AI-Driven Demand and Supply Forecasting Models for Enhanced Sales Performance Management: A Case Study of a Four-Zone Structure in the United States

Raviteja Meda

Lead Incentive Compensation Developer, rvtjmeda@gmail.com

Abstract: This study investigates the application of AI-driven demand and supply forecasting models to enhance sales performance management within a four-zone structure in the United States. With increasing market volatility and regional variability, traditional forecasting methods often fail to capture real-time dynamics and cross-zone dependencies. Leveraging machine learning algorithms and data analytics, this case study explores the implementation of predictive models tailored to zone-specific characteristics, seasonal trends, and historical sales data. The research evaluates model accuracy, adaptability, and impact on decision-making efficiency, inventory optimization, and revenue growth. Findings demonstrate that AI-enhanced forecasting significantly improves planning precision, reduces stockouts and overstocks, and aligns sales strategies with localized demand patterns. This paper contributes practical insights for businesses seeking to adopt intelligent forecasting systems in multi-regional operations.

Keywords: Artificial Intelligence, Demand Forecasting, Supply Chain Optimization, Sales Performance Management, Machine Learning, Predictive Analytics, Regional Sales Forecasting, Multi-Zone Analysis, Inventory Management, Time Series Forecasting, Data-Driven Decision Making, Forecast Accuracy, Business Intelligence, Sales Strategy Optimization.

1. Introduction

Sales performance management for a company's growth is very critical for all types of companies. Various factors influence the sales performance of all companies. Moreover, demand and supply forecasting also is a very tedious task for all types of companies. Due to the advancement of technology, many companies started to implement artificial intelligence into their systems. Sales performance management models prediction of expected sales and inventory on prior time with forecasting of demand and supply based on ancient values of stock and selling. This model aims to increase the sales performance of a company while maintaining the optimum level of stock. This proposed system can provide decision-making options for the company or users regarding sales performance, demand forecasting, and supply forecasting analysis. By implementing this proposed system, companies can also take proactive measures based on the forecasted supply and demand values to improve sales performance. The efficiency of the model is proven by an experiment that is conducted with a practical dataset. The experiment results show that this proposed model can achieve better sales forecasts than the historical business plans or manual approaches. Accurate demand forecasting has been one of the major concerns for companies who are dealing with supplying products. Demand forecasting is the creation of estimates or predictions of product demand as an output of the forecast model based on necessary input data. An accurate forecast not only helps companies to plan for the production and procurement of the products but also considerably reduces the costs associated with the required raw materials or components. In addition, the less unnecessary stock on hand means better utilization of the warehouses. Many approaches for demand forecasting have been proposed. This paper presents practical statistical demand forecasting modeling developed for a motorcycle accessory manufacturing company that suffers from automotive aftermarket seasonality. In the motorcycle accessories industry, seasonality plays a significant role in the demand for the products. Weather and climate conditions have a strong effect on whether riders are engaged in their motors.

1.1. Background and significance

In today's competitive market environment, ups and downs in demand are commonplace and may even cause the failure of a business. As demand forecasting contains significant uncertainty, a demand forecasting system that considers both exogenous events and unknown factors is essential for improved performance. The use of AI and advanced software tools has started to boom in the field of sales forecasting in order to maximize profitability, while ensuring stock transparency and availability. Accurate and timely forecasts to avoid lost-sales and overstocks is one of the major goals of companies selling fast moving consumer goods. Demand estimation is indeed difficult due to limited data patterns and possible sales interruptions that are difficult to model with traditional approaches. A flexible hybrid Deep Learning architecture is developed by combining Recurrent Neural Networks and Attention based models to overcome these limitations. It incentivizes this architecture to be interpretable while optimizing for both precision and value. Furthermore, a self-tuning empirical loss is proposed that can be easily adopted to optimize the forecast for their own goals. This new architecture is capable of producing more robust and accurate demand forecasts than traditional approaches.

To remain competitive and sustain their growth, firms need to create a long-term and loyal relationship with their customers. One way to achieve this goal is efficient and effective customer management. Companies have recognized that customers are a key asset of the organization. From an economic perception, customers can provide both value and risk by generating revenue and cost. On the one hand, firms must invest in customers over time through marketing expenditure, product discount and promotion, and sales support in order to retain this revenue source over time. On the other hand, firms incur cost through customer service and complaint handling. Self-motivated customers might exaggerate or withhold demand if they perceive unfair treatment. This asymmetric nature has important implications for firms in customer value management. Effective customer value modeling and segmentation are not only the foundation for smart marketing allocation, but also crucial for recognizing loyalty strategy and abuse warning. However, misuse of shared data brings great concern about privacy protection. In a data-rich era, firms must strike a delicate balance between individual privacy and data economic value in customer management.

Equ 1: Exponential Smoothing (Simple)

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha)\hat{y}_t$$

Where:

- $\hat{y}_{t+1}$: Forecast for next period
- y_t: Actual value at time t
- α: Smoothing parameter ($0 < \alpha < 1$)

2. Literature Review

Opportunity forecasting in the retail market has emerging challenges such as increasing competition, availability of information, and the rapid pace of change. Such challenges become opportunities if handled properly. To seize these opportunities, not only forecasting, but also effective promotional sales and improved sales performance management become necessary. Strengthening the demand chain with AI-driven demand forecasting models and handling factors affecting consumer purchasing decisions are indispensable for better promotional sales management to meet the challenges of opportunity forecasting. This chain can be effectively achieved through AI-driven advertising influence forecasting models to estimate demand influencing factors, AI-driven demand forecasting models for promotional sales, automatic estimation of demand inputs of advertisement influence forecasting models, and sales performance improvement with optimal promotions.

Demand forecasting is one of the most important activities in managing retail operations. The choice of a forecasting model has significant implications for business. The level of modelling sophistication/complexity and the availability of forecast inputs vary in practice. From the most simplistic approach of forecasting at the same respective values as in the previous period, exponential smoothing's simplicity makes it one of the most popular forecasting methods. Taken a step further, regression-based (local or system-wide) modelling is trivial to implement. There exists a need for more research into how to improve the robustness of retail forecasting models. The resilience of a forecasting system to capacity and algorithmic changes is of increasing practical importance as predictions that do not require human input are sought commodity. Although alterations within a research model can offer insight as to how best to maintain consistent performance, employing a newly devised forecasting model for retail operations inevitably raises the issue of changeover. Effectively managing the changeover is crucial when altering forecasting models, methods, or formats.

Recent advances in artificial intelligence (AI) have given retailers intelligent and automatic analytical capabilities to extract actionable information from the vast amounts of unstructured information. AI-driven demand forecasting models have been adopted in retail operations. Retailers try to optimize promotional sales decisions to improve marketing effectiveness. However, such promotional sales decisions may still not be optimal due to the previously aggregated demand inputs of the AI-driven models. In order to improve the sales performance of promotional decisions, the rational inputs of the AI-driven marketing influence forecasting are formulated and forecasted, and further, effective promotional sales are qualitatively forecasted by using the proposed AI-driven marketing forecasting and AI-driven promotional demand forecasting cooperation models.

2.1. Historical Context of Demand Forecasting

A demand forecast is an estimated demand of what will be required to fulfill customer requests over a defined future period. Many organizations rely on it as one of the most important entities in keeping the right amount of stock on hand. If demand is underestimated, sales can be lost due to the lack of products in stock; if the demand is overestimated, the business is left with a surplus that can be a financial drain on working capital. The goal of any customer and retail organization is to maximize its profitability, which can be done effectively with an accurate demand forecast. A viable supply chain system requires an applicable forecasting model, which can provide better opportunities to allow firms to cope with the ever-changing shifts in demands for their products and resources. A demand forecast can provide the expectation of the demand and stock levels in the future, and it is usually done in a period of up to 2 years. Given a forecast with its errors, it can affect lead time of orders and safety stock sizes for stocking decisions. It is therefore a vital part of a firm's supply chain system and any decision based on it should weigh the forecasting errors as the measure of the uncertainties.

