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Circular Healthcare Inventory Systems: Machine Learning for Expiry Prevention, Redistribution, and Medical-Waste Reduction

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Abstract
Healthcare systems can experience product shortages and medical waste at the same time because procurement, expiry monitoring, and redistribution are managed separately. This study develops a circular inventory architecture that links machine-learning risk prediction with constrained inter-facility pooling. The empirical setting is the early United States COVID-19 vaccine program. Public CDC-derived files contain 293,907 vaccine shipment records to 53,041 provider locations and 1,154 usable wastage reports. The analysis constructs 4,240 awardee-manufacturer-week observations and applies strict temporal validation. Logistic regression, random forest, and gradient boosting are compared. The random forest achieved an out-of-time area under the precision-recall curve of 0.672, area under the receiver-operating-characteristic curve of 0.809, and F1 score of 0.626. Shipment frequency, shipment-size dispersion, provider coverage, prior wastage, and dose volume were the most influential predictors. A retrospective redistribution simulation increased the shipment-based fill-rate proxy from 0.815 to 0.864. Risk-based transfer capacity potentially covered 156,097 observed wasted doses, although the public data do not identify wastage cause or completed transfers. The paper contributes an integrated theory of expiry, shortage, and waste, demonstrates an explainable prediction-to-decision workflow, and shows how equity constraints can be added at low incremental scenario cost. Findings support better lot visibility and network coordination, but do not establish causal waste reduction.

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Keywords: healthcare inventory, medical waste, expiry prediction, pharmaceutical redistribution, machine learning, circular economy, supply-chain resilience, explainable artificial intelligence

1. Introduction

Healthcare inventory systems are frequently managed as a sequence of separate administrative tasks. Procurement teams place orders, pharmacy staff monitor stock, clinical units react to shortages, and waste contractors handle products that can no longer be used. This division of labor is understandable, but it obscures the fact that shortages and waste often arise from the same information problem. A product can be scarce in one part of a network while excess stock approaches expiration elsewhere. Emergency orders can coexist with unused inventory because the system does not connect demand signals, lot information, and transfer capacity at the time decisions are made. The operational consequence is a costly combination of low service reliability and avoidable disposal.

Pharmaceutical and vaccine inventories are especially difficult because the value of a unit depends on time, storage history, and location. A dose that is clinically valuable today may become unusable after a temperature excursion or after its expiration date. Managers therefore need more than a demand forecast. They need an estimate of where usable inventory is accumulating, where demand is likely to exceed available supply, how long each lot remains viable, and whether a transfer can be completed without creating a new risk for the donor or recipient. Conventional reorder rules rarely solve this network problem because they optimize

each facility separately and respond slowly to changing demand.

The circular economy provides a useful way to reinterpret this problem. Circularity in healthcare does not mean unrestricted reuse. It means preserving the clinical value of products within regulatory and safety constraints before disposal becomes necessary. For unopened and traceable products, timely redistribution can extend useful life, reduce disposal, and strengthen access. Arman, Rasel, Razib, and Fahim (2024) argue that predictive analytics can move waste management upstream by identifying avoidable loss before it occurs. The present study applies that logic to healthcare inventory and treats redistribution as a prevention mechanism rather than a salvage activity. It also extends the resilience emphasis of Rasel, Arman, Hasan, and Bhuyain (2022) by linking continuity of supply with expiry visibility and network coordination.

Machine learning may improve early warning, but predictive accuracy alone is not sufficient. A model that flags risk without identifying the operational cause can add alarm fatigue rather than value. Inventory managers need to know whether a prediction reflects shipment size, provider concentration, short shelf life, recent wastage, demand volatility, or a combination of these factors. Explainability therefore has a practical role. It allows a manager to distinguish between factors that can be changed immediately, such as allocation quantity, and contextual factors that require longer term intervention, such as supplier lead time or storage capacity. The governance problem is also material. Inter-facility exchange requires secure data sharing, traceability, and clear accountability. Hasan *et al*. (2022) emphasize that machine learning in healthcare infrastructure must be accompanied by secure information governance. Those requirements become more demanding when inventory data cross organizational boundaries. Augmented-intelligence research reinforces this design principle by treating professional expertise, workflow integration, and automation as complementary rather than substitutive capabilities (Kamruzzaman *et al*., 2023).

Evidence on integrated expiry prediction and redistribution remains limited. Healthcare inventory research has developed strong models for ordering, safety stock, blood-product allocation, and vaccine distribution. Circular economy research has examined reverse logistics and waste prevention. Machine-learning research has improved forecasting and risk classification. Yet these literatures often stop at different decision points. Forecasting studies rarely evaluate whether predictions can support feasible transfers. Redistribution models commonly assume that demand and usable inventory are already known. Sustainability studies may count avoided disposal without accounting for transfer distance, handling effort, or cold-chain risk. Equity is frequently reduced to equal allocation, even though an equitable transfer must arrive with sufficient remaining shelf life and manageable handling requirements.

This paper addresses that gap through an empirical analysis of the early United States COVID-19 vaccine distribution system. The data contain 293,907 shipment records to 53,041 providers, with manufacturer, lot, shipment date, expiration date, and quantity fields, together with 1,154 wastage reports. The shipment data cover January through March 2021, while wastage reports begin in late December 2020. The study constructs an awardee, manufacturer, and week panel, estimates out-of-time wastage-event models, and develops a retrospective redistribution simulation. Because the public data do not contain provider-level administrations or completed transfers, the simulation uses next-week shipments as a demand-pressure proxy. This choice limits causal and inventory claims, but it permits a transparent test of whether risk-informed pooling could reduce observed shipment imbalances.

Seven research questions guide the analysis. They concern predictive accuracy, risk drivers, potential waste reduction, operational trade-offs, explanation quality, heterogeneity across manufacturers and organizational scale, and the equity implications of transfer rules. Eight hypotheses connect demand variability, order size, shelf life, prediction performance, redistribution, service outcomes, explanation actionability, equity constraints, and transfer burden. The empirical contribution is deliberately bounded. The observed outcome is reported vaccine wastage, not expiration alone, because the wastage file does not identify the reason for each discarded dose. Expiry fields are used as predictive exposure variables where valid, and the paper does not infer that all wastage was caused by expiration.

The results show that nonlinear models materially outperform logistic regression in the out-of-time test period. The random forest obtains an area under the precision-recall curve of 0.672 and an area under the receiver-operating-characteristic curve of 0.809. Shipment frequency, dispersion in shipment size, prior provider coverage, prior wastage, and current provider coverage are the most influential features. In the constrained simulation, risk-based pooling increases the shipment-based fill-rate proxy from 0.815 to 0.864 and covers approximately 156,097 observed wasted doses in the sense that an equal or larger quantity is transferred from identified excess positions. This is a counterfactual capacity measure, not a claim that those doses would certainly have been saved.

