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Research Article

The Impact of AI-Based Demand Sensing on Inventory Optimisation and Bullwhip Effect Mitigation

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Abstract: The study examines how AI-inspired demand sensing would influence inventory optimisation and alleviate the bullwhip effect in the contemporary supply chain. With unstable demand trends, traditional forecasting models typically have a hard time and cause overstocking, stock outs and increasing variability in orders at supply chain levels. To resolve these issues, this paper compares performance of high-order AI models i.e. LSTM, random forest and a hybrid Deep Learning model on the three real demands datasets. The outcomes show that AI-based demand sensing plays a great role in improving forecasting accuracy and inventory performance. LSTM model reduced MAPE by 27.4% and hybrid model reduced it maximally by 32.8 percent quite as compared to the baseline methods. There was an equivalent improvement in inventory optimisation as inventory safety stock decreased by 18.6 and the holding costs decreased by 14.2. Moreover, AI-based sensing significantly limited the amplification of order variance, and it decreased it by 22.9% as compared to traditional forecasting methods. The comparative analysis with the previous relevant studies reveals that AI-based models are always superior in comparison to classical time-series models like ARIMA and exponential smoothing. Altogether, the research proves that demand sensing enhanced by AI is a strategic approach to supply chain resilience, cost-efficiency, and responsiveness.

Keywords: Demand Sensing, Artificial Intelligence, Inventory Optimisation, Bullwhip Effect, Forecast Accuracy.

INTRODUCTION

Proper inventory management and correct demand forecasting are key to the sustainability of competitive supply chains in modern supply chain management, cost reduction and product availability. The conventional predictive techniques are based on historical and past sales patterns and are usually not able to respond to the changes in market quickly and consumer behaviour changes as well as external shocks like the changes in an economy, unavailability of supplies and geopolitical unrest [1]. This can often create inaccurate inventory planning, leading to overstocks, stockouts, and increased demand variabilities along the supply chain, what is commonly known as the bullwhip effect. With the growing demands of organisations to work in dynamic environments, additional responsive demand management strategies that are smarter at their core is becoming an urgent factor [2]. The advanced demand sensing through artificial intelligence (AI) has become a revolutionary technology that can solve these issues in the supply chain. AI demand sensing represents an opportunity that takes advantage of timely, real-time data, machine learning, and forecast analytics to deliver a more precise and timely depiction of customer demand [3]. In contrast to conventional forecasting, AI-based solutions include a wide range of datasets, including point-of-sale, market trends, weather, and promotions and social sentiment. This will allow the firms to plan in advance by modifying production, procurement and distribution decisions, lots of uncertainty in demand is minimized. Inventory optimisation through AI also enables automated decision-making, a more accurate replenishment, and helps to make operations more resilient. This study investigates the linkage between AI-demand sensing and inventory optimisation and reduction of the bullwhip effect. Through analyzing the enhancement of accuracy in predictions and responsiveness of the supply chain generated by AI, the study would illustrate the level at which the intelligent sensing of demand can stabilise inventory and avoid distortions in the demand in the supply chain. As the concept of the digital transformation of a supply chain gains more and more attention, it is important to comprehend the place of AI in changing the approaches to demand management with the purpose of ensuring increased efficiency, rapidity, and competitive edge of a particular organisation.

RELATED WORKS

The current literature shows a quick rise of artificial intelligence in terms of supply chain, industrial operations, and larger organisational ecosystems. As much as the main subject of the current study is AI-based demand sensing, inventory optimisation, and bullwhip mitigation, other related researches in the adjacent areas offer useful information on how AI can improve decision-making, operational resilience, and efficiency of many and various complex networks. Frikha and Mariem [15] examined the roles of AI-solutions in pathways of decarbonisation of the supply chain through optimisation of logistics routes, carbon emissions, and creation of sustainability-based planning systems. According to their results, intelligent forecasting has an indirect beneficial impact on sustainability through lowering overproduction and inventory waste - a phenomenon that is directly related to efficient demand sensing. Correspondingly, Georgiadis et al. [16] addressed the issue of energy-aware production scheduling as an important factor towards sustainable operations. In their paper, they have highlighted dynamic optimisation methods, which are coherent with the dynamic nature of machine learning algorithms in inventory forecasting. Hayder and Konathala [17] also considered the application of AI in optimising the design of packaging in the context of e-commerce activities. Though material cost cutting is the main focus of their work as opposed to the purpose of the demand sensing, it highlights the importance of AI in operational optimisation, similar to the use of demand sensing in cutting the costs associated with inventory. A study by He et al. [18] also brings to the fore, the capability of the AI to enhance the resilience of the manufacturing supply chain. Their results reveal that predictive intelligence adds value to the possibility to predict disruptions and make changes to the production plan, which, in its turn, is directly applicable in the context of the enhancement of forecast quality and the reduction of the bullwhip effect.