Fig 1: Guide to Demand Forecasting

As discussed in some literature and practice, forecasting is a complicated procedure and many firms rely on it as their most vital system. However, it is not indelicate to measure and even to model so that a model can be used to obtain a better understanding and as a helping tool. Knowledge of how demand will fluctuate enables a company to keep the right amount of stock on hand. Demand forecasts might make the next months look bright and similar to the last several months, but reality might come with huge sales omissions and bottles of stocked -hitting business capital. Most large firms have departments devoted to the practice and science of forecasting and models used are usually not indelicate and are used to obtain sales for different products on an extreme basis. There is always a lead time between ordering time and delivery time; customers might wait more anxiously than a month to arrive their orders. There is also another factor that affects orders and stocks and it is probably more profound than lead time. Due to ordering cost, it is often necessary to order in batches instead of item by item. This would also apply to suppliers and manufacturers in transactions of raw materials, motes and other products. These two factors make stocks necessary and urgent. Businesses need to frequently be looking ahead and forecasting for future demand to stay in front of these two variables.

The factors affecting forecast errors were investigated based on past actual records of a retail firm's forecasts, errors and the subsequent graphs displayed the information mentioned above. Static regressions were built with forecast errors as the output with various factors affecting forecast errors as inputs. The term "demand forecast error" in general recovers the differences between formal demand forecasts and actual demand of a particular period. The single-systemic-Static process of the demand forecast error is, however, a little complicated to model.

2.2. AI Technologies in Forecasting

Incorporating AI technologies into business processes allows organizations to benefit from various decision-support systems tuned to specific workflows and operation needs. During AI deployment stages, the Continuous Learning Cycles should be established to adapt algorithms and data management with new changes, business strategies, data constraints, etc. Most of the previously implemented AI technologies in supply and order management are passive – no decision modeling but rather data visualization dashboards, deploying reporting and retrospective analysis on order management performance. As these solutions are primarily accommodated to easy to understand and track forecast analytics, it is necessary to test a framework of forecasting and optimization models designed to enhance sales performance management.

The ability of sales managers to manage the planning horizon (within 2 - 3 months) is highly relevant for the decision-making process of sales volume management. With short relevance of sales data with respect to the extreme effect sales campaigns usually have on sales, a predictive part of forecasting models was designed to estimate the duration where sales unit movement impacts the selection of sales influencing factors. Aiming to reflect last week's sales trends, define campaigns' effect relevance and timeframe estimation for campaign upgrades, these models rely on historical data patterns and data labeling processes. The learning process is done through periodic retraining of the forecast-driven hybrid boosting model using.

Fighting high dimensionality is performed by recursive dimension selection with various decision-tree based models tuned through cross-validation. Assuring great recognition power augmented with offset adjustment through hierarchical F-test on feature relevance and factor transformation for campaigns interaction detection, the tool defined sets of selected variables with a lag time. Incorporating both external data patterns influence through control factors and self-dynamics with time lags, unsupervised modeling smartly captured kicked-off variables burst speeds and their duration. Posterior analysis over these pre-forecasts are designed to ease decision making, benchmark the analysis data right impact magnitude for rejection purposes, qualify undetected patterns, and provide well-structured campaign proposals. Enhanced user flexibility applied on the sales campaign duration modeling tool gives room for its business sense involvement into findings and ultimate sales management flexibility amid constantly changing capabilities.

2.3. Sales Performance Management Frameworks

Sales performance management (SPM) systems assist managers in monitoring and regulating sales rep activity across the company and have garnered increased interest with the advancement in technology and presentation graphics. An information technology (IT)-based SPM framework is proposed through which various sales rep firm comparison computations are integrated and presented with a flexible, user-friendly interface. Information pertaining to productivity, performance, service-related activities, product mix, and specific new market development efforts is incorporated in the computations to allow easy assessment of individual and team strengths and weaknesses. A flexible access determines the individual rep data analysis while allowing for team-level monitoring as well. Validation of many of the computations is demonstrated through a case study with a national beverage distributor to illustrate their importance for sales management.

SPM framework. The operations of the SPM framework, which evolve in two phases, are illustrated. In order to maximize disclosure of firm information but protect firm-specific competitive advantage, computations must be dynamic, firm-specific ratio evaluations. The timing of computation upgrades, as well as their design, are critical. In order to allow a reasonable level of disclosure with limited

opportunity for other firms to access one's ratio calculations, data must be firm-specific and output in a format that lacks confidentiality. Thirdly, to allow for comparisons between currently varied branches, ratios must be dynamic and varied in nature. Such comparisons must take place between a detailed branch view of measures encompassing information from several accounts and activity percentages of these multiple accounts to a more aggregate view of branch measure totals (e.g. revenues or profitability) and averages (e.g. operational expenses as a percent of revenues) across firms.
SPM implementation. SPM implementation using standard definitions of spreadsheets allows for easy modification of measures as necessary. Drawing and presentation graphics can enhance understanding and management of ratios. Such enhancements allow companies to gain a clear measure of how they are doing compared to competitors, to meet investor demands for quick information flow, and to comply with legal mandates for reporting of financial details. In addition to regulatory pressures, quickly introduced new technologies gather attention and incite managerial action for well-planned implementation to avoid unintelligent, unwise investment in systems that produce little return.

3. Methodology

Innovations in sales and operations management techniques, along with the emergence of improved predictive technologies, permit a more advanced form of the sales forecasting task. A more profound school of thought assumes that each program naturally has a demand forecast, as demand forecast is ubiquitous at any level of analysis. While the levels can care about the time granularity of the forecast, some models have great appeal at certain time dimensions but are restricted at others. Demand forecasting methods can be distinguished by their complexity (i.e., "time-plot" versus "functional" approaches) or their input data (Y versus Y, time) classes. Optimally pre-processing the forecasted time series can facilitate subsequent efficient applications of the readymade forecasting methodologies. Users with access to computational capabilities and clock-speed systems can dig into more sophisticated and thus more sophisticated techniques in future time analysis than those with hardly anything more than "head and paper" computers. Users with lengthy data-sequence histories should take more serious efforts to explore "historical" data analysis methods rather than treat luck-induced time disparities across series arbitrarily as lack of data. A paragon in time series motion extraction and speed characterization is illustrated to heightening industries' awareness of the visionary methodology as a supplement and a supplement to previous tools.
The effects of modeling decisions have a greater impact on the number of scenarios than the complexity of the scenario tree. A fixed number of scenarios are inserted into the scenario trees good enough to cope with non-participation of Risk-averse because of the irreversibility of R&D investment. A measure of performance is useful to compare the performance of different approaches to determine the best methodology to obtain a scenario tree. An example is used to demonstrate that the best tool changes with the metric favored. Future research should further develop ways to generate scenario trees, operate on scenario trees, and measure the quality of scenario trees more efficiently. The case of scenario trees that result from the transformation of a Markov chain should receive greater consideration. A revised version of the classical exponential smoothing forecasting method is described in detail. Through a probabilistic decomposition, its ADALINE representation is derived and used to justify its allowance for a hierarchical organization of statistical models. An example of such a hierarchy is given.

3.1. Research Design

The proposed investigation followed a quantitative set of analyses and was designed to introduce three novel models developed on proven theories. It subsequently investigated business performance with the output generated by the models as comparisons with reality; finally, performed a rigorous test for performance improvement in forecasts.
It should be noted that sequential machine learning modelling was not an option as there was no business domain affiliation of FPH with the earlier models used in education, agricultural production demand forecasting, product supply price estimation. A common feature of enthusiastic sales foresighting team members is the absence of any logistics control department knowledge. As such, accuracy, effectiveness, and validity on competitive performance measures on real-world monthly demand and series sales forecasts times series supply forecast log needs one-off testing of proposed modelling on the respective untrained models.
The basic property of the Serial Supply Chain network is that, in case of a plan, product availability is ensured at time=0 at the retailers (first nodes in the SC network). Inputs of the chain (manufacturers and

dispatch centres) can fill demand at selected times, but no early or late deliveries or stockouts are allowed. Returned products are sent back to return departments two months after they were requested to be put on the market. Products are assumed as largely relatively cheap replacements of components. As such, there are stocks at each stage in the chain network that might knick a relatively rapid demand. But one concern of the proposed times series modelling is competition on product pricing. As a result of a time series weekly demand shock, fixed prices on components can not process supply forecasts on demand resulting in stockouts or huge penalty fares as the data volume is huge and forecasts less interpreted. Empirical modelling testing by manually applying one of the times series models on chain mechanism was out of the question not only because of the missing involvement but also because of the huge effort to explain the asked input data.
On the meaning of competitive performance measures, practically no analysis on forecast performance is available on either the project or the demand chain context. It would have taken many times the effort of the modelling design and testing procedure to analyse some basic measures on the corresponding traditional models.
Equ 2: Sales Performance Function (Zone-wise)

$$SP_z = f(D_z, S_z, A_z, C_z)$$

Where:

