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Artificial Intelligence-Based Early Warning System for Detecting Hospital Supply Shortage Risk Using Procurement Logs, Consumption Rates, Vendor Delay Patterns, Procedure Forecasts, and Inventory Thresholds

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Abstract

Unpredictable hospital supply shortages can compromise patient care, interrupt clinical workflows, and force costly emergency purchasing. These shortages are often preceded by signals embedded in procurement activity, consumption patterns, vendor behavior, and inventory movement. Current hospital inventory practices frequently depend on manual review, static reorder points, and retrospective averages. These methods cannot adequately synthesize predictive data from procurement systems, clinical demand sources, supplier feeds, and inventory thresholds. This article proposes an AI-based early warning system that ingests procurement logs, real-time consumption rates, vendor delay patterns, procedure forecasts, and inventory thresholds. The system computes a dynamic shortage risk score for each monitored hospital supply item. The framework includes data ingestion pipelines, a machine learning prediction engine, a vendor risk assessor, a procedure-to-supply demand mapper, and an alert dashboard. These components convert fragmented operational data into actionable shortage risk intelligence. The system would provide actionable lead time for proactive reordering, substitution planning, vendor escalation, and redistribution across hospital locations. It could also learn from historical shortage events to support more resilient supply chain planning. A predictive, AI-augmented supply chain could transform hospital materials management from reactive replenishment to anticipatory risk mitigation. Such a system would support safer, more resilient, and more efficient hospital logistics.

Keywords Artificial intelligence, Hospital supply chain, Shortage prediction, Procurement analytics, Vendor delay, Inventory management

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Introduction

Hospital supply shortages create operational risk because essential products such as medications, PPE, blood products, implants, and surgical consumables are embedded in everyday clinical care. Predictive work on drug shortages shows that shortage events can be modeled as operational signals rather than treated only as administrative surprises [1]. Inventory optimization research similarly indicates that static stock policies may be insufficient when demand patterns and replenishment conditions shift [2]. In hospital pharmacy and clinical logistics, shortages can force substitutions,

procedural delays, emergency procurement, and additional staff coordination, making shortage detection a patient safety and operations problem rather than only a purchasing problem [3].

Many shortage signals are available before a stock-out occurs, but they are distributed across procurement, inventory, vendor, and clinical systems. Procurement logs may reveal delayed receipts and repeated backorders, while consumption records may show accelerating demand at the point of care [4]. Vendor reliability and lead-time variability can alter risk even when current inventory appears adequate, because replenishment may not arrive before a threshold is breached [5]. Digitalization studies in healthcare supply chains show that data fragmentation across ERP, inventory, and clinical systems can limit the ability of managers to see these signals together [6].

Artificial intelligence can support hospital supply chain teams by fusing these disconnected signals into a dynamic early warning framework. AI-based healthcare supply chain research has emphasized that machine learning can support prioritization and decision-making when operational data are heterogeneous and time-sensitive [7]. Demand forecasting studies in blood supply chains demonstrate how clinical and operational information can be integrated to anticipate future supply needs [8]. Broader analytics research also suggests that healthcare supply chain decisions benefit when predictive systems combine data integration, operational context, and interpretable decision support [9].

This article proposes an AI-based early warning system that predicts hospital supply shortage risk by integrating procurement logs, consumption rates, vendor delay patterns, procedure forecasts, and inventory thresholds. The system is designed as a conceptual AI Systems/Frameworks contribution rather than an experimental report, so it does not present performance results or numerical claims. Its core thesis is that shortage risk should be computed dynamically at the item level, with procurement and vendor signals treated as supply-side predictors and procedure forecasts treated as demand-side predictors. This framing extends recent work on AI-enabled healthcare supply chains and intelligent pharmaceutical inventory management toward an integrated hospital early warning architecture.

Background

Hospital supply chain vulnerabilities

Hospital supply chains are vulnerable because they must maintain product availability while controlling cost, waste, storage space, and supplier complexity. The COVID-19 pandemic exposed how fragile medical product supply lines can become when global demand surges and supplier capacity becomes constrained [10]. Research on healthcare supply chain resilience shows that hospitals require visibility, redundancy, and adaptive coordination rather than reliance on lean inventory practices alone [11]. Evidence from pandemic-era healthcare logistics further suggests that resilience depends on the ability to detect supply stress early and coordinate responses before disruption reaches the bedside [12].

