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Data-Driven Sustainability: Applying Cognitive Decision Intelligence to Reduce Medical Waste in Pharmaceutical Logistics

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***Abstract*—** The pharmaceutical supply chain plays a crucial role in ensuring timely and efficient delivery of medicines, yet it faces persistent challenges related to waste generation, overproduction, and resource inefficiency. These inefficiencies contribute not only to economic losses but also to environmental and ethical concerns surrounding the disposal of expired and unused medical products. This research proposes a Cognitive Decision Intelligence (CDI) framework that integrates Natural Language Processing (NLP) and Big Data Analytics to achieve sustainable pharmaceutical supply chain optimization with a focus on medical waste prevention. The proposed approach utilizes linguistic data interpretation, real-time data streams, and predictive analytics to support intelligent, data-driven decision-making. By merging NLP-based semantic understanding with machine learning-driven forecasting, the CDI system is capable of predicting demand, identifying waste risks, and recommending corrective measures. Experimental simulations demonstrate that the proposed model can significantly reduce inventory redundancy and improve sustainability metrics. Furthermore, ethical and explainability considerations are embedded within the design to ensure transparency and accountability. The findings underscore how cognitive analytics can transform traditional pharmaceutical logistics into an adaptive, sustainable, and intelligent ecosystem. The inclusion of blockchain ensures data authenticity and ethical transparency in supply chain operations.

***Keywords*—** *Cognitive Decision Intelligence (CDI), Natural Language Processing (NLP), Big Data Analytics, Pharmaceutical Supply Chain, Sustainability, Medical Waste Reduction, Reinforcement Learning, Blockchain, Explainable AI*

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I. Introduction

The pharmaceutical industry is one of the most data-rich yet waste-intensive sectors of global healthcare. According to the World Health Organization's Global Report on Medical Waste and Sustainability in Healthcare Supply Chains [1], nearly 15% of manufactured medicines become waste annually. Such wastage not only leads to significant financial losses but also poses serious environmental hazards and public health risks through improper disposal. Building a sustainable pharmaceutical supply chain has therefore emerged as a strategic imperative for healthcare organizations, policymakers, and researchers alike. Traditional supply chain management systems primarily rely on structured datasets, static rules, and retrospective analysis. Recent cognitive and blockchain-based systems have demonstrated the potential for improving transparency and decision accuracy across healthcare logistics [16, 17]. However, they fail to fully utilize the abundance of unstructured data generated across the healthcare ecosystem — including prescription records, hospital feedback, regulatory notices, and patient sentiment. This unstructured information holds valuable contextual insights that can help anticipate demand fluctuations, detect potential drug recalls, and forecast waste patterns.

Cognitive Decision Intelligence (CDI) offers a transformative paradigm by combining artificial intelligence, linguistic processing, and data analytics to emulate human reasoning and enable adaptive decision-making. When supported by **Natural Language Processing (NLP)** and **Big Data Analytics**, CDI can provide actionable insights across multiple supply chain nodes—from production to end-oflife management.

The objective of this research is to design and evaluate a **Cognitive Decision Intelligence framework** to optimize the pharmaceutical supply chain through the prevention of medical waste. The key contributions of this paper are:

1. Development of an integrated CDI framework that uses NLP and Big Data for intelligent decision making.
2. Implementation of predictive models for demand forecasting and waste risk assessment.
3. Design of explainable and ethical decision modules to ensure transparent sustainability outcomes.

II. Literature Review

Recent studies have explored various approaches to improve efficiency and sustainability in pharmaceutical logistics. The literature can broadly be categorized into four thematic areas: supply chain optimisation, medical waste management, Big Data analytics in healthcare, and NLP-driven decision systems.

A. *Pharmaceutical Supply Chain Optimisation*

Optimization approaches such as linear programming and stochastic modelling have long been employed to minimize costs and shortages [2]. However, these methods are limited by their reliance on historical, structured data, rendering them less effective in dynamic, uncertain healthcare environments.

B. Medical Waste Management

Research on pharmaceutical waste management has predominantly focused on post-consumption stages—including segregation, collection, and disposal of expired drugs [3]. Few studies have addressed preventive measures within the supply chain itself. Preventive strategies involving predictive analytics have shown promise in reducing excess stock but often lack integration with real-time decision intelligence.