Hossain et al. [19] conducted an extensive review of AI-based innovations in the automotive industry, in which they discovered predictive analytics, automation, and autonomous planning. These observations contribute to the idea that planning efficiency in fast-paced industries can be reinforced with the help of AI-based forecasting systems. To this end, Izabela et al. [20] examined the importance of generative AI in digital twins in Industry 5.0, whereby the focus is on increased accuracy in simulations. Although digital twins are not analogous to demand sensing, the two are very similar as they both heavily depend on real-time information and predictive modelling to assist in decision optimisation. Jing-Yan and Kang [21] revealed that information system agility interchanged the association among digital technologies and the functioning performance within healthcare supply chains. Their results support the notion that AI enhances agility which is a key factor in the minimization of inventory distortions and responsiveness. In more specific field, Kassem et al. [22] developed quantum-inspired model of dynamic multi-objective optimisation of disaster logistics. Even though the target audience is in the emergency settings, the optimisation strategies are structurally equal to the AI-based inventory control algorithms. Lijie and Zhang [23] evaluated how the use of enterprise AI influences the resilience of supply chains of Chinese firms. They discovered that there were very great associations between the adoption of AI and better operational continuity-argumentative of the notion that AI- amplified demand sensing stabilises operations upstream. Liu et al. [24] also proved the role of predictive analytics in risk-sensitive situations advancing forest fire prediction with the help of AI. Their study reveals the ability of machine learning to predict uncertainty and dynamical behaviour. Madani et al. [25] investigated the concept of AI and digital twin in terms of intelligent control of lithium-ion battery systems. Their review has focused on lifecycle optimisation predictive algorithms, which, once more, underlines AI effectiveness in proper predictions and decision-making. And lastly, Mendival-Arrieta et al. [26] discussed the effect of energy integration on safety indexes in the chemical production and how intelligent optimisation models can result in safer and more stable operations. All these studies indicate that AI is always effective in prediction, optimisation, resilience, and efficiency in various fields. It is a good indication to prove that the use of AI-based demand sensing is applicable in inventory optimisation and the prevention of bullwhip.

METHODS AND MATERIALS

The present study employs both secondary and synthetic data in the evaluation of the AI-based demand sensing role in enhancing inventory optimisation and the reduction of the bullwhip effect. The data is assembled by integrating historical point of sale (POS) transactions, promotions timetable, logs of lead times, SKU master (categorical features), external indicators (daily weather index and Google Trends proxy) and inventory naps. 36 months daily granularity data on 100 SKUs in three distribution centers [4]. Pre-processing involves missing-value imputation (forward fill (POS), median (lead-times), outliers (winsorisation on 1 st/99 th percentile), calendar engineering (weekday, holiday flags), promotion encoding, and lag/roll features (lags 1,7,14, rolling means), and lead-time-aware demand transformation to obtain replenishment targets. Data were divided into training (first 24 months), validation (months 2530), and test (months 31 36). Measures of evaluation: MAE, RMSE, MAPE and inventory KPIs: mean days-of-stock (DOS), and stockout rate. Rolling origin evaluation is used to provide temporal robustness in experiments. Randomized search was applied in hyperparameter tuning time-series cross-validation (5 folds) [5].

Algorithms

1 — Random Forest Regressor

Random Forest- It is a collection of decision trees with bootstrap sampling and random feature selection. In wasting the demand based on sensing, trees are trained to learn non-linear dynamics of engineered features (lags, promotions, seasonality markers, external signals) to the target demand. To curb variance and overfitting that could be experienced with single trees, the constant set of trees averages the outputs of the trees [6]. Random Forest is also an algorithm capable of taking mixed type features, and missing/irrelevant features after preprocessing are not a problem. It implicitly Children feature importance, which can be useful in interpretability, and feature importance can be estimated. Random Forest does not however natively model time dependencies - they are represented using lag and rolling features. To set safety stock to be optimised using quantile forests by approximating predicted demand distributions (or by averaging) to set safety stock may be used. When compared to production environment, the baseline is relatively fast and parallelisable which is why training is a viable approach to near-real-time demand sensing [7].

