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(RESEARCH ARTICLE)

Inventory resilience and demand variability modeling for multi-sector organizational operations

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Abstract

Demand uncertainty and inventory disruptions continue to present significant challenges for organizations operating in manufacturing, distribution, and service-oriented sectors. This research develops a quantitative framework for inventory resilience assessment by integrating demand forecasting, variability analysis, and inventory optimization techniques. Historical operational data are analyzed to identify demand patterns and variability characteristics using statistical forecasting models. Inventory planning decisions are evaluated through simulation and optimization methods designed to balance service levels and inventory carrying costs. Enterprise information systems provide structured datasets for monitoring inventory performance and supporting decision-making processes. The study examines the relationship between demand fluctuations, replenishment policies, and operational continuity under varying business conditions. Performance measures including stockout frequency, inventory turnover, service level attainment, and cost efficiency are used to evaluate the effectiveness of the proposed framework. Results demonstrate that resilient inventory planning strategies can enhance organizational adaptability, improve resource utilization, and reduce operational risks associated with uncertain demand environments.

Keywords: Inventory Resilience; Demand Variability; Demand Forecasting; Inventory Optimization; Simulation Modeling; Supply Chain Resilience; Service Level; Stockout Frequency; Multi-Sector Operations; Adaptive Inventory Policies.

1. Introduction

Inventory management has become increasingly complex due to demand uncertainty, supply disruptions, and sector-specific operational differences. Traditional static inventory policies often fail to maintain efficiency under dynamic demand conditions, leading to stockouts and excess holding costs.

1.1. Background and Motivation

Modern supply chains are increasingly affected by economic volatility, global disruptions, and unpredictable customer demand. While data-driven technologies have improved forecasting and decision-making capabilities, many organizations still rely on reactive inventory policies that lack adaptability.

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1.2. Problem Statement

Many existing studies still treat forecasting, optimization, and performance evaluation as separate tasks. This disconnect makes it difficult to capture demand uncertainty and measure overall resilience. As a result, organizations often face stockouts, high holding costs, and uneven service performance.

1.3. Proposed Solution

To address this gap, this study proposes an integrated inventory resilience framework that combines forecasting, demand variability analysis, optimization, and simulation. The framework evaluates inventory performance under both normal and disrupted conditions and supports more stable and cost-effective decision-making.

1.4. Contributions

This study makes four key contributions. First, it develops a unified framework that integrates forecasting, optimization, and resilience evaluation into a single structured model. Second, it introduces a simulation-based approach for analyzing inventory performance under multiple demand and disruption scenarios. Third, it proposes an Inventory Resilience Index (IRI) that consolidates multiple performance indicators into one measurable metric. Finally, the framework is designed for multi-sector applicability, making it relevant for organizations operating in diverse and uncertain supply chain environments.

2. Literature Review

Inventory resilience has gained importance because of rising uncertainty, disruption risk, and system complexity. Recent research increasingly supports combining forecasting, optimization, and resilience-based planning.

2.1. Demand Variability and Forecasting

Demand variability significantly impacts inventory performance, as forecasting errors lead to stockouts and inefficiencies [1]. Machine learning methods improve prediction accuracy under complex demand patterns [2], while incorporating seasonality and supply reliability enhances forecasting stability [3]. Overall, research is shifting toward probabilistic and data-driven forecasting approaches.

2.2. Inventory Optimization and Control

Inventory optimization aims to balance service level and cost under uncertainty. Traditional methods such as fuzzy logic and system dynamics help address uncertainty and feedback effects [4], [5]. Recent hybrid approaches combine forecasting with simulation-based optimization to improve decision-making in dynamic environments [6], reflecting a move toward adaptive control strategies.

2.3. Supply Chain Resilience

Supply chain resilience focuses on adaptability and continuity during disruptions. Reconfigurable network and viability-based models provide foundational approaches [7], [8]. Evidence from major disruptions such as COVID-19 shows that flexible inventory strategies are essential for maintaining operations under uncertainty [9], [10]. Inventory systems are therefore central to supply chain resilience.