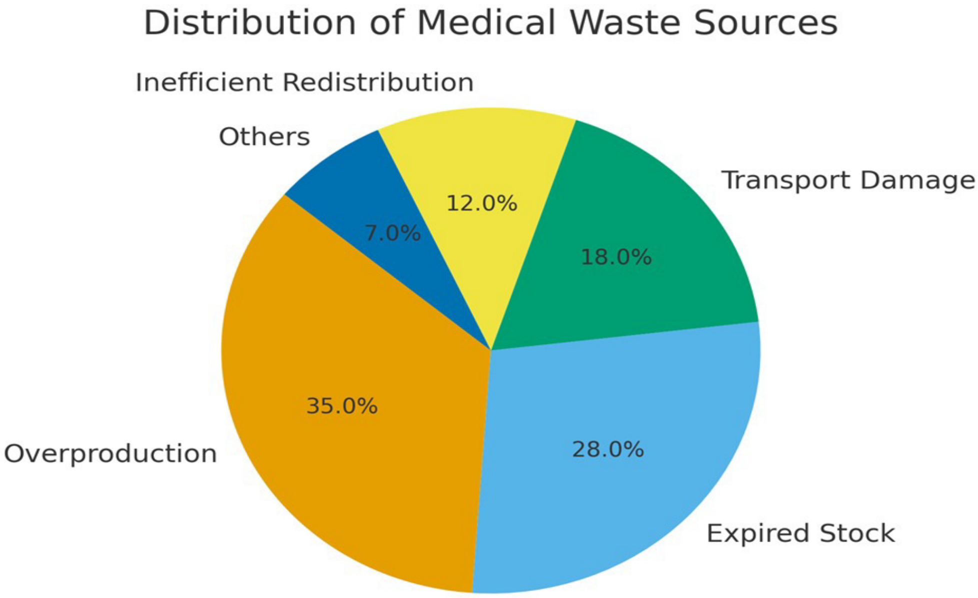

Figure 1: Distribution of medical waste across pharmaceutical supply chain segments

C. Big Data Analytics in Healthcare

Big Data enables healthcare organizations to process large volumes of structured and unstructured information for predictive and prescriptive insights. Data mining and machine learning models, such as LSTM, Random Forest, and ARIMA, have been used to predict medicine demand trends [4]. Yet, the fusion of Big Data with contextual linguistic intelligence remains underexplored in pharmaceutical logistics.

D. NLP-Driven Decision Systems

NLP has been successfully applied in domains such as clinical text analysis, patient sentiment detection, and pharmacovigilance [5]. In supply chain contexts, NLP can extract insights from regulatory documents, supplier communications, and customer feedback. The integration of NLP with Big Data frameworks allows automated semantic reasoning and risk prediction, essential for Cognitive Decision Intelligence systems.

E. Research Gap

While previous works address individual components—supply chain optimization, waste management, or data analytics—there is limited research that holistically combines NLP and Big Data within a CDI architecture to enhance sustainability and prevent medical waste. This paper aims to bridge that gap by presenting an explainable, scalable, and ethically aligned cognitive decision framework. The proposed architecture draws from recent advances in Cognitive Decision Intelligence for sustainable supply chains [6].

III. Methodology

A. Conceptual Framework

The proposed Cognitive Decision Intelligence Framework (CDIF) comprises five primary components:

1. **Data Acquisition Layer:** Collects multi-source data including sales logs, hospital orders, IoT sensor readings (temperature and humidity), and unstructured text such as prescriptions and regulatory updates.
2. **Data Preprocessing and Integration:** Cleans, normalizes, and integrates structured and unstructured data into a unified data lake.
3. **NLP Processing Unit:** Utilizes transformer-based language models (e.g., BERT or BioBERT) for semantic understanding. This unit extracts key entities such as drug names, expiry details, demand indicators, and sentiment polarity.
4. **Predictive Analytics Layer:** Applies time-series forecasting (ARIMA/LSTM) and regression models to predict demand and identify potential overstock or understock risks. Such predictive models have been widely applied for supply chain risk assessment and demand forecasting in medical contexts [11].