Procurement and consumption data in hospitals

Procurement and consumption data provide complementary views of shortage risk because purchasing records show intended replenishment while consumption records show actual clinical use. Purchase orders, receipt dates, substitutions, cancellations, and partial deliveries can reveal supply-side friction, while automated cabinets, operating room documentation, and manual charge capture can reveal demand-side pressure [13]. ERP adoption studies indicate that hospital supply chain data become more useful when procurement and inventory workflows are digitally connected rather than maintained in isolated systems [6]. However, healthcare supply chain analytics research also shows that data quality, item standardization, and integration remain persistent barriers to predictive use [9].

Vendor performance and lead-time uncertainty

Vendor performance is a central predictor of shortage risk because current inventory levels are only safe if replenishment is reliable. Pharmaceutical supply chain reliability research shows that disruptions can arise when supplier lead times

vary, orders are delayed, or product availability becomes uncertain [5]. Drug shortage reviews further indicate that backorders and procurement delays can propagate through hospital pharmacy operations and reduce the effectiveness of standard inventory controls [4]. A hospital early warning system should therefore convert vendor delivery history, current shipment status, and recent late-order patterns into item-level risk features rather than treating vendor performance as background information.

Procedure forecasts and clinical demand drivers

Clinical demand is shaped by procedure schedules, patient census, service-line activity, and specialty-specific supply preferences. Blood product forecasting research demonstrates that future demand can be better anticipated when inventory decisions incorporate clinical activity and historical usage patterns [14]. Integrated forecasting and inventory ordering studies for red blood cells show that operational planning can link demand forecasts to inventory decisions rather than treating them as separate tasks [8]. For surgical supplies and implants, the same logic implies that scheduled procedures and preference-card histories should inform expected consumption before products are removed from inventory.

AI for supply chain and inventory prediction

AI can support healthcare supply chain prediction by learning complex relationships among demand, inventory, procurement, and supplier variables. A prioritized multi-task learning approach for healthcare supply chains illustrates how machine learning can address multiple operational tasks within a shared predictive structure [15]. Research on AI success factors in healthcare supply chain management highlights the importance of data readiness, organizational adoption, and decision-support integration [7]. Intelligent inventory management approaches for pharmaceutical products further show that predictive methods can help manage perishable or clinically sensitive stock where shortages and overstock both create risk [15].

System Overview

High-level architecture

The proposed system continuously ingests procurement orders, receipt records, consumption data from electronic cabinets and manual charge capture, vendor shipment feeds, procedure schedules, and current inventory counts. Healthcare supply chain digitalization research supports this architecture because visibility across operational data streams is necessary for timely logistics decision-making [13]. The system time-aligns these data at the item level so that each monitored supply has a current risk profile based on inventory position, recent use, replenishment status, and expected future demand. Its output is not a deterministic declaration of shortage but a dynamic risk signal that materials management staff can review before a critical threshold is reached.

Figure 1 presents the proposed AI-based early warning architecture for converting procurement, consumption, vendor, procedure, and inventory signals into interpretable item-level shortage risk alerts.

