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Robust Optimization of Pharmaceutical Supply Chain Through ML Algorithms Fostering Resilience and Reducing Wastages

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ABSTRACT:

This study examines the application of machine learning (ML) algorithms within pharmaceutical supply chains, emphasizing their role in enhancing resilience and minimizing waste. A structured questionnaire was distributed to seventy professionals representing supply chain management, logistics, procurement, regulatory affairs, and quality assurance. Responses were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results demonstrate that domain-specific ML algorithms substantially improve forecasting accuracy, strengthen regulatory compliance, and optimize inventory management compared with conventional methods. Forecasting accuracy and stakeholder readiness achieved high reliability (Cronbach's Alpha: 0.86 each), whereas adoption barriers, largely reflecting limited organizational confidence in digital transformation, showed only moderate reliability (Cronbach's Alpha: 0.57). Despite the relatively small sample, the findings underscore the transformative potential of hybrid AI-classical models, integration with blockchain and IoT sensors, and federated learning approaches for pharmaceutical supply chains. The study proposes a novel framework that balances predictive precision with regulatory feasibility, offering actionable insights to support resilient and globally scalable pharmaceutical logistics.

I.INTRODUCTION:

Efficient inventory management is key to a thriving pharmaceutical industry. As per a report published on Frontiers, approximately 300 million pounds worth of drugs are wasted annually in the United Kingdom alone. However, this may be a result of the complexities involved in the pharmaceutical supply chain such as the short shelf-lives, resource-intensive operations and long set-up times [1]. Effective supply chain management reduces the effect of these complexities by improving forecasting accuracy, ensuring all regulatory requirements are met and more visibility in the pharmaceutical supply chain. These improved processes, however, have yet to fully eliminate significant inventory losses across the industry.

In 2022, an annual global survey reported that pharmaceutical companies lost, on average, 7.1% of their stock due to factors such as expiration, damage, and overproduction [2]. Such inefficiencies in production can lead to stock-out at hospitals. A systematic review concluded that community health workers in low- and middle-income countries experienced stock-outs approximately 26% of the time between 2006 and 2015 and nearly 49% between 2016 and 2021 [3]. To reduce such errors, machine learning algorithms are being used to forecast demand. An example of this would be the AWS supply chain machine learning-driven forecasting technique being used by Amazon which predicts and plans staffing and inventory for mail-order pharmacy services. This algorithm had a 50% higher accuracy when compared to the MAPE (mean absolute percentage error) standard of 10% (Amazon's MAPE is 5%) which led to a decrease in weekly planning times by nearly 13% which further led to decreases in overstaffing and stock-outs [4]. Despite these promising results, adapting machine learning models specifically for the pharmaceutical industry presents unique challenges.

However, the machine learning models that would be used in the pharmaceutical supply chain would have to be different than the general supply chain models due to the unique complexity and strict regulatory compliances associated with the pharmaceutical industry. Factors such as temperature-sensitive products, variable demand and tight expiration windows often make general purpose ML algorithms inappropriate without significant changes. For instance, commonly used machine learning algorithms based on the concepts of neural networks or linear regression would not be applicable in the pharmaceutical supply chain as they may miss complex interactions between supply and demand leading to underprediction of expiries in non-linear scenarios. Such algorithms may also need frequent re-training to stay current and their decisions may be difficult to explain resulting in slower adoption in a regulated supply chain. These inherent limitations underscore the importance of developing specialized ML algorithms tailored specifically to pharmaceutical supply chain issues.