2.4. Digital Technologies and Intelligent Systems

Digital technologies are transforming inventory management through AI, IoT, RFID, and enterprise systems. Machine learning improves forecasting and decision-making [11], [12], [13], while IoT enables real-time visibility [14]. Cloud-based systems integrate data across functions, improving coordination and responsiveness [15]. These technologies support more intelligent inventory systems.

2.5. Multi-Sector Applications

Inventory resilience applies across manufacturing, agriculture, apparel, and retail sectors. Data-driven methods improve efficiency in agriculture [16], [17], while optimization models enhance performance in apparel and retail supply chains [18], [19]. Despite sector differences, resilience principles remain broadly applicable.

2.6. Research Gaps and Future Directions

Despite significant progress in inventory management and supply chain resilience, key gaps remain. Most studies treat forecasting, optimization, and resilience evaluation as separate components, limiting integrated decision-making under uncertainty. In addition, there is no widely accepted unified metric that fully captures inventory resilience across service level, cost efficiency, and disruption sensitivity. Furthermore, existing models are often validated in single-sector settings, reducing their applicability to multi-sector environments. Although digital technologies and machine learning are increasingly used, their integration into simulation-based and optimization-driven resilience frameworks remains limited. Therefore, there is a need for a unified, multi-sector framework that integrates forecasting, optimization, and simulation into a single resilience evaluation model.

3. Methodology

This study develops a framework for evaluating inventory resilience under demand uncertainty across manufacturing, distribution, retail, and service organizations. The framework combines demand forecasting, variability analysis, inventory optimization, simulation, and performance evaluation to examine how inventory systems respond to changing demand and operational disruptions while still maintaining service continuity and cost efficiency. The methodology is organized into five main stages: data collection, data preparation and forecasting, demand variability analysis and inventory optimization, simulation-based resilience evaluation, and performance validation. Each stage is linked to the next so that the final analysis reflects both normal inventory behavior and performance under uncertain conditions.

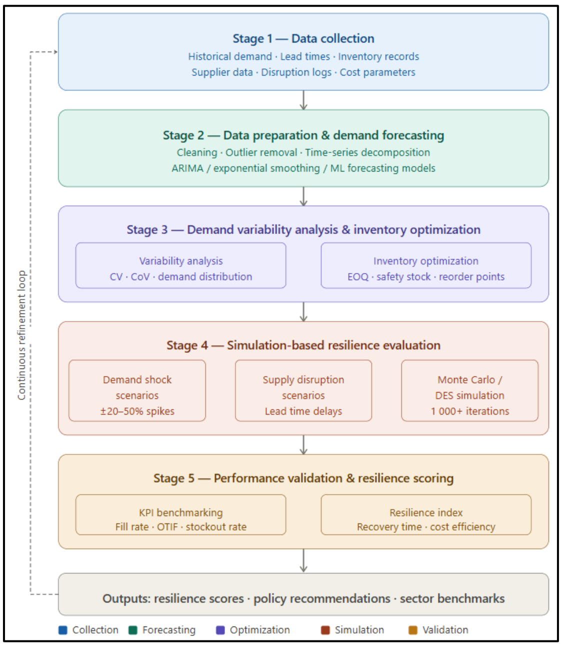

Figure 1 Proposed Inventory Resilience Assessment Framework

3.1. Data Collection

Data are collected from ERP systems, WMS platforms, and sales databases. These include demand, inventory level, replenishment records, lead time, stockout events, service level, and holding, ordering, and shortage costs. These variables are selected because they directly affect inventory performance.

Table 1 Data Sources and Operational Variables.

