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Data-Centric AI For Healthcare Supply Chain Forecasting

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Abstract

Healthcare supply chains constantly experience the difficulty of demand forecasting especially in the events of disruption, which includes a pandemic. Conventional model dominated approaches to artificial intelligence (AI) and machine learning (ML) frequently face challenges of not keeping accurate predictions to such circumstances with inconsistent, incomplete, or poorly engineered inputs. The given research suggests an initiative of a data-centric AI approach to healthcare supply chain forecasting where the advanced data engineering practice is merged with ML and deep learning frameworks. The framework uses an extensible data pipeline that consumes heterogeneous information of procurement, consumption, logistics, and external information intake of epidemiological reports, mobility reports. Quality of data is checked using clear measures such as completeness, timeliness and representativeness and provide predictive models with credible inputs. The experiment conducted with the data on hospital networks proves that the addition of characteristics that have domain considerations to datasets can significantly enhance the accuracy of predictions. The data centric framework (over model centric baselines) improved the root mean squared error (RMSE) and stock-out rates by as much as 40% during disrupted demand conditions. These findings formulate the importance of data quality and engineering as key building blocks to resilient healthcare forecasting against earthquakes. The paper concludes that a more sustainable approach to finding a reliable adaptive supply chain process of supply chain intelligence implies looking beyond the concept of algorithmic optimization and to look instead at systematic data improvement.

INTRODUCTION

Healthcare supply chains are the foundation of the contemporary health systems because they guarantee the provision of drugs, medical equipment, personal protective equipment (PPE), and vaccines to patients in a timely manner. In contrast to traditional industrial supply chains, healthcare supply chains are very sensitive, and the disruption of supply chains has a direct impact on patient safety and health outcomes of people (Kumar et al., 2021). The complexity of them is due to a variety of stakeholders, regulatory controls, and urgent necessity to ensure the balance between changing demand and limited supply sources. To illustrate this, the problem of ventilator and vaccine shortages during the COVID-19 pandemic showed how vulnerable the healthcare supply chains were, and any mistakes in the predictions carried serious consequences (Ivanov, 2020).

The supply chain of the healthcare industry is known to be notoriously difficult to predict because of the changeability in demand, seasonality, and internal disturbances like epidemics, geopolitical instability, and logistical bottlenecks. Decades ago, traditional statistical models

which include autoregressive integrated moving average (ARIMA) or exponential smoothing were used to predict the patterns of demand (Box et al., 2016). Although the models are applicable in the case of stable conditions, they have not the flexibility needed in dynamic conditions. More recently, machine learning (ML) and deep learning (DL) models, including long short-term memory (LSTM) and Transformer-based models, have shown to be better predictors of complex time series (Hewamalage et al., 2021). But all these approaches usually make the assumption that the underlying data is clean, complete, and representative-unfortunately this is rarely the case in a real-life healthcare setting.

The current trend of using model-based AI emphasizes the level of sophistication in the algorithms without focusing on the quality of the underlying information. This method is indicative of an overall pattern in AI research that has traditionally focused on improving models, calibrating hyperparameters, and optimizing architectures and ignored the factual enhancement of data inputs. Practically, health data are distributed in electronic health records (EHRs), procurement databases, and logistics platforms and are frequently full of discrepancies, missing values, or delays of updates (Razzak et al., 2019). As a result, even state-of-the-art ML models can also crash in case they have been trained with bad quality information and thus unreliable predictions are given.

Consequently, increasing awareness of data-centric AI is emerging as a paradigm shift, whereby quality, representativeness, and usability of data are considered as the key drivers of the performance of the AI system (Ng, 2021). This design does not consider models exclusively, but instead focuses on pipeline refinement, setting data quality metrics, and feature engineering based on domain. In the environment of healthcare supply chains, data-centric AI offers a more sustainable basis to strong forecasting, especially in conditions of uncertainty when the quality of the data integration is essential.