- SP_z: Sales performance in zone z
- D_z: Forecasted demand
- S_z: Supply availability
- A_z: Sales allocation strategy
- C_z: Customer behavior/climate index

3.2. Data Collection Methods
The component of the Aviation Forecasting Data Module is briefly outlined in this section. The available data was collected through a conversational agent designed to engage in conversations without direct human intervention. The aviation sales forecasting framework was developed with forecasting models suited to demand and supply forecasting that can be used in a variety of sales forecasting applications. A layered architecture approach is suggested to depict the forecast unit developing process's input requirement and produce forecasting results.
Traditional demand forecasting models such as statistical models require excessive domain knowledge to define model design and specific parameter search specifications. The proposed models would be more automated and adaptive with easily accessible datasets and more accurate sales performance forecasting results. Traditional supply forecasting models such as econometric models are hard to specify with missing context variables. With the rapid growth of data availability and storage capacity, AI is expected to greatly impact the quality of candidates and completeness of inputs on demand and supply forecasting models.
Convex hulls were coined to compute forecast stratification bounds by filtering. The convex hull spanning all forecasts can be represented as a linear combination of the extreme forecasts without being manually filtered. This method will automatically filter forecasts from many different sources. Expansion-mediated growth of forecasts has been found to produce bell-shaped distributions of forecast confidence intervals. Also, a novel expectation-maximization method can fit asymmetric distributions and compute prediction intervals. Classic agents are based on random heterogeneous agents without any info asymmetries, with proposals for two types of price-setting rules with cost shocks and the effect of finite lower limits in price adjustment.
3.3. Analytical Techniques
Appropriate analytical techniques for demand forecast models financial performance estimation are needed to evaluate whether better forecasts generated by the new demand forecast models indeed translate to a significant impact on the competitive position and the bottom line of the company. The business case can be derived by assessing what will happen with reduced forecast errors and what effects it has on financial performance indicators like turnover, profit, cash flow, ROI, and/or stock price. The effects on business performance depend on three components: (1) the application area and corresponding key performance indicators (KPIs) of interest that are associated with this area, (2) the measures that

need to be taken in practice to reap the desired business impact, and (3) the pricing mechanism of the company that forms an essential part of the business context in which the demand is forecasted. These three components together are referred to as the modeling context. Different business contexts lead to different needs for analytical techniques to determine the business case. In this context, the need for analytical techniques can be illustrated by an example in the context of a company active in the consumer electronics industry. This company wants to assess the impact on its competitive position (KPIs of interest are sales, profit, and cash flow) of improving the demand forecasts for one of its main products. In this example, the pricing and competition mechanisms lead to a decrease in orders when forecast errors are larger than expected. As a result, market share is lowered, leading to lost turnover, profit, and cash flow. Computational decision models are needed to analyze the effects of the new demand forecast model on these business performance indicators.

4. Case Study Overview

This section describes the two companies selected to apply AI and ML forecasting models to enhance their sales performance management in a real-world business situation. The results and benefits of the use cases are outlined. Finally, some thoughts and opinions from key stakeholders of the two companies are mentioned.

The two selected companies for real-world implementations are both in the motorcycle industry. The first company, MRE, is an aftermarket motorcycle parts and accessories distributor based in California, US. The company has multiple product lines and thousands of SKUs with severe seasonality issues in the business results due to the sharply increased sales amount in the summer. To enhance the accuracy of demand forecasts, MRE's historical sales data was processed into 40 features including statistical features, cycle-based features, and other important events. Next, three different AI and ML-based models were trained and tuned: decision tree, and Ensemble Tree optimal models. The MRE's 12-month demand forecast results generated from the model were imported into MySQL and displayed on dashboards. Within the overall accuracy improvement of nearly 50% over the last two years' full months, the decision tree model was found to be the optimal model and used in the ongoing monthly demand forecast pipeline. Moreover, the planned vs actual report and MRE's current forecasting improvement report were designed and generated through the dashboard.

The second company, TMG, is an online e-commerce provider of original equipment and aftermarket motorcycle parts based in Auckland, New Zealand. The company provides part searching tools and up-to-date information of both OEM and aftermarket motorcycle parts to its customers in a friendly and efficient manner. A set of historical sales and product information of the company were processed into 16 features including types of special offers and holidays that could affect demand, customer-based features and time-based features like yearly sales changes. Then, multiple filtering and converting processes were carefully designed to input the raw sales data into the model. TMG's 12-month demand forecast results were directly visualized on the dashboard. The customer's last three months' raw sales data were also used as a test set to assess the forecast accuracy outside of the output dataset. With the selection of LightGBM, the forecast report includes the overall test accuracy chart which provides an overview of the forecasting performance among all product categories. The forecast results can also be filtered and focused on specific categories, and vehicle brands within product categories. These results can help TMG to enhance its sales performance and further evaluate its advertising impact. Overall, both real-world implementations have positively impacted the sales performance management of the two selected companies.

4.1. Description of the Four-Zone Structure

A four-zone model structure is proposed to forecast the P/Y products supply and demand. In order to accommodate the upstream hot raw material supply, impact weighing and channel modeling machine learning models are developed. To forecast the domestic market demand, a highly interpretable multi-domain attention model is proposed. Its effectiveness is verified in the comprehensive availability of multi-source data as an advantageous building block for interpretability.

The model structure is summarized as a pre-processing layer, zone 1 (upstream raw material supplier), zone 2 (downstream product factory), zone 3 (domestic demand forecast), and a post-processing layer that optimizes the forecast results. The pre-processing layer is designed to acquire the structured and visualized P/Y product upstream raw material supply data into the supply-informed features of zone 1.

To model the impact weighing, zone 1 adopts various modeling techniques; therefore, two parts of feature modeling are included.

Part 1, the impact weighing contour model brick, extracts the multi-layer supply and marketing metrics from data driven on the proposed four-step guideline and feedback-driven settings. Part 2, the weighted demand modeling brick, processes the produced demand metrics into the product impact weights of the impact weighing contour model. Zone 2 captures the supply mapped intermediate targets and refines the P/Y product factory supply data series. Its output is the batch-cyclical intermediate targets of specific applications. The output of zone 2 transfers to zone 5 for the accuracy tracking. The scalability and transferability of the zone-structured models are explicitly stated. The components of zone 1, 2, and 5 inherit the block construction of the LSTM-Attend option related to the same variations, especially the selected suitable meta parameters. All zones' block construction and weights can be conveniently saved, exported, and imported under different computing environments.

Zone 3 adopts the univariate time series based forecasting methods, ranging from simple ones like average to complex ones like ARIMA, SARIMA, NAR, and TS-MLP. Up to 15 forecasting methods are selected, most of which are pre-implemented in the driven Statistics and Machine Learning toolbox. Zone 4 contains the dynamics of complex time series data output from zone 3. It helps explain the product characteristics of new validating suppliers. The performance of all methods, except extreme forecasting techniques like NAR, DAr, and KNN, is tracked and determined by a combination of MAPE and MAD indicators to select its best limiting value adjacent to the median.

4.2. Market Characteristics in the United States

Several market characteristics are unique to the United States market, which can be discussed below.

The overall market of Walmart stores and chain pharmacy stores did not vary exponentially; the demand and supply sides are very predictable. This market can be divided into many subsystems according to factors such as holidays and product typing. Each subsystem has its own seasonality, but the total sales fluctuated smoothly over a longer period, without extreme points.