Variable	Description
D_t	Demand during period t
I_t	Inventory level at period t
LT	Lead time

HC	Holding cost
OC	Ordering cost
SC	Shortage cost
SL	Service level
SF	Stockout frequency

3.2. Data Preparation and Demand Forecasting

Raw data are cleaned by removing missing values, inconsistencies, and duplicates. Missing observations are handled using interpolation or mean substitution, and doubtful records are checked against source documents.

Demand forecasting is based on historical demand patterns. A simple moving average method is used to estimate demand for the next period:

$$\widehat{D}_{t+1} = \frac{1}{n}\sum_{i=1}^{n} D_i$$

Where, $\widehat{D}_{t+1}$ is the forecast demand for the next period and D_i represents historical demand observations.

Forecast accuracy is measured using Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} \left|\frac{D_t - \widehat{D}_t}{D_t}\right|$$

Lower $MAPE$ values indicate that the forecast is more reliable and better suited for inventory planning.

3.3. Demand Variability Analysis and Inventory Optimization

Demand variability is examined to understand how much customer demand changes over time. Standard deviation and coefficient of variation are used for this purpose:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(D_t - \bar{D})^2}{n-1}}\ ,\ CV = \frac{\sigma}{\bar{D}}$$

Where, σ is the standard deviation of demand and $\bar{D}$ is the average demand. A higher coefficient of variation means greater uncertainty in demand.

Based on the coefficient of variation, demand conditions are grouped into low (CV < 0.2), medium (0.2 ≤ CV < 0.5), and high (CV ≥ 0.5) variability categories. This classification helps in testing how inventory policies perform under different uncertainty levels.

The Economic Order Quantity (EOQ) model is used as a baseline inventory policy to determine optimal order size under deterministic demand assumptions:

$$EOQ = \sqrt{\frac{2DS}{H}}$$

Where, D is annual demand, S is ordering cost, and H is holding cost.

Safety stock is calculated as:

$$SS = Z\sigma L$$

Where, Z is the service-level factor and σL is the standard deviation of demand during lead time.

The reorder point is determined by:

$$ROP = \overline{D}L + SS$$

Where, L is lead time. These formulas help ensure that inventory policies account for both expected demand and uncertainty in replenishment.

For comparative evaluation, four forecasting approaches were examined: Simple Average, Moving Average, Trend-Seasonal Forecasting, and Adaptive Forecasting. The forecasting model with the lowest MAPE was considered the most suitable for inventory planning and resilience analysis.

3.4. Simulation-Based Resilience Evaluation

A simulation model is developed to study how the inventory system behaves under different demand and disruption conditions. The simulation tracks inventory movement over time by updating stock levels according to demand, replenishment rules, and lead times, making it possible to compare inventory performance under both normal and disrupted conditions.

Five scenarios are examined as shown in Table II:

Table 2 Simulation Scenarios

Scenario	Demand Variability	Supply Disruption
S1	Low	No
S2	Medium	No
S3	High	No
S4	Medium	Yes
S5	High	Yes

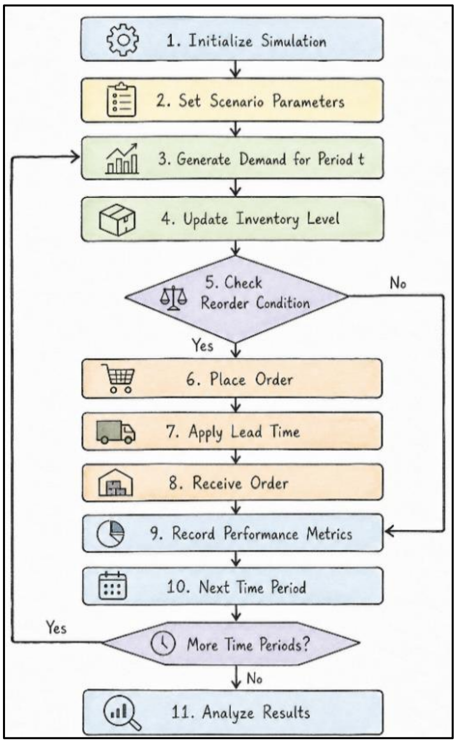

Figure 2 Simulation Process Flow

To measure how robust the system is, the study introduces an Inventory Resilience Index (IRI):