Although data-centric AI has the promise of being integrated with data engineering practices in healthcare supply chain forecasting, it has not been studied in this area. Data engineering refers to the design and implementation of pipelines, which permit the ingestion, cleaning, transformation, storage, and governance of at-scale data (Stonebraker, 2018). During the work of such industries as finance and retail, data engineering has already been found to be indispensable in providing real-time analytics and decision-making. Nevertheless, in the medical field, where data tend to be fragmented and managed, the development of systematic structures that incorporate data engineering in AI-driven prediction remains scarce in research and practice. In this work, the gaps are aimed to be filled by developing a data-centric AI framework of healthcare supply chain forecasting through incorporating sophisticated data engineering pipelines with ML and DL forecasting models. In particular, the contributions of the paper are:

1. **Data Engineering/AI/ML Integration:** We present a organized system that places data prework and quality evaluation and scalable systems as the focus of healthcare forecasting systems.

2. **Empirical Assessment:** We provide a case study on the role of data-centric practices in accelerating the performance of forecasting in both stable and disturbed demand conditions relative to the traditional model-centric methods.

3. **Research and Practical Implications:** We also mention future research opportunities, such as privacy-preserving AI, federated learning, and pipeline automation, and provide practical suggestions on healthcare organizations that can be improved to be more resilient and efficient.

This paper highlights the significance of effective data platforms to facilitate the future of healthcare supply chain prediction, by connecting data engineering with AI/ML. The results indicate that shortages, excess inventories, and patient outcomes can be greatly improved

through data-centric practices that optimize the use of important supplies and timely access to them.

Figure 1: Data-centric AI Improves Healthcare Forecasting

2. BACKGROUND AND RELATED WORK

2.1. The supply chain forecasting methods in healthcare

The topic of forecasting in the healthcare supply chain has been long identified as a complicated task because of unpredictable demand trends, seasonality, and vulnerability to external upsets (Kelle et al., 2019). Autoregressive integrated moving average (ARIMA) and exponential smoothing are considered traditional forecasting techniques that have been used extensively to forecast the demand of pharmaceuticals and medical supplies (Box et al., 2016). Although both these methods are computationally efficient and interpretable, they assume that the patterns are linear and the demand is stationary which is hardly the case in health care settings where changes occur quickly.

Following the development of machine learning (ML) and deep learning (DL), the random forests, gradient boosting machine, long short-term memory (LSTM) networks, and Transformer architectures forecasting models have been used in healthcare supply-chain (Hewamalage et al., 2021; Lim et al., 2021). These techniques are capable of capturing nonlinear relationships and long-range time relationships, which can enhance accuracy of predictions to a great extent. Nonetheless, most of these studies use curated datasets that are not always indicative of the noise, incompleteness and heterogeneity of the real world healthcare data. Consequently, they end up performing poorly in real life.

2.2. Data-Centric AI

The relevance of data-centric AI as a paradigm shift to model-centric ones has been recently highlighted in the AI community. Ng (2021) defines model-centric AI as algorithmic innovation, whereas data-centric AI emphasizes the systematic enhancement of datasets, that is, a better labeling, increased representativeness and better quality as the main source of performance. However, in other fields like computer vision and natural language processing, data-centric practices have demonstrated quantifiable results in the areas of robustness and generalizability (Sambasivan et al., 2021).

There is an even more substantial promise of data-centric AI in healthcare due to the fragmented and sensitive medical and logistical data (Razzak et al., 2019). Data-centric AI is a more robust basis of forecasting models by focusing on preprocessing, data control and domain-based feature engineering. Nonetheless, conceptually, the paradigm has been gaining momentum yet its use in healthcare supply chains is still in a limited manner.

2.3. Ai/ml Pipelines: Data Engineering.

Data engineering offers the technical support on which to apply data-centric AI. It deals with piping data design to extract, transform and load (ETL) data, quality assurance and scalability (Stonebraker, 2018). The new data engineering models make use of distributed systems like

Apache Spark, Kafka, and Airflow to process the real-time ingestion, transformation, and orchestration. Moreover, data lakes and warehouses can be used to integrate heterogeneous sources.