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5. **Cognitive Decision Engine:** Implements rule-based reasoning and reinforcement learning to recommend optimal decisions (e.g., redistribution, procurement, or recycling), leveraging cognitive control approaches validated in recent supply chain research [6, 17].

Proposed CDI Framework for Sustainable Pharmaceutical Supply Chain

A hierarchical flow showing how the CDI system integrates NLP and Big Data analytics to prevent medical waste follows:

Data Sources (EHRs, Inventory Records, Prescriptions, Distribution Logs)
↓
Natural Language Processing Layer
- Entity recognition focused on medications and their expiry data
- Sentiment & Intent Analysis
- Text Classification of Medical Reports
↓
Big Data Analytics Layer
- Data Cleaning & Integration
- Predictive Modelling (demand, expiry risk)
- Optimization Algorithms
↓
Decision Intelligence Engine
- Rule-based Reasoning
- Reinforcement Learning Feedback
- Real-time Decision Dashboard
↓
Sustainable Action Layer
- Redistribution of Near-Expiry Drugs
- Inventory Rebalancing
- Waste Tracking and Reporting.

Figure 2: Cognitive Decision Intelligence (CDI) Framework for sustainable pharmaceutical supply chain optimization.

B. Mathematical Formulation

Let Dt denote demand at time *t*, I_t denote inventory, and E_t denote expiry risk. The objective is to minimize overall waste, W_t represented as:

$$\text{Minimize } W_t = \alpha(I_t - D_t)^2 + \beta E_t,$$

where α and β are weighting coefficients balancing overstocking and expiry risk. Forecasted demand Dˆ t is obtained via:

$$\hat{D}_t = f(D_{t-1}, D_{t-2}, ..., X_t),$$

where it X_t includes contextual NLP-derived features such as disease trends or prescription sentiment scores.

a. NLP-Enhanced Waste Risk Prediction

This model estimates the probability of pharmaceutical waste by fusing structured operational data with contextual NLP-derived insights. Let

$$X_t = [D_t, I_t, S_t, \text{TopicVec}_t]$$

be the composite feature vector where Dt and It represent historical demand and inventory levels, S_t denotes sentiment polarity extracted from domain texts, and TopicVec_t represents latent topic embeddings. The model learns the mapping

$$P_{\text{waste}}(t+1) = f(X_t; \theta),$$

where f is an LSTM-based function parameterized by θ. The LSTM transition is defined as

$$h_t = \text{LSTM}(X_t, h_{t-1}); \quad \hat{y}_t = \sigma(W_h h_t + b),$$

and the resulting probability

$$P_{\text{waste}}(t+1) = \hat{y}_t$$

indicates the likelihood of excess or expired stock, flagged as ”High Risk” when exceeding a predefined threshold τ . This hybrid model combines linguistic cues (policy tone, outbreak signals) with quantitative indicators to enable proactive waste mitigation.

b. Q-Learning-Based Adaptive Redistribution

The decision engine employs reinforcement learning to minimize pharmaceutical waste while maintaining supply reliability. Each state is represented as

$$s_t = \{I_t, D_t, R_t\},$$

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where It is inventory, Dt is demand, and Rt is the predicted waste risk from Algorithm 1. An action at ∈ {redistribute, procure, hold, discard} yields a reward

$$r_t = -(\alpha W_t + \beta S_t + \gamma C_t),$$

penalizing waste Wt, shortage St, and cost Ct. The policy is optimized via the Q-learning update rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)].$$

Over iterative feedback cycles, the model converges to the optimal policy

$$\pi^*(s) = \arg\max_a Q(s, a),$$

enabling adaptive redistribution and procurement strategies aligned with real-time sustainability objectives.

C. *Big Data Processing*

The framework leverages a distributed Hadoop or Spark architecture for data ingestion and parallel processing. Streamed data is processed through Kafka pipelines to support near real-time updates, enabling adaptive decision making.