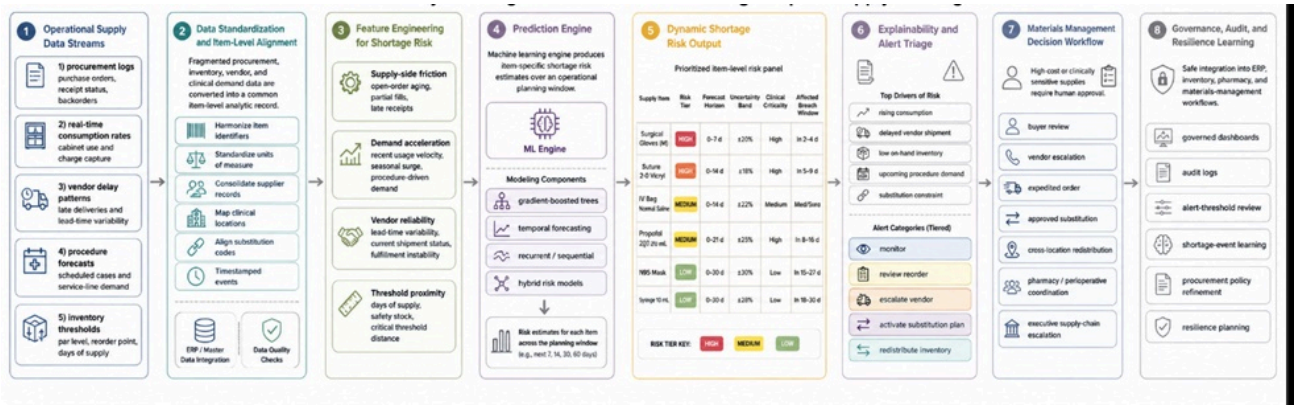


Figure 1. AI based early warning architecture for detecting supply risk

Core inputs and outputs

The core inputs include item-level procurement history, location-specific consumption rates, vendor on-time delivery metrics, daily procedure forecasts by clinical service, and inventory levels relative to par and reorder thresholds. Digital ERP-enabled supply chain studies suggest that these inputs must be standardized across item identifiers, units of measure, supplier records, and clinical locations before they can support reliable decision-making [6]. The outputs include a prioritized list of items at risk, an explanation of the contributing factors, and recommended actions such as reorder review, vendor escalation, substitution planning, or redistribution. AI decision-making research in healthcare supply chains supports this kind of prioritization because human teams need interpretable risk ranking rather than unfiltered predictive output [16].

Design principles

The system is designed to be real-time, predictive, adaptive, transparent, and embedded in materials management workflow. Real-time monitoring is needed because consumption and shipment status can change faster than periodic manual inventory review can capture. Predictive adaptability is important because resilience research shows that healthcare supply chains face changing disruption patterns during pandemics, natural disasters, and supplier instability [11]. Transparency is equally important because supply chain managers must understand whether a risk score is driven by rising consumption, delayed vendors, low stock, or upcoming clinical demand before choosing an intervention [17].

Data Sources and Feature Engineering

Procurement logs and vendor delay features

Procurement logs contain purchase order dates, ordered quantities, supplier identifiers, requested delivery dates, receipt dates, backorder notices, substitutions, cancellations, and outstanding order status. Predictive drug shortage research shows that pharmacy and procurement data can support shortage risk modeling when they are structured into usable operational features [1]. Vendor delay features could include recent late deliveries, lead-time variability, repeated partial fills, open-order aging, and supplier-specific fulfillment instability. Supply-chain-informed forecasting in the pharmaceutical industry demonstrates that upstream supply information can improve demand and risk interpretation when combined with downstream operational data [18].

Consumption rates and inventory thresholds

Consumption rates describe how quickly supplies are used across clinical locations, including operating rooms, inpatient units, pharmacies, supply rooms, and automated dispensing systems. Hospital pharmacy inventory optimization research shows that reorder policies should reflect both current stock and the rate at which demand is depleting available inventory

[2]. Inventory threshold features would include on-hand quantity, par level, safety stock, reorder point, days of supply, and recent acceleration in usage. Structural modeling of hospital pharmacy inventory performance also indicates that inventory practices affect broader supply chain performance, so the early warning system should treat threshold breach risk as both a clinical and operational signal [19].

Procedure forecasts and clinical demand signals

Procedure forecasts translate scheduled clinical activity into expected item consumption by linking cases, service lines, preference cards, clinical protocols, and historical usage records. Reviews of blood demand forecasting show that novel computational methods can connect clinical demand patterns with supply planning in ways that are relevant beyond transfusion services [20]. Smart blood bank forecasting research similarly illustrates how machine learning can support demand anticipation when historical use is combined with structured operational data [21]. In the proposed framework, scheduled procedures, emergent workload patterns, patient census, and seasonal clinical demand would be converted into forward-looking demand features for each monitored item.

Table 1 maps each major hospital supply-chain data domain to the shortage-risk features, predictive contribution, and operational interpretation required for item-level early warning.

Table 1. Data-to-Risk Feature Architecture for an AI-Based Hospital Supply Shortage Early Warning System