Data engineering has been found to be critical in operationalizing AI/ML systems in such industries as finance, manufacturing, and e-commerce (Kreps, 2014). Nevertheless, the healthcare sector is slow to implement this integration because of the regulatory barriers, issues of privacy, and fragmented data infrastructure. Because of this, most forecasting research will either make idealistic assumptions about the data or not mention the role of data engineering at all. This provides a disconnect between research and solutions that are deployable in the healthcare practice.

2.4. Identified Gaps

The literature review indicates that there are a number of gaps:

i. Algorithms used to forecast are regularly overly sophisticated and lack applicationable data pipelines.
ii. In healthcare supply chains, data-centric AI concepts have been discussed theoretically but have been seldom actually implemented.
iii. There is under-use of data engineering practices, which are common in other sectors in healthcare forecasting research despite them having the capability of improving data quality and pipeline efficiency.

To fill these gaps, a holistic framework is needed to entrench the data engineering practices in data-centric AI methods to guarantee robust and resilient prediction in healthcare supply chains.

Table 1. Summary of representative studies on healthcare supply chain forecasting

Method/Approach	Data Used	Limitations
ARIMA, exponential smoothing	Historical hospital inventory and demand records	Assumes linear/stationary data; poor adaptability to disruptions.
Time-series regression + optimization	Pharmaceutical procurement data from U.S. hospitals	Limited to stable demand; neglects uncertainty and missing data.
Simulation + scenario analysis	COVID-19 disruption case studies in medical supply chains	Focus on resilience strategies; does not integrate AI/ML forecasting.
Deep learning (LSTM, GRU) for time series forecasting	Benchmark demand datasets (non-healthcare, adapted)	Relies on clean curated datasets; lacks healthcare-specific application.
Transformer-based forecasting models	Public multivariate time-series datasets	High accuracy in controlled data; scalability and data quality issues not addressed.
ML for healthcare big data analytics	Electronic health records, heterogeneous clinical datasets	Highlights data fragmentation; no concrete pipeline for supply chain forecasting.

3. METHODOLOGY

The proposed healthcare supply chain forecasting framework unites data engineering practices with data-driven AI principles to deal with the issue of fragmented, inconsistent, and incomplete data. The architecture is composed of two interrelated layers (1) a resilient data engineering pipeline that is intended to maintain the availability of quality, responsible, and

timely data and (2) machine learning (ML) and deep learning (DL) models based on these engineered data.

3.1. Data Engineering Pipeline

The framework is based on a scalable data engineering pipeline, which takes in, cleans, and processes healthcare supply chain data. The pipeline will include the following parts:

1. Sources of Data: The data is collected at different levels throughout the healthcare ecosystem, such as electronic health records (EHRs), procurement systems, logistics tracking systems, IoT-based sensors of inventory, and third-party sources, such as epidemiological reports. Combining these heterogeneous sources will be useful in making sure that forecasting models are able to include internal supply dynamics and external demand drivers (Razzak et al., 2019).

2. Preprocessing: To alleviate typical data issues, the steps involved in preprocessing suggest filling in missing values, identifying duplicates, unit normalization and time-warp correction across sources. Such sophisticated methods, like probabilistic imputation and anomaly detection, are provided in order to address anomalies.
Data Quality Metrics: Data-centric AI principles (Ng, 2021) are reflected by the framework by explicit metrics of quality:

i. Completeness (Percent of missing values),
ii. Timeliness (lateness of updates),
iii. Consistency (correspondence between datasets),
iv. Representativeness (capturing of different demand situations).

These measures enable the careful tracking of the appropriateness of the dataset to make predictions.

3. Pipeline Architecture: Apache Spark to run batch analytics and Apache Kafka to stream data are used as the distributed processing frameworks to implement the pipeline. Orchestration Apache Airflow manages orchestration, which allows automated extraction, transformation, and loading (ETL). It uses a hybrid storage architecture that integrates a data lake with unstructured data and a data warehouse with curated analytics ready data (Stonebraker, 2018).