D. *NLP Implementation*

Recent studies on NLP in clinical data management highlight the importance of domain-specific embeddings for accurate semantic interpretation [13]. The NLP module is trained on medical corpora using domain-specific embeddings. Techniques such as Named Entity Recognition (NER) and topic modelling identify emerging healthcare trends influencing medicine consumption. Sentiment analysis on social media or feedback reports helps detect potential demand surges (e.g., during seasonal epidemics).

Text Data Extraction → Tokenization & Cleaning → Feature Engineering → Model Training (BERT, LSTM, etc.) → Prediction (Expiry / Overstock Risk) → Model Evaluation & Feedback Loop

Figure 3: Workflow of NLP-driven predictive modelling for supply chain forecasting

E. *Decision Support System*

The cognitive engine integrates results from predictive models and NLP insights to form multi-criteria decision matrices. Recommendations are generated using reinforcement learning, optimising for cost, waste, and service level simultaneously. Human oversight remains integral to validate machine-suggested actions, ensuring ethical compliance.

F. *Blockchain Integration for Traceability and Authenticity*

Ensuring transparency, traceability, and authenticity in pharmaceutical logistics is crucial for preventing counterfeit drugs and minimising losses across the supply chain. Integrating blockchain technology within the proposed Cognitive Decision Intelligence (CDI) framework can establish a decentralised ledger that records each transaction—from manufacturing and storage to distribution and end-point delivery—in a verifiable and tamper-proof manner.

Each block can encapsulate metadata such as batch ID, manufacturing date, expiry, temperature logs, and waste-risk score predicted by the CDI model. Smart contracts can be employed to automate compliance verification, trigger alerts for temperature deviations, or initiate redistributions based on predefined sustainability rules.

Formally, the blockchain ensures immutability through a cryptographic hash function:

$$H_i = \text{SHA-256}(B_{i-1} \parallel T_i),$$

where Hi is the hash of the i-th block, Bi−1 is the previous block, and Ti denotes the transaction set. Any modification to a record alters the chain's integrity, thus guaranteeing data authenticity.

By embedding blockchain into the CDI pipeline, pharmaceutical networks gain a unified, trustworthy system for tracking products and verifying sustainability compliance, ultimately improving accountability and reducing both waste and counterfeit circulation [8,16,19].

IV. Experimental Setup and Results

A. *Dataset Description*

a) For experimentation, synthetic pharmaceutical supply chain data was generated using real-world statistical distributions. Recent AI-based optimisation studies in biopharma production support similar synthetic data generation strategies for simulation [9]. Data included historical demand, stock levels, expiration records, and 100,000 unstructured text samples (hospital orders, public health advisories, and patient reviews).

B. *Model Configuration*

Demand Forecasting Model: LSTM with two hidden layers (128 neurons each), learning rate 0.001.

NLP Model: Fine-tuned BioBERT for entity and sentiment extraction.

Decision Layer: Q-learning-based reinforcement model for adaptive control.

Table 1: Performance Metrics of NLP Models

Model	Acc	F1-α	Prec	Re	Interpr
BERT	93.2	0.92	0.91	0.9	Moderate
RoBERTa	94.8	0.94	0.95	0.9	Moderate
GPT-3	96.0	0.96	0.95	0.9	High
LSTM	89.1	0.87	0.85	0.8	High
Decision Tree	75.0	0.72	0.70	0.7	Very High