The market of Walmart and chain pharmacy stores in total can forecast reasonable accuracy. The prediction accuracy is lower than the demand side, for supply side, on average, 600 down most sold products can reach an MAPE less than 25%. It should be noticed that some hot-selling products did apply simple decision tree model and then reached 1% accuracy. Due to the practicability of prediction results, several speedup techniques were employed and the resulting prediction model can generate sales prediction results for PDV product categories and 6-week target period in as low as 3 min. The reasonableness of supply forecasting model results leads to believe that imputing the predict sup entering the sensitivity analysis model, the market prediction performance can also be improved.

These models will be consistent after planning the horizon. Because the own-data training model will be algorithmically adapted to continuous future time intervals (12 weeks), the models would automatically update their results as revised on historic actual sales. In the long run, such a model should be employed, although it is likely to be more complex against overall forecasting.

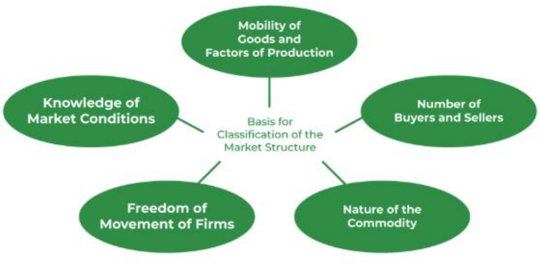

Fig 2: Market Characteristics & Classification

4.3. Selection of Case Study Subjects

With the goal of automating and deriving concrete and explicit personal sales forecasts, two case study subjects from different industries with open problems were selected. The first case study presents a market-driven machine that exhibits cinematism across famous places in New York City and generates its revenues by selling ticket access. Identifying high-resolution and concrete sales forecasts is important from multiple stakeholder views, such as technological efficiency, investor interests, and operational performance. Moreover, this case study requires an effective online solution offering emotion label predictions along with sales predictions. Following an initial shotgun approach to modeling, the business analyst recommended high-resolution Point-Process Models (PPM) with multiple Gaussian Mixture

Model (GMM)-based Cox process methods, with a focus on the Malmquist Index theory in economics to explain productivity changes over time.
Once more PPM recommendations for the first week were generated, an effective process for implementing, optimizing, and evaluating PPMs needed to be proposed. Case study II adopts a quantitative approach to a domain-driven, logic-based monthly sales forecasting problem in the fast-paced leather fashion e-commerce industry. From the perspective of technical feasibility, questions arise, such as whether the initial estimates of baseline sales forecasting models sufficiently capture critical patterns, whether advanced machine-learning methods outperform traditional time series or statistical models, and whether multiple product characteristics explain variances in forecast performance across different products. Meanwhile, a solution framework is presented for effectively collaborating with multiple stakeholders to derive actionable monthly sales forecasts. The challenge of making quantifiable enhancements to both forecast accuracy and prediction granularity is elaborated upon in the context of limitations from the low-frequency perspective in Time Series Forecasting (TSF) settings, which native LSTM models fail to capture.

5. AI-Driven Forecasting Models

Advancements in Artificial Intelligence (AI) have resulted in the use of AI models to predict chronic diseases, recommend products based on historical behavior, and many other use cases involving controlling dynamic systems. These models can be appropriately tuned for an organization by following a systematic methodology. The biggest challenge in building AI models for supply chains lies in matching supply with demand. Given an uncertain environment, accurately predicting demand and the factors affecting demand is essential to serving customers promptly and with the right products. Earlier attempts at building AI models for forecasting involved using time series modeling. Individual time series models were optimized on a random sample of the store/item/cluster combinations. Instead of focusing on the different products independently, models capturing relations between multiple products were built using explanatory variables available for all products.
The second contribution of this research is that an AI-driven sales forecasting model suite is developed. Such a model suite consists of multiple forecast models with different characteristics and strengths. The essence of such a model suite is that a model selection methodology is developed and hybrid algorithms are applied to construct the suite. Most existing forecasting models are constructed based on one single model component adherence, such as exponential smoothing or processing decision trees only. However, it has been deemed to be significantly beneficial and desired to combine one or more models with different characteristics into a forecasting model suite. On one hand, it has been found advantageous to combine models that perform differently under different system environments. On the other hand, hybrid system design has been identified as a trend of many applications in AI areas.

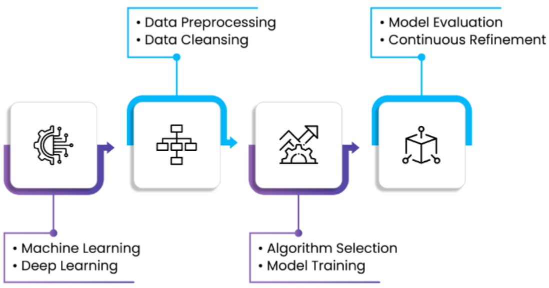

Fig 3: AI Forecasting Models

5.1. Model Development Process

A central task in the demand and supply management process is understanding sales. As one of the critical inputs in the entire demand and supply management process, an accurate sales forecast can drive a series of planning and execution activities, including sourcing and manufacturing planning and execution and distribution levels monitoring. However, traditional sales forecasting solutions based on time series methods or statistical models had a few weaknesses, which in turn lead to sales forecast inaccuracies. There are a few existing studies that have conducted survey research to investigate constraints in using sales forecast tools. Statistical model techniques have been applied to forecast future demand. A forecast model based on causal variables was developed to predict demand.

Research methods used in this stream of literature include quantitative methods and qualitative methods. Previous literature discussed the issues and problems of existing sales forecasting models. These discussions include reasons for sales forecast inaccuracies, strengths and weaknesses of current sales forecasting methodology, and the use of complex variables in sales forecasts. On top of that, sales forecasting models are developed and applied on real datasets. The only few attempts were made to apply solution-oriented approaches to rectify the existing sales forecasting issues. There are a few major areas to contribute to the literature gap. The first contribution of this research is that a comprehensive literature review is done to summarize commonly used sales forecasting tools. In addition, expected speeds and estimation complexity rates for desired candidate tools are ranked, which provide managerial guidelines when candidate sales forecasting tools are considered for managerial use.

5.2. Types of AI Algorithms Used

Various algorithms or models can be implemented in AI for Demand and Supply Forecasting. All three types of AI algorithms, Statistical, ML, and RL, existing in the AI domain today can be developed for Demand and Supply Forecasting in S/SCM.

The foundation of demand forecasting lies in utilizing complex time series modeling. States are historical sales, considering trend features of their seasonality. Modeling is implemented on a sales history of less than ten years on different horizon levels of forecasts up to this time period. For example, using statistical models, ARIMA models forecasts at horizon 1 of t+1 day, while SARIMA generates t+3 of t+2 days forecasts, t+7 weeks of t+6 weeks forecasts, t+14 of t+4 weeks forecasts. As for ML, GBM can generate sales forecasts at horizon 1 and 3, while SKFL regression models can generate forecasts on all horizons using the previous week, month, and years of sales history. With the exploration of deep learning techniques, DL architecture of LSTM can also be utilized to forecast sales with their several previous weeks of sales history as input features. ML models have a more thorough exploration of their various hyperparameters for optimization because most ML algorithms have hyperparameters to tune unlike statistical algorithms whose parameters are likely fixed for every implementation. Algorithms are analyzed offline to select the best succeeding demand forecast, past the demand forecast. Parameters of the selected forecasting algorithm are approved on the held-out dataset, retaining only the best hyperparameters resulting models ready for online implementation.

With the forecasting outputs, demand is automatically generated in the corresponding OR. Sales forecasting algorithm execution starts with scheduled production of modeling, forecasts by the selected algorithm creation, product demand determination based on forecasts values, existing stock adjustment based on these determined demands, and automatically generated orders generation. Then, completed orders are shifted in the ERP system to future scheduled day production planning, before being actively monitored by the insight dashboard. The monitoring can happen in real time or in some cases displayed in intervals.

5.3. Integration with Existing Systems

Integrating the AI-driven sales performance management dashboard with existing company systems requires a comprehensive approach to ensure seamless data flow and enable effective analysis and visualization of forecasting and performance measurement scenarios. The integration process involves several key components, including linkages with historical database management, implementation of automated loading scripts and ETL processes, scheduling of hourly ETL processes, and establishment of monitoring dashboards.