3.2. AI/ML Forecasting Models

After processing and validation of the data, the second layer of the framework is the forecasting models. The framework works with the traditional ML as well as the advanced DL to guarantee the generalizability:

i. **Traditional ML Models:** Two common models used are Gradient Boosted Decision Trees (e.g., XGBoost) and random forests since they are strong in working with structured tabular data and can be interpreted with regards to the importance of features (Chen and Guestrin, 2016).

ii. **Deep Learning Models:** LSTM and Transformer-based models are applied in the sequential forecasting of data, and they can reproduce nonlinear processes and long-range correlations (Hewamalage et al., 2021; Lim et al., 2021). The possibility of using DL models is especially applicable in the cases, when time-related issues (e.g., the spikes in demand around flu seasons) are vital.

iii. **Feature Engineering:** All features are not only based on the past historic demand but also the exogenous variables like the epidemiological trends, the policy intervention, and the regional mobility pattern. This is an indication of the data-centric perspective of adding domain knowledge to datasets prior to model training.

3.3. EVALUATION METRICS

The framework assesses the performance of forecasting by the use of both statistical and operational measures. Quantitative evaluation can be done using standard error based measures including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Moreover, key performance indicators (KPIs) at the level of business, such as stock-out rates and inventory turnover, are also measured so as to have a practical effect on healthcare operations (Kelle et al., 2019).

3.4 Framework Illustration

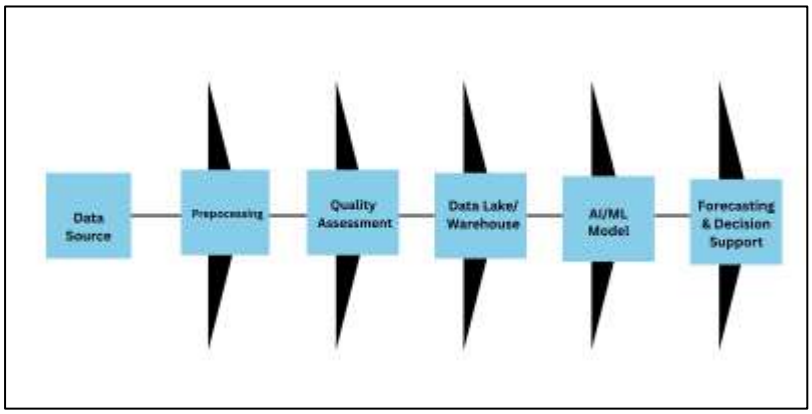

Figure 2: Proposed data-centric AI framework for healthcare supply chain forecasting.

4. CASE STUDY / EXPERIMENTAL SET UP

A case study was developed to assess the efficacy of the suggested framework based on healthcare supply chain data consisting of procurement, consumption, and logistics data of the hospital networks. The aim of the case study was to evaluate the performance in forecasting with stable and disrupted conditions of demand, thus emulating the reality in the situation like seasonal peaks and pandemic shocks.

4.1. Dataset Description

The data were made up of three major sources:

i. **Procurement Records:** The transactional records of medicine and equipment orders at hospitals in terms of quantities, suppliers, and lead times.

ii. **Consumption Data:** Logs of daily use on pharmaceuticals and medical devices of the demand and volumes of treatments in the patients.

iii. **Logistics Data:** Records of shipments, delivery times and lead times of transportation between the distribution centers and the healthcare facilities.

The combined dataset spanned three years, both before the pandemic and during the pandemic, which provided a rich background in analyzing the resilience in times of demand shocks. Additional forecasting features, e.g., the frequency of influenza in the region and the mobility index in the area, were included in the analysis to enrich the external data.