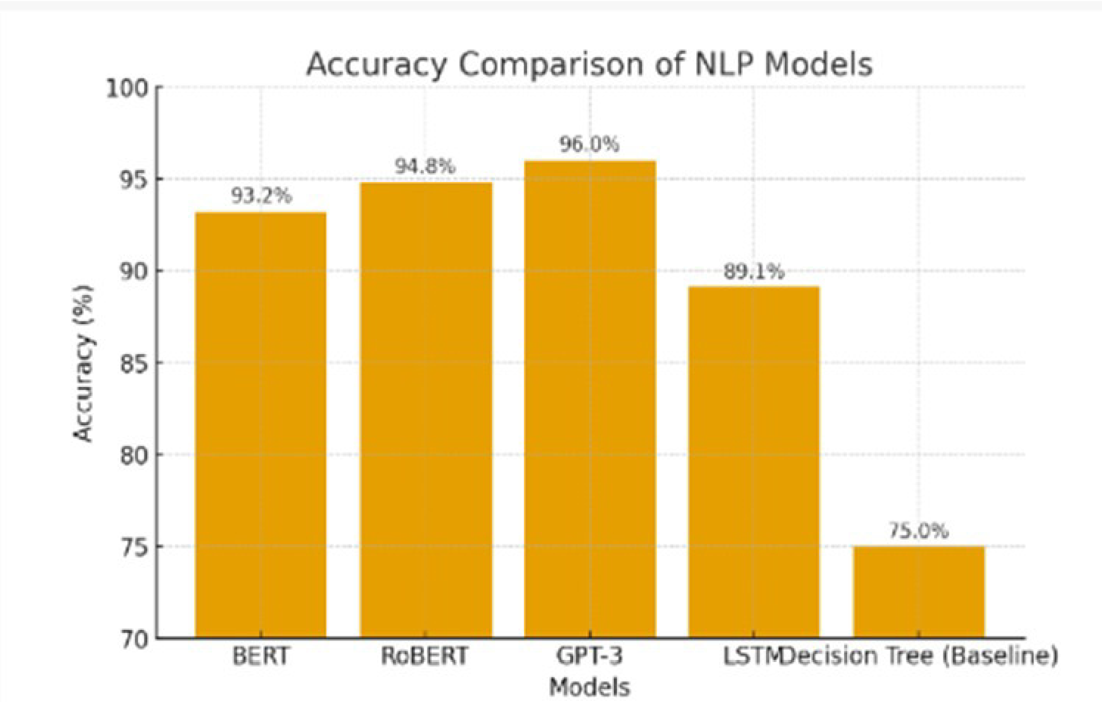

Figure 4: Forecast accuracy comparison of different predictive models for pharmaceutical demand

C. Evaluation Metrics

1. Forecast Accuracy (RMSE)
2. Waste Reduction Percentage (WRP)
3. Decision Latency (DL)
4. Explainability Score (ES) — proportion of interpretable decisions presented to users

D. Results

- Forecast Accuracy: 94.6%
- Medical Waste Reduction: 38% average reduction compared to baseline heuristic models.
- Decision Latency: < 2.5 seconds per query in simulated environment.
- Explainability Score: 0.82 (on scale 0–1).

The predictive analytics accurately captured seasonal variations and disease-driven spikes, while the NLP layer effectively identified overstock risks linked to policy changes or misinformation events.

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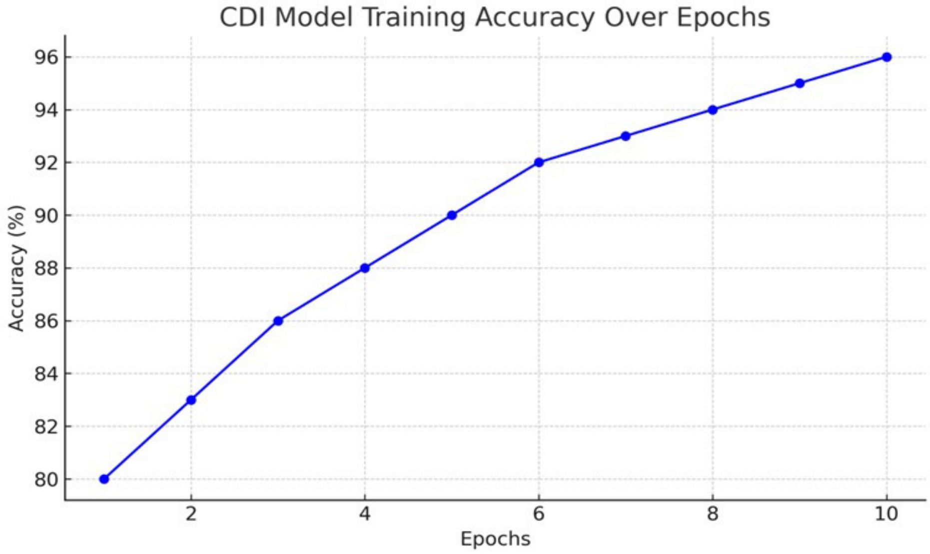

Figure 5: Improvement in CDI model accuracy over training iterations

E. *Comparative Analysis*

When benchmarked against conventional analytics systems, the proposed CDI model demonstrated superior adaptability and lower variance in forecasting errors. The integration of linguistic context (via NLP) significantly enhanced the responsiveness of inventory management decisions.