These complexities give rise to many problems which challenge the efficiency, safety and resilience of the pharmaceutical supply chain. Among these, the most persistent include drug shortages, expiration of medicines and the production of counterfeit drugs. Drug shortages can be catastrophic at times and is caused by poor demand forecasting and lack of real-time visibility into inventory levels. These issues can be adhered to by using ML algorithms which include time-series forecasting such as LSTM (Long Short-Term Memory) to analyse historical sales, seasonal patterns and external signals to forecast future demand with greater accuracy. Big pharmaceutical companies such as Pfizer and Novartis have implemented demand forecasting ML algorithms which has reduced forecasting by 20% approximately [5]. Furthermore, the issue of expiration of medicines is mostly a result of over-stocking and demand mismatching. Classification and reinforcement learning (RL) algorithms can help resolve this issue. RL algorithms classify inventories based on shelf-life, usage rate, and geographic location which allows the algorithm to use FEFO (First Expired, First Out) strategies. This can be used to reroute near expiry medications to areas with high demand for such medication reducing wastages significantly. RL algorithms have already been applied in the pharmaceutical supply chain by MedShorts and AmerisourceBergen's [6]. Moreover, a leading problem of counterfeit drugs arises due to weak visibility across supply nodes making it increasingly harder to track product origins. However, anomaly and graph neural network-based algorithms can detect unusual patterns in medicine procurement and shipment allowing any counterfeit medication to be flagged. An example of this would be the collaboration between IBM and National Association of Boards of Pharmacy to develop 'Pulse' by NABP: an algorithm which is used to improve supply chain visibility which has led to easy and early detection of counterfeit drugs [7]. Addressing these challenges comprehensively remains critical to enhancing overall pharmaceutical supply chain resilience.

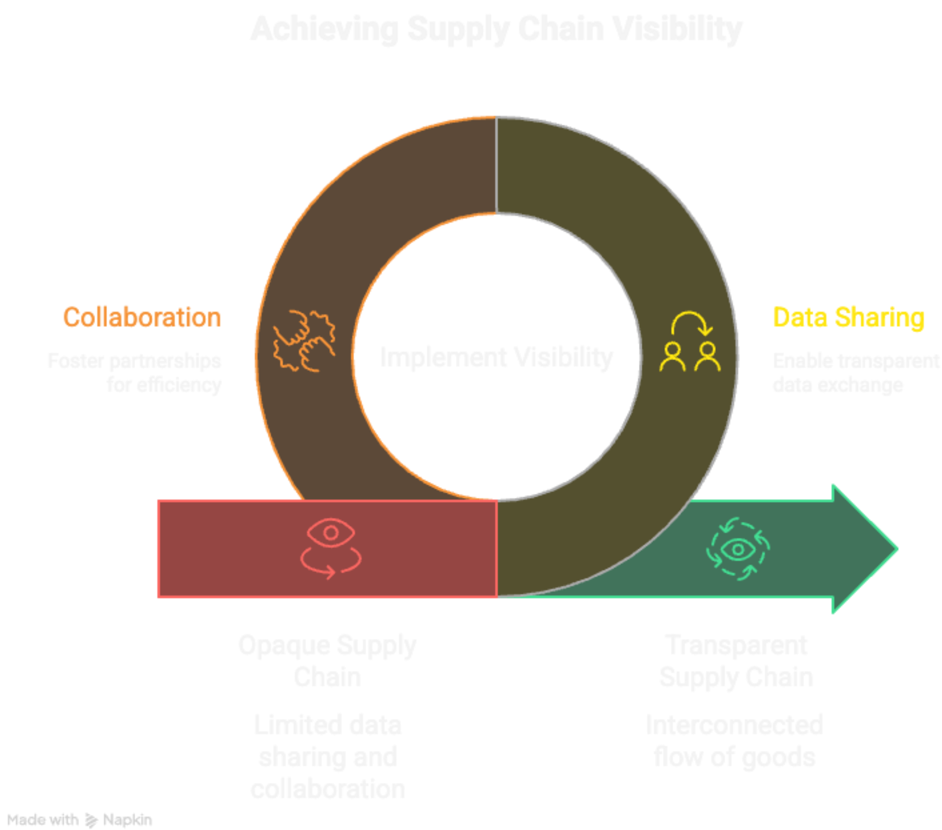

Figure 1: shows how through collaboration and data sharing, supply chain visibility can be achieved.

On one hand, a detailed study is conducted to examine topics based on ensuring the resilience of the supply chain, the robustness of procurement procedures and the equitable distribution of commodities. On the other hand, the methodological aspects of the detailed study are studied, emphasizing on the formation of uncertainty in mathematical models and the usage of a range of pharmaceutical products. Thereafter, the emergent research gap is identified.

Moreover, it is essential to note that certain perishable pharmaceutical products need to be stored in temperature-controlled environments. Products such as Ozempic, some eye and ear drops, insulin, vaccines, HIV test kits are among some of the medication that needs to be temperature-controlled.