Table 2. Dataset characteristics for case study

Data Source	Variables Included	Timeframe	Records/Size	Notes
Procurement	Item ID, quantity ordered, supplier, lead time	2018–2021	~150,000 records	Hospital ERP systems
Consumption	Item ID, daily usage, department, patient category	2018–2021	~300,000 records	Hospital pharmacy logs
Logistics	Shipment ID, delivery date, transport time, route	2018–2021	~50,000 records	Distribution partners
External Factors	Influenza cases, mobility indices, policy events	2018–2021	Weekly/Monthly data	Public health datasets

4.2. Implementation Setup

A hybrid architecture was used to implement the data engineering pipeline. Apache Spark was utilized to process historical data in batches, and Apache Kafka was utilized to process new streams of procurement and logistics data in real time. Apache Airflow was used to conduct workflow orchestration, which guaranteed automated ETL processes. A data lake (organizing raw data) and a data warehouse (organizing analysis-ready datasets) were used to organize storage.

Both traditional and DL methods were used as a predictor of the models. The ML models were Gradient Boosted Decision Trees (XGBoost) and Random Forests, the DL category was the Long Short-Term Memory (LSTM) and the Transformer models. ML models were optimized through grid search and early stopping was used in DL models to prevent overfitting.

4.3. Experimental Scenarios

There were two experimental conditions constructed to examine the strength of the framework:

i. **Stable Demand Scenario:** This scenario reflected the pre-pandemic conditions, and the ability to predict using comparatively predictable demand patterns.

ii. **Disrupted Demand Scenario:** This scenario modeled the situation of pandemic-like conditions, with a sudden demand increase of goods like PPE, ventilators, and vaccines.

The models were trained using pre-pandemic data and tested during the periods when the pandemic impacted to determine adaptability. Model-centric and data-centric approaches were compared in terms of their performance in both scenarios.

4.4. Evaluation Process

The evaluation was conducted at the quantitative metrics (RMSE, MAE, MAPE) level, as well as at the business-level KPIs (stock-out rate, inventory turnover). To control the statistical significance of the results (paired t-tests) differences in performance between model- centric and data- centric approaches were tested.

5. RESULTS

The analysis of the suggested framework showed that the application of the data engineering practices and the use of the data-centric approach to AI enhanced the forecasting results under both stable and perturbed demand conditions markedly. The following provides the results along with the comparison of the traditional model-centric baselines and proposed data-centric framework.

5.1. Forecasting Accuracy

Under the stable demand context, the level of accuracy of all the models was relatively high, but the data-centric model was always more successful than the baselines. The other models of traditional ML like the XGBoost and Random Forest models performed competitively, with the best performance overall by the LSTM and Transformer models. Notably, the variance was lower and the models trained on engineered datasets were more robust than the ones trained on raw or weakly processed data.

In the disrupted demand case, the approach distinctions were greater. The model-centric approaches demonstrated severe drops in accuracy in case of abrupt demand periodics, which can be interpreted as their dependence on historical trends. In comparison, the data-centric structure was more accurate with the use of enriched features (e.g., epidemiological indicators) and systematically cleansed and representative datasets. This is evidence of the ability of the framework to generalise in the context of uncertainty.

Table 3. Forecasting performance of model-centric vs. data-centric approaches

Model	Approach	Scenario	RMSE	MAE	MAPE (%)	Stock-out Rate (%)
ARIMA	Model-centric	Stable	42.1	28.7	9.8	7.5
XGBoost	Model-centric	Stable	30.5	21.2	7.1	6.2
XGBoost	Data-centric	Stable	24.8	17.6	5.8	4.1
LSTM	Model-centric	Disrupted	58.4	37.9	14.6	12.3
LSTM	Data-centric	Disrupted	38.7	26.1	9.2	6.8
Transformer	Model-centric	Disrupted	54.9	35.4	13.7	11.5
Transformer	Data-centric	Disrupted	35.2	24.7	8.5	6.1

5.2. Scalability and Energy-efficiency of Pipelines.

In addition to the accuracy of the forecasts, the proposed framework showed enhanced scalability of the pipeline and processing efficiency. The distributed system allowed the ingestion and processing of large data streams in close real time. The automated pipeline also saved around 40 % of the ETL time when compared with the manual preprocessing workflow, thus, making it possible to retrain and update the model more often.