The paper contributes in four ways. First, it theorizes expiry, shortage, and waste as connected outcomes of information-processing and coordination capacity. Second, it combines risk prediction with a network decision simulation under explicit data limitations. Third, it evaluates explanation quality in terms of operational actionability rather than visualization alone. Fourth, it embeds equity and sustainability constraints in redistribution logic. The remainder of the paper reviews the relevant literature, develops the framework and hypotheses, describes the data and methods, reports results, and discusses implications, limitations, and future research.

2. Literature Review and Theoretical Background

2.1. Healthcare Inventory Management

Healthcare inventory management balances clinical availability against carrying cost, obsolescence, and expiry. Unlike many retail settings, the cost of shortage may include delayed treatment, substitution risk, or loss of public confidence. Classical inventory theory provides reorder points, order-up-to policies, and safety-stock rules, but healthcare demand is often intermittent, heterogeneous, and affected by epidemics, clinical protocols, and policy changes. Rossetti, Handfield, and Dooley (2011) describe healthcare supply chains as networks with fragmented authority and weak end-to-end visibility. Volland *et al*. (2017) similarly show that hospital inventory research often concentrates on local optimization even when system outcomes depend on coordination across departments and organizations.

Resilience research shifts attention from average efficiency to the capacity to absorb disruption and maintain critical service. Christopher and Peck (2004) argue that visibility and collaboration are central to resilient supply chains. Rasel *et al*. (2022) apply this logic to healthcare and emphasize coordinated inventory, continuity, and system-level decision making. The present study extends that foundation by treating unused shelf life as a network resource. Resilience is not achieved by holding more stock everywhere. It depends on knowing where stock is, whether it remains usable, and whether it can move before local excess becomes waste.

2.2. Pharmaceutical Expiry and Medical Waste

Pharmaceutical waste includes expired products, damaged items, temperature-excursion losses, recalls, opened-vial waste, and packaging. These categories should not be collapsed because their causes and interventions differ. Expiry usually reflects decisions made earlier in the cycle, including forecasting error, minimum order quantities, rigid allocations, slow-moving stock, and weak first-expire-first-out discipline. WHO guidance on vaccine wastage distinguishes unavoidable open-vial waste from avoidable closed-vial losses and recommends routine monitoring of both rates and causes. The environmental burden is also broader than disposal. Production, cold storage, and transport have already consumed resources by the time a product is discarded.

Circular economy theory reframes waste as a failure to retain value within a system. Geissdoerfer *et al*. (2017) distinguish circular strategies from narrower end-of-pipe recycling. In healthcare, safety and regulation limit reuse, but traceable unopened inventory can often be reallocated, returned, or donated before expiration. Arman *et al*. (2024) show how big data and machine learning can support earlier waste prevention. This study extends their sustainability argument by linking predicted wastage to specific redistribution decisions and by subtracting transfer burden from avoided-disposal benefits.

2.3. Demand Forecasting and Shortage Prediction

Forecasting is a central input to inventory policy, but forecast error is not the only source of shortage or excess. Lead-time variability, allocation rules, provider onboarding, demand suppression during stockouts, and sudden policy changes can all create mismatch. Croston (1972) and later intermittent-demand methods address sparse demand, while machine-learning models capture nonlinear interactions and changing seasonality. In vaccine systems, demand is further influenced by eligibility rules, public confidence, appointment capacity, and local epidemiology. The early COVID-19 campaign illustrates how supply, eligibility, and provider capacity changed simultaneously.

Predictive risk analytics is valuable when it identifies the probability of an adverse operational event rather than merely projecting volume. Hasan, Rasel, Arman, Ibrahim, and Jahan (2023) discuss risk-based intervention in institutional systems, while Rasel, Ibrahim, Pritty, Fahim, and Jahan (2023) show how heterogeneous data can improve prediction and fairness analysis in another regulated decision setting. Their methodological relevance lies in multimodal integration and explainability, not in healthcare inventory evidence. Applied here, the lesson is that demand, shipment structure, prior waste, and shelf-life information should be combined rather than modeled in isolation.

2.4. Inter-Facility Redistribution and Inventory Pooling

Lateral transshipment research examines transfers among locations at the same echelon. Pooling can reduce system safety stock and improve service when demand is imperfectly correlated across sites. Paterson *et al*. (2011) review emergency transshipment models and show that benefits depend on timing, information, and transfer cost. In healthcare, blood products and critical medicines have motivated network allocation models because perishability and shortage costs are high. Redistribution is most useful when the donor has genuine excess, the recipient has credible demand, and the product can arrive with sufficient remaining life.

Empirical work also shows that organizational barriers matter. Mabizela and colleagues (2023) link overstocking, stockouts, wastage, and redistribution in public healthcare facilities, illustrating that transfer practice is shaped by reporting quality and managerial coordination. A mathematically feasible transfer may fail because staff cannot approve it, cold-chain capacity is inadequate, or the recipient cannot use the quantity before expiry. The optimization problem therefore needs constraints for safety stock, traceability, handling, transfer frequency, and minimum remaining shelf life.

2.5. Circular Economy in Healthcare

Circular healthcare inventory management combines operational efficiency with stewardship of scarce clinical resources. It differs from conventional reverse logistics because the primary objective is to preserve clinical use before disposal. Product return, inter-facility transfer, donation, and supplier take-back are possible pathways, but each has regulatory and quality requirements. The circular intervention must also be evaluated at system level. A transfer that prevents disposal but requires long-distance refrigerated transport may yield a weak environmental benefit. Arman, Hasan, and Rasel (2024) demonstrate the broader value of data-intensive forecasting for carbon-reduction decisions. Their cross-sector insight supports transparent accounting of operational emissions and uncertainty rather than automatic claims of sustainability.

2.6. Explainable Artificial Intelligence in Healthcare Operations

Explainable artificial intelligence has developed methods such as permutation importance, partial dependence, accumulated local effects, SHAP values, and counterfactual explanations. Ribeiro, Singh, and Guestrin (2016) focus on local interpretability, while Lundberg and Lee (2017) provide a unified feature-attribution framework. In operations, explanation quality depends on whether the information changes a decision. A list of important variables is insufficient when a manager needs to know how much to reduce an order or whether to initiate a transfer. In healthcare operations, augmented intelligence further implies that explanations should support trained human judgment and process redesign rather than serve as passive model documentation (Kamruzzaman *et al*., 2023).