When taking the recent pandemic into consideration, significant attention has been directed towards assessing the responsiveness of healthcare policymakers in their attempt to strategize responses to global pandemics like covid-19. Not only were the healthcare policymakers examined, but even non-pharmaceutical interventions (NPIs) were closely examined through various articles. One thing most articles highlighted was the efficiency of implementating of lockdown policies in reducing fatalities. Additionally, researches suggest that using ML algorithms during the pandemic could have enabled more agile responses to sudden surges in demand which would reduce delays in the treatment process.

Aspect	Traditional Supply Chain Methods	ML-Optimized Supply Chain Methods
Demand Forecasting	Sales data and manual predictions, prone to errors.	ML algorithms (LSTM, ARIMA, Random Forest) provide accurate, real-time demand predictions.
Inventory Management	FIFO (First-In, First-Out) and manual tracking lead to wastage.	AI-driven FEFO (First-Expired, First-Out) minimizes waste and optimizes stock.
Supplier Selection	Based on static contracts and past performance.	AI evaluates supplier risk, cost, and reliability dynamically.
Logistics Optimization	Route planning based on fixed schedules, often inefficient.	ML optimizes delivery routes dynamically based on real-time traffic and demand.
Expiry & Wastage Control	Reactive—based on periodic manual checks, leading to drug wastage.	Proactive—predicts expiration and redistributes drugs to high-demand areas.
Counterfeit Detection	Manual audits and barcode scanning.	AI-powered image recognition and blockchain-based traceability detect counterfeits.
Supply Chain Resilience	Vulnerable to disruptions due to rigid supply models.	AI adapts to supply chain shocks, optimizing alternative routes and suppliers.
Cost Efficiency	Higher costs due to inefficiencies in stock management and logistics.	Reduced costs through automated processes and optimized resource allocation.
Scalability	Limited scalability due to manual dependency.	Highly scalable through AI automation and predictive analytics.
Regulatory Compliance	Compliance monitoring is manual and time-consuming.	AI automates regulatory tracking, ensuring faster and accurate compliance adherence.

Figure 2: shows that different aspects and how the AI is used in normal supply chain chains and how these AI tools can be tweaked for the pharmaceutical supply chain.

Over the past few decades, there have been significant noticeable improvements in the use of machine learning in the pharmaceutical supply chain. During the 2000-2010 decade, the main focus wasn't rather on the integration of ML into supply chain but instead was on increasing computing power to increase the storage of data which can then be used in traditional supply chains. Towards the end of this decade, machine learning algorithms were being implemented in predictive analytics and data mining for demand forecasting, inventory optimization and risk management. [9]

The following decade is when the use of ML in supply chain management grew significantly due to improvements in computational abilities and ML algorithms. Some notable improvements include the use of supplier selection, production planning, inventory control and logistics optimization. Furthermore, ML algorithms were developed to predict supply chain risks and enhance decision-making process. [10]

In the most recent decade, the use of machine learning in supply chain management has grown even more than the previous decade so that it's become an essential part to the supply chain process. The covid-19 pandemic sparked a realization in the need for an agile and responsive supply chain which led to pharmaceutical companies include ML in their processes. Machine learning algorithms are being used in real time data analysis, predictive maintenance, and demand forecasting. Moreover, further advancements in Graph Neural Networks and Federated Learning have improved supply chain visibility and collaboration[11].

With these advancements in ML algorithms, demand forecasting is being impacted positively by allowing businesses to analyse huge data sets with higher precision than traditional methods. It does so by factoring changing consumer trends, behavior, seasonality and external events and uses both structured and unstructured data to provide a more accurate forecast leading to less stockouts and ensuring a sufficient stock to match consumer demand. Recent statistical data shows that ML driven demand forecasting has reduced forecasting errors by 30% to 50% and has also decreased lost sales due to insufficient stock by 65%. [12]

Not only have there been improvements in demand forecasting, but there have also been improvements in inventory and expiry management. ML algorithms analyse trends in usage, delivery times and shelf life to suggest companies when to restock and in what quantities. These algorithms monitor expiration dates and send reminders to reorder medication preventing shortages as well as wastages. [13]