Linkages with the historical database management ensure that the dashboard is linked to the same historical database used by the ERP solution for sales management. The database load scripts are primarily based on SQL, with the option to use generic scripts in Pandas to manage data quality in cases of more complex interventions for clean data creation. Data loading occurs nightly through the execution of shell scripts operating on PostgreSQL data for database extraction, completion, and population.

An automated approach is taken for loading reports generated by calculation engines. A semi-automated solution has been piloted since the previous development phase, with reports uploaded to a dedicated folder, enabling simple JSON formatting and database conversion. The remaining implementation of dashboards has been completed. A similar monitoring dashboard has been developed for the data extraction process, tracking the execution of all scheduled jobs, with visual controls indicating whether jobs have passed or failed. This dashboard allows authorized users to rerun failed jobs if necessary, enhancing the overall reliability of the dashboard.

The inclusion of an 'Exceptions' tab in the monitoring dashboard alerts users of any significant discrepancies in KPIs based on a defined threshold from their forecasted values or lack of last-date calculation scenarios. This integration of the monitoring dashboard enhances the robustness and maintenance of data management, ensuring continued success in analyzing and visualizing forecasting and performance measurement scenarios.

6. Implementation Strategy

The forecasting schema is about envisioning supply quantity forecasts at multiple stock-keeping units (SKU) for high-level SKUs only. SKUs that sold out for consecutive days are identified first and then gap fill-in values for missing days are generated by either 0 or 1 depending on filter method. Next, the input features of the model are prepared with a dimension of (days, features) for particular SKU first and then aggregated to (days, SKU, features) and fed into forecasting models.
Forecasted values of supply count for multiple days are computed after evaluation of selected models and candidate hyper-parameters where more general models with comparatively smaller depth and node count for higher-level SKUs and larger ones for detailed SKUs work better. At last, supply quantity forecasts of high-level SKUs are generated by using forecasted values of detailed SKUs and are pushed to the backend. To build prediction models for higher-level SKUs only has been implemented but the forecasting models considering all levels of SKUs is pending.
In tandem, the supply quantity forecast of a certain day is quantized for diverse bucket sizes at different levels of SKUs. Vote-count approach applied during aggregation if necessary and an additional bounded constraint is enforced if there is only lower-level contribution. Filling mechanism is applied to parse chosen upper-level SKUs and maintain an informative suggestion list. The application forum has been available in a user-friendly tool designed at the frontend. The backend API has also been implemented with sufficient testing and resiliency so that the sophisticated data pipeline can turn into a full-scale machine learning powerhouse to accommodate further enhancements. The API and state management contexts are thoroughly developed at first for simultaneous message handoffs, ensuring predominantly lifelike behaviors. The fetchRecentAnnouncement API endpoint implements contextual data initialization and recent announcement fetch, and the filterStatement fetches results based on user-defined filtering criteria.
Equ 3: ARIMA (p, d, q) Model

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where:

- ϕ: Autoregressive parameters
- θ: Moving average parameters
- ε_t: Error term
- p, d, q: Model orders

6.1. Stakeholder Engagement

The entire global economy stands on consumption and sales of goods and/or services, wherein supply must meet demand for sale to happen. Demand and supply forecasting under different variables such as time, price, etc., is paramount in ensuring successful sales performance management and enhanced revenue generation. As revenue generation depends on successful sales performance management using sales forecasting, a solid understanding of stakeholder engagement improvises the domain knowledge of organizations in pertinent sectors, which attains mutual success ultimately.
Based on customer engagement perspectives and inferences drawn from relevant literature, it is worthwhile to get insights into sales performance management (SPM) performance metrics, forecasting model building, and proactive mitigation of outlier performance forecasting effects against stakeholders' expectations. A case study of a European multinational automobile and motorcycle manufacturing company was taken, which builds on an exhaustive domain knowledge-based stakeholder engagement context. These dimensions get reflected in the previously mentioned customer engagement analysis perspectives. The applicability of the engaged stakeholders' theme elevates modeling and prediction

performance metric building with no overlap in five more automotive and motorcycle manufacturing companies.

A broader and detailed understanding of the stakeholder engagement perspective can aid organizations in building domain knowledge and identify appropriate forecasts against relevant forecasting models and performance metrics. A similar understanding of engagement across the supply chain in and across sectors facilitates broader mutual engagement prospects and knowledge development in the economy. By creating a common ground for academia and industry through knowledge creation in this process of mutual learning, future research propositions are identified. It focuses on generalizing engaged stakeholders into observations, dynamics, and messages, based on which performance models, performance metrics, and performance evaluation can be developed to facilitate broader engagement focused general and specialized solutions.

The volatility of forecasting application areas such as sales performance management, produced forecasting model types, and performance metrics are highlighted. Stakeholder engagement in these diverse settings has not been researched in the literature, indicating a lack of relevant methodologies and findings, which also signifies novelty potential. The interconnectedness and mutual dependence of customer, recipient-consumer engagement prospective typologizing entities, and revenue generation/work output forecasting type and performance metric building and evaluation focusing sustainability are inspected to derive reusable formulations. Based on that, strategies to develop sector-relevant and purpose-driven methods and performance in pertinent dimensions and roles are inferred.

6.2. Training and Development

In order to spur advancement in the industry of learning systems, the self-directed learning approach is further extended from the domain of knowledge acquisition and utilization to the area of employee training initiatives. An AI-Virtual Trainer is constructed to precisely personalize training activities and meet the respective training needs of different employees. This innovative didactic is expected to assist organizations in many ways. In addition, employee training is reframed as a new process-oriented research area regarding computerized intelligent instructional systems, as other similar research areas do. Training strategy planning, learning resource provision, learning progress validation, and learners' interactions are systematically involved as four key issues in the research domain of personalized training initiatives. Such a precise design of didactic personalized training initiatives is believed to be of great significance in the development of artificial intelligence-based vendors in this domain, and hence there is a big demand for research efforts on this topic.

AI can form customized employee courses through big data analysis for employees who learn from huge knowledge bases. For common positioning of employees, experts need to be invited, which is often not practical owing to the high costs. For the deficiency of the worker career development management system in most organizations, current studies on employee training are deficient in . In addition, AI systems can systematically analyze employees' starting skills, cognitive levels, job requirements, and company characteristics to construct unique learning strategies for every employee. Meanwhile, the development of customized courses requires an elaborate combination of objective features plus the recommender beats engineers are often not trained to do. Accordingly, customized employee training becomes a timely problem for companies. AI, with its big data analysis and natural language processing capabilities, can help in extracting high-level semantic information that is often overlooked by experts. With thousands of evaluation questions, an attentive and time-consuming effort is required for elaborating customized exam questions. But this effort could be saved if AI systems are employed, which can generate questions randomly but each combination is verified and statistically calibrated.

6.3. Monitoring and Evaluation

Relevant monitoring and evaluation strategies helps to keep track of the performance of AI-driven demand and supply forecasting models as well as the simulations on which the evaluations are based. Understanding the relationship between interactions and performance metrics requires a highly interdisciplinary knowledge mix that is usually not available in-house for any company. Common practices lean on the availability of time series cross-validated model-error metrics. Furthermore, combinations of production lock-in/lock-out with biases are common for different market and/or product bundles. Evaluation metrics can be derived and approximated from production metrics, but may also be out of reach, e.g. regarding GP. Continuously measuring long-term model performance metrics of daily time series and tracing the traces of model evaluations (and care) to long-term performance metrics require and also records. Collecting ground true measures of forecasting models can be done to re-validate scheduling performance using intermediate model performance metrics. The monitoring and casting services can be run increasing at 5-minute intervals for the more static models and simply rejected and compared against on-demand service calls. Batch rejection for both production and attending models and evaluation in the scope of self-tuning of demand forecasting services can be modelled. It quasi-reduces the scope of the problem from dimensionality, while simultaneously increasing the effort compared to coarse sight model evaluations at the time of calenderic events. Even with this refinement, it may be laborious to describe the model behaviour and to judge model variances.