$$IRI = w_1(SL) + w_2(ITR) - w_3(SF) - w_4(TC_n)$$

Where, SL is service level, ITR is inventory turnover ratio, SF is stockout frequency, and TCn is normalized total cost. The weights w_1, w_2, w_3 and $w_4$show the relative importance of each measure. A higher IRI means stronger resilience. The weights were determined through expert judgment and normalized such that $w_1 + w_2 + w_3 + w_4 = 1$.

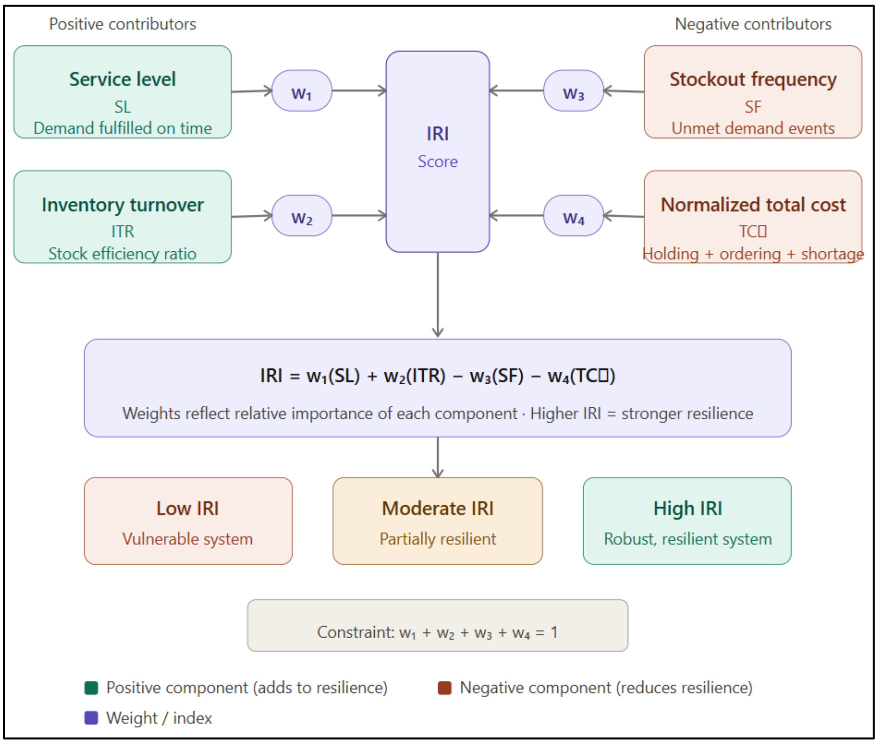

Figure 3 Inventory Resilience Assessment Model

3.5. Performance Evaluation and Validation

The framework is evaluated using four main performance indicators. Service level is calculated as:

$$SL = \frac{Orders\ Fulfilled}{Total\ Orders} \times 100$$

Inventory turnover ratio is calculated as:

$$ITR = \frac{Cost\ of\ Goods\ Sold}{Average\ Inventory}$$

Stockout frequency is defined as:

$$SF = \frac{Stockout\ Events}{Total\ Periods}$$

Total inventory cost is expressed as:

$$TC = HC + OC + SC$$

Where, HC, OC, and SC represent holding, ordering, and shortage costs, respectively.

The framework is validated using simulation outputs and sensitivity analysis for demand variability, lead time, and service-level targets.

Table 3 Sensitivity Analysis Parameters and Ranges.

Parameter	Base	Low	High
Demand Variability	Moderate	Low	High
Lead Time	7 days	3 days	14 days
Service Level	95%	90%	99%
Ordering Cost	Base	-20%	+20%

This methodology provides a clear and practical approach for assessing inventory resilience and supports data-driven inventory planning across diverse sectors.