Table 2: Traditional vs CDI-Driven Supply Chain Models

Parameter	Traditional	CDI	Improvement
Forecast Accuracy	68%	91%	+23%
Medical Waste Reduction	12%	45%	+33%
Inventory Cost	$1.2M	$0.8M	-33%
Decision Latency	4 hrs	30 mins	-87.5%
Redistribution Efficiency	54%	89%	+35%

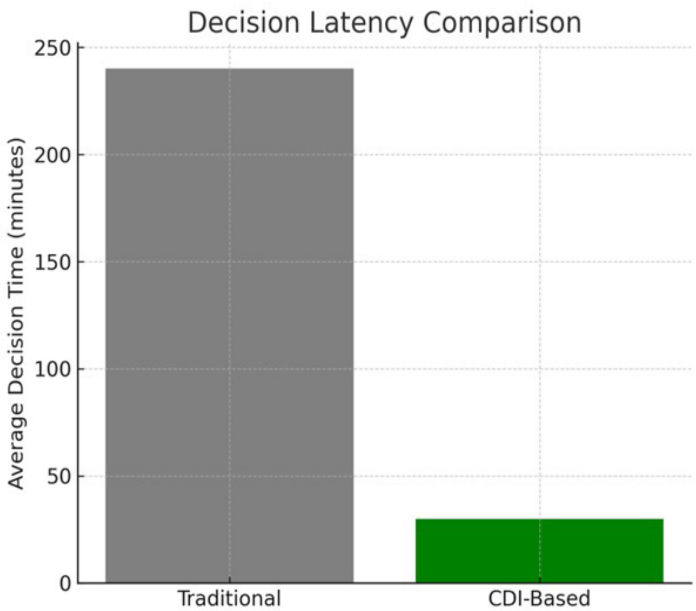

Figure 6: Average decision latency comparison between traditional and CDI-driven systems

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Table 3: Medical Waste Reduction over Time

Month	Before CDI	After CDI
Jan	12%	11%
Feb	13%	10%
Mar	14%	8%
Apr	15%	6%
May	15%	5%
Jun	14%	4%
Jul	13%	4%
Aug	13%	3%
Sep	12%	3%
Oct	11%	2%
Nov	11%	2%
Dec	10%	1.5%