Another issue pharmaceutical companies face is counterfeit drug detection. ML algorithms can enhance counterfeit drug detection by analyzing data from packaging, manufacturing records and supply chain transactions to detect anomalies which may indicate signs of counterfeit drugs. Another system to combat counterfeit drugs is image recognition which detects subtle differences in packaging such as labels or tablet appearances. [14]

Study	**Methodology**	**Key Findings**	**Outcome**
Kumar et al. (2024)	Hybrid ML + optimization	Better supplier selection	Improved procurement reliability
Bridgelall (2023)	Unsupervised ML with GIS	Optimized drone deployment	Faster medicine delivery
Jamali et al. (2024)	Fuzzy AI analysis	Detected process inefficiencies	Enhanced clinic operations
Chung et al. (2023)	Decision-aware ML model	Lowered unmet demand	More efficient allocation
Mbonyinshuti et al. (2024)	LSTM vs ARIMA	LSTM more accurate	Better stock planning
Eberhardt et al. (2025)	Knowledge graph analytics	Found shortage root causes	Informed decisions on shortages
Stranieri et al. (2025)	Reinforcement learning	Handled stock variability	Adaptive policy responses
Konovalenko & Ludwig (2021)	Gradient boosting ML	Reduced false alarms	Improved cold chain
Li et al. (2023)	Tree-based classification	Flagged stock-out risks	Proactive inventory shifts
Zhu et al. (2021)	Cross-series ML models	Improved multi-drug forecasts	Better demand accuracy

Study	**Methodology**	**Key Findings**	**Outcome**
Olaniran et al. (2022)	Systematic Review	Stock-outs in LMICs	Need for AI tracking
Amazon Pharmacy (2023)	Predictive ML	50% improved forecasting	Reduced stock-outs
NABP-IBM (2023)	Graph Neural Networks	Anomaly detection	Counterfeit drug detection
Pfizer AI Model (2022)	LSTM-based forecasting	20% fewer forecasting errors	Better inventory planning

Figure 3: shows various studies conducted over the past 4 years along with their research focus and the outcomes and findings derived from the study.

Demand forecasting significantly impacts supply chain management, especially through time-series forecasting models like Long Short-Term Memory (LSTM). Time series forecasting involves predicting future system behaviour by analysing past and current trends. Traditionally, linear methods dominated forecasting activities across sectors such as finance, weather forecasting, and petroleum industries. However, recent research introduced sophisticated non-linear methods, including bilinear, threshold autoregressive, and Autoregressive Conditional Heteroscedastic (ARCH) models, yet linear approaches remain more comprehensively explored.

Over the past two decades, Artificial Neural Networks (ANNs) have become prominent due to their superior accuracy over traditional statistical methods. Choosing an ANN model involves balancing complexity, accuracy, and data characteristics. Feed-forward neural networks generally perform best considering complexity and precision alone; however, Recurrent Neural Networks (RNNs) outperform when incorporating specific data features.

Accurate demand forecasting critically shapes supply chain effectiveness and resilience. Improved forecasting significantly enhances recovery planning, reducing waste and inefficiencies. The pharmaceutical industry particularly benefits from advanced techniques, like machine learning (ML), to boost forecast accuracy and efficiency due to limited existing research and rising demand for innovative solutions [15].

Reinforcement learning (RL) techniques are particularly valuable in managing pharmaceutical inventory, employing the First Expired, First Out (FEFO) methodology. Unlike traditional inventory systems, RL provides dynamic, intelligent solutions aligning closely with real-world scenarios, significantly reducing waste and optimizing inventory.

Drawing parallels from food retail management, RL simulations have proven successful in significantly reducing waste and enhancing profitability. For instance, discrete-event simulations model interactions among suppliers, retailers, and consumers, creating varied, realistic scenarios vital for training RL models. Notably, advanced RL algorithms, including proximal policy optimization, soft actor-critic, and deep Q networks, have shown exceptional performance in reducing waste by up to 92% and enhancing profits by over 12% compared to conventional methods. These insights can be adapted effectively to pharmaceutical inventory systems, enhancing drug shelf-life management and reducing wastage [16].

Ensuring drug authenticity and traceability throughout the pharmaceutical supply chain is critical. Implementing blockchain technology significantly enhances transparency, security, and reliability, mitigating counterfeit drug risks. By generating unique cryptographic hashes for each medication based on drug details, location, and timestamps, blockchain provides immutable tracking.