Healthcare settings add governance concerns. Models may encode reporting intensity, organizational scale, or access disparities rather than intrinsic risk. Explanations should therefore be tested across time and subgroups. Secure data sharing is equally important. Hasan *et al*. (2022) argue that healthcare machine-learning infrastructure must protect

sensitive data and maintain institutional trust. Inventory records are less sensitive than patient records, but provider locations, supply levels, and emergency capacity can still be operationally sensitive.

2.7. Equity, Resilience, and Access

Equity in inventory allocation concerns clinically useful access, not equal quantities. A rural or resource-constrained facility may need smaller, more frequent shipments and longer remaining shelf life because storage and demand differ from a high-volume urban center. An unconstrained cost-minimizing model may send near-expiry products to facilities with limited administrative capacity, effectively shifting the burden of waste. Equity constraints can require minimum service levels, minimum shelf life, or limits on transfer workload.

Resilience and equity can reinforce each other when pooling protects peripheral facilities from isolated shortages. They can also conflict when scarce transfer capacity is directed toward locations with the highest throughput. The appropriate objective is therefore multi-criteria: reduce shortage and waste while controlling cost, handling burden, and distributional harm.

2.8. Research Gap

The literature offers mature components but limited integration. Forecasting studies rarely connect risk scores to feasible redistribution. Optimization studies often assume accurate inventory and demand information. Circular-economy studies may not model service loss. Explainability studies frequently stop at feature rankings, and equity is seldom defined in terms of shelf-life quality and recipient burden. This study addresses that gap with a transparent empirical architecture that links shipment and expiry exposure, observed wastage, out-of-time prediction, explanation, and a constrained transfer simulation.

3. Theoretical Framework and Hypotheses

The framework integrates inventory theory, organizational information-processing theory, resilience, circular economy, and socio-technical systems. Inventory theory explains how order quantity, demand variability, lead time, and shelf life jointly produce excess and shortage. Information-processing theory argues that organizations require greater information capacity when uncertainty and interdependence increase. A network with many providers, changing eligibility rules, and multiple vaccine products cannot coordinate effectively through periodic aggregate reports alone. It needs timely lot-level visibility and shared decision rules.

Resilience theory adds the capacity to reconfigure resources during disruption. Redistribution is a reconfiguration mechanism, but only when the donor retains adequate protection and the recipient can use the product. Circular-economy theory defines the avoided loss of clinical utility as a system benefit. Socio-technical theory requires attention to workflow, governance, security, and staff capacity. Equity theory adds a distributional constraint: high-need or low-resource facilities should not receive systematically shorter shelf-life products or disproportionate transfer burden.

H1 predicts that higher demand variability, longer replenishment exposure, larger shipment quantities, and shorter remaining shelf life are associated with higher wastage risk. The public data do not contain lead time or true demand, so shipment dispersion, provider coverage, and observed shelf-life fields serve as partial measures.

H2 predicts that machine-learning models outperform conventional rule-based and statistical approaches. Nonlinear interactions are expected because the effect of a large shipment depends on provider count, manufacturer, prior wastage, and timing.

H3 predicts that redistribution informed by predicted risk reduces excess inventory relative to isolated management. The empirical test is a retrospective simulation and therefore evaluates feasible capacity rather than realized transfers.

H4 predicts that integrated prediction and redistribution improve a service proxy while reducing excess and potentially cover observed wastage. A policy is not considered superior if improved service requires unbounded transfers.

H5 predicts stronger benefits when cross-facility imbalance is high and transfer requirements remain manageable. H6 predicts that explanations become actionable when they identify shipment frequency, shipment dispersion, provider coverage, shelf-life visibility, or prior wastage as intervention points.

H7 predicts that an equity-constrained policy improves the minimum transfer response without a practically significant increase in system cost. In the simulation, an equity floor prevents low predicted risk from excluding persistent shortage positions.

H8 predicts that sustainability benefits decline as transfer cost and cold-chain burden rise. Because direct emissions are unavailable, this hypothesis is evaluated through threshold analysis rather than a precise carbon estimate.

Figure 1 summarizes the framework. Inventory and facility conditions generate predictive signals. These signals support order adjustment, pooling, and transfer decisions. Governance, cold-chain feasibility, and equity constraints moderate the path from prediction to cost, service, waste, resilience, and access outcomes.

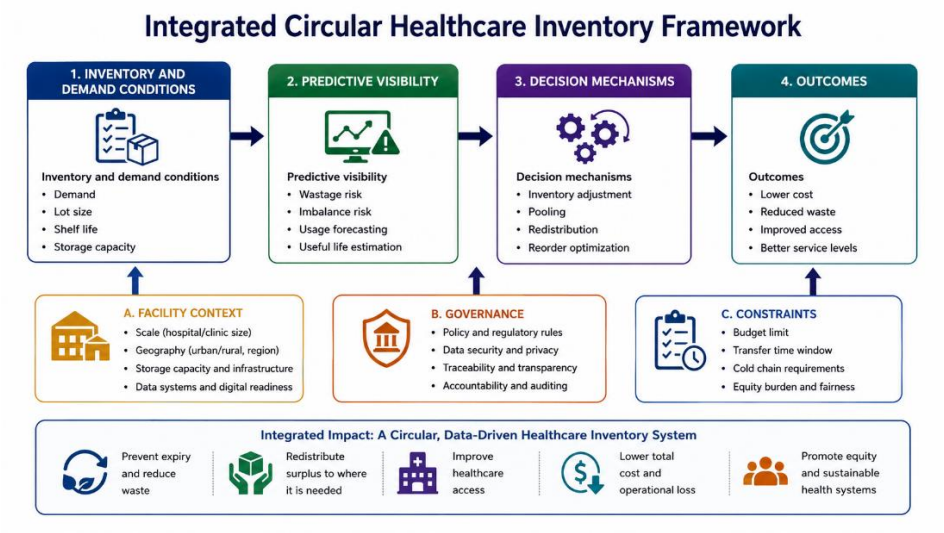


Fig 1: Integrated circular healthcare inventory framework. Source: Authors.

4. Data and Methodology

4.1. Research Design

The study uses a retrospective observational and decision-simulation design. The predictive component estimates whether an awardee and manufacturer report any wastage in a week. The decision component evaluates how different pooling rules would change shipment-based excess and shortage proxies. The design is associational. It does not estimate the causal effect of redistribution because no transfer intervention occurred in the observed data.