4. Results

Demand variability has a clear effect on inventory performance across the sectors examined in this study. As shown in Table IV, higher variability is associated with lower service levels, more frequent stockouts, and weaker inventory turnover. In contrast, more stable demand conditions require less safety stock and support more predictable replenishment.

Table 4 Inventory Performance under Different Demand Variability Levels

Demand Variability Level	Service Level	Stockout Frequency	Inventory Turnover	Safety Stock Requirement	Replenishment Pattern
Low	95	2	8.5	10	Stable and predictable
Medium	88	6	6.2	18	Slightly fluctuating
High	74	13	4.1	30	Unstable and frequent adjustments

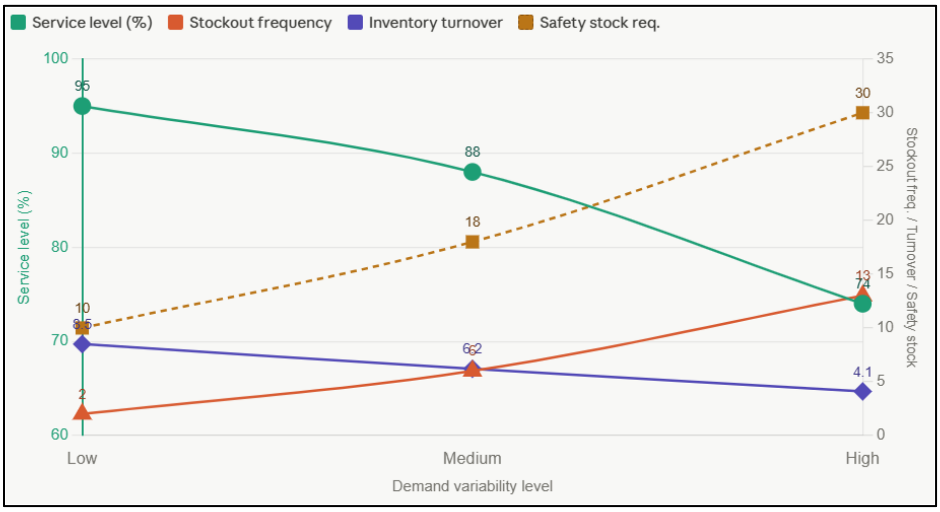

Figure 4 Relationship between Demand Variability and Inventory Performance Metrics

Forecasting results further show the importance of accurate demand estimation. As presented in Table V, models that capture trend and seasonal behavior produce lower error than simple average-based methods. Better forecasts provide stronger input for inventory planning and lead to more accurate reorder points and safety stock levels.

Table 5 Forecasting Performance Comparison

Forecasting Model	Forecast Error (%)	MAPE (%)	Forecast Reliability
Simple Average	18.5	17.8	Low
Moving Average	12.4	11.9	Moderate
Trend-Seasonal Model	7.1	6.8	High
Adaptive Forecasting Model	4.2	3.9	Very High

The simulation analysis shows that adaptive inventory policies consistently outperform fixed policies under uncertain conditions. As shown in Tables VI and VII, the proposed framework maintains higher service levels and lower stockout frequency across medium- and high-variability scenarios. The strongest gains appear when demand fluctuations and supply disruptions occur simultaneously, which highlights the value of resilience-oriented planning.