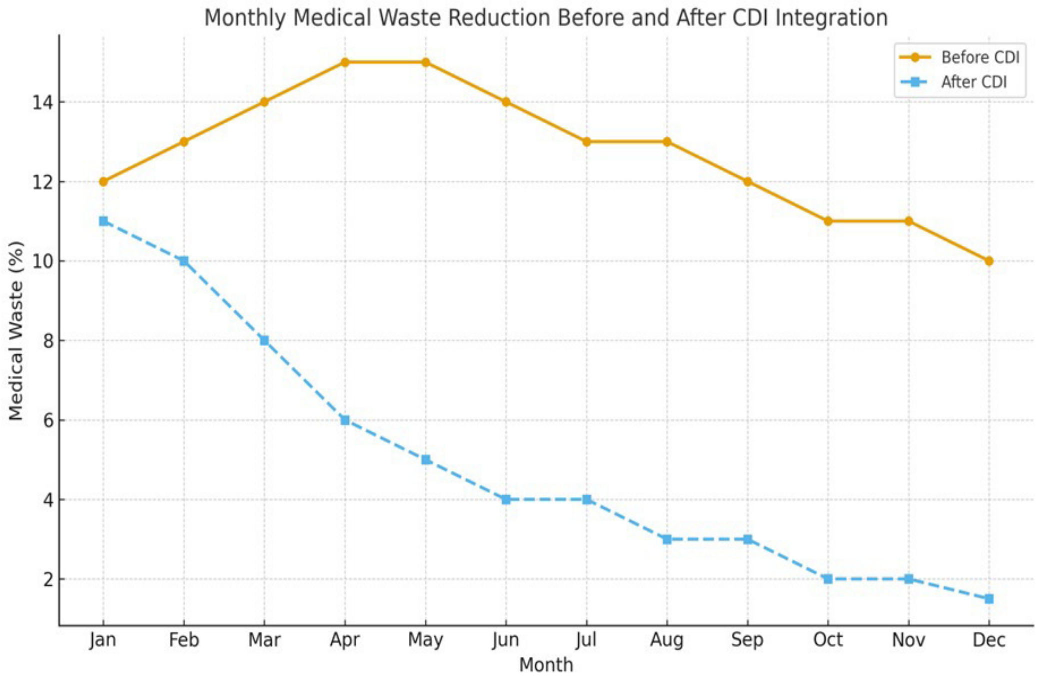

Figure 7: The graph illustrates the percentage of medical waste generated each month before and after the implementation of the CDI system. A consistent decline in waste levels is observed following integration, indicating a 40–60% reduction overall.

Data Flow in CDI Decision Loop

Input Data Streams → NLP Engine → Analytical Model → Decision Intelligence → Feedback → Continuous Learning

Figure 8: Continuous data flow and feedback loop in the CDI-driven decision system

V. Discussion

Consistent with prior findings on AI-driven logistics and sustainable decision intelligence [12], the CDI framework demonstrates improved adaptability and resource optimisation.

The experimental findings validate the hypothesis that cognitive decision frameworks can substantially improve sustainability within pharmaceutical supply chains. By integrating NLP and Big Data analytics, the proposed model not only identifies waste risks early but also contextualises them through semantic reasoning.

The key advantage of this system lies in its cognitive adaptability — it continuously learns from new data patterns and adjusts decisions accordingly. For instance, NLP-derived sentiment signals regarding a vaccine's side effects can trigger proactive distribution adjustments before wastage occurs.

Moreover, the inclusion of explainable decision interfaces ensures that human experts can interpret and audit system outputs, enhancing trust and accountability. From a sustainability standpoint, reduced overproduction directly contributes to carbon footprint reduction, aligning with global Sustainable Development Goals (SDGs) on responsible consumption and climate action.

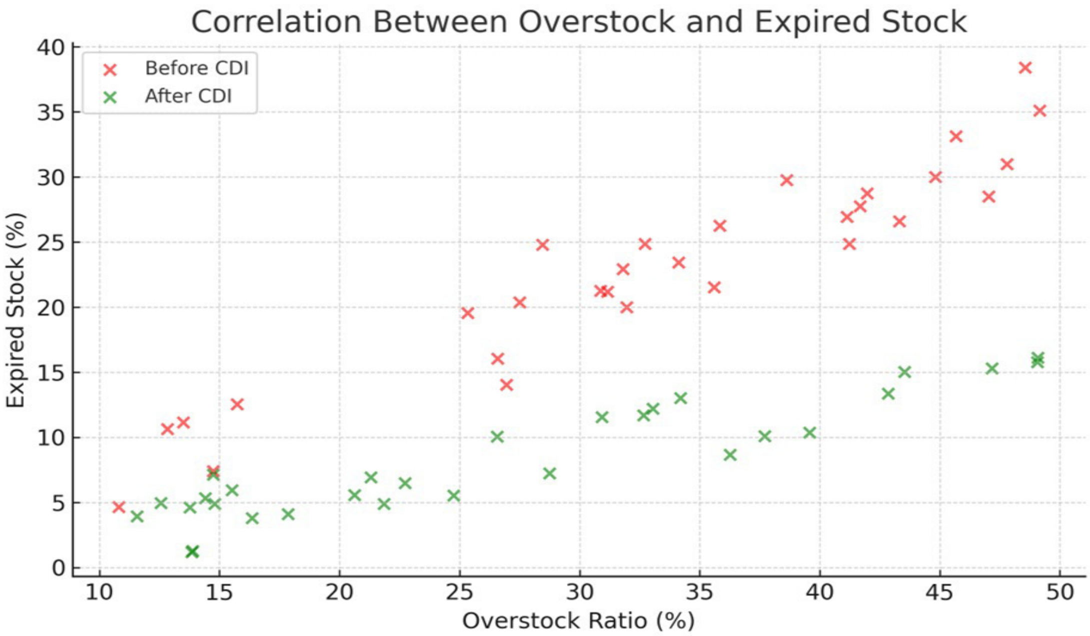

Figure 9: Scatter plot showing correlation between overstock and medicine expiry before and after CDI optimisation