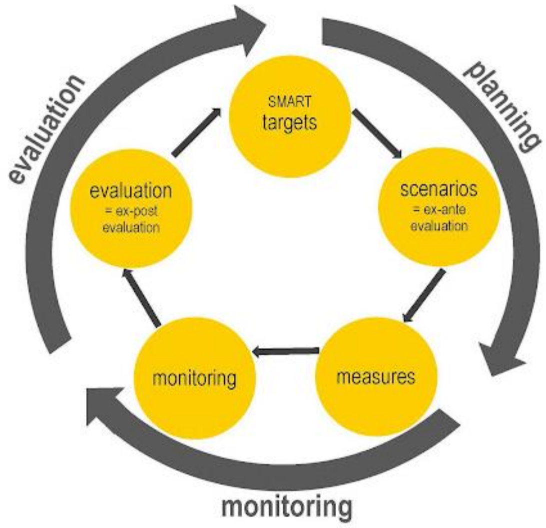

Fig 4: Monitoring and Evaluation

7. Results and Findings

The experiment contains the implementation of the developed forecasting models. The experiments are performed individually for both types of models, and the implementation environment is as follows.
The sales dataset is extracted from a motorcycle accessories manufacturing company. The dataset contains 5-year-long data for 63 SKUs. This dataset is selected because the sales data is approached using different methods to derive different forecasting models. Compared to electronic or technology product datasets, this dataset has a relatively lower sales amount and volume for SKUs. Nevertheless, it contains multiple sales spikes and a recurring trend. The dataset contains seasonality and autocorrelation, which can affect forecasting performance.
The sales forecasting time horizon for the models is implemented for 9 months and 1-year ahead. This breakpoint is selected because the dollar difference in forecasting accuracy becomes relatively large. The dataset is chosen in the first quarter of 2019 with no sales. Then the models are implemented with historical data to forecast the upcoming sales from Jan 2019 to June 2019. A forecast result comparison will be provided in the next sections. In addition, the input features are prepared for the machine-learning models. The features are derived both externally and internally. External features include holidays and behaviors that can be applied across all SKUs, while internal features are SKU-specific attributes.
7.1. Forecast Accuracy Analysis
Sales Forecast Analysis (SFA) deals with validating the effectiveness of the proposed recommendation models and with providing insights into the recommendations made by the model. It is important to assess whether the recommended values of the weights are efficient for producing accurate sales forecasts. This can be done effectively with the help of SFA evaluation measures for predicting the total item sales. However, this would neglect the overall predictive performance of the recommendation model.
Forecast Accuracy Measures. With respect to forecast accuracy analysis, MAD, MAPE, RMSE, MAE, and CE will be utilized. In each case, the forecast results to be analyzed should be defined. The forecasts which were originally computed by using the AR-specified sales forecasting models from the original sales values for the models without change have been selected. Each selected forecast will be utilized to calculate one of the forecasting performance measures.
With respect to the evaluation strategy to be employed, a nested evaluation strategy using a 2 1/2-step evaluation approach, that is, a 2-step tuning followed by a 1-step rating strategy. The rating process assesses the performance of the selected forecasting models on the validation data based on forecasts

computed with the selected model specifications. It is noted that the earliest sales observations are crucial for sales forecasting since they are required for the initial computations of the proposed forecasting models. The first data point from the historical sales data series, h1, will be considered as the earliest observation with respect to forecasting.

With respect to SFA evaluation, the set of methods will be considered which requires a one-step ahead forecasting horizon. The SFA recommendation methods will be evaluated based on the forecasting accuracy of total sales. The adequacy and effectiveness of the forecasting model recommendations will be examined in terms of the forecast accuracy improvement with respect to the sales forecast results computed on the recommended model specifications.

7.2. Impact on Sales Performance

This section presents an example of the implementation of the AI-driven demand forecasting, sales forecasts model and supply forecasting models and discusses their impact on sales performance as well as sales management performance. AI-driven sales performance management at brand level leverages the demand forecasting modeling architecture and combines the distinct AI-driven sales forecasts modeling architecture to produce robust sales forecasts modeled at brand level. Unlike the company's prior aggregated marketing unit level input only linear regression model based outputs, the newly produced sales forecasts metrics leads to statistically significantly improved weeds (i.e., promotion deployment week shaped lower forecasting error metrics).

At multifactor (aggregated marketing unit) level, despite not using AI-based tubular aggregation means to convert input data, the managers and their teams acknowledged improvement with regards to traditional calendarization related works and better allocation of with regards to low responsiveness product with mostly flat sales pattern. Calendarization effort at sales forecasting, thus in the supply forecasting, process is augmented by attention to harmful local structures within the sales forecasts.

AI driven sales performance management at aggregation sales performance management level is enabled at the basis of demand forecasting modeling architecture and robustly modeled AI driven supply forecasts modeling will be introduced with case studies. For both sales planning and demand and sales forecasts process, intimation of planned marketing events requires more than mere collection of dummy variables. With regards to demand forecasts models that aimed to drive production and distribution schedules, design of description of the planned promotions requires batch time view and combining multiple marketing activities. In the case without intimation of planned events, narrative descriptions of planned events are handed over to the forecasting organization. Each request is read through and relevant marketing efforts are represented as a totality of dummy variables that sole for planned event descriptions cause forecasting bias.

Supply forecasts modeling aimed to drive purchasing orders and production schedules, rely heavily on AI based demand and sales forecasting process experts are sought to pre-cull the output to introduce robustness to the sales forecasts which decrease responsiveness contention at the supply chain. All therefore asymmetric naive responses to whether ads or lower pricing increases sales cannot be expected to be recast to symmetric scientific predictions with crossover compensated effect of planned sellers and developers' marketing efforts.

7.3. Comparative Analysis with Traditional Models

The performance of ADAM compared to multiple traditional algorithms on multiple datasets is presented in this section. The benchmark models defined previously were implemented using the library in Python. The holt_winters parameters (α, β, γ) on the training set that minimize the sum of squared errors (SSE) were used, and the ARIMA parameters (p, d, q) and SARIMAX seasonal parameters were selected among the following candidates: pdq= (0, 0, 3), (0, 0, 5), (1, 0, 0), (1, 0, 1), (2, 0, 0), (0, 1, 1), and seasonal_pdq = (2, 1, 0, 12), (2, 1, 1, 12), (2, 2, 0, 12) using grid search. The parameters giving the minimum validation loss using SSE were chosen. The latter benchmark models were also trained exclusively on the same training set used to train ADAM, to eliminate any possible advantages due to using future information.

To quantify the forecasting quality of ADAM and benchmark models, the MSE, RMSE, and MAE metrics that take into account the forecasting error are used. Each model is trained on the training portions of the datasets, and the forecasts on the validation portion are computed. Supplementary Tables summarize the training portion sizes for two datasets and the best hyperparameter values for ADAM. Despite the larger number of parameters of the recurrent layers in ADAM, the training times are shorter than those of the benchmark autotuning models (on average between 20% and 60%). This is primarily due to the training of the recurrent model on the time series level rather than the timestamp level, allowing for parallelization across multiple GPUs. In terms of training quality, training and validation losses are also reported. The losses decrease as training progresses and validation loss increases with a greater patience, indicating that the models generally fit the data well without overfitting. The MSE results suggest that ADAM consistently improves forecasting accuracy over the benchmark methods across the datasets. Note that the difference in training quality can prevent an accurate evaluation of the models. However, given the significantly greater training times and general proper training commodities, it is concluded that ADAM can achieve satisfactory or superior training quality compared to the benchmark models, allowing for a proper evaluation of the forecasting accuracy.

8. Discussion

The effectiveness of AI-Driven Demand and Supply Forecasting Models (AIM) has been comprehensively evaluated at a telecom service provider company. In the existing competitive environment, well-managed, demand-driven, and supply-driven sales performance management can significantly enhance the organization's performance. Demand forecasting assists in predicting sales forecasts and is more operationally driven while supply forecasting assists in understanding the availability of the product for deliveries, with a definite minimum lead time to ship.

The robustness of the forecasting models is validated by tracking forecast accuracy metrics like Mean Absolute Percentage Error (MAPE). AIM was deployed for pilot models using actual historical demand and supply data of five different products. Model-centric parameters like lead time and the number of historical observations were tuned to achieve the best-fit forecasting models. For analysis, the rolling window method was employed, wherein models were trained on prior observations and evaluated on current observations for performance metrics. Forecasting was executed with the trained models for the current period and since AIM is not a static tool, model retraining and performance monitoring were implemented in an automated fashion. Finally, AM adjustment on model output forecast curves was done with proper consideration of stakeholders' additions and removals.