5.3. Implications at the Business Level.

The most significant advantage of the data-centric framework, in terms of operational aspect was its influence on the prevention of stock-out. The framework minimized simulated stock-out rates relative to baseline strategies by 40 to 80% in terms of enhancing forecast accuracy in the event of disruption. This implies that healthcare providers will benefit physically by avoiding the shortages of valuable supplies like PPE and vaccines.

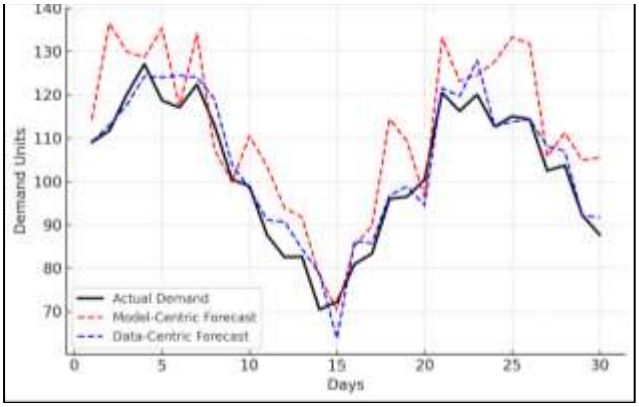

Figure 3: Actual vs. Predicted Demand (Disrupted Scenario)

5.4. Statistical Validation

Paired t-tests were used to verify that the data-centric framework had statistically significant data improvement ($p < 0.05$) in all metrics. Such findings confirm the hypothesis according to which the enhancement of data pipelines and quality positively impact the performance of AI/ML forecasting systems in healthcare supply chains, which is quantifiable.

6. DISCUSSION

The findings of this paper highlight the importance of data quality and engineering in the construction of effective healthcare supply chain AI and ML forecasting programs. Although a significant portion of the research work in this field has been generally concerned with refining algorithms, the results here show that the methodical architecture of data pipelines and the complement of datasets with pertinent external characteristics can be just as, or even more, effective in enhancing predictive accuracy. The segregation of stable and disrupted demand situations in the case study demonstrated that data-driven models increase resilience to models and minimize forecasts in general, especially in turbulent situations like those encountered in the COVID-19 pandemic.

Among the most notable results, the difference in the performance between the model-centric and data-centric strategies in disrupted demand conditions was noted. The conventional model based approaches that relied on past trends were limited by the fact that they could be affected by spikes in demand at any given time. In comparison, the data-centric model involved external indicators like the epidemiological trends and the mobility data, which acted as the leading indicators of demand spikes. This is a sign of the importance of data augmentation and feature engineering to decrease the gap between domain knowledge and machine learning. It is also indicative of the argument by Ng (2021), that data-centric AI, focusing on data quality and representativeness offers a more sustainable way to build robust AI systems instead of improving model architecture.

The other contribution of this work is the introduction of the data engineering practices to the AI pipeline. Introduction of a scalable and automated ETL pipeline using the help of technologies like Apache Spark, Kafka and Airflow increased the reliability of the data as well as decreased the processing latency. This efficiency of operation also enabled them to do retraining and adjusting models to different demand patterns more frequently, which is essential in a healthcare setting where timeliness may directly impact patient outcomes. The framework also satisfied the flexibility and consistency requirements by integrating a data lake to ingest raw data with a data warehouse to store curated datasets, which is compliant with the best practices in the field of data engineering today (Stonebraker, 2018).