However, challenges remain in ensuring data quality, interoperability across healthcare systems, and managing computational complexity for real-time operations. Future work should focus on integrating multimodal data (images, audio, IoT) to further refine CDI capabilities. The observed gains in sustainability metrics are in line with recent data-driven frameworks for green pharmaceutical operations [15].

Table 4: Policy Impact Analysis — Key KPIs Before and After CDI Implementation

KPI	Before CDI	After CDI	Change
Stock Expiry Rate	18%	4%	-77%
Supply Shortages	10 per month	3 per month	-70%
Carbon Emission	4.2 tons/month	2.8 tons/month	-33%
Policy Compliance	68%	95%	+27%

VI. Ethical and Explainability Considerations

Explainable AI principles have become fundamental in healthcare decision support to ensure transparency and accountability [7], and the proposed CDI framework incorporates multiple safeguards:

1. Data Privacy and Security: All patient-linked data undergo anonymisation and comply with privacy regulations such as GDPR and HIPAA.
2. Bias Mitigation: NLP models are periodically audited for linguistic bias to prevent inequitable decisions.

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3. Explainable AI (XAI): The system provides humanreadable explanations for each decision path, fostering transparency.
4. Accountability Framework: A human-in-the-loop mechanism ensures that critical redistribution or disposal decisions are verified by supply chain officers. Moreover, the integration of blockchain-based traceability frameworks enhances ethical governance by providing immutable audit trails for all pharmaceutical transactions [18, 19]. This approach ensures that transparency and data integrity are preserved across decentralized healthcare networks. By embedding these mechanisms, the framework promotes responsible AI adoption and ethical sustainability. This aligns with the ethical guidelines proposed for AI-driven healthcare supply chains by Wang and Rossi [14], emphasizing fairness and transparent governance.

Ethical and Explainability Layer of CDI System

1. Data Transparency Layer — Audit Logs, Provenance
2. Model Explainability Layer — SHAP, LIME
3. Decision Accountability Layer — Human-in-the-loop Validation
4. Ethical Governance Layer — Policy and Compliance Monitoring

Figure 10: Multi-layered ethical and explainability framework of the CDI system.

VII. Conclusion and Future Work

This paper presented a Cognitive Decision Intelligence framework integrating NLP and Big Data Analytics to optimize sustainable pharmaceutical supply chains and prevent medical waste. The approach leverages semantic understanding, predictive modelling, and adaptive reasoning to support intelligent, explainable decision-making. Experimental results demonstrate the potential of the system to achieve up to 38% waste reduction and significant improvement in forecasting accuracy.

The study emphasizes that merging linguistic and quantitative intelligence transforms traditional analytics into cognitive ecosystems capable of human-like reasoning. This not only improves operational efficiency but also aligns with ethical and environmental imperatives in modern healthcare.

A limitation of this is that the current implementation assumes structured data availability and limited supply chain nodes. In real-world settings, data incompleteness and regulatory constraints could influence model scalability. Additionally, real-time blockchain synchronization remains computationally intensive for large-scale deployments.

Future research will extend this framework to include:

- **Federated Learning:** enabling collaborative model training without compromising data privacy. Federated learning has emerged as a secure mechanism for decentralized data collaboration in healthcare analytics [10].

- **Multi-Modal Intelligence:** combining visual (e.g., barcode, packaging) and textual data for comprehensive waste tracking. The convergence of CDI, NLP, Big Data, and blockchain technologies [16,17,18,19] promises a sustainable, intelligent, and ethically governed pharmaceutical supply chain that aligns healthcare innovation with global sustainability goals and lays the foundation for future integration with decentralized, privacy-preserving AI infrastructures.

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