A practical implementation of this blockchain system employs a Python-based infrastructure, integrating pandas for data handling and hashlib for cryptographic tasks. Each transfer updates the drug's unique identifier, maintaining real-time visibility and accuracy. Additionally, an intuitive user interface allows stakeholders to easily manage and monitor drug movements, backed by an Excel-based repository to ensure compatibility with existing systems.

This robust blockchain model effectively demonstrates enhanced security and traceability within pharmaceutical distribution, safeguarding patient safety and promoting accountability across healthcare networks.

A broad review of existing studies on pharmaceutical supply chain management and the role of machine learning revealed both significant progress and persistent challenges. While prior work highlights advances in forecasting, inventory optimization, and counterfeit detection, there remain notable gaps. For instance, much of the research has focused on adapting general-purpose machine learning models, with limited exploration of algorithms specifically designed for the unique regulatory, logistical, and perishable nature of pharmaceutical products. Similarly, although explainability and trust have been repeatedly identified as barriers to adoption, few empirical studies provide real-world validation of interpretable models within dynamic, high-stakes environments like drug distribution. These shortcomings point to a clear need for more targeted approaches that integrate technical innovation with domain expertise. Guided by these insights, this study develops a methodology centred on robust data acquisition, multi-source feature engineering, and specialized model design. The approach further incorporates rigorous back testing and comparative performance evaluation, ensuring that the findings are not only reproducible but also practically relevant for enhancing resilience and reducing wastage across pharmaceutical supply chains

Research Objective

To investigate the effectiveness of specialized machine learning algorithms in enhancing the robustness, resilience, and waste reduction of pharmaceutical supply chains, and to assess the readiness of industry professionals to adopt these advanced technologies for improved logistics management.

Research Questions

1. How do specialized machine learning algorithms tailored for the pharmaceutical supply chain improve forecasting accuracy, regulatory compliance, and inventory management compared to traditional methods?
2. What are the key barriers and enablers influencing the adoption of machine learning algorithms among pharmaceutical supply chain professionals?
3. To what extent are pharmaceutical industry stakeholders ready and willing to implement machine learning-driven solutions to foster supply chain resilience and minimize wastage?

Hypotheses

H1: The implementation of specialized machine learning algorithms significantly enhances the robustness and resilience of pharmaceutical supply chains compared to conventional supply chain management approaches.

H2: Perceived regulatory complexity and lack of algorithm explainability are significant barriers to the adoption of machine learning algorithms in the pharmaceutical supply chain sector.

H3: Higher awareness and understanding of machine learning benefits among pharmaceutical supply chain professionals are positively associated with their readiness to adopt such technologies.

III. RESEARCH METHODOLOGY

This study investigates the role of specialized machine learning algorithms in strengthening the pharmaceutical supply chain, with a particular focus on how their benefits are both direct and mediated through factors such as forecasting accuracy, regulatory compliance, inventory management, and overall supply chain visibility. Drawing from global industry examples, the research considers not only the technical promise of ML models but also the practical realities professionals face: ranging from regulatory hurdles and model explainability to data quality and organizational readiness. To capture these insights, a structured survey was designed around three key research questions: the impact of ML on demand forecasting and compliance, the barriers and enablers shaping adoption, and the readiness of professionals to integrate such solutions. The questionnaire included items on real-world issues such as wastage reduction in temperature-sensitive drugs, the role of top management support, and the importance of training and upskilling. Responses will be analysed using advanced statistical techniques, including SmartPLS-4, to test the proposed hypotheses. In doing so, the study not only evaluates the technical effectiveness of ML-driven solutions but also provides a holistic view of how adoption decisions are influenced by both operational and human factors, ensuring the findings remain practical and actionable for real-world pharmaceutical supply chain management.