Data domain	Operational source examples	Shortage-risk signal captured	Derived feature logic	Why this adds predictive value	Human interpretation for materials-management teams
Procurement activity	Purchase orders, order dates, requested delivery dates, receipt dates, cancellations, substitutions, partial deliveries, outstanding order status	Whether replenishment is progressing normally or showing early friction	Open-order age, delayed receipt count, partial-fill frequency, cancellation history, substitution frequency, backorder recurrence	Detects supply-side stress before inventory is fully depleted	“The item is at risk because ordered stock is not arriving as expected.”
Real-time consumption	Automated supply cabinets, operating room documentation, pharmacy dispensing systems, manual charge capture, supply-room issue logs	Whether demand is accelerating faster than routine inventory assumptions	Recent usage velocity, consumption acceleration, location-specific depletion rate, abnormal demand spike, rolling days of supply	Identifies demand-side pressure that static reorder points may miss	“The item is being consumed faster than its current replenishment plan can support.”
Vendor reliability	Supplier identifier, historical delivery performance, shipment feeds, late-order history,	Whether expected replenishment is uncertain even when current	Lead-time variability, recent vendor delay score, fulfillment reliability index, current	Adjusts risk upward when replenishment depends on an	“The current stock may be insufficient because the vendor has

	fulfillment instability, lead-time records	stock appears adequate	shipment status, supplier-specific risk flag	unreliable or delayed vendor	become unreliable.”
Procedure and clinical demand forecasts	Procedure schedules, service-line forecasts, preference cards, historical item use by case type, patient census, seasonal demand indicators	Whether upcoming clinical activity will increase near-term item demand	Procedure-to-item demand estimate, expected case-driven consumption, service-line demand forecast, surge-adjusted demand estimate	Converts future clinical workload into forward-looking supply need	“Upcoming procedures are expected to consume this item before replenishment arrives.”
Inventory position and thresholds	On-hand quantity, par level, reorder point, safety stock, critical threshold, location-level stock balances	How close the item is to clinically or operationally unsafe inventory levels	Threshold proximity, days of supply, safety-stock breach probability, location-level imbalance, criticality-weighted stock status	Links predictive risk to operationally meaningful inventory boundaries	“The item is close to its critical threshold and requires review.”
Substitution and clinical criticality	Approved substitutes, formulary or product equivalents, implant constraints, pharmacy restrictions, perioperative preference constraints	Whether shortage consequences can be mitigated through substitution or redistribution	Substitution availability flag, clinical criticality tier, restricted-use indicator, service-line dependency score	Distinguishes manageable shortages from high-consequence supply risks	“This alert requires escalation because substitution options are limited.”
Historical shortage outcomes	Prior stock-outs, emergency purchases, cancelled or delayed procedures, vendor escalation records, redistribution events	Which patterns previously preceded real shortage events	Shortage-event label, near-miss label, emergency procurement trigger, alert-to-action history	Allows the model to learn from past shortage and near-shortage episodes	“This pattern resembles earlier shortage events and should not be ignored.”
Governance and workflow metadata	Alert thresholds, reviewer actions, override reasons, procurement authority rules, audit logs	Whether alerts are actionable, explainable, and aligned with policy	Alert acceptance rate, override frequency, review time, action completion status, threshold adjustment history	Supports continuous refinement and prevents unmanaged automation	“The system learns which alerts are useful while preserving accountability.”

Shortage Risk Prediction Engine

Model selection and rationale

The prediction engine could use gradient-boosted tree models, recurrent neural networks, temporal hierarchy models, or hybrid forecasting approaches depending on the data structure and interpretability requirements. Temporal hierarchy modeling for hospital pharmacy demand suggests that time-structured forecasting can help represent demand at different aggregation levels [22]. Cross-temporal deep learning research in supply chain forecasting further supports the conceptual value of models that learn patterns across time scales and operational hierarchies [23]. Gradient-boosted models may be especially appropriate when procurement, vendor, inventory, and procedure-derived features are tabular and heterogeneous, while sequential models may be useful when recurrent consumption and disruption patterns are central.

Input feature vector and preprocessing

For each monitored item and time interval, the system would create a feature vector that combines procurement status, inventory position, consumption velocity, vendor reliability, procedure-derived demand, and threshold proximity. Predictive drug shortage modeling highlights the need to transform raw pharmacy and supply data into features that capture both current operational state and historical shortage patterns [3]. Preprocessing would address missing receipt dates, inconsistent units of measure, item substitutions, delayed manual entries, censored demand during stock-outs, and sparse labels for rare shortage events. Because data quality affects model usefulness, healthcare supply chain analytics research suggests that preprocessing should be treated as a core system function rather than a one-time technical step [9].