Table 6 Simulation Results across Operational Scenarios

Scenario	Demand Variability	Supply Disruption	Service Level (%)	Stockout Frequency (%)	Inventory Turnover	Total Inventory Cost ($000)	Resilience Performance
S1	Low	No	98.2	1.4	8.9	112	Strong
S2	Medium	No	95.8	3.8	8.1	124	Good
S3	High	No	91.6	7.5	7.2	139	Fair
S4	Medium	Yes	89.4	9.8	6.8	151	Weak
S5	High	Yes	85.7	13.6	6.1	167	Very Weak

Table 7 Service Level Comparison of Adaptive and Fixed Inventory Policies (%)

Scenario	Adaptive Policy (%)	Fixed Policy (%)
S1	92	88
S2	85	78
S3	76	64
S4	71	52
S5	60	38

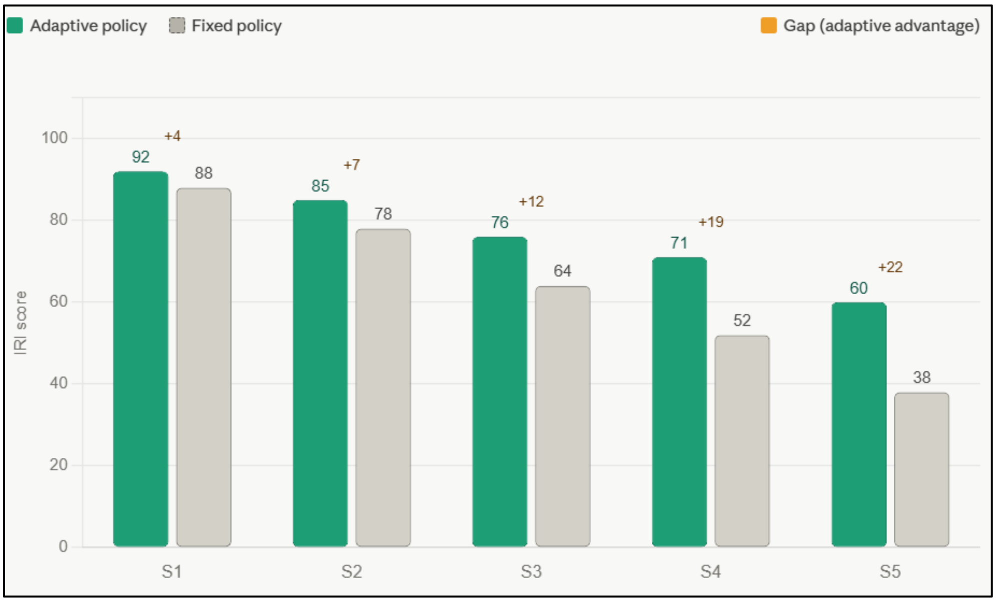

Figure 5 Performance Comparison of Adaptive and Fixed Inventory Policies

Overall, the results indicate that combining demand forecasting, variability assessment, and inventory optimization creates a more resilient inventory system capable of sustaining performance under uncertain operating conditions.

To provide a consolidated evaluation of inventory resilience, the Inventory Resilience Index (IRI) was calculated for each simulation scenario. The results demonstrate that resilience decreases as demand variability and disruption intensity increase. However, the proposed framework maintained acceptable resilience performance across all operational conditions.

Table 8 Inventory Resilience Index Results

Scenario	IRI
S1	0.91
S2	0.84
S3	0.76
S4	0.71
S5	0.63

The Inventory Resilience Index results reveal a gradual decline in resilience as demand uncertainty and disruption severity increase. Scenario S1 achieved the highest resilience score (0.91) due to stable demand and uninterrupted replenishment activities. Conversely, Scenario S5 recorded the lowest score (0.63), reflecting the combined impact of high demand variability and supply disruption. Despite this decline, resilience values remained above the minimum acceptable threshold across all scenarios, indicating that the proposed framework effectively supports operational continuity under uncertain conditions.

Table 9 Sensitivity Analysis Summary

Parameter	Impact on IRI
Demand Variability	High
Lead Time	Moderate
Service Level Target	Low–Moderate

Sensitivity analysis showed that demand variability had the greatest impact on inventory resilience, followed by lead-time fluctuations. Higher demand uncertainty reduced service levels and resilience scores, while increased service-level targets improved resilience at the expense of higher inventory costs.