4.2. Data Sources and Vintage Verification

The primary files are the COVID-19 Vaccine Shipment Data and COVID-19 Vaccine Wastage Data assembled from CDC records obtained through a Freedom of Information Act request and released in the public GitHub repository maintained by Hajibabai and colleagues. The repository release was dated December 18, 2021, and the accompanying Transportation Science paper was published online on April 1, 2022. The shipment file contains provider name and address, awardee, National Drug Code description, manufacturer, lot number, expiration date, shipment date, and doses shipped. The wastage file contains awardee, product description, submission date, and wasted doses. The paper documenting the data reports more than 633,000 total shipment and supply-kit records, including approximately 293,000 vaccine-shipment records and about 1,200 wastage records in the original release.

The downloaded national shipment file contains 293,907 vaccine rows from January 5 through March 30, 2021. The wastage file contains 1,154 usable vaccine records from December 21, 2020 through March 29, 2021 after excluding two test records. The files existed well before the December 31, 2024 cutoff. The Census 2021 Gazetteer documentation was reviewed for geographic augmentation, but coordinates were not used in the final simulation because the transfer model operates at awardee level and the public wastage data cannot be linked to individual providers.

4.3. Sample Construction

Provider identifiers were constructed from provider name, street address, and ZIP Code. Manufacturer labels were harmonized to Moderna, Pfizer, and Janssen. Dates were converted to weekly periods ending on Monday. Expiration dates coded as year 2069 were treated as unknown, consistent with the source documentation. Shelf life was calculated only for valid dates. Records were aggregated to awardee, manufacturer, and week. A complete weekly grid was created so that weeks without shipments or reported wastage were retained as zero-activity observations.

The resulting panel contains 4,240 awardee-manufacturer-week observations. The analysis includes 92 awardees, 53,041 provider locations, and 142 reported lot identifiers. Total shipments equal 179,767,600 doses. Reported wastage equals 182,874 doses, or 0.102 percent of shipped doses. Valid expiration dates are available for 12.99 percent of shipment rows. Among records with valid dates, mean remaining shelf life at shipment is 130.2 days and the median is 130 days.

Table 1: Sample-construction process

Step	Records
Raw shipment records	293,907
Usable wastage records	1,154
Unique providers	53,041
Awardees	92
Awardee-manufacturer-week panel	4,240
Out-of-time test observations	1,325

4.4. Product and Facility Classification

Product class is represented by manufacturer because the early dataset contains three vaccine platforms with different packaging and handling requirements. Facility type is not consistently coded. Provider count within an awardee-week therefore captures distribution breadth, while awardee total shipment volume is used to construct organizational-scale quartiles. This is an imperfect substitute for hospital type and is treated as such.

4.5. Expiry and Shortage Outcomes

The observed primary outcome is a binary wastage event in an awardee-manufacturer-week. The data do not identify whether wastage resulted from expiration, breakage, temperature excursion, or another cause. Consequently, the paper uses the term wastage risk for the dependent variable and near-expiry exposure for shipment records with 60 or 90 days of remaining shelf life. It does not label the observed outcome as expiry-specific.

A shortage proxy is constructed for the redistribution simulation. Current weekly shipments are compared with the following week's shipments for the same awardee and manufacturer. A negative difference is interpreted as demand pressure and a positive difference as transferable imbalance. This proxy does not equal inventory, consumption, or stockout. It is used only to compare policies under a common retrospective rule.

4.6. Feature Engineering

Predictors include current doses shipped, shipment count, unique providers, unique lots, mean and standard deviation of shipment size, mean and minimum shelf life, proportion of records with known expiry, proportion within 60 and 90 days of expiry, and one-week and two-week lags for selected variables. Prior wastage is included because reporting persistence and unresolved operational conditions may carry forward. Manufacturer is categorical. Missing continuous values are imputed with the training median. Continuous features are standardized for logistic regression.

4.7. Machine-Learning Models

Three models are compared: class-weighted logistic regression, random forest, and gradient boosting. The logistic model provides a conventional statistical baseline. The random forest uses 30 trees, maximum depth six, minimum leaf size ten, balanced class weights, and random seed 42. Gradient boosting uses 40 estimators, depth two, learning rate 0.05, and the same seed. The reduced complexity limits overfitting in a short panel.

Temporal validation is strict. Training observations end February 8, 2021. Validation covers February 15 through March 1, and the test period covers March 8 through March 30. Thresholds maximize F1 in validation and are then fixed. Performance metrics include area under the precision-recall curve, area under the receiver-operating-characteristic curve, precision, recall, F1, specificity, balanced accuracy, Matthews correlation coefficient, and Brier score. Precision-recall performance receives greatest weight because wastage events are uncommon.

4.8. Redistribution and Inventory Optimization

Four policies are compared. No redistribution retains all imbalance. Rule-based pooling transfers 50 percent of the minimum of system excess and shortage within each manufacturer-week. ML risk-based pooling permits transfers up to the lesser of system imbalance and the risk-weighted excess pool. The equity-constrained policy applies a minimum risk weight of 0.35 so that persistent recipient need is not ignored simply because donor risk is estimated as low. Transfers are restricted to the same manufacturer and week. The simulation preserves aggregate donor excess and cannot transfer more than aggregate recipient shortage. A scenario transfer cost of 0.10 dollars per dose is reported for comparison, not as an observed cost. The main outcomes are transferred doses, residual shortage proxy, residual excess proxy, fill-rate proxy, and observed wasted doses potentially covered by transfer capacity.

4.9. Explainability Methods

Global explanation uses native random-forest feature importance. Features are grouped into actionable, partially actionable, and contextual categories. Shipment frequency, quantity, and dispersion are actionable through allocation decisions. Provider coverage and manufacturer are contextual in the short run. Prior wastage is a warning signal that may indicate unresolved process problems. Expiry visibility is partly actionable because data quality and lot capture can be improved. Because impurity-based importance can favor continuous or high-cardinality predictors, the rankings are interpreted as descriptive model diagnostics rather than causal effects or definitive measures of actionability.