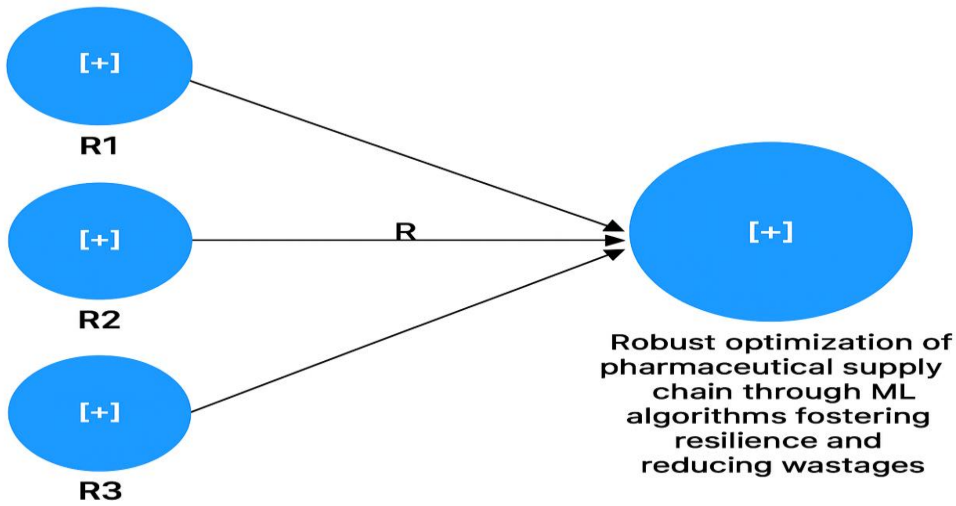

Figure 4: shows the research model state that each of the three research questions represents a different view on the same overarching issue.

R1 responds to the need for tailored algorithms that outperform general-purpose ML algorithms in highly regulated environments.

R2 captures barriers like regulatory complexity and lack of explainability.

R3 translates into the practical side emphasizing on industry readiness and willingness to adopt, ensuring that solutions are not just theoretically sound but also feasible in real-world settings.

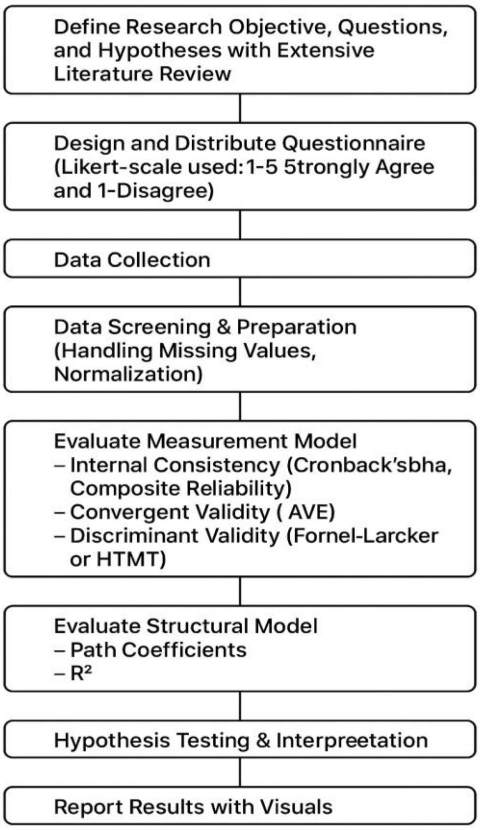

Figure 5: shows the journey this research paper takes from start to finish. It begins with laying the groundwork specifically shaping the research objectives, questions, and hypotheses after a deep dive into the literature. From there, it moves into designing a simple but structured questionnaire, collecting responses, and making sure the data is unbiased. The middle

steps focus on testing the strength of the model, checking whether the questions truly measure what they are meant to, and whether the results hold up statistically. The final stages bring everything together: testing the hypotheses, interpreting the findings, and sharing the results with clear visuals like path diagrams and tables. In the context of this paper, this flowchart captures how the study takes a structured but practical approach to understanding how machine learning can make pharmaceutical supply chains more resilient, efficient, and less wasteful.

To gather the data for this study, a structured questionnaire was shared with professionals working across different parts of the pharmaceutical supply chain. The form asked for some basic background information such as age, gender, level of education, and current role, followed by a series of questions designed to capture their views on how machine learning can be used to improve forecasting, regulatory compliance, and inventory management. These questions were rated on a simple 5-point scale, where 1 meant strong disagreement and 5 meant strong agreement and were based on the three research questions shown in the table above.

