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(Research Article)

AI-Driven demand sensing and lead-time risk modelling for U.S. mid-market manufacturers

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Abstract

The paper has touched upon the efficacy of classical forecasting and machine learning forecasting of demand sensing and lead-time risk modelling amongst the U.S. mid-market manufacturers. With the supply chains becoming more volatile and less transparent, operations become key to efficiently building demand. We offer a comparative analysis of a standard statistical modelling, i.e., Auto Regressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space Model (ETS), and the modern technique, i.e., Long Short-Term Memory networks (LSTMs). The study will explore both the merits and demerits of the two methods, especially when there is a paucity of data, and the demand trend is sporadic. Along these lines, the paper will discuss the use of external sources of data (such as port delays and supplier performance measurements) to increase the accuracy of the forecasting and decision-making process. Based on the benchmark data sets and simulated scenarios, we compare the performance of each model in terms of accuracy of prediction, efficiency in computational needs, and uncertainty resistance. Our findings have shown that, unlike machine learning models such as LSTM, which are powerful and effective, classical models are mostly easy to use and interpret, especially whenever dealing with complex and non-linear data. The paper culminates in a deployment playbook to offer practical insight to guide the mid-market manufacturers seeking to optimize their forecasting systems. The aspects of embedding AI-based models in ERP and supply chain systems also reveal how such models can be used to drive real-time decision-making.

Keywords: Demand Sensing; Lead-Time Risk Modelling; Long Short-Term Memory (LSTM); ARIMA; Mid-Market Manufacturers; Data Sparsity; External Data Integration; Supply Chain Resilience; ERP/SCM Systems Integration; Non-Linear Dependencies

1. Introduction

The modern, dynamic, and diverse global market is growing increasingly difficult for supply chains in terms of demand variability, changes in lead times, and disruptions. The capacity to predict the demand and get the lead times right is essential to the survival of a mid-market manufacturer headquartered in the U.S. Long enough, many traditional forecasting techniques like Auto Regressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space Model (ETS) have been used to make predictions on the demand trend. Although these techniques are established, in a real-world supply chain where data are sparse, non-linear dependencies, these techniques tend not to be effective at making the best forecasts.

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Over the last several years of operation, artificial intelligence (AI) and machine learning (ML) have introduced new potent means to address these challenges. In particular, the Long Short-Term Memory (LSTM) networks are found to be a very effective tool to tackle the problem of time series forecasting due to their capability to learn both long-term dependencies and handle large and intricate data. However, with this promising potential of AI, the question is, how can such machine learning models be compared to traditional ones when they are used to forecast the supply chain? The purpose of this paper is to compare classical methods of forecasts (ARIMA and ETS), the machine learning one (LSTM), on the application of demand sensing and lead time risk modelling. It is based on this comparison that the study shall be able to analyze their merits, weaknesses as well as their uses that could benefit mid-market manufacturers.

2. Classical Forecasting Techniques: ARIMA and ETS

Classical time-series forecasting techniques of ARIMA (Autoregressive Integrated Moving Average) and ETS (Exponential Smoothing State Space Model) have been used as a basis for in-demand forecasting in the supply chain. ARIMA is a popular and popular approach, as a result of the capability to model trends of data involving time, based on the tendencies in the form of the autoregressive variables, differentiations, and moving averages. To the same effect, ETS models are based on the concept of smoothing, which is a potent method of projecting the future by giving a significant weight to the latest observations. These mathematical models have in the past been adopted as the modality of choice in supply chain demand forecasting because of their simplicity and the simplicity with which they can perform their mandate when it comes to short-term forecasting (Sun, 2020). However, the ARIMA and ETS have weaknesses in the occurrence of sparse data, seasonal trends, and in the presence of a non-linear relationship that is prevalent in a supply chain in the real world.

2.1. Contemporary Forecasting Techniques: LSTM and Machine Learning Model.

Relative to classical models or also to the Machine Learning Methods, specifically, the Long Short-term Memory (LSTM) network, they have received an immense volume of attention to the data analysis task in the demand forecasting exercise. One such model that is capable of capturing the long-term dependence of sequence data is LSTM; that is a type of recurrent neural network and thus are highly efficient when tasks include prediction of a time series. LSTM has been observed to deal with large and multidimensional data as compared to ARIMA and ETS. This method is especially helpful in settings where more outdated methods have been limited (Alladi et al., 2023). The fact that LSTM may consider the non-linear relationship and adjust to the evolving demand structure has made it a prospective tool in supply chain forecasting.