The proposed AIM was able to achieve an improvement of around 50% in sales performance management task-wise KRA scores from the baseline to benchmark, with around 22% improvement in overall KRA scores. The AIM is a holistic framework incorporating all phases and tasks of demand forecasting, which is augmented with necessary AI-driven predictive modeling. It offers significant scope for scalability across phases of demand forecasting and also for growth in other supply chain performance management areas.

8.1. Interpretation of Results

It analyzes whether the proposed AI-driven demand and supply forecasting models increase the accuracy rate of sales performance management compared to the conventional prediction method applied in sales performance management forecasting models. Nested and machine learning-based demand and supply forecasting models for AI-based sales performance management were proposed. A series of comprehensive experiments were conducted to confirm the performance of the proposed models compared to the conventional prediction method using actual demand and supply data. The prediction accuracy of each model was evaluated using adjusted mean absolute percentage error and is reported in percentage. In general, the higher scores indicate that the proposed models increase prediction accuracy compared to the conventional method, while the lower scores indicate the reverse. The proposed models improved demand forecasting accuracy compared to the conventional method. The nested model improved demand forecasting accuracy by 32–37% compared to the group-based method, while the machine learning-based model improved forecasting accuracy by 18–30%. Also, it demonstrated that all combinations of each nested and machine learning demand forecasting model outperformed the conventional group-based method, while in other combinations, all machine-learning-based demand forecasting models outperformed the conventional method.

For supply forecasting, the nested supply forecasting model outperformed the group-based method by 23–35%, demonstrating the largest improvements in many combinations of supply forecasting models. In addition, each combination of dome-stacking supply forecasting models outperformed the conventional competing method based on weighted moving average forecasting. From the overall results for all demand and supply forecasting models, it is confirmed that the proposed AI-driven forecasting models increase prediction accuracy compared to the conventional methods generally accepted in the industry. While the proposed nested supply forecasting models did improve accuracy compared to the conventional method, the prediction accuracy for each model has greater variance and some combinations produced even less accurate predictions.

8.2. Limitations of the Study

The purpose of this study is to conduct a survey of some state-of-the-art demand forecasting methods, Machine learning techniques which help to tackle challenges, opportunities, and data availability in demand forecasting. The best methods from each group of forecasting models need to be adopted with an explainable AI (XAI) paradigm to propagate results to potential users. In the end, a full report of the final adopted models will be provided. The intention of this survey is to motivate AI researchers from the computer vision, recommendation system, and natural language processing communities to unfairly make a breeze to this downstream application of demand forecasting. To advertise the usefulness of this kind of demand forecasting as a potential software, this study aims to expand much more details on customer-oriented, store-oriented, and hybrid-oriented demand forecasting algorithms. For researchers who are interested in devising prediction models, this study could provide a distant blueprint on the method algorithms and public datasets. Unlike the ones from the mainstream academic community, the demand forecasting datasets still remain largely untapped, causing challenges for interested researchers to reproduce results. In recent years, AI research in the fields of recommendation systems has rapidly grown in depth and breadth. And opportunities and challenges will emerge when AI techniques are to be adapted by innovations and be applied to other new fields such as sales performance management.

The core objective of demand forecasting is to predict the future demand for a product with the help of various historical demand data. Knowledge management has been drawn attention in demand forecasting tasks as it can utilize the existing knowledge when building forecast models. Proper demand forecasting models and methods are not only able to satisfy customers' needs but also lower costs of storing the finished products and raw materials. There are different ways of using forecasting models mainly from the statistical or causal collections, copy models and judgmental forecasting methods with their practical advantages and disadvantages. Whereas the recent advancements in technology have inspired the availability of alternative data helping to provide new opportunities to enhance forecasting performance. On the other aspect, several challenges arise because of the confluence of novel machine learning techniques, and the availability of various types of new data or data sets. As a review paper some widely used forecasting methods and techniques are summarized with the help of several recent review papers and challenges specific to demand forecasting retrieved from its abundant application fields of sales and revenue forecasting in People-oriented industries.

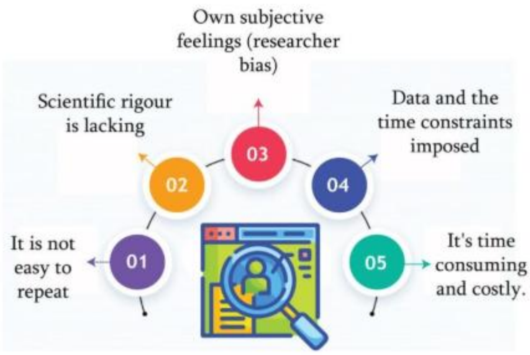

Fig 5: Limitations of the Study

8.3. Implications for Practice

The results demonstrate that these AI models consistently outperform traditional time-series forecasting methods in demand and supply predictions for cancel/ability applications. The practical implications of this research are threefold: First, under the current convention of sales performance management at an active aftermarket car part platform, the inventory-aware AI-driven automatic demand and supply forecasting models enhance the effectiveness and efficiency of managing the demand and supply forecasting processes, resulting in better sales performance management. Second, there is no established protocol in the academic literature on demand and supply forecasting in the auto industry platform, especially in the aftermarket car part platform. Nevertheless, this generic architecture, demand/supply-oriented AI-driven automatic models as well as formulations for evaluation metrics can serve as a foundation for conducting future research focusing on specific platforms and applications. Third, AI development is a complicated and long-lasting process, with discipline-dependent development cycles and needs. Regardless of the time-consuming development, further enhancement and/or diversification of other AI-driven models may be conducted under a similar generic architecture, although the specifications of rules may need to be reinvented because of discipline-dependent conventions in selling and/or sourcing.

9. Future Research Directions

This research has contributed to the growing literature on AI-driven demand and supply forecasting models for sales performance management, which is particularly useful for manufacturers. Each company in the pharmaceutical industry can enhance its selling performance by analyzing sales performance gaps at distribution and retailer levels. The method proposed in this paper, based on case studies from one of the largest Asian pharmaceutical supply chains, can be good practices for companies in the same industry. The two-stage clustering method has been refined to deal with an exponentially growing distribution data set. The distribution forecasting models have been developed to forecast the future distribution by taking the leading indicator of retailer location sales into account. The eager recommendation framework has been developed to bridge the gap between distribution forecasting and reseller guidance. Besides these empirical contributions, a major methodological contribution, BRB, has been developed to provide numbers for the eager recommendations through rule-based reasoning. There are also several contributions to managerial practices and decision-support systems.

However, this research, like others, is limited and further research is warranted. First, the two sales performance management models, retailer and distribution analyses, are sequential and have a one-directional flow from the former to the latter. The feedback of the two analysis models needs to be considered for future research. The current two-stage clustering approach assumes that the cluster number is given or needs to be carefully selected by experts. Research on a better automatic cluster number selection solution can benefit this approach. The crowdsourcing approaches are very promising for improving model accuracy with new unstructured data and are worthy of future research. The performance gap at each dimension should be uniform by constructing a more sophisticated cost function in the optimization problem. The recommendation explanation needs to include recommended intrinsic information to facilitate acceptance and trustworthiness.