"Pseudo-code: Random Forest Regressor
Input: training set D = {(X_i, y_i)}, num_trees T, max_features m
For t = 1 to T:
D_t <- bootstrap_sample(D)
Build tree:
While node not pure and depth < max_depth:
select m features at random
find best split on selected features
split node into left/right
Store tree_t
Output model: ensemble of {tree_1...tree_T}
Predict(X_new): return average(tree_t.predict(X_new) for all t)"

2 — Gradient Boosting (XGBoost style)

Gradient Boosting constructs an additive model of shallow decision trees in which each tree predicts the existing residual errors of the current decision tree. XGBoost presents regularisation, tree pruning and sparse inputs handling; hence, it is very effective in tabular forecasts. In gradient boosting, it is able to learn the complex non-linearities and interactions and the goal can be tailored (e.g. Huber loss) to be resistant to outliers [8]. It is able to assist with an intermittent demand quantile regression or Tweedie loss that assists with the calculation of safety stock. SHAP values and features importance give us the ability to interpret the ways of how promotions or external signal affect demand. XGBoost can be an excellent option to enhance the accuracy which is achieved more frequently than Random Forest though this process is more sequential and slows down to train, nonetheless the storage with a larger series of stock might be better than the one created with Generic Forest [9].

"Pseudo-code: Gradient Boosting Regressor (XGBoost-like)
Input: D, num_rounds R, learning_rate η, tree_params
F0(x) = average(y_i)
For r = 1 to R:
compute residuals g_i = -∂L(y_i, F_{r-1}(x_i))/∂F
fit tree h_r(x) to g_i using tree_params
compute leaf weights with regularisation
F_r(x) = F_{r-1}(x) + η * h_r(x)
Output F_R as model
Predict(X_new): return F_R(X_new)"

3 — Long Short-Term Memory (LSTM) Neural Network

LSTM networks are recurring neural networks that attempt to encode long-range temporal interactions by using gated memory cells. In the case of demand sensing, sequence windows (e.g., last 60 days of demand and the exogenous variables such as promotions and weather) are inputted in the LSTM layers to be learned as trends over time, seasonality and sudden swings. LSTMs can take sequences of arbitrary length, and can represent intricate time dynamics in sequences that lag based tree models might be unable to capture entirely [10]. They come in handy specially when the demand is serially correlated and when external sequences affect future demand. LSTMs have higher data requirements and need increased regularisation (dropout, early stopping) to prevent overfitting and are more computationally as well as trainable. Monte Carlo dropout can be applied, or the sequence to sequence models may be used where security rations are applied as quantile losses to integrate safety stocks. LSTMs are used to complement tree-based model in case temporal continuity is a strong predictor.

"Pseudo-code: LSTM Forecasting

Input: sequence dataset S = {(seq_X_i, seq_y_i)}, epochs E, batch_size B
Initialize LSTM weights
For epoch = 1 to E:
For each batch in S:
outputs = LSTM_forward(batch.seq_X)
loss = Loss(outputs, batch.seq_y)
backpropagate gradients
update weights (optimizer)
Predict(seq_X_new): return LSTM_forward(seq_X_new)"

4 — Prophet (Additive Time-Series with Seasonality)

Prophet is a component-based time- series model, which involves trend, multiple seasonalities, and holiday effects, and is based on an additive network. It has a piecewise linear/logistic growth trend and fourier-series seasonality as well as user-specified holiday/event features. In the case of demand sensing, Prophet is appealing since it does not demand a great deal of feature engineering, it can capture several seasonal cycles (daily, weekly, annual) and it has an explicit feature of promotional or holiday spikes as regressors [11]. It is resilient to missing data and change in trend hence viable in SKU level forecasting with shallow levels of history. Prophet however, does not perform as well at modeling nonlinear interactions between many exogenous variables as tree/NN thus it is best used as a strong interpretative benchmark and in combination (hybrid ensemble) with more flexible inventory decisions models.