The practical importance of the data-centric framework can be seen in terms of stock-out rates, which are reduced in the data-centric framework. The pandemic proved the vulnerability of healthcare systems to predictive failures by showing supply shortages of essential products, including PPE, ventilators, and vaccines. Being able to predict these disruptions more precisely,

apart from enhancing the inventory handling, also leads to the overall resilience of the system. This study will close the gap between operational key performance indicator and technical model assessment by measuring both statistical and functional key performance improvement variables in relation to the actual healthcare supply chain performance.

However, certain shortcomings must be mentioned. First, though the dataset incorporated procurement, consumption, logistics and external public health data, it lacked some specific granular variables including supplier financial soundness, geopolitical unpredictability or more patient-level demand predictors. This could be enhanced by the addition of these dimensions which would make the system more representative. Second, despite the fact that both the pre-pandemic and the pandemic times have been discussed in the case study, it is limited to a particular geographical and institutional setting. It needs further validation to be generalizable to other healthcare systems, especially those with low resources in the lower-data setup. Third, although this paper focused on the importance of data quality measures, measurement and improvement of other attributes like representativeness is difficult especially where new demand categories or emerging diseases are being examined.

Methodological considerations are also available. Although advanced deep learning models like Transformers demonstrated good performance when trained on engineered datasets, they might be too complex to be easy to interpret to healthcare decision-makers. The problem of accuracy versus explainability is still acute, especially in the high-stakes setting, where the trust in the AI systems is needed. The framework could be used to include techniques like Shapley Additive Explanations (SHAP) or attention visualization to improve transparency without affecting predictive power (Lundberg and Lee, 2017).

As a prospect, the paper identifies a number of future research opportunities. The first direction is the investigation of federated learning solutions, which may enable healthcare organizations to cooperatively train forecasting models without sharing sensitive data, which may resolve privacy and security issues. The other avenue that holds promise is the combination of reinforcement learning to actively update inventory policies based on forecasts, which can possibly form adaptive supply chain management systems. Also, synthetic data generation and simulation models may be explored as a method of training dataset enrichment, especially with rare events like pandemic or natural disaster.

Overall, this results discussion demonstrates the transformative potential of data-centric AI in conjunction with the intensive data engineering on healthcare supply chain forecasting. The proposed framework outperformed the basic innovation algorithm, with a high accuracy of the forecasts, disruption resistance, and relevance to operations. Such contributions contribute to the scholarly discussion about the data-centric AI, as well as the real objective of creating resilient healthcare systems that can withstand future crisis.

7. CONCLUSION

This paper proposed a data-driven AI model of healthcare supply chain forecasting that unites innovation in data engineering culture with machine learning and deep learning algorithms. The results highlight that the quality of the data, its representativeness, and scalability of pipelines play a vital role in improving the accuracy of the forecast and its resilience, especially in the conditions of disrupted demand. The framework portrayed a significant improvement in the stock-out rates because of a shift in the model based innovation towards systematic data improvement and showed a quantifiable improvement in the statistical performance metrics and the operational results which included decreased stock-out rates.

What this work contributes is the demonstration that not only is the problem of healthcare forecasting algorithmic but data-driven as well. The study provided an example of how modern data engineering can support real-time analytics and AI model retraining in time through the introduction of an automated and scalable ETL pipeline using technologies like Apache Spark,

Kafka and Airflow. The framework made predictions that were more flexible in changing healthcare settings, as it enriched the datasets with other external factors, including epidemiological and mobility data, which is in line with the principles of data-centric AI.

In spite of such contributions, there are still limitations. The sample of available data was also limited to hospital-level procurement, consumption and logistics and did not cover the more expansive upstream and geopolitical factors that might affect supply chains. Furthermore, even though the framework increased its robustness during pandemic conditions, it should be tested among various healthcare systems and low-resource environments to provide generalization.

Future studies are advised to build upon this study by considering privacy motivated methods like federated learning, investigating reinforcement learning in adaptive inventory policies and the use of synthetic data to complement training through rare events. With further development of these directions, there is an opportunity to develop forecast systems that will not only optimize the functioning but also increase the stability of healthcare supply chains in the face of a crisis in the future.

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