Output: shortage risk score and forecast horizon

The model would output a shortage risk score indicating whether an item is likely to fall below its critical inventory threshold within an operational planning window. Nomogram-based drug shortage prediction work illustrates how shortage risk can be represented as a decision-support estimate rather than a simple binary inventory status [24]. The score should be paired with uncertainty information and escalation logic so that buyers can distinguish routine monitoring from urgent review. In an AI Systems/Frameworks article, this output should be understood conceptually: the system could support earlier action, but its risk thresholds and alert rules should be evaluated prospectively before clinical or procurement automation is trusted.

Integrating Procedure Forecasts and Clinical Demand Signals

Mapping procedures to supply items

Procedure-to-supply mapping would connect scheduled clinical activity with the items likely to be consumed during each case, using historical preference cards, procedure protocols, and actual usage patterns. Blood demand forecasting research shows that clinical activity can be translated into operational demand signals when historical usage is modeled alongside expected care needs [20]. Machine learning applications in hospital pharmacy similarly suggest that supply chain optimization benefits when item demand is linked to clinical workflows rather than treated only as a purchasing trend [25]. In the proposed system, procedure-specific demand estimates would be probabilistic because actual consumption may vary by surgeon preference, patient complexity, substitution availability, and emergent intraoperative needs.

Temporal alignment of procedure schedules and consumption

Procedure schedules must be aligned with procurement lead times because some supplies need to be available before the clinical event occurs rather than replenished after consumption is recorded. Temporal forecasting work in hospital

pharmacies supports the idea that demand should be represented across planning horizons rather than as a single retrospective average [22]. Cross-temporal supply chain forecasting further indicates that models can learn relationships between near-term demand signals and longer replenishment cycles when data are structured appropriately [23]. The early warning system would therefore compare upcoming clinical demand with vendor lead time, open order status, and current inventory so that risk is detected while an intervention is still operationally feasible.

Accounting for surge events and seasonal patterns

Hospital supply demand can shift during influenza seasons, trauma surges, pandemic waves, or service-line disruptions, so the model should include seasonal and disruption-sensitive signals where available. Research on healthcare supply chain resilience during COVID-19 shows that disruption can rapidly change the relationship between routine consumption and actual supply needs [11]. Sustainability-oriented healthcare supply chain forecasting also suggests that predictive systems should account for changing operational conditions rather than assuming stable historical patterns [26]. The proposed system would use surge indicators, seasonality features, and recent abnormal consumption trends to adjust risk estimates when ordinary clinical demand patterns no longer reflect current conditions.

Interpretability and Actionable Alerts

Explaining shortage risk to supply chain managers

Interpretability is essential because hospital supply chain managers need to know why an item is flagged before deciding whether to reorder, substitute, expedite, or investigate. AI success-factor research in healthcare supply chain management emphasizes that organizational adoption depends not only on model capability but also on whether users trust and understand the decision-support output [7]. The system could explain risk by showing that the score is driven by a combination of rising consumption, delayed vendor shipments, low on-hand inventory, and upcoming procedure demand. Drug shortage prediction studies further support the value of presenting risk in a form that can guide operational review rather than leaving users with an opaque model output [24].

Tiered alerting and decision support

Tiered alerting would help prevent alert fatigue by separating routine monitoring from situations requiring procurement review or urgent escalation. Healthcare analytics research indicates that predictive systems are more useful when they are embedded in decision workflows and connected to actionable operational responses [17]. For low-risk items, the system would continue monitoring; for moderate-risk items, it could recommend reorder review; and for high-risk items, it could prompt vendor escalation, substitution planning, interdepartmental redistribution, or executive supply chain review. Recent drug shortage prediction work also suggests that machine learning outputs should be translated into practical shortage-management actions rather than treated as abstract probability estimates [27].

Integration into Hospital Materials Management Workflow

Embedding in supply chain dashboards and ERP systems

The early warning system would be most useful if risk scores were embedded into existing ERP, inventory, pharmacy, and materials management dashboards rather than presented as a separate analytics product. ERP-focused research shows that digital supply chain systems can improve hospital logistics when they connect procurement, inventory, and operational cost information within routine workflows [6]. Healthcare supply chain digitalization studies also emphasize that analytic benefits depend on integration with the systems already used by buyers, inventory managers, and clinical supply coordinators [13]. In practice, the dashboard would allow staff to filter risk by item criticality, clinical location, vendor, service line, and recommended intervention.