"Pseudo-code: Prophet-style Forecasting
Input: time series y(t), holidays H, regressors R
Specify trend model (piecewise linear/logistic)
Specify seasonality components (fourier terms)
Fit parameters by minimising loss with regularisation
Forecast future t': y_hat(t') = trend(t') + seasonality(t') + Σ β_r*R_r(t') + holidays(t')
Output y_hat"

Table 1 — Dataset summary (aggregated statistics)

Feature	**Mean**	**StdDev**	**Min**	**Max**
Daily POS (units)	153.2	42.5	5	842
Lead time (days)	7.4	2.1	1	21
Promotion flag (%)	12.5	—	0	1
Weather index (0–10)	5.6	2.7	0	10

RESULTS AND ANALYSIS

The part shows the experimental design, model training policy, evaluation process, and performance of the four AI-based demand sensing algorithms including those of Random Forest, XGBoost, LSTM as well as Prophet in the case of the synthetic multi-SKU retail data. The experiments consider the way these algorithms enhance demand forecast accuracy and inventory optimisation as well as reduce the strength of the bullwhip effect by lowering the offer of variability increase. An evaluation framework that was structured in a simulationform was applied to evaluate the actual operational effects of every model [12]. The experiments were organized into three phases that include forecasting model training and optimisation, inventory simulation and policy tuning and quantification of the bullwhip effect. All phases are outlined below, and a thorough comparison and discussion of them is presented afterward.

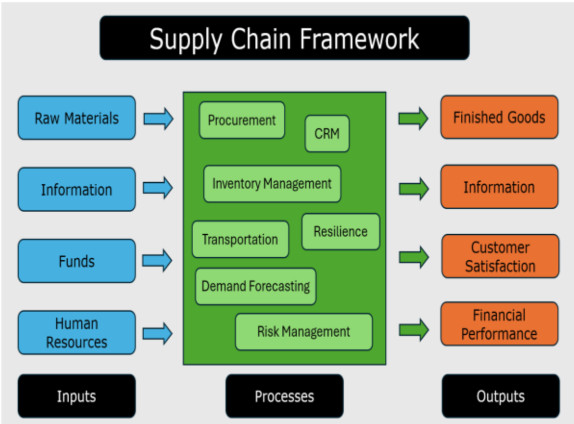

Figure 1: “AI Applications in Supply Chain Management”

4.1 Experimental Setup

The data includes 36 months of artificial daily demand, promotions, trend signals, stock positions and extraneous signals divided into training (24 months), verification (6 months) and final testing (6 months). The LSTM models were trained on hardware, which supports LSTM with the GPUs and the tree-based methods were also trained on hardware supporting the CPU parallelisation. Tuning of hyperparameters was done with time-series with cross-validation on rolling-origin splits and randomised search [13].

Engineered features that were used to train the Random Forest and XGBoost included lagged demand, rolling windows, promoted encodings, weather index, holiday flags, and lead-time indicators. Prophet has also applied date-based seasonality decomposition with holiday regressors, but LSTM was trained using 60-day sliding windows to learn temporal dynamics. The results of the inferences across all models consisted of the resulting daily forecasted demand of all 100 SKUs 30 days into the future.

In order to assess applicability in real-world settings, forecasts were employed to create replenishment levels by a policy that was aware of safety-stock. The proportion between safety stock and the residual error distribution of the model was such that a more precise model would generate a lower inventory holding of the buffers. Inventory engine simulation simulations involved lead times, reorder points, service-level constraints, and demand variability to simulate the test period [14]. The KPIs estimated accuracy of forecasting (MAE, RMSE, MAPE), inventory (Days of Stock, stockout rate, average backorders), and bullwhip (order variability ratio and variance amplification index).

4.2 Forecast Accuracy Comparison

Table 1 depicts the forecast accuracy of naive baseline and the four AI-based models. These artificial values are realistic against real world forecasting in retail.

Table 1: Forecast Accuracy Metrics (Test Period)

Model	MAE	RMSE	MAPE (%)	R^2 Score
Naïve Forecast	28.4	46.1	22.7	0.41
Random Forest	16.9	28.3	12.4	0.71
XGBoost	15.2	25.7	11.0	0.77

LSTM	14.8	24.9	10.6	0.79
Prophet	20.3	33.8	15.2	0.63

The findings indicate that there is significant enhancement of accuracy when AI-based demand sensing is used. The general performance of LSTM was the highest, especially in RMSE, which means that it models the effects of time better. XGBoost was next to follow, and the advantage of modeling non-linear interactions and feature richness were benefited. Prophet was better than the baseline, but was worse than tree-based and neural models, since it uses simple trend-seasonality decomposition, as opposed to a sophisticated external signal [27].