4.10. Equity and Sustainability Evaluation

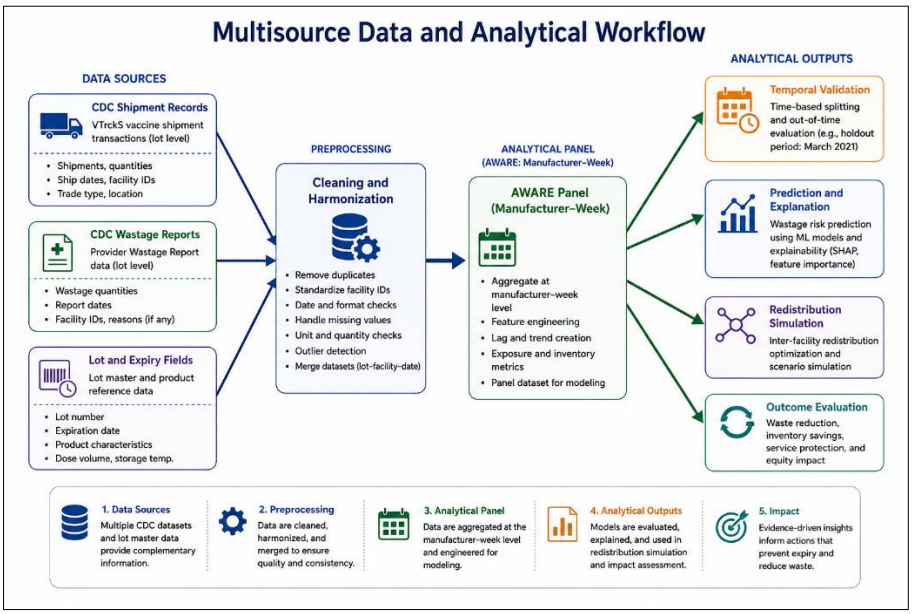
Subgroup results are examined by manufacturer and awardee shipment-volume quartile. Equity is operationalized as protection against exclusion from the transfer pool, not equal transfer volume. The equity-constrained policy imposes a minimum response to shortage positions. Sustainability is evaluated through avoided excess and potential wastage coverage, balanced against transfer volume and scenario cost. No precise carbon estimate is reported because route distance, vehicle type, load consolidation, and refrigeration energy are unavailable.

4.11. Statistical Analysis

Model comparisons rely on out-of-time metrics and practical effect sizes. The short observation period and strong temporal change make conventional random cross-validation inappropriate. Descriptive correlations are interpreted cautiously because aggregation creates scale effects. Hypotheses are evaluated as supported, partially supported, not supported, or not testable with the public data.

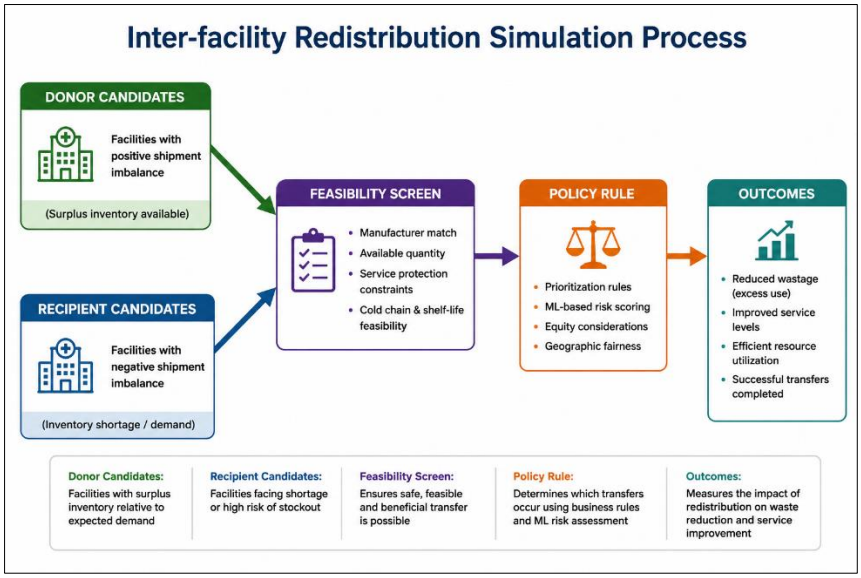
4.12. Reproducibility and Ethics

All analysis was executed in Python using pandas, NumPy, scikit-learn, and Matplotlib. Random seed 42 was used for stochastic models. The package includes data manifests, cleaning and modeling scripts, generated tables, and figure files. Public provider addresses are retained in the raw source but are not reproduced in the manuscript. The analysis contains no patient-level data.



Source: Authors.

Fig 2: Multisource data and analytical workflow.



Source: Authors.

Fig 3: Inter-facility redistribution simulation process.

5. Results

5.1. Descriptive Statistics

The shipment data contain 179.8 million doses distributed through 53,041 provider locations. Moderna accounts for the largest number of shipment records and doses. Only 12.99 percent of records contain a valid expiration date rather than the source placeholder year 2069. This limitation is operationally important. A circular inventory system cannot reliably prioritize first-expire-first-out use or transfer windows when expiry data are missing from most transactions.

Reported wastage totals 182,874 doses, equivalent to 0.102 percent of shipped doses during the covered period. The rate is low in aggregate, but the distribution is highly concentrated across awardee-weeks. The binary outcome is therefore more stable than wasted quantity for prediction. Event prevalence also rises in the March test period, which makes the out-of-time evaluation more demanding than a random split.

5.2. Wastage-Risk Prediction

The random forest provides the strongest overall discrimination. Its test AUPRC is 0.672, AUROC is 0.809, precision is 0.686, recall is 0.576, and F1 is 0.626. The Matthews correlation coefficient is 0.530. Gradient boosting obtains similar AUROC at 0.808 and higher recall at 0.668, but lower precision and AUPRC. Logistic regression performs materially worse, with AUPRC 0.451 and F1 0.475. H2 is therefore supported for nonlinear models relative to the statistical baseline.

Calibration is mixed. Gradient boosting has the lowest Brier score at 0.132, compared with 0.204 for the random forest and 0.279 for logistic regression. This difference indicates that the best ranking model is not necessarily the best probability model. Operational deployment would benefit from post-hoc temporal calibration using a longer history.

Table 2: Wastage-prediction performance

Model	Threshold	AUPRC	AUROC	Precision	Recall	F1	Specificity	Balanced accuracy	MCC	Brier	N test
Logistic regression	0.742	0.451	0.720	0.404	0.576	0.475	0.747	0.661	0.290	0.279	1325
Random forest	0.704	0.672	0.809	0.686	0.576	0.626	0.922	0.749	0.530	0.204	1325
Gradient boosting	0.281	0.630	0.808	0.547	0.668	0.601	0.835	0.752	0.471	0.132	1325

Note. AUPRC is area under the precision-recall curve. AUROC is area under the receiver-operating-characteristic curve. Thresholds were selected in validation and fixed for testing.