Automated responses and workflow triggers

Automation should be governed by clinical criticality, financial controls, and organizational policy because not every shortage risk signal should trigger an automatic purchase. Intelligent inventory management research in pharmaceutical supply chains supports the use of AI-driven recommendations while recognizing that human oversight remains important for clinically sensitive or high-cost items [28]. For pre-authorized routine supplies, the system could generate a purchase requisition or task when risk crosses a defined threshold; for high-impact items, it would route the alert to a designated reviewer. This balance between automation and manual review would allow the system to support speed without removing accountability from materials management, pharmacy, or perioperative leadership.

Table 2 translates AI-generated shortage risk tiers into governed operational responses, oversight requirements, safeguards, and evaluation priorities.

Table 2. Alert-to-Action Governance Framework for AI-Generated Hospital Supply Shortage Risk Signals

Alert tier	Risk interpretation	Typical model drivers	Recommended operational response	Required human oversight	Governance safeguard	Evaluation focus
Routine monitoring	Item remains above risk threshold, but signals continue to be tracked	Stable consumption, reliable vendor performance, adequate days of supply, no near-term procedure-driven demand spike	Continue monitoring through standard dashboard review	No immediate approval required beyond routine materials-management review	Maintain visibility without unnecessary alerts	Low false-alert burden and stable dashboard usability
Reorder review	Item shows early warning signs but has not reached urgent risk	Rising consumption, declining days of supply, approaching reorder point, modest vendor delay	Buyer reviews reorder status, confirms par level, checks open purchase orders, verifies location-level stock	Materials-management buyer or inventory coordinator	Require explanation display before action is taken	Timeliness of review and relevance of moderate-risk alerts
Vendor escalation	Risk appears driven by unreliable or delayed replenishment	Late shipment, partial fill, open-order aging, vendor lead-time variability, repeated backorder notices	Contact vendor, request updated delivery estimate, identify alternate supplier, consider expedited order	Buyer plus procurement lead for high-value or critical items	Document vendor communication and escalation rationale	Reduction in preventable stock-outs linked to delayed orders
Demand-driven	Risk appears driven by	Procedure forecast,	Confirm substitute	Clinical supply	Restrict substitution	Appropriateness of substitution

substitution planning	upcoming clinical demand rather than procurement failure	scheduled cases, service-line surge, preference-card demand, seasonal utilization increase	availability, notify pharmacy or perioperative leaders, prepare approved alternatives	coordinator, pharmacy leader, or perioperative representative	recommendations to approved clinical policies	recommendations and clinician acceptance
Cross-location redistribution	System detects location-level imbalance before enterprise-wide shortage	One location has low stock while another has surplus, uneven consumption, local surge pattern	Transfer inventory between units, campuses, pharmacies, or procedure areas	Materials-management supervisor or logistics coordinator	Track redistribution source, destination, and downstream impact	Improvement in local availability without creating secondary shortages
Urgent shortage mitigation	Item is likely to breach a critical threshold within the planning window	Low on-hand quantity, high consumption velocity, delayed replenishment, limited substitutes, high clinical criticality	Activate urgent procurement, vendor escalation, executive notification, substitution protocol, and clinical communication	Senior materials-management, pharmacy, perioperative, or supply-chain leadership	Require auditable approval for emergency purchasing or high-impact substitution	Lead time gained before stock-out and reduction in emergency purchasing
Automation-eligible replenishment	Low-risk routine item meets predefined policy criteria for automated task generation	Reorder threshold reached, reliable vendor, low clinical sensitivity, approved purchasing rules	Generate purchase requisition or task for reviewer confirmation	Human review may be limited but should remain auditable	Automation restricted to approved item classes and spending limits	Accuracy of automation triggers and override frequency
Post-alert learning and threshold refinement	Alert outcome is used to improve future system performance	Alert accepted, alert dismissed, stock-out occurred, emergency purchase avoided, false alert identified	Update alert thresholds, retrain model when appropriate, refine item criticality and vendor-risk rules	Governance committee or designated supply-chain analytics owner	Preserve audit trail and review model changes prospectively	Calibration, alert usefulness, user trust, and workflow sustainability

Evaluation Strategy

Predictive accuracy

Evaluation should assess whether the system can identify shortage risk in a way that is clinically and operationally useful, without relying on unsupported claims in the conceptual framework. Predictive drug shortage studies provide a methodological basis for evaluating discrimination, calibration, and the practical usefulness of shortage risk scores [1]. Hospital pharmacy prediction research also indicates that rare shortage events require careful validation because ordinary accuracy measures may not reflect decision value [3]. The proposed system should therefore be evaluated prospectively against existing reorder practices, with attention to whether risk scores are reliable enough to guide earlier human review.