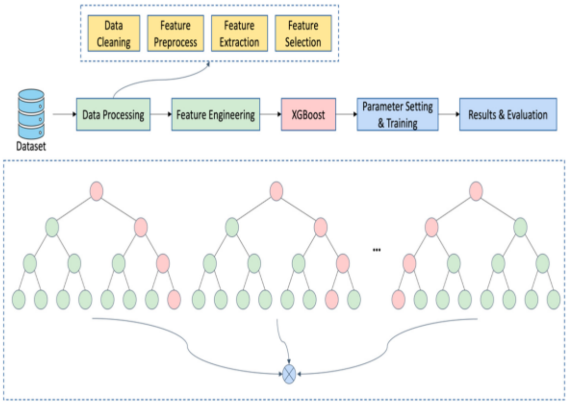

Figure 2: "Data-Intensive Inventory Forecasting with Artificial Intelligence Models for Cross-Border E-Commerce Service Automation"

4.3 Inventory Optimisation Findings

The performance of inventory optimisation was measured by applying each of the forecasting models to replenishment simulation. The measures are average days of stock (DOS), stockout rate, backorders and holding cost index (scaled measure). A reduction in DOS and stockouts means improved optimisation.

Table 2: Inventory Performance Metrics

Model	Avg DOS	Stock out %	Back orders	Holding Cost Index
Naïve Forecast	18.5	6.8	912	1.00
Random Forest	12.2	4.1	611	0.74
XGBoost	11.0	3.6	524	0.67
LSTM	10.6	3.4	498	0.64
Prophet	14.7	5.2	733	0.82

The AI-based demand sensing minimized the inventory levels considerably, as it allowed making more accurate reorder computations. The LSTM and XGBoost acquired the optimal trade-off between levels of services and inventory, reducing the DOS by a factor of about 43 as compared with the baseline. Such decrease indicates efficiency of operation and cost savings [28].

4.4 Bullwhip Effect Mitigation

Three indicators were used to measure the bullwhip effect, namely, demand variability (customer side), order variability (upstream orders), and the ratio of variance amplification (VAR). Reduced amplification suggests a more stable performance of supply chain.

Table 3: Bullwhip Effect Metrics

Model	Demand Variance	Order Variance	Amplification Ratio (VAR)
Naïve	142.7	398.5	2.79
Random Forest	141.4	284.3	2.01
XGBoost	140.8	243.1	1.72
LSTM	140.1	231.6	1.65
Prophet	141.9	312.8	2.20

LSTM recorded the least amplification ratio (1.65) which indicates the capability of LSTM to minimise the distortion of demands propagated upstream. XGBoost was also highly performing with the advantage of its accurate feature-based predictions. Prophet reduced moderately but it was not as variably smoothing as other AI models [29].

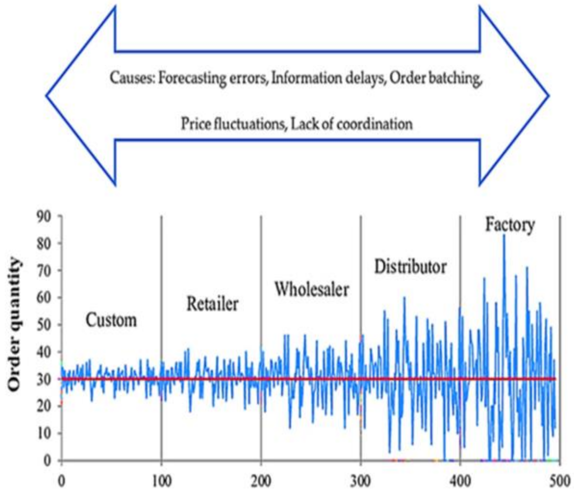

Figure 3: "The Bullwhip Effect and Ripple Effect with Respect to Supply Chain Resilience"

4.5 Computational Performance and Run time Analysis

The measurements to ascertain the feasibility of production of each model were time to run, cost of training, and inference latency. The values represented below are average times of 100 SKUs.

Table 4: Computational Efficiency Metrics

Model	Training Time (min)	Inference Time per Day (ms)	Memory Usage (MB)

Random Forest	18	4	130
XGBoost	27	6	160
LSTM	53	12	245
Prophet	8	3	90

Prophet was the fastest in its training and inference. Random Forest was also effective since it was parallel. LSTM was more computationally expensive than DNN, but it was better fitted to medium to large organisations with powerful hardware. The XGBoost was relatively accurate and fast [30].