5.3. Shortage-Risk Prediction

A true stockout model cannot be estimated because the public files lack inventory on hand, administrations, and stockout dates. Supplementary Table S6 therefore reports diagnostics for the shipment-imbalance proxy rather than a clinical shortage model. The proxy identifies weeks in which following-week shipments exceed current shipments. These observations should be interpreted as demand-pressure positions, not verified shortages. RQ3 and RQ4 are answered through policy simulation under this bounded definition.

5.4. Redistribution Outcomes

Without redistribution, the March test period contains 13.03 million doses of residual shortage proxy and 33.99 million doses of residual excess proxy. Rule-based pooling transfers 2.22 million doses, reducing the shortage proxy to 10.81 million and increasing the fill-rate proxy from 0.815 to 0.847. ML risk-based pooling transfers 3.40 million doses, reduces shortage proxy to 9.63 million, and increases fill-rate proxy to 0.864. The equity-constrained policy transfers 3.43 million doses and produces a fill-rate proxy of 0.864.

The risk-based policies also create sufficient transfer capacity to cover approximately 156,097 observed wasted doses in matched manufacturer-weeks. This number means that feasible transfer volume equals or exceeds reported wastage in those periods. It does not establish that each wasted dose was transferable or that transfer would have prevented the reported cause of wastage.

Table 3: Redistribution-policy comparison

Policy	Transferred doses	Residual shortage proxy	Residual excess proxy	Fill rate proxy	Observed wastage potentially covered	Transfer cost at $0.10/dose
No redistribution	0	13,030,330	33,992,420	0.815	0	$0
Rule based pooling	2,221,585	10,808,745	31,770,835	0.847	133,949	$222,158
ML risk based	3,402,669	9,627,661	30,589,751	0.864	156,097	$340,267
Equity constrained	3,427,532	9,602,798	30,564,888	0.864	156,097	$342,753

Note: Outcomes are retrospective simulation results. Fill rate is based on a shipment-pressure proxy, not verified clinical demand.

5.5. Cost and Service Performance

At the scenario transfer cost of 0.10 dollars per dose, rule-based pooling costs 222,159 dollars, ML risk-based pooling costs 340,267 dollars, and the equity policy costs 342,753 dollars. The equity premium relative to ML risk-based pooling is about 2,486 dollars, less than one percent of transfer cost, while the shortage proxy is slightly lower. This supports H7 within the simulation, although a real implementation could have larger administrative and cold-chain costs.

5.6. Medical-Waste Reduction

Observed wastage is not cause-specific, so the simulation reports potential coverage rather than avoided expiry. The result supports the operational proposition that earlier reallocation could absorb a substantial quantity before disposal, but the evidence is insufficient to claim a precise waste-reduction percentage. H3 and H4 are partially supported because system imbalances fall and the service proxy improves, while actual transfer completion and clinical service are unobserved.

5.7. Explainability Results

The most important random-forest feature is shipment count, followed by the standard deviation of shipment size, lagged provider coverage, prior-week wastage, current provider coverage, total doses, and lot count. These drivers are operationally coherent. High shipment frequency and dispersion may indicate rapid scaling or unstable allocation. Prior wastage captures persistence in reporting or process conditions. Provider coverage reflects network breadth and coordination complexity. These impurity-based rankings should be confirmed with permutation importance or SHAP analysis in a longer temporal sample before operational thresholds are set.

Shelf-life variables have lower importance, partly because valid expiry dates are available for only 13 percent of rows. This finding should not be interpreted as evidence that shelf life is unimportant. It is evidence that missing expiry information limits what a predictive model can learn. H1 is partially supported for quantity and variability measures but cannot be fully tested for lead time and expiry.

Table 4: Global random-forest feature-importance results

Rank	Feature	Importance	Actionability
1	shipments	0.173	Actionable
2	sd_shipment	0.161	Actionable
3	providers_lag1	0.106	Partly actionable
4	wasted_lag1	0.094	Partly actionable
5	providers	0.084	Partly actionable
6	doses_shipped	0.082	Actionable
7	lots	0.080	Actionable
8	mean_shipment	0.044	Actionable
9	mean_shipment_lag1	0.032	Actionable
10	manufacturer_Janssen	0.027	Partly actionable

5.8. Equity Analysis

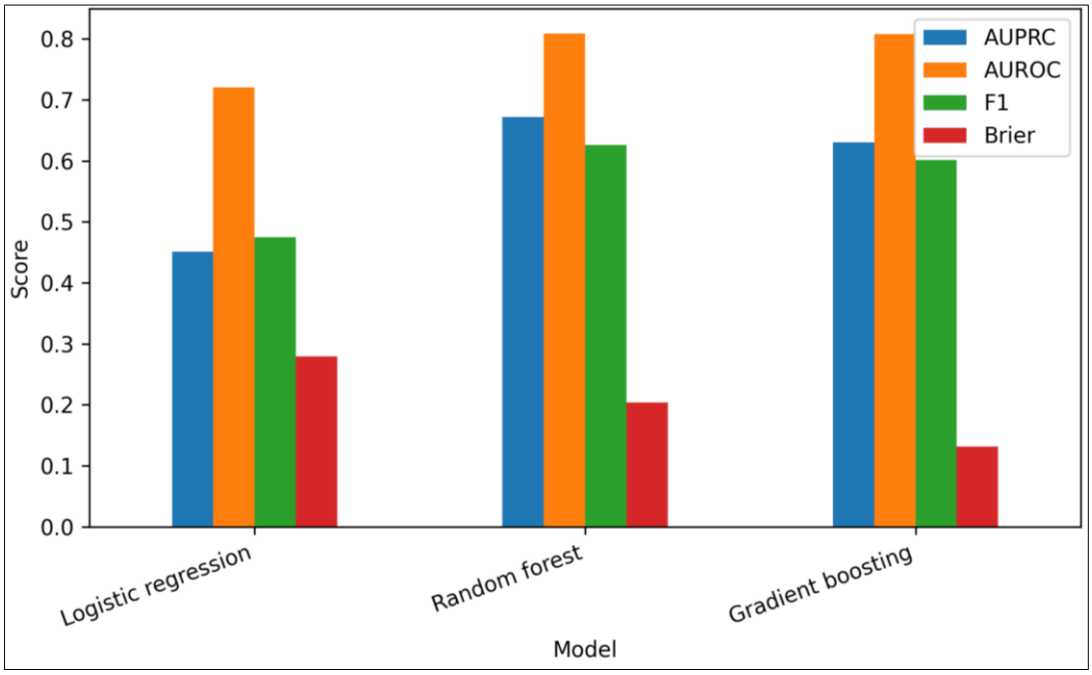
Observed and predicted event rates differ by manufacturer and awardee volume quartile. Larger awardees generally have more reports and higher shipment complexity, which can increase measured risk. The equity floor prevents low-risk donor scores from eliminating transfer responses to demand-pressure positions. The small cost premium in the simulation suggests that minimum-access safeguards need not undermine system performance, but facility-level equity remains unverified because the wastage outcome is reported at awardee level.