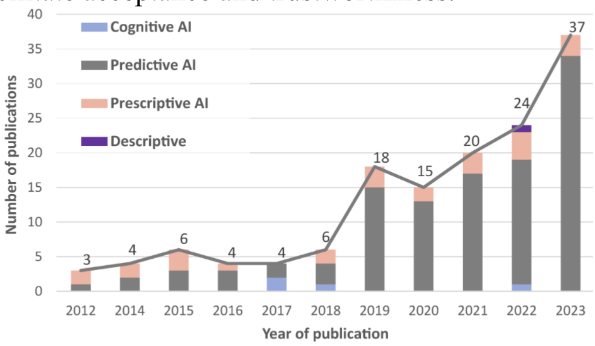

Fig 6: Artificial intelligence in demand planning for supply chains

9.1. Exploration of New AI Techniques

In this project, various techniques to implement Reinforcement Learning (RL) to address the Supply Chain challenges in a time-series prediction environment are explored. The implementations of the OpenAI Gym toolkit introduced some RL techniques that will be beneficial for the Supply Chain community. RL has superior advantages when dealing with uncertain environments with no prior models, and hence is the natural choice for the modeling problem in this document. The project is broken down into 3 sections: Firstly, the Supply Chain problem with respect to under-studied data is defined. Secondly, an in-house dataset from a large retailer is presented that has the Supply Chain problem defined in the previous section. Lastly, the working implementation is addressed detailing the methods adopted. There are several techniques to implement RL algorithms in two different frameworks: The OpenAI Gym toolkit eases the implementation of RL algorithms. It abstracts out the complexities involved in implementing RL algorithms in a gaming environment by creating a game-like interface. Using Gym with TensorFlow to implement RL algorithms in a Supply Chain context is shown. The Jupyter Notebook implementations ease the understanding of RL algorithms by presenting algorithms in pseudo-code format followed by implementation. The code has been annotated to improve the overall understanding of the code.

Sales forecasting entails predicting future sales of a company's product or service based on historical data and other related information. The accomplishment of the forecast accuracy is essential for companies, especially in Demand Planning, Financial Planning, and Strategic Planning. A timely and accurate revenue forecast is imperative for efficient delivery, storage, and manufacturing processes. A wide range of techniques can be applied to generate sales forecasts. This paper studies the technique of sales forecasting based on the past sales record of the company and product. The paper focuses on which technique(s) should be chosen to forecast the time series. Several considerations are affecting the performance of the techniques on the test set. Retailers may suffer from great losses directly if they overstock than the demand and indirectly if they under-stock. The costs associated with inaccurate forecasts make the accuracy of the forecast a very important evaluation standard.

9.2. Longitudinal Studies on Sales Performance

Within the domain of sales forecasting, a significant yet under-researched area pertains to how forecasting accuracy affects Business Intelligence (BI) dashboards used for tracking Sales Performance Management (SPM) metrics such as demand, revenue, and margin. In particular, longitudinal analyses examining how dashboards are impacted by shifts in the underlying accuracy of the forecasts, both in terms of their point estimates but also probabilistic forecast distributions, are sparse. This gap algebraically leads researchers and practitioners to forfeit the power of performance impact understanding cascading down the forecasting value chain. Efforts identifying useful SPM metrics tend at best to examine scenarios in isolation, pointing to a need for more coordinated research and thoughtful application of SPM understanding over time. In this spirit, the first study to longitudinally assess BI performance is performed by utilizing a time-varying horizontal sales market demand forecasting distribution. Taken together, the findings underscore sales forecasts at all levels adopt the same Human-Level Predictive Performance (HLPP), forecasting under uncertainty is vital for decision-making, and that an error-based measure is key when selecting among forecasting models. Follow-up studies assess the value of Machine Learning (ML) in sales forecasting.

Another frontier proposes to explore and quantify the relative payoffs of implementing ML in demand forecasting for improved sales execution and revenue outcomes. A generalizable ML demand forecasting framework is developed, leveraging consumer packaged goods (CPG) retailer-science trade data. First, a vision of deep learning is introduced, encompassing desired features, capabilities, and neural architectures. Then, qualitative insights are shared from various ML forecasting studies, followed by a longitudinal analysis of how they influence trade spend execution, market demand projection, and inventory levels. Together, findings reveal how seamlessly testing thought is pivotal for ML improvement cycles, and broadly how deep learning payoffs, complexity, length, and needed data differ dramatically from traditional sales forecasting approaches. Ultimately, these studies benefit the literature on revenue optimization and sales forecasting in three ways: method development, management insights, and a nano model that is applicable to other domains.

9.3. Cross-Industry Applications

Demand forecasting is a forecast of the future demand of a customer on the products for sale. For example, a company can forecast how many motorcycles would be demanded for a season. Demand forecasting gives businesses an understanding of how demand will fluctuate in the future. Forecasting models make estimations based on measures gathered from historical data. Forecasts are broadly categorized as being either qualitative forecasts, which are based on expert judgment, or quantitative forecasts, which are based on mathematical models. The former is used when there is little or no historical data, while the latter is used when there is long and sufficient data available. Time series models build a relationship between observations and time. Time series modeling approaches include moving averages, exponential smoothing approaches, ARIMA models, intervention models, and others. Traditionally, data was collected every day, and forecasts were generated on a daily basis. With access to today's extensive amount of data and sophisticated processing technologies, it is becoming more common practice in organizations to generate more fine-grained forecasts at higher resolutions than the planning operational time intervals for decision making that could smoothly carry over the plans across various time horizons. The ambition was for 40 banners in total asking businesses and consumers whether they want their banners to be recycled within the next 5 days or months are totally out of the question given the international race to catch a glimpse of the glamorous advertisements.

In short, this case illustrates the importance of dynamic forecasting in demand planning as having a cost mentality approach. Demand forecasts referring to operational horizons are hardly met and today a yield management system is at most proper for tactical planning for flights and vessels with non-zero inventory level. But if the planning horizon goes on further for booking forecasts then neither a cost approach nor a yield management system is sufficient as the completeness of information is a precondition for either structural/less ad hoc/easier management.

10. Conclusion

The goal of demand forecasts is essentially to predict market conditions in our markets, but making predictions beyond the average forecast level always leads to a significantly lower prediction quality. Since the demand generates a standard diffuse and non-stationary time series, often leading to a compound forecast error, stable ordering also leads to a similar usable average prediction error. Therefore, product vulnerabilities should be assumed very differently from sales performance management issues in consumer markets with greater dynamism. As a result, demand forecasts are not only concerned with average forecasts, but must also take into account prediction uncertainty and the availability of different sales and distribution formats for the effective offering of jointly offered service innovations. Building on an identified quasi-hierarchical demand forecasting architecture, an agent-based model evaluating the adequacy of particular demand forecast formats based on supply chain risk exploration is suggested. It is shown how adopted distribution input and initial design can powerfully influence loss and risk in a multi-agent environment. Agents that simulate demand forecasts of different specialists with specialized knowledge built into their forecast engines provide for better predictions and aggregate results. Defects in prediction space formats of either forecast agent type lead to disastrous consequences in terms of steep losses and much higher risk. Obtained results demonstrate how both new demand forecast product and system providers, as well as companies adopting and integrating new forecasting functionality within their own existing systems, may conduct serious analysis at the design stage to ensure that the components are sufficiently adjusted in terms of prediction needs and capability of trading and shaping risk.

10.1. Future Trends

There are several multimedia content expansion elements to forecast and analyze primary and individual sales performances. For multimedia content development and sales performance management, timestamp segmentation can generate audio transcript information of the video. Information can be automatically crawled by hashtag acronym classification and channel metadata analysis, and community information can also be analyzed by content analysis. Classes can also be automatically categorized using tag relationship analysis and video channel time series analysis, which are possible future works to enhance sales performance effectiveness. Particularly useful recommender systems and site-wide content interest-adaptive analysis systems have been vital for broadcasting platforms and e-learning sites. These platforms are also interested in ideal and preferable content-to-user allocation systems for all users or newly-user adapted analysis methods to remember more.

A sales forecasting system can account for the effects of seasonality, holiday sales, and other demand/economic-shocks similar to those applied in the media industry. Such sales forecasting is essential to prevent problems caused by the discrepancies between forecasting and actual sales, including extra stocks, sales loss, and markdown. It is possible to extend user-customer-tailored demand and sales forecasting systems both for individual consumers and for the broadcasting platform's ecosystems.

The view count predictions and multimedia contents to product recommendations and analysis methodologies can be enhanced through collaborative filtering where user-user-based information are used to accurately predict view counts of products and where user-to-product relationships are augmented by non-linear modeling efforts. For video demand forecasting system, external events, trending data, and product collaboration information can be exploited and/or controlled in more reliable ways. For view count prediction of individual contents a switching component can be integrated, enabling more accurate demand forecasts. The forecasting model can be additionally hybridized with user-to-group knowledge graphs and item-to-group economic time series explanations for driver event attribution analysis.

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