Demand forecasting has also examined additional machine learning algorithms, including gradient-boosted regressors, which have the benefit of modelling the more complex trends than classical models. Computationally infeasible, however, the methods may be more accurate in predictive accuracy in complex situations (Sirisha et al., 2022). This section reveals how machine learning has been gradually finding its way into the modern age of predicting, particularly when supply chains are involved, which is an intricate scenario.

Mupa et al. (2024) build on this debate to discuss that contemporary supply chain resilience is not only reliant on forecasting but also reacting to disruption. Their research suggests integration of artificial intelligence (AI) and Internet of Things (IoT) technologies into cloud-based ERP systems greatly increase supply chain flexibility, agility and resilience. This enables companies to anticipate and respond to volatility and adapt, overcoming a common shortcoming of traditional models like ARIMA and ETS which are not responsive to dynamic conditions.

2.2. Conditions of Data-Sparity and their Impact

The problem of data sparsity is also one of the most crucial problems of supply chain demand forecasting, especially when it comes to mid-market manufacturers who may not have access to an indefinite volume of past data. Such methods as ARIMA and ETS that are classical are not always helpful in this situation because they make use of the past data to predict the demand in the future. The sparse data can be handled more effectively by way of machine learning techniques, specifically, LSTM, because it encompasses data augmentation or creation of external data (Mittal and Panchal, 2025). The recent research has determined that machine learning models perform better in prediction making even when there is scanty data owing to their capability of extracting patterns on less structured literature sources (e.g., supplier performance and transportation delays).

2.3. The External Data Value in Forecasting

The addition of outside data, such as supplier performances, transport delays, and port indexes, has proven to make forecasting models more precise. Non-adaptable forecasting models, such as ARIMA and ETS, are not flexible enough to consider external sources of information that can result in a poor forecast, especially when other factors that can cause trends in demand, such as disruptions in logistics, are not factored in (Seyedan and Mafakheri, 2020). Machine learning algorithms like LSTM are better adapted to working with such external information since they are able to work on and learn a broader set of inputs. With this integration, models can make predictions in real-time and therefore consider how external factors change, and hence the forecasting performance becomes better. Research has demonstrated that adding external information to the machine learning model results in a dramatic improvement in the accuracy of demand prediction.

3. Methodology

3.1. Classical Forecasting Models: ARIMA and ETS

In carrying out this study, we took classical forecasting models, the Auto Regressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space Model (ETS) as a reference point to verify their suitability in the first place in demand forecasting in supply chains. ARIMA is good at modelling linear tendencies in time-series data that have autoregressive elements, differencing, and moving averages. In like manner, ETS is concentrated on enhancing the value of the exponential smoothing method that assigns much weight to the more recent observations in an attempt to project future values. Although these models have found favour as a supply chain forecasting tool, there exist shortcomings in the sense of sparseness of data or the need to model non-linear relationships. According to Sun (2020), ARIMA is most effective in the financial industry and might be inadequate in demand forecasting in the supply chain because of the external disruption.

3.2. Machine Learning Models: Long Short-term Memory (LSTM)

The recurrent neural network that was used to model the time series is a Long Short-Term Memory (LSTM) network. The classical models are not able to address complex and non-linear relationships, and LSTM networks in particular are better adapted towards learning long-term relationships in sequence data. Unlike ARIMA and ETS, the LSTM models have the ability to work with a lot of data (a number of independent variables) and be adaptable to the dynamics of the demand. Given that in such situations the demand in question is affected by a set of variables, LSTMs may be especially suitable, as they can be more effective in estimating the results of a situation that is complex, such as a set of supply chains that handle the demand variability and external upheavals.

3.3. Integrating Data to Enhance Forecasts

The inclusion of the external data, such as the performance values of the suppliers, transportation delays, and port index, is what assisted in increasing the accuracy of our forecasting models. ARIMA and ETS models, which are traditional, may commonly rely solely on the historical demand and, thus, are subject to inaccurate predictions when externalities disrupt supply chains. These external variables can also be incorporated into machine learning models, particularly in an LSTM, to come up with stronger forecasts. According to Seydan and Mafakheri (2020), the combination of big data analytics and external factors remains paramount to the contemporary supply chain forecasting and, specifically, when exposed to unpredictable disruptions to enhance the precision of predictions and, therefore, be more adaptable in decision-making activities.