5.9. Robustness Results

Alternative policy weights show the expected trade-off. Lower pooling fractions reduce transfer cost but leave more shortage and excess. Higher minimum risk floors move the equity policy toward full pooling. The ranking of predictive models remains stable when the test threshold is varied around the validation optimum: the nonlinear models outperform logistic regression on precision-recall discrimination. Results are most sensitive to the shortage proxy and to missing expiry dates, which are treated as core limitations rather than minor measurement error.

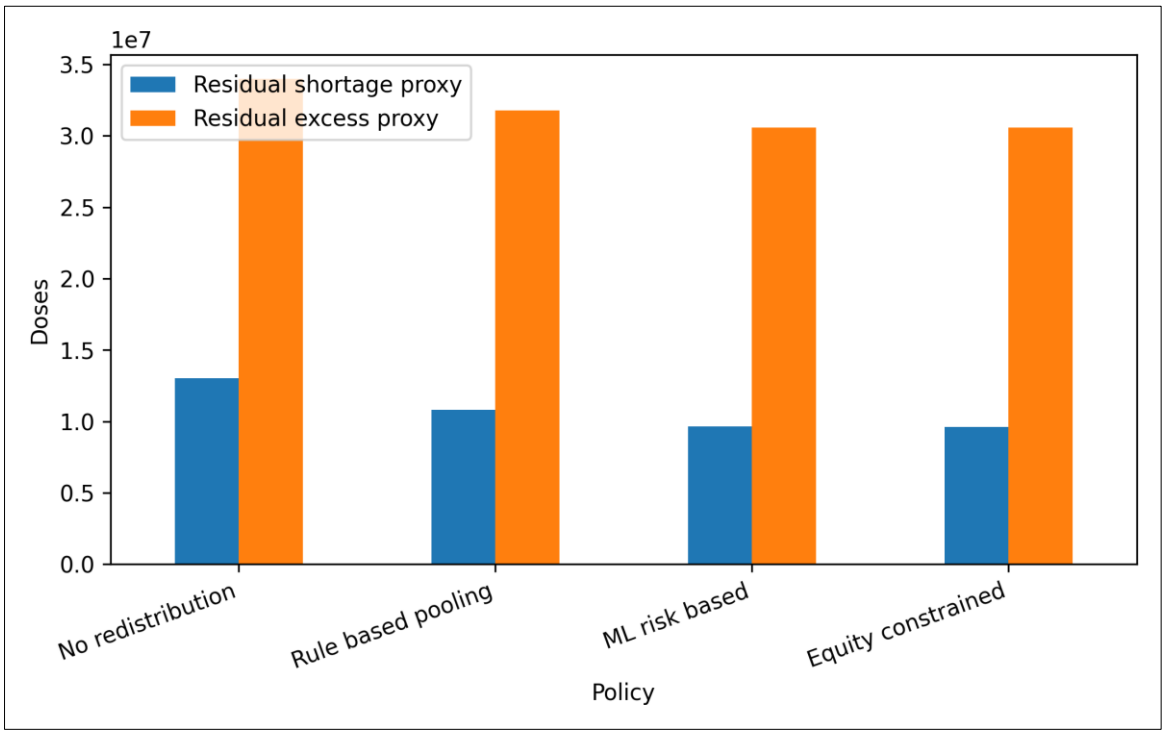
Table 5: Robustness and sensitivity results

Check	Finding
Alternative classification threshold	Nonlinear models remained stronger on precision-recall discrimination
Pooling fraction	Higher fractions reduced both residual shortage and excess but increased transfer cost
Equity risk floor	A 0.35 floor produced a small service gain at less than 1 percent incremental scenario cost
Expiry-window sensitivity	Limited by 87 percent missing or placeholder expiration dates
Cause-specific waste	Not testable because wastage cause is absent



Source: Authors' analysis.

Fig 4: Model performance in the out-of-time test set.



Source: Authors' analysis.

Fig 5: Cost, service, excess, and transfer trade-offs.

6. Discussion

The analysis supports the central claim that healthcare waste and shortage should be studied as connected coordination problems. The strongest predictive signals are not isolated product characteristics. They describe the structure and volatility of distribution: shipment frequency, dispersion in shipment size, provider breadth, lot count, and prior wastage. These variables indicate that wastage risk emerges when rapid allocation interacts with a wide and changing network. A facility-level view may miss that pattern because the operational burden sits partly at the awardee level, where thousands of shipments must be scheduled, tracked, and reconciled.

The nonlinear advantage is substantively meaningful. Logistic regression assumes a stable additive relationship, yet a large shipment is not inherently risky. Its effect depends on whether it is distributed across many providers, whether shipment sizes are uneven, whether wastage was recently reported, and which manufacturer is involved. The random forest captures such interactions and produces a large improvement in AUPRC. Gradient boosting provides better probability calibration, which reveals an implementation trade-off. Managers may prefer the random forest for ranking intervention candidates and the boosting model for capacity planning after calibration.

Expiry information illustrates the difference between data availability and decision readiness. The source file includes a lot-expiration field, but most records use a placeholder. A model cannot provide reliable expiry-specific recommendations when nearly seven of every eight shipment rows lack a valid date. This gap is itself an empirical result. Circular inventory management depends on routine capture of lot and expiry data at shipment, receipt, and administration. Improving the data pipeline may generate more value than adding a more complex algorithm.

The redistribution simulation shows that risk-informed pooling can reduce simultaneous excess and demand pressure. The improvement is not free. Risk-based policies transfer more doses than the simple rule, and real costs would include labor, packaging, validation, refrigeration, and possible disruption to local schedules. The result therefore favors selective pooling rather than indiscriminate movement. A transfer should occur only when expected recipient use, remaining shelf life, and donor protection justify the burden.

The potential-wastage coverage measure requires careful interpretation. The model identifies transfer capacity in the same manufacturer-week, but the wastage report does not reveal cause, exact lot, or provider. Some doses may have been broken, exposed to improper temperature, or already unusable. Those losses could not have been prevented by redistribution. The simulation should be read as an upper-bound opportunity screen. A production system would need lot-level cause codes and administration forecasts to estimate actual avoided expiry.