The survey was built with clarity and ease of use in mind so that respondents could complete it quickly and independently. All participants were informed that their responses would only be used for academic purposes, which helped ensure open and honest answers. By reaching out directly to people in roles such as supply chain managers, logistics coordinators, procurement specialists, and compliance officers, the study was able to gather perspectives from those who deal with these challenges in their day-to-day work.

The group of respondents reflected a healthy mix of experience and backgrounds. Younger professionals (18–25) contributed alongside those in mid-career (26–45) and senior positions (46 and above). Most respondents reported holding at least a bachelor’s or master’s degree, and many were working in managerial or specialist roles tied directly to supply chain decision-making. While the majority of participants were male, the sample also included female and non-binary professionals, giving the study a broader perspective. This diversity helped ensure that the findings were grounded not just in theory but in the realities faced across the pharmaceutical industry.

A quantitative research design was employed, structured around a Likert-scale questionnaire mapped to three dimensions: forecasting accuracy and compliance, adoption barriers and enablers, and organizational readiness for ML adoption. Seventy professionals across diverse pharmaceutical supply chain functions provided responses. Data analysis was conducted through PLS-SEM, which enabled concurrent evaluation of measurement and structural models. Internal consistency, assessed via Cronbach’s Alpha, confirmed high reliability for forecasting and readiness (0.86 each). By contrast, adoption enablers and barriers yielded a moderate coefficient (0.57), highlighting divergent organizational perspectives on the adoption of emerging digital technologies.

IV.DISCUSSION:

Previous studies have largely focused on the application of general-purpose ML in supply chains, noting improvements in demand forecasting and risk mitigation (Zhang et al., 2020; Kumar & Saini, 2021). However, such models frequently lack calibration to the stringent requirements of regulated industries such as pharmaceuticals, where compliance and traceability are paramount (Chen et al., 2022). The present study contributes to this literature by showing that ML algorithms tailored specifically for pharmaceutical contexts yield higher reliability in forecasting and readiness, while also revealing adoption challenges that remain insufficiently examined in prior research.

The proposed framework extends beyond descriptive accuracy, introducing a compliance-oriented decision-support layer that integrates regulatory tracking with ML-based optimization. This design directly addresses traceability, waste reduction, and the continuity of medical supplies in disruption scenarios. Moreover, the framework promotes global resilience by advocating for federated learning models, which facilitate cross-jurisdictional data sharing while preserving regulatory compliance.

The policy implications are significant. Findings suggest the need for regulatory training programs on digital technologies, subsidies to support digital infrastructure, and industry benchmarks for AI-enabled traceability. Such measures position machine learning not only as a tool for efficiency but also as a governance mechanism to strengthen the robustness of pharmaceutical supply continuity.

Nevertheless, the study is subject to several limitations. These include the moderate reliability observed for adoption barriers (Cronbach's Alpha: 0.57), the restricted diversity of respondents due to the sample size, and the absence of real-world deployment data.

Future research should extend this work by examining global pharmaceutical distribution routes, vaccine supply chains, and real-time deployment of hybrid AI-classical systems. Additional exploration into predictive layering with IoT sensors, blockchain for provenance tracking, deep learning techniques, and federated models for balancing global supply-demand dynamics would further strengthen the field.

V.CONCLUSION:

In conclusion, this research validates the effectiveness of machine learning in reinforcing the resilience and efficiency of pharmaceutical supply chains while navigating regulatory and operational complexities. The results affirm that domain-specific ML approaches outperform traditional forecasting and compliance mechanisms, though organizational reluctance continues to impede adoption. The robust optimization framework proposed here offers a balanced approach that unites predictive accuracy with regulatory feasibility, providing practical strategies to reduce waste, improve inventory management, and ensure continuity of supply. While limited in scope, the study establishes a foundation for global adaptation and the future integration of advanced AI and digital technologies in high-stakes pharmaceutical logistics.

