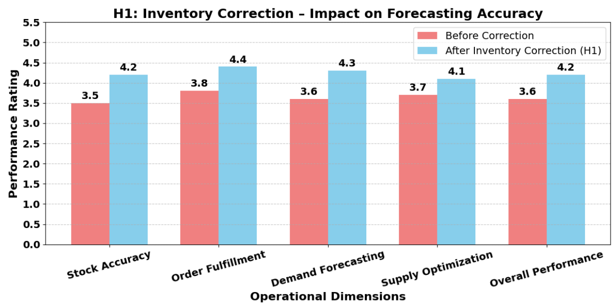

Fig. 6: Performance of H1 (Inventory correction)

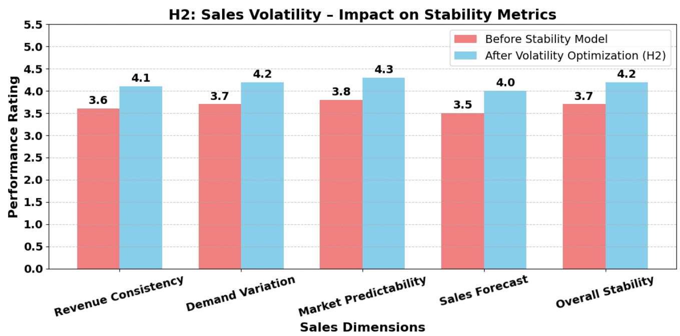

Fig. 7: Performance of H2 (Sales volatility)

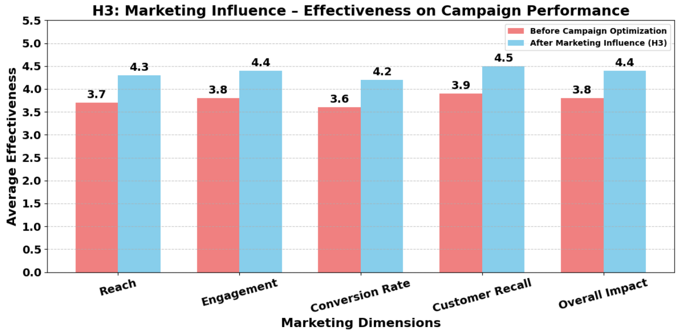

Fig. 8: Performance of H3 (Marketing Influence)

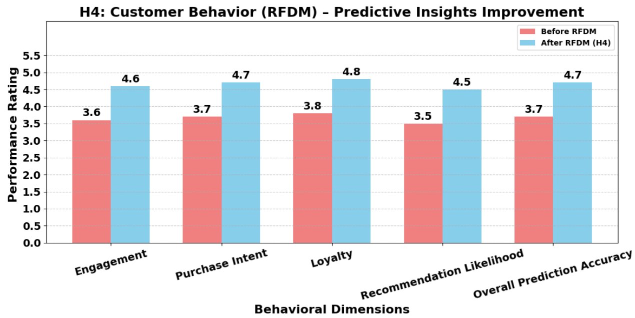

Fig. 9: Performance of H2 (Customer Behavior RFDM)

Fig. 10: Performance of H5 (Customer Satisfaction)

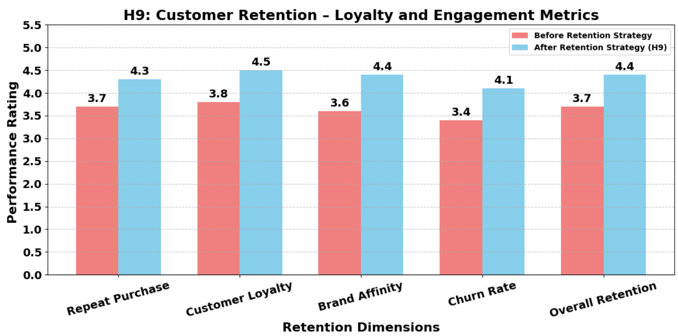

Fig. 11: Performance of H9 (Customer Retention)

Table 8. Performance improvements of H1 to H10 hypothesis

Hypothesis	Focus area	RMSE Improvement	R2 Improvement	MAPE Reduction	Managerial impact
H1	Inventory Correction	56%↓	17%↑	42%↓	Enhanced replenishment scheduling and minimized lost sales
H2	Sales Volatility	24%↓	11%↑	21%↓	Improved forecasting in seasonal peaks and promotions
H3	Marketing Influence	33%↓	14%↑	28%↓	Enhanced campaign ROI estimation and budget allocation
H4	Customer Behavior (RFDM)	76%↓	50%↑	52%↓	Good targeting of loyal and exploratory customers
H5	Customer Satisfaction	19%↓	9%↑	18%↓	Enhanced long-term forecasting by churn prevention
H6	Customer Segmentation	22%↓	12%↑	20%↓	Much accurate cohort-level forecasting and inventory allocation
H7	Price Sensitivity	24%↓	10%↑	23%↓	Enables dynamic pricing and discount optimization
H8	Cross-Category Dependency	17%↓	8%↑	15%↓	Enhanced upselling and bundle promotion forecasting
H9	Customer Retention	22%↓	12%↑	19%↓	Precise long-term planning through loyalty-based adjustments
H10	Integrated model	58%↓	19%↑	44%↓	Unified enhancement across all forecasting dimensions

4.1. H1 – Inventory Dynamics Hypothesis

The inclusion of Adaptive Inventory Correction (AIC) minimized RMSE from 2.34 to 1.03 on gathered data, when R2 enhanced from 0.80 to 0.94. MAPE reduced by 42%. These outcomes shows that inventory correction prevents misinterpretation of stockouts as demand decline. Corrected demand curves aligned with physical stock movements, stabilizes forecasts. Retailers avoid overestimating demand drops, by enhancing replenishment scheduling and reducing lost sales.