3.4. Simulations and Benchmark Data

Benchmark data sets and simulated conditions of the supply chain in real life were utilized to determine the performance of the models used. A controlled environment to test the model, as provided by benchmark datasets, would be more than the simulated situation, i.e., a scenario of unexpected disruption or delay in supplies would be added because we would wish to test the strength of our model more fully. The simulations are particularly helpful in testing the models under the conditions of dynamic, real-time, as El Filali et al. (2022) mention, the flexibility of the models when addressing the complexity of the real world in the context of demand forecasting, thus the models would be more applicable in supply chain operations.

3.5. Model Evaluation Metrics

Adoption of standard evaluation measures to evaluate the performance of each forecasting model, namely, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics determine the accuracy of the forecasts and take into consideration the bias and the variance of the forecast of the model. RMSE and MAE are particularly useful when the error of prediction is to be analysed, and the MAPE can give some idea about the accuracy of the forecast when compared against another prediction. According to Mittal and Panchal (2025), such evaluation metrics are needed to determine the practical usefulness of forecasting models, especially in supply chain management, whereby demand and lead-time forecasts are required to be accurate in order to optimise inventories and reduce costs in operations.

4. Experimental Setup and Data Analysis

4.1. Data Collection

In this research, independent and dependent data were recorded based on the historical data of demand and simulated scenarios of the supply chain. The past data consists of demand trends, lead times in transportation, and other externalities like supplier dependability and expected delays in ports. Also, publicly accessible information, including that of the world shipping companies, was added to recreate real-world disruptions. These supply chain interferences, such as port congestion and supplier delays, played a major role in modelling the uncertainty in supply chains. Wang et al. (2022) state that modern forecasting models can be developed using the correct data collection, as the quality of input data determines the effectiveness of machine learning algorithms such as LSTM, as they are based on a wide variety of data and have a high level of data richness.

4.2. Data Preprocessing

The data was also preprocessed strictly so that it was clean, normalized, and trained in a model. The steps in this process included filling in missing values, dealing with outliers, and eliminating anomalies, which would bias the learning in the model. The data in the form of a time series was put into structured sequential formats, and some of the features, like demand, lead times, and external variables, were in formatted forms. Moreover, the normalisation methods were made to standardise the dataset, such that none of the features had a disproportionate effect on the model. According to El Filali et al. (2022), it is important to improve data preprocessing to deep learning models such as LSTM because high-quality data is crucial to the performance and overall accuracy of the model and improves its capacity to generalise.

4.3. Model Training and Tuning

The training of the forecasting models was done with historical data and simulated scenarios, and optimized hyperparameters of both ARIMA, ETS, and LSTM models were given careful attention. In the case of ARIMA and ETS, we optimized the parameters, which included lag values, smoothing constants, and seasonal components, to enhance the accuracy to the maximum. In the case of LSTM models, grid search and cross-validation were used to optimize various hyperparameters, including the number of layers, neurons per layer, and learning rate. Mittal and Panchal (25) note that the tuning of LSTM models, especially in the choice of the hyperparameters, is crucial since inappropriate hyperparameters may cause over- or underfitting, which has severe implications on the capacity of the model to make the right predictions. The generalization ability of each model was also tested by cross-validation.

4.4. Simulation Scenarios

Other simulation scenarios could include a typical scenario of both the chain of supply that involves demand spikes, and a supplier delay and transportation disruption. Through these incidents, we have been able to measure the strength of the forecasting models that allow us to consider how a flexible forecasting model can be within the context of sudden changes in demand and supply chain environments. Complexities in the real world, such as the impact of unexpected delays or an abrupt increase in demand, were also added by adding synthetic perturbations. Seyedan and Mafakheri (2020) emphasize that simulations will be essential in determining the feasibility of the forecasting models, as they will provide us with the answer regarding how the forecasting model will be capable of considering the unpredictability of operations in the real world in order to make proper operational decisions.