Usability and alert burden

Usability evaluation should examine whether materials management teams understand the alerts, trust the explanations, and can respond without excessive cognitive or administrative burden. AI adoption research in healthcare supply chains shows that success depends on organizational readiness, human workflow alignment, and perceived usefulness rather than model design alone [7]. Digitalization research similarly indicates that supply chain analytics must fit real operational routines if they are to improve decision-making rather than create parallel work [13]. Alert burden should therefore be assessed through user feedback, review time, alert relevance, and the extent to which the system supports timely action without overwhelming staff.

Operational and financial impact

Operational evaluation should consider whether the system supports fewer stock-outs, fewer emergency purchases, better substitution planning, and more balanced inventory levels after implementation. Inventory optimization research indicates that stock policies should balance shortage prevention against overstock, waste, and carrying cost [2]. Hospital pharmacy inventory performance research further suggests that inventory management affects broader supply chain outcomes, including operational efficiency and cost performance [19]. Because this article is conceptual, these outcomes should be framed as evaluation targets for future pilot studies rather than as reported results.

Limitations

Data fragmentation and adoption

A major limitation is that hospital supply chain data often reside in fragmented systems with inconsistent item identifiers, delayed updates, incomplete consumption capture, and variable integration between procurement, inventory, pharmacy, and clinical platforms. Healthcare supply chain analytics research shows that data quality and interoperability problems can restrict the value of predictive models even when relevant operational data exist [9]. ERP adoption studies also indicate that digital infrastructure varies across hospitals, which means the same early warning framework may require different implementation strategies across organizations [6]. Adoption may also be slowed if buyers, pharmacy staff, perioperative leaders, and finance teams disagree on alert thresholds, substitution rules, or purchasing authority.

External supply shocks and unpredictable events

The system cannot fully predict sudden external shocks such as supplier bankruptcy, geopolitical disruption, natural disasters, regulatory action, or unexpected manufacturing failures before those events generate observable signals. COVID-19 supply chain research shows that healthcare organizations can face severe disruptions that exceed normal planning assumptions and rapidly change product availability [10]. Resilience studies nevertheless suggest that visibility and early coordination can improve preparedness once disruption signals appear in procurement, vendor, or consumption

data [12]. The model should therefore be understood as an early warning and decision-support system, not as a guarantee that all shortage events can be anticipated or prevented.

Conclusion

The proposed AI-based early warning system reframes hospital supply shortage risk as a dynamic prediction problem involving procurement logs, consumption rates, vendor delay patterns, procedure forecasts, and inventory thresholds. Instead of relying only on static reorder points or retrospective consumption averages, the system would continuously synthesize operational signals into item-level risk scores. This architecture would help materials management teams identify emerging shortage risk before inventory falls below a critical threshold. It would also support more coordinated decisions across procurement, pharmacy, perioperative services, and clinical supply operations.

The key strength of the framework is its multi-source data fusion. Procurement records indicate whether replenishment is progressing as expected, consumption data show how quickly supplies are being used, vendor delay patterns reveal replenishment uncertainty, and procedure forecasts provide forward-looking clinical demand. By combining these signals, the system could generate actionable forecasts rather than isolated operational reports. Embedding these forecasts into supply chain dashboards would make shortage risk visible within the workflows where purchasing and inventory decisions are already made.

Important challenges remain before such a system could be deployed safely and effectively. Hospitals would need reliable data infrastructure, standardized item identifiers, timely vendor feeds, and clear governance for alert thresholds and automated workflow triggers. Prospective validation in live hospital supply chains would also be necessary to determine whether alerts are useful, interpretable, and operationally sustainable. Human oversight would remain essential, especially for clinically sensitive items, high-cost supplies, and situations requiring substitution approval.

Pilot implementations should be prioritized in large health systems with integrated perioperative, pharmacy, procurement, and inventory data. These environments are well suited to testing whether procedure forecasts and vendor delay patterns can improve shortage risk detection when combined with real-time consumption and inventory thresholds. Future implementations should evaluate resilience, workflow fit, procurement responsiveness, and return on investment without overstating what predictive models can guarantee. A carefully governed AI-based early warning system could help hospitals move from reactive shortage management toward anticipatory, data-informed supply chain resilience.

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