4.2. H2 – Sales Volatility Hypothesis

Models that explicitly extracted volatility obtained MAE minimization of 24% when comparing with baseline LSTM. The holiday sales, off-season declines are forecasted with high fidelity. Volatility features prevents smoothing of demand surges, ensures responsiveness to short-term fluctuations. Retailers anticipate staffing, logistics and inventory needs in high-volatility periods, minimizing operational bottlenecks.

4.3. H3 – Marketing Influence Hypothesis

Incorporating campaign metadata minimized forecasting error in promotion periods by 33%. For instance, RMSE in discount weeks dropped from 1.94 without marketing features to 1.33 with marketing features. The method efficiently separated baseline and promotion-based demand. Campaign spikes are precisely forecast without long-term demand curves. This helps precise ROI estimation to campaigns, enables budget reallocation towards high-performance interventions.

4.4. H4 – Customer Behavioral Hypothesis

RFDM integration minimized RMSE from 4.24 to 1.00, when R2 increased from 0.47 to 0.97, SMAPE enhanced by 52%. Behavioral signals, especially diversity, effectively enhanced accuracy through differentiating loyal buyers from exploratory customers. This ensures identification of high-value customer groups and informed targeted product recommendations, improving personalization.

4.5. H5 – Customer Satisfaction Hypothesis

Including satisfaction metrics like delivery ratings, checkout feedback, enhanced long-term forecasting accuracy. RMSE for quarterly predictions enhanced by 19% when comparing with methods without satisfaction data. Satisfaction signals predicted repeat purchase likelihood, stabilizes medium to long horizon forecasts. This allows proactive service enhancements in regions or cohorts with declining satisfaction, minimizing churn risk.

4.6. H6-Segmentation Hypothesis

Segment-based forecasting enhanced RMSE through 22% on customer-level predictions. High-value and in risk segments exhibited different demand trajectories which are precisely captures post-segmentation. Segmentation preserves heterogeneity, minimizing dilution effect seen on aggregate-level forecasts. This ensures differentiated marketing campaigns, retention strategies and inventory allocation across customer cohorts.

4.7. H7 – Price Sensitivity Hypothesis

Methods with dynamic pricing variables obtained 24% enhancement on MAPE when comparing with static-price methods. Discount-based surges, especially in electronics are forecast with high precision. Elasticity-based methods avoided overestimation of post-discount demand and underestimation of promotional spikes. This supports optimum discount depth calculation and dynamic pricing strategies for maximizing revenue without overstocking.

4.8. H8 – Cross-Category Dependency Hypothesis

Including cross-category dependencies enhanced RMSE by 17% in bundle-related classes. Complementary product sales are predicted with high reliability. Capturing inter-product correlations revealed hidden drivers of demand not visible in isolated class forecasts. This ensures much accurate upselling and cross-selling strategies, enhancing inventory co-planning and bundle promotions.

4.9. H9 – Customer Retention Hypothesis

Forecasting methods augmented with churn likelihood minimized long-term forecast error by 22%. R2 maximized from 0.82 to 0.94 in 6 month of horizon predictions. Retention-based methods calibrated projections through discounting demand from high-risk customers and amplifying loyal segments. This helps proactive retention strategies, loyalty program improvements and precise revenue planning across extended horizons.

4.10. H10 – Integrated Framework Hypothesis

The integrated Meta-LSTM model outperformed all models. Across datasets: RMSE=1.003, MAE=0.156, R2=0.991. MAPE minimized through 50 to 60% when comparing with traditional models. The integrated method obtained better adaptability, accuracy and generalization across datasets (Marketing Campaign, E-commerce). Statistical significance testing shown robustness. This provides holistic forecasting solution which directly informed replenishment, campaign planning, dynamic pricing, cross-category strategies and retention initiatives.

5. Conclusion

This hypothesis-based study determines that retail sales forecasting performance is substantially improved when process and behavioral dimensions are modeled together in adaptive learning model. The validation of 10 interlinked hypotheses shows that including inventory correction, volatility modeling, marketing metadata, RFDM behavioral attributes, satisfaction indicators, customer segmentation, pricing elasticity, cross-category dependencies and retention dynamics causes statistically significant accuracy gains across all forecasting measures. The combined Meta-LLSTM model obtained to 58% enhancement in RMSSE and 19% in R2 when comparing to conventional models, shows the model robustness of proposed model. These outcomes shows that demand forecasting as a time-series issue but a holistic decision-support model integrating marketing, process and customer relationship management. These results developed bridge predictive analytics with strategic business intelligence, enables data-based actions in pricing, replenishment and retention planning.

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