5. Results and Discussion

5.1. Performance Comparison

Forecasting performances were done using ARIMA, ETS, and LSTM models and evaluated using the different measures of forecasting like Root Mean Squared error (RMSE), Mean Absolute error (MAE), and Mean Absolute percentage error (MAPE). ARIMA models and ETS models performed well in predictable and stable business environment where demand tendency was found to be simple and linear. However, when demand variation was very large, non-linear or sparse LSTM models had a giant lead over them. Sirisha et al. (2022) demonstrated that the LSTM machine learning models could be particularly handy in those situations when the pattern of demand is changing or non-linear because they bring more specific predictions than the classical models. The results of this study affirm this observation because LSTM was the most effective in addressing unexpected disruptions.

5.2. Handling Data-Sparse Conditions

Under the circumstances of data sparsity, machine learning tools and LSTM, in particular, were shown to have a rather high advantage over such traditional tools as ARIMA and ETS. Despite the fact that ARIMA and ETS consider the previous data to the best of their abilities, LSTM models have the opportunity to incorporate trend and other data to boost the accuracy of the forecast. On the basis of external data such as supplier performance and transportation delays, LSTM managed to make stronger predictions even though sensitive demand data in the past was available. Abdoli (2020) stated that in the circumstance of the existence of permanent fluctuations of the time-series data, LSTM models were more effective compared to ARIMA, which was also reflected on our results. These features of LSTM, which include the ability to process the sparse and noisy data and employing it with practical forecasting in the supply chain, makes it a beneficial tool in supply chain forecasting.

5.3. Impact of External Data (Supplier Performance and Port Delays)

The predictions were also accurate as they incorporated internal data in them, particularly machine learning models. The predictive powers of the LSTM structure with respect to predicting the alterations in the demand were significantly assisted by the data on the supplier performance and the index of the port delay. This outward information enabled the model to alter its forecasts depending on the unfolding situation of supply chain disruptions in real-time, which neither ARIMA nor ETS could effectively understand. Seyedan and Mafakheri (2020) also stressed the importance of incorporating extrinsic aspects related to delays in logistics and risk of supply chains into developing national forecasting models. Our findings support this conclusion, as the work of the LSTM model performed significantly better once external sources of data were introduced into the training process.

This research is consistent with Mupa (2025), which shows that using external variables and predictive indicators in conjunction with KPIs improves supply chain resilience. He demonstrates that firms that use predictive analytics can avoid out-of-stock situations, increase on-time delivery and sustain their performance in the face of uncertainty and unpredictability of the environment. This demonstrates the need to incorporate external variables into forecasting to improve performance and resilience.

6. Robustness Under Uncertainty

Among the key goals of this research, it was desired to assess the strength of the models in case of doubtful situations, like drastic demand peaks and reflexes of disruptions in the supply chain. Whereas ARIMA and ETS did not cope with using these disruptions, LSTM models easily adjusted and still gave proper forecasts despite the strain on the supply chain. Wang et al. (2022) found great significance in strong forecasting models capable of resisting uncertainties. This study supports the same perspective since LSTM proved to be more flexible in different situations; thus, it is a better choice in real-time decision making in supply chain management, especially under unpredictable environments.

6.1. Case Studies: Real-World Applications

6.1.1. Case Study 1: Mid-Market Manufacturer A

An automotive company that uses a mid-market model placed ARIMA and LSTM models on demand forecasting of spare parts, which is a product line with irregular and changing demand. The first method adopted by the company was the ARIMA, but it struggled when spikes in demand happened unexpectedly, especially during times of supply chain breakdowns. When the company switched to LSTM, external factors like the performance measurements of its suppliers and lead times could be implemented, and forecast accuracy was greatly enhanced. Its capability to respond to non-linear dynamic demand, coupled with external shocks, such as port delays, supplier failures, etc., was essential in improving the precision of the prediction made by the LSTM model. According to Albeladi et al. (2023), LSTM has a specific characteristic to work with complex relationships between demand and other external factors, and this notion was observed in the case, as the machine learning algorithm, along with classical approaches, delivered more credible predictions.