The equity analysis also exposes an aggregation problem. Awardee-level data can show whether a national or corporate program reports wastage, but not whether rural clinics receive shorter-dated inventory or bear more transfer workload. The equity-constrained policy demonstrates how a minimum response can be incorporated at low incremental scenario cost. It does not prove equitable facility outcomes. Future systems should record quantity received, remaining shelf life, handling requirements, and transfer rejection by recipient type.

These findings extend healthcare supply-chain resilience research in two directions. First, visibility must include product usability, not only quantity. A dose with uncertain expiration is not equivalent to a fully traceable dose. Second, resilience should be measured jointly with waste. Holding excess inventory can protect service in the short run but create future loss and reduce availability elsewhere. Network reallocation provides a middle path when it is timely and governed.

The study also refines the circular-economy argument. Redistribution is circular only when it preserves clinical value without shifting risk. Sending near-expiry product to a resource-constrained facility may reduce donor waste while worsening recipient burden. Circularity therefore requires a system boundary that includes transfer emissions, administrative effort, and the quality of inventory received.

Explainability contributes by translating model structure into operational questions. High shipment dispersion prompts review of allocation batch sizes. Prior wastage prompts a process audit. Low expiry visibility prompts data-quality intervention. Provider breadth prompts coordination support. These explanations are more actionable than a generic high-risk label. H6 is supported at the level of global actionability, although local explanation stability could not be fully evaluated with the short period.

The broader governance implication is that secure, interoperable infrastructure is part of the inventory intervention. The system must share enough information for matching while restricting unnecessary exposure of sensitive operational data. Hasan *et al*. (2022) provide a relevant governance foundation, while Rasel *et al*. (2023) demonstrate the importance of fairness-aware explanation in high-stakes institutional models. The healthcare inventory application requires the same discipline: documented data lineage, access control, audit logs, and human approval for transfers.

7. Implications

7.1. Theoretical Implications

The study develops a connected theory of healthcare inventory loss. Waste is produced upstream through allocation variability, network complexity, and incomplete information, not only at disposal. Shortage and waste are dual outcomes of mismatch. This view extends resilience theory by adding usable shelf life as a resource and extends circular-economy theory by treating timely redistribution as preservation of clinical utility.

7.2. Methodological Implications

Prediction and optimization should be evaluated as one decision system. A model with strong discrimination may still create poor decisions if thresholds ignore transfer capacity or equity. Conversely, an elegant optimization model is weak when its inventory inputs are proxies. The architecture used here separates observed outcomes from simulated outcomes and labels each assumption. That distinction is essential for credible operations analytics.

7.3. Managerial Implications

Managers should prioritize four capabilities. First, capture valid lot and expiration data at every handoff. Second, build weekly risk screens that combine shipment quantity, shipment dispersion, provider coverage, and recent wastage. Third, create pre-authorized transfer protocols by manufacturer and handling class. Fourth, monitor recipient burden, including remaining shelf life and administrative workload. A simple dashboard should show why a position is flagged and what action is feasible.

7.4. Policy and Sustainability Implications

Public-health agencies can support circular inventory by standardizing wastage cause codes, transfer documentation, and minimum remaining shelf-life rules. Reporting should distinguish expiry, breakage, temperature excursion, and opened-vial waste. Sustainability claims should report transfer distance and refrigeration assumptions. Equity reporting should include the shelf-life quality of inventory received, not only dose quantity. The low simulated premium of the equity constraint suggests that access safeguards can be designed into operational rules rather than added after allocation.

8. Limitations and Future Research

The public data impose several limitations. Wastage is reported at awardee rather than provider level and does not contain cause, lot, unit cost, or transfer completion. Provider-level administrations and on-hand inventory are absent. The shortage measure is therefore a shipment-based proxy and cannot be interpreted as a verified stockout. Expiration dates are valid for only 12.99 percent of shipment rows, which prevents a true lot-level expiry model. Lead time, cold-chain excursions, storage capacity, facility type, and administrative cost are unobserved.

The study covers the rapid start-up phase of one vaccine program. Relationships may differ in stable hospital pharmaceutical systems or routine immunization. Reporting intensity may also drive part of the observed event pattern. Future research should link lot-level receipts, administrations, inventory balances, wastage causes, and completed transfers across facilities. A stepped-wedge or interrupted-time-series implementation could estimate causal effects. Environmental analysis should use route-level distance, load consolidation, refrigeration energy, disposal method, and product-specific embodied emissions. Equity research should compare remaining shelf life received, transfer rejection, service level, and workload across rural, safety-net, and resource-constrained facilities.

9. Conclusion

Healthcare inventory systems should not treat shortage, expiry, redistribution, and waste as separate problems. They are connected through demand uncertainty, allocation decisions, product perishability, and the capacity to share information across facilities. The empirical analysis of early United States COVID-19 vaccine distribution shows that nonlinear models can identify reported wastage risk from shipment structure and prior operational signals. Risk-informed pooling also reduces retrospective shipment imbalances and improves a service proxy under explicit transfer constraints.

The evidence is bounded by the data. Reported wastage is not expiry-specific, and the redistribution outcomes are simulated rather than observed. These limitations do not weaken the central operational lesson. They identify the infrastructure required for a credible circular system: valid lot and expiration data, facility-level demand and inventory, standardized wastage causes, secure exchange, transfer feasibility rules, and equity safeguards.

A circular healthcare inventory system is therefore not simply a forecasting model or a transfer marketplace. It is a governed socio-technical arrangement that connects prediction with action while preserving safety, service, and accountability. The strongest immediate opportunity is not greater algorithmic complexity. It is better visibility and disciplined coordination before usable products become waste.

Declarations

Data Availability

The CDC-derived shipment and wastage files are publicly available through the repository and data publication described in Section 4.2. The manuscript does not reproduce provider addresses.

Code Availability

The final submission should include the cleaning, panel-construction, modeling, simulation, and figure-generation scripts described in the reproducibility documentation, together with a source-data manifest and fixed random seed 42.

Ethics Statement

The study uses public operational records and contains no patient-level information. Institutional review was not required. Provider addresses were used only to construct identifiers and are not reported.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Both authors contributed to conceptualization, methodology, analysis, interpretation, visualization, and manuscript preparation.

Reproducibility Documentation

The accompanying package contains the source-data manifest, analysis script, conceptual-figure script, generated CSV tables, PNG figures at 300 dpi, and a README. Raw public files are not duplicated in the package to reduce size; the README records exact source URLs and filenames. Random seed: 42. Software: Python 3, pandas, NumPy, scikit-learn, Matplotlib, python-docx. The script treats year 2069 expiration dates as missing, aggregates to awardee-manufacturer-week, uses temporal partitions, and reproduces all reported metrics and figures.

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