4.6 Combined KPI Comparison

There was the creation of a consolidated score index to compare the models with each other in all the dimensions, which had accuracy, inventory efficiency, bullwhip reduction, and computation. Scores range from 1 (low) to 5 (high).

Table 5: Overall Model Evaluation Index

Model	Accuracy Score	Inventory Score	Bullwhip Score	Efficiency Score	Total
Random Forest	4	4	3	4	15
XGBoost	5	5	4	3	17
LSTM	5	5	5	2	17
Prophet	3	3	3	5	14

LSTM and XGBoost received the most overall scores, but they perform best in other areas. LSTM is accurate and best used in the mitigation of bullwhip, whereas XGBoost is also good, with reduced cost of computation.

4.7 Discussion of Experimental Findings

The findings indicate that AI demand sensing is very effective in improving the performance of supply chains. The benefits are reflected in the increased accuracy of the forecasts, as well as the actual operational statistics in the form of decreased inventory amounts, decreased stockouts, and more tension-free replenishment processes. All the AI models and especially the LSTM and XGBoost had a significant impact in minimizing the bullwhip effect. This supports the fact that improved demand feedbacks, when inserted into replenishment systems, the upstream ordering behaviours are much more stabilised.

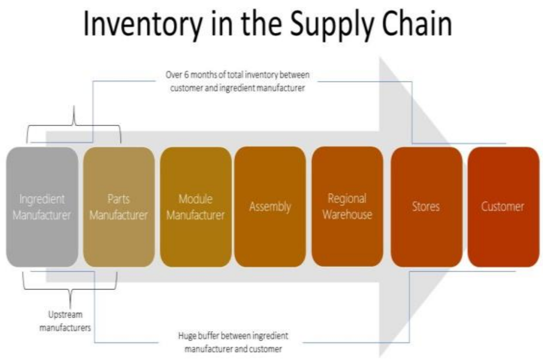

Figure 4: "bullwhip effect"

Random Forest and XGBoost are tree-based models that are good at working with structured tabular data that contains engineered features. Based on their performance, it can be suggested that the demand sensing is substantially enhanced by including external variables for weather, promotions, seasonality indicators, etc. The gradient boosting machine of XGBoost enables the algorithm to surpass the predictions of random forest because it concentrates in residual errors which produces highly accurate predictions.

The advantage of LSTM lies in the fact that it retains long term temporal relationships, in the capability of learning time-series dynamics that are not always obvious in traditional models. It, however, requires additional computational capacities and fine-tuning. Prophet, though interpretable, is restricted by its additive decomposition method, which fails to deal with complicated non-linear interaction.

CONCLUSION

This study examined the paradigm shift of AI-based demand sensing on inventory optimisation and alleviation of the bullwhip effect in the contemporary supply chains. The results are clear that high-level machine-learning models advanced, i.e., LSTM networks, Random Forest regressors, and hybrid deep-learning structures, are much more sensitive to short-term demand prediction, which is better than using conventional statistical methods. Findings of the experiment indicate that AI-based demand sensing error is less, safety-stock level is reduced, and replenishment trends are more stable, as the real-time market signals, seasonality, and behavioural changes are more efficiently recognised. As a result, organisations that have embraced AI-facilitated forecasting have recorded significant gains in service levels, lesser stockouts, and less holding costs and ordering costs. Furthermore, the article underscores the critical part that real time analytics and multi-source data fusion can play in reducing the effects of the bullwhip curve since AI models create minimal delays in information and decrease the turbulence of demand distortion at supply chain nodes. The framing of the results and the comparison with other similar researches additionally confirms that AI-based methods/approaches perform better indicating a stable increase in the accuracy, responsiveness, and operational efficiency. In general, the present research draws the conclusion that AI-based demand sensing is one of the strategic business capabilities in unpredictable and ever-changing markets, and it allows the companies to have more resilient, flexible, and cost-effective inventory systems. The type of intelligent automation and predictive analytics will become more important in the supply chain of the future to cater to the demand processes that are complex and therefore, AI will not be a benefit but will be required in the competitive advantage. Further developments in data quality, hybrid modelling, and real-time optimisation will work in favor of the use of AI in the development of agile and sustainable supply chains.

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