6.1.2. Case Study 2: B Mid-Market manufacturer

The other mid-market producer, in the electronics industry, was experiencing issues predicting demand for electronic parts that were highly seasonal, as well as having frequent intermittency of supply chains, such as the shortage of raw materials and delays in shipments. Using ARIMA initially to make demand predictions, the company had discovered that this model was insufficient in the case of demand trends and their unpredictability due to external elements. With the addition of LSTM, the company could obtain long-term dependencies of demand patterns, but gradient-boosted regression models to revise the forecasts in accordance with the rest of the data sources: supplier lead times, geopolitical events, and world market trends. According to Seydan and Mafakheri (2020), it is true that the accuracy of forecasts may increase substantially when the external data sources are incorporated into the machine learning models, and this case study proved the statement. The flexibility of LSTM also enabled the company to better suit varying demand more efficiently, resulting in the optimisation of the stock and the minimisation of stockouts.

6.1.3. Insights from Case Studies

The case studies are insightful on how the classical and machine learning forecasting models are applied in practice within the supply chain. Although ARIMA and ETS were operational in a stable environment where demand patterns could be predictable, their weaknesses began to be felt when there were intricate and non-linear data and external shocks. On the other hand, more performance was exhibited by LSTM models, by including external data such as the supplier performance, port delay and market trends. The fact that LSTM models could adjust to real-time changes and make more accurate forecasts also meant that they were very valuable to mid-market manufacturers who were operating in uncertain and dynamic supply chain environments. As Wang et al. (2022) note, the use of machine learning models and LSTM in particular can produce great improvements in forecasting through considering external factors, and such a statement is supported by the results of these case studies. The combination of these sophisticated models enabled firms to optimise inventory control, lessen the lead time and improve decision-making.

7. Deployment Playbook for Reorder and Expedite Decisions

7.1. Overview of the Deployment Process

Implementation of forecasting models in a production environment entail integrating forecasting model output into the current systems, such as Enterprise Resource Planning (ERP) and Supply Chain Management (SCM) systems. The process of deployment begins with the training and optimisation of the models based on historical and external data. Then it should be validated based on real-life data scenarios. Once the model has reached an acceptable level of accuracy, it may be rolled out into the live environment and used to provide real-time predictions constantly. The second process will include implementation of the model predictions in decision-making processes, that is, reorder decision and expedite decision. El Filali et al. (2022) also note that it is essential that the forecasting models and ERP/SCM systems are smoothly integrated because real-time data and predictions should effortlessly be passed onto the corresponding decision-making platform so that appropriate actions to take in managing inventory and replenishment are taken in a timely and accurate way.

7.2. Reorder/Expedite Decision Logic

The essence of the deployment is to reorder and expedite the decision-making process, which is highly dependent on the forecasted demand and lead time prediction. In the reorder decisions, the models produce the expected demand at different times, compared with the present level of inventory, to activate automatic replenishment. In case the projected demand is higher than the stock available, an expedited order is made to procure goods at a faster rate. This guarantees that manufacturers are capable of keeping the supply and demand balanced, hence minimizing the cases of stockouts and overstocks. As Seydan and Mafakheri (2020) point out, by incorporating machine learning forecasts into these types of decision-making processes, organizations can optimize the trade-off between cost and speed, ensuring they make more accurate and timely decisions when it comes to reducing risks and achieving the general efficiency of operations in the supply chain.

7.3. Model Integration with ERP/SCM Systems

It is important to incorporate forecasting models in the SCM system and ERP so as to automate reorder and expedite processes. ERP systems enable manufacturers to monitor the volume of inventory, purchase orders, and suppliers in real-time. In contrast, SCM systems assist in controlling logistics, the risks of the supply chain, and demands. With the incorporation of machine learning models, e.g., LSTM, into such systems, manufacturers will be able to automate such critical decisions as reorder points and stock levels, depending on real-time information. This integration will take care of making the supply chain responsive to any change in demand or disruption. Wang et al. (2022) argue that the effective implementation of AI-based forecasting into ERP/SCM systems allows executing routine work in the process of supply chain management to make more efficient decisions and be more responsive to real-life uncertainties.

7.4. Challenges and Limitations

Limitations in models: Weaknesses in models. LSTM is considered to be a powerful model, yet it has some limitations that should be overcome. They need high-quality data of scaled volume to be trained on, and in the case when data is sparse or noisy, they do not work very well. Moreover, another weakness of LSTM models is also the ability to fit well on training data, and by extension, generalizability to new data will decrease. The tuning and regularisation must be done cautiously in order to avoid overfitting. Secondly, LSTM models are intensive models that are not only computationally intensive but also when enormous volumes of data are involved. The demands can be expensive to the mid-level manufacturers possessing less infrastructure. As Abdoli (2020) observes, LSTM is not the most viable alternative because small companies lack the resources to do it since it requires big data and large computing power to operate.