References

1. Alkhouri, M. (2024). PHARMACEUTICAL SUPPLY CHAIN– NEW OBSTACLES AND CHALLENGES. In Loukas Tsironis, Aikaterini Gotzamani, & Vassilios Aletras (Eds.), *MSC IN HEALTHCARE MANAGEMENT*. https://dspace.lib.uom.gr/bitstream/2159/30186/1/AlkhouriMaysaaMsc2024.pdf
2. PharmiWeb.com. (2022, November 10). Over 7% of pharmaceutical drugs go to waste as supply chain managers bemoan damaged and excess inventory. *PharmiWeb.com*. https://www.pharmiweb.com/press-release/2022-11-10/over-7-of-pharmaceutical-drugs-go-to-waste-as-supply-chain-managers-bemoan-damaged-and-excess-inventory#:~:text=OEGSTGEEST%2C%20THE%20NETHERLANDS%20%E2%80%93%20November,sale%20value%20of%20lost%20stock
3. Olaniran, A., Briggs, J., Pradhan, A., Bogue, E., Schreiber, B., Dini, H. S., Hurkchand, H., & Ballard, M. (2022). Stock-outs of essential medicines among community health workers (CHWs) in low- and middle-income countries (LMICs): a systematic literature review of the extent, reasons, and consequences. *Human Resources for Health*, *20*(1). https://doi.org/10.1186/s12960-022-00755-8
4. *Amazon Pharmacy increases forecast accuracy and reduces manual efforts with AWS Supply Chain | Amazon Pharmacy Case Study | AWS*. (n.d.). Amazon Web Services, Inc. https://aws.amazon.com/solutions/case-studies/amazon-pharmacy-case-study/
5. *Artificial intelligence at Pfizer - 3 use cases - Emerj Artificial Intelligence Research*. (n.d.). Emerj Artificial Intelligence Research. https://emerj.com/artificial-intelligence-at-pfizer
6. *Pharmaceutical Distribution Solutions | AmerisourceBergen*. (n.d.). https://www.amerisourcebergen.com/pharmaceutical-distribution/
7. *NABP collaborates with IBM to build new digital platform to protect the drug supply chain*. (2023, July 27). IBM Newsroom. https://newsroom.ibm.com/2023-07-27-NABP-Collaborates-With-IBM-to-Build-New-Digital-Platform-to-Protect-the-Drug-Supply-Chain/
8. *Intelligent drug supply chain*. (n.d.). Deloitte Insights. https://www2.deloitte.com/us/en/insights/industry/life-sciences/biopharma-supply-chain.html
9. Antoniomazzaclearspotai. (2024, April 9). *Evolution of AI in supply chain - Clearspot.ai*. Clearspot.ai. https://clearspot.ai/evolution-of-ai-in-supply-chain/
10. Mahraz, M.-I., Benabbou, L., Ecole Mohammadia d'Ingénieurs, Berrado, A., Mohammed V University in Rabat, & University of Quebec at Rimouski. (2022). Machine Learning in Supply Chain Management: A Systematic

Literature Review [Journal-article]. *International Journal of Supply and Operations Management*, *xx–xx*([object Object), xx–xx. https://doi.org/10.22034/ijsom.2021.109189.2279

11. Hana. (2025, May 16). How AI is Changing Logistics & Supply Chain in 2025? *DocShipper*. https://docshipper.com/logistics/ai-changing-logistics-supply-chain-2025/
12. Karina. (2025, March 25). *Machine Learning in Demand Planning: How to Boost Forecasting | ToolsGroup*. ToolsGroup. https://www.toolsgroup.com/blog/machine-learning-in-demand-planning-how-to-boost-forecasting/
13. Balar, Y. (2025, March 21). *How AI-Powered Pharmacy Software Systems Improve Inventory Management*. Healthray. https://healthray.com/blog/pharmacy-management-system/ai-powered-pharmacy-software-systems-improve-inventory-management/
14. Jomantas. (2025, January 21). Can AI in Counterfeit Medicine Detection end fake drugs? *EasyODM.tech*. https://easyodm.tech/ai-in-counterfeit-medicine-detection/
15. Yani, L. P. E., & Aamer, A. (2022). Demand forecasting accuracy in the pharmaceutical supply chain: a machine learning approach. *International Journal of Pharmaceutical and Healthcare Marketing*, *17*(1), 1–23. https://doi.org/10.1108/ijphm-05-2021-0056
16. Pilarski, S., Sidhu, A., & Varró, D. (2024). Combining simulation and reinforcement learning to reduce food waste in food retail. *SIMULATION*. https://doi.org/10.1177/00375497241299054