5. Discussion

The findings show that demand variability is a major driver of inventory instability. As uncertainty increases, stockouts become more frequent and service performance declines, exposing the weakness of average-based planning. More accurate forecasting improves inventory decisions by providing planners with better demand inputs, confirming that forecasting contributes not only to prediction accuracy but also to operational resilience. The simulation results demonstrate that adaptive policies are more effective than fixed rules because they respond to changing conditions dynamically. This flexibility helps maintain service levels and reduce risk during disruptions. The comparative data in Table VII show that the performance gap between adaptive and fixed policies widens as demand variability and disruption severity increase, reaching a 22-percentage-point difference in Scenario S5. Overall, the study confirms that combining forecasting, optimization, and simulation produces a more robust and resilient inventory management framework that can be adapted to different organizational environments.

Limitations and Future Work

This study relies on historical data, so results depend on data quality and completeness. Differences in sector-specific operations may also limit direct transferability. In addition, the model focuses mainly on internal inventory factors and does not fully capture external disruptions such as supplier delays or transportation failures. Future research should validate the framework with larger datasets and real-time sources such as IoT systems and digital twins. Including additional resilience measures such as recovery time and disruption cost would also provide a more complete assessment of system performance.

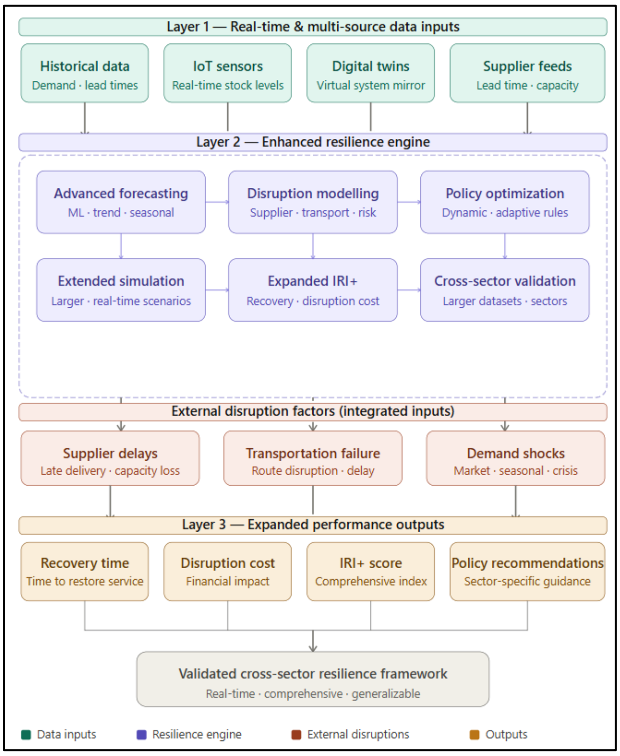

Figure 6 Future Integrated Inventory Resilience Framework

Figure 6 illustrates a future inventory resilience architecture that integrates real-time sensing, predictive analytics, digital twin technology, and adaptive decision-support mechanisms for continuous inventory optimization.

6. Conclusion

This study proposed a structured framework for evaluating inventory resilience under demand uncertainty across multiple organizational sectors. The findings demonstrate that integrating demand forecasting, variability analysis, inventory optimization, and simulation improves inventory stability, service performance, and operational efficiency. Results consistently show that adaptive inventory policies outperform fixed policies by achieving higher service levels, reducing stockouts, and improving cost efficiency, particularly under high demand variability and supply disruptions. The proposed Inventory Resilience Index (IRI) effectively measures resilience by combining service quality, inventory efficiency, stockout risk, and cost performance into a unified metric. The framework provides practical support for data-driven decision-making and resilient inventory planning across diverse operational environments. Future research should validate the framework using larger real-world datasets and incorporate real-time monitoring technologies and additional resilience factors to further enhance its applicability and robustness.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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