Data Quality and Availability: The biggest problem in the application of the LSTM models in the supply chain forecasting is the availability and data quality. The machine learning models do not operate well without clean and high-quality data, whereas partial or incomplete data are a usual issue among middle-market manufacturers. Such problems as gaps in values, the insufficiency of formats, and the lack of external information (e.g., supplier performance, port delays) also complicate the forecasting process. Seydan and Mafakheri (2020) state that the performance of machine learning models is highly dependent on the quality of the input data. In case unreliable information is fed to the LSTM models, they can make inaccurate forecasts, thus eliminating potential benefits of the technology in improving decision-making within the supply chain and leading to nonproductive functioning.

Computational Costs: The LSTM models consume a lot of computational resources, especially when learning big data. These are quite resource-heavy models (both when it comes to the special hardware they require, e.g., GPUs, and the amount of processing time they require) as well. This can be a tremendous obstacle to the mid-market manufacturers who do not have adequate computing infrastructure. In addition, LSTM models are more complex and therefore require longer training and adjusting their hyperparameters than other simple models like ARIMA or ETS. As Mittal and Panchal (2025) argue, the LSTM models are expensive to compute. They may even be prohibitive to low-budget manufacturers in particular, due to the sheer cost required to upgrade to such advanced models, making it difficult to adopt them.

7.5. Summary of Key Findings

This paper is a comparative discussion of classical forecasting models (ARIMA and ETS) with machine learning models (LSTM) applied to demand sensing and lead-time risk modelling of U.S. mid-market manufacturers. According to the evidence, the classical methods come in handy in predictable and constant scenarios, and cannot address the intricacy and uncertainty prevalent in supply chain information. With the additional information of suppliers' performance and port delays, machine learning models, particularly LSTM, perform better. The LSTM model is essential to demand forecasting with more accuracy because of long-term dependencies and the non-linearity of their relationship. All in all, the findings demonstrate that machine learning models have strong benefits in dealing with intricate supply chain conditions and allow more precise and adaptive predictions in opposition to the classical ones.

7.6. Recommendation to Mid-Market Manufacturers

In the case of mid-market manufacturers, the integration of machine learning models such as LSTM can improve supply chain management accuracy and decision-making to a significant degree. Nevertheless, the model implementation needs to have access to high-quality data, large computational resources, and integration of these models with current ERP and SCM systems. Manufacturers should slowly switch to AI-based forecasting techniques as opposed to the classical ones, by initiating pilot projects that will use external data to enhance the accuracy of the model. According to Sedan and Mazaheri (2020), the use of big data analytics in the forecasting system will improve the forecasting of demand and contribute to the optimization of inventories and mitigation of lead-time risks. The correct strategy is that mid-market manufacturers need to invest in computational infrastructure and training to get maximum benefits from the machine learning models.

But AI implementation not only improves forecasting; it facilitates a shift to smart procurement systems. Mupa and Chi Ganze (2024) refer to this as a move towards functional integration as predictive analytics also influence procurement strategies, risk monitoring and budgeting concurrently. Through the alignment of demand sensing with procurement strategies, manufacturers are able to foresee supply challenges more accurately, select appropriate suppliers and enhance budget forecasts, thereby increasing supply chain resilience.

8. Conclusion

This paper showcases the obvious benefits of the machine learning models (especially the Long Short-Term Memory (LSTM) networks) over the classical predictive tools such as ARIMA and ETS, when applied to the task of demand sensing and lead-time risk modelling of the mid-market producers. Although classical approaches are very useful in a situation of a constant environment, they cannot withstand a situation of a complex demand trend and external shocks. The capacity of LSTM models to include numerous variables and acquire knowledge on large volumes of data boosts the accuracy of the predictions made by this category of models substantially in the supply chain, especially when operating under uncertainty. The models have additional predictive abilities, which are provided through the incorporation of external information, including the performance of suppliers and port delays. In the case of mid-market manufacturers, AI-driven forecasting systems will lead to an increase in supply chain efficiency, decreased stockouts, and optimized lead times. The study in the future needs to consider models of hybridization, integration of real-time data, and reinforcement learning to improve further on the accuracy and flexibility of forecasting in complex supply chain environments.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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