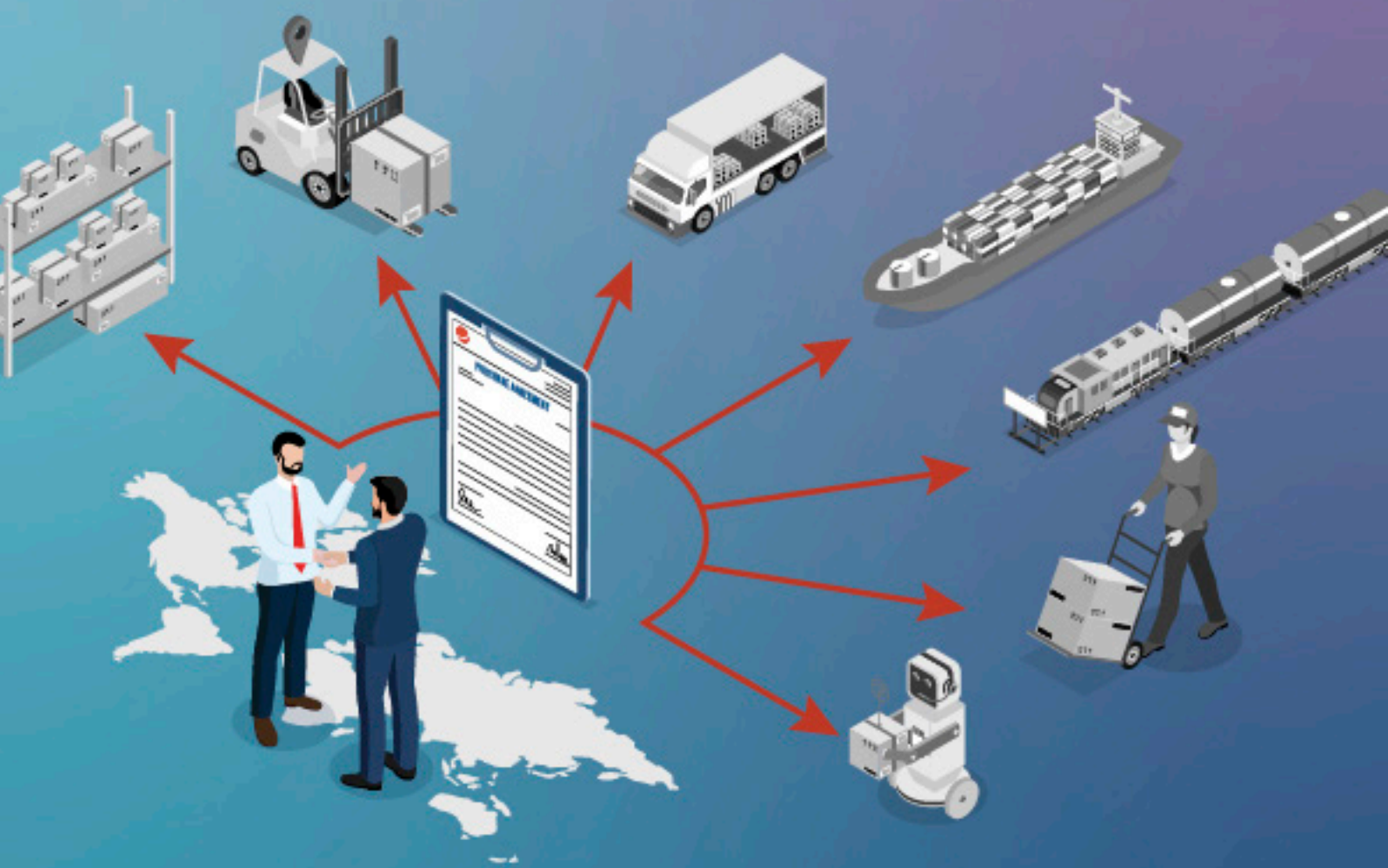




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Artificial Intelligence and Pharmaceutical Supply Chain Resilience: A Proposed Administrative Decision-Support Model for Improving Efficiency and Managing Operational Risk

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ABSTRACT

Pharmaceutical supply chains face demand uncertainty, multi-tier dependencies, strict quality controls, cold-chain requirements, and serious consequences when medicines are unavailable. Existing studies examine AI applications, supply-chain risk, resilience, visibility, and governance, but do not consistently integrate these strands into a pharmaceutical-specific administrative decision-support model. This study develops such a model through an integrative review and framework synthesis of 24 purposively selected scholarly and authoritative sources published between 1955 and 2026. Sources were chosen for their relevance to supply-chain theory, AI applications, pharmaceutical quality, risk, resilience, and governance. The synthesis identifies five findings: AI creates value as an organizational capability; visibility and data quality connect analytics with efficiency; risk sensing and scenario analysis support resilience when linked to accountable workflows; governance and human-AI collaboration shape decision quality; and pharmaceutical quality, traceability, and patient availability constrain acceptable decisions. The model's theoretical contribution is an integrated explanation linking AI capability to efficiency and resilience through visibility, risk sensing, scenario analysis, and decision quality, with data quality, digital integration, governance, and human oversight as enabling conditions. Its practical value is a decision process for translating AI outputs into accountable action while preserving professional judgment. The review does not estimate pooled effects or empirically validate the model. Future empirical research should test the framework using organizational and operational evidence.

INTRODUCTION

contract organizations, distributors, hospitals, pharmacies, regulators, procurement authorities, and patients across multiple tiers. Medicine supply therefore involves more than the physical movement of products. It requires the coordinated movement of information, quality evidence, financial commitments, and accountability. A forecasting error, supplier failure, temperature excursion, manufacturing deviation, or transport delay can raise cost and reduce service, but it can also interrupt treatment and place pressure on health institutions.

The operating environment is difficult to manage because demand and supply can change for different reasons and at different speeds. Demand may be affected by disease patterns, seasonal outbreaks, tender cycles, reimbursement rules, clinical practice, and public procurement decisions. Supply may be disrupted by manufacturing capacity, shortages of active pharmaceutical ingredients, quality investigations, transportation constraints, geopolitical events, and regulatory actions. A systematic review by Jaberidoost *et al.* (2013) shows that pharmaceutical supply chain risks arise across internal operations, suppliers, logistics, finance, regulation, markets, and political conditions. Reliability analysis further shows that supplier configuration, disruption probability, and recovery speed influence both the likelihood and duration of medicine shortages. Pharmaceutical supply chains are administrative

systems with direct consequences for public health, institutional performance, and patient confidence. They connect manufacturers, active-ingredient suppliers, (Tucker & Daskin, 2022).

Traditional planning systems often rely on periodic reports and decisions taken within separate functions. This arrangement can delay information and conceal dependencies among demand, inventory, supplier performance, production capacity, quality events, and distribution conditions. A stock dashboard may report quantity without showing supplier exposure, remaining shelf life, product criticality, or cold-chain status. The central management problem is therefore not a lack of data alone. It is the conversion of heterogeneous data into timely, reliable, and actionable information.

Artificial intelligence (AI) can support this conversion. Machine-learning models can identify nonlinear demand patterns, anomaly-detection methods can flag unusual transactions or sensor readings, optimization models can compare inventory and sourcing alternatives, natural-language processing can extract signals from notices and reports, and digital-twin methods can support disruption scenarios. Reviews of AI in supply chain management identify applications across forecasting, procurement, production, inventory, transport, and risk management (Pournader *et al.*, 2021; Toorajipour *et al.*, 2021). These applications expand analytical capacity, but a model

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does not improve a decision merely because it produces a prediction. Poor data, weak integration, unstable processes, opaque recommendations, and overreliance on automation may introduce additional risk.

The research gap lies in the connection between analytical capability and accountable administrative action. Existing studies explain important parts of the problem, including AI applications, predictive analytics, risk management, resilience, visibility, and governance. They do not consistently integrate those elements into a sector-specific decision model that reflects pharmaceutical quality requirements and the public consequences of medicine availability. The need is particularly important where decisions affect essential products, product release, supplier qualification, allocation, recall, or public procurement.

This study addresses that gap by developing an administrative decision-support model for pharmaceutical supply chains. It asks how AI capability can influence efficiency and resilience, which mechanisms carry that influence, and which organizational conditions make AI-supported decisions reliable and legitimate. The study contributes an integrated explanation in which visibility, risk sensing, scenario analysis, and decision quality connect AI capability with operational outcomes. Data quality, digital integration, governance quality, and human-AI collaboration are treated as enabling conditions rather than secondary controls. The model also extends supply chain efficiency beyond cost reduction by including quality, availability, waste, response time, and continuity of service.

LITERATURE REVIEW

Pharmaceutical Supply Chain Risk and Public Value

Supply chain risk management concerns the identification, assessment, treatment, communication, and monitoring of events that can prevent a network from meeting its objectives. Tang (2006) distinguishes recurring operational risk from disruptions that alter normal flows and require coordinated responses. In pharmaceutical systems, these risks include inaccurate forecasts, inventory imbalance, supplier quality failures, manufacturing deviations, equipment downtime, transport delays, temperature excursions, cybersecurity events, counterfeit infiltration, regulatory non-compliance, and communication failures. Risks may also propagate. A forecast error can reduce inventory protection; a supplier delay can then produce a stockout; an emergency order can rely on a less established route; and a temperature excursion can reduce the usable quantity.

Pharmaceutical supply chains differ from many consumer-product networks because product quality can deteriorate through temperature, contamination, expiry, or handling. Demand may be clinically urgent and difficult to substitute. Supplier or production changes may require regulatory review, and records must support traceability and recall. The World Health Organization (WHO, 2010) emphasizes control over procurement, storage,

handling, transportation, documentation, and quality across distribution activities. The U.S. Food and Drug Administration (FDA, 2025) similarly treats traceability and supply-chain integrity as central safeguards against illegitimate products. These requirements mean that cost, service, quality, compliance, continuity, and equity must be considered together.

Quality risk management provides a related decision discipline. The International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH, 2023) defines quality risk management as a systematic process of assessment, control, communication, and review across the product lifecycle. ISO 31000 also emphasizes integration, structured analysis, stakeholder participation, and continuous improvement in risk management (International Organization for Standardization [ISO], 2018). Both perspectives support proportional controls, documented reasoning, and review rather than a single numerical risk score.

Artificial Intelligence as an Organizational Capability

AI is used here as an umbrella term for computational methods that learn from data, recognize patterns, generate predictions, optimize choices, detect anomalies, interpret language or sensor signals, and support decisions. The term includes machine learning, deep learning, natural-language processing, optimization, expert systems, computer vision, and selected generative-AI applications. These methods are not interchangeable. A demand-forecasting model, supplier-risk classifier, optimization engine, and language model require different data, validation procedures, controls, and interfaces.

The literature presents AI in supply chain management as a portfolio of applications rather than a single intervention. Toorajipour *et al.* (2021) identify forecasting, inventory, logistics, procurement, manufacturing, and risk as major application areas. Pournader *et al.* (2021) likewise show that AI can support operational choices across the supply chain. Demand-forecasting research indicates that machine-learning methods can be useful when demand is nonlinear or influenced by multiple variables, although performance depends on data preparation, baseline selection, and the characteristics of the forecasting problem (Carbonneau *et al.*, 2008). Dauda (2026) reports that AI and analytics are linked to forecasting improvements in food and beverage supply chains when data quality and organizational maturity are adequate. Sheikh *et al.* (2025) compare machine-learning models for forecasting U.S. retail supply chains and assess forecast accuracy, inventory optimization, service reliability, and cost efficiency. These studies provide adjacent-sector evidence for the model's forecasting and efficiency pathways, but they do not directly validate pharmaceutical supply-chain outcomes.

Bounded rationality explains why analytical capability matters. Decision makers work with limited information, time, and computational capacity (Simon, 1955). A

pharmaceutical manager may need to evaluate thousands of products, suppliers, batches, lead times, quality events, and demand signals under time pressure. AI can expand the analytical search space and compare alternatives, but it cannot define organizational values or remove uncertainty. The relevant outcome is improved decision support, not the elimination of managerial responsibility. Organizational information processing theory adds that information-processing capacity must match task uncertainty and complexity. Digital integration, shared identifiers, timely transactions, analytical models, and cross-functional routines can raise that capacity. Visibility becomes a decision resource because it allows managers to see supply conditions, dependencies, and exceptions. Healthcare supply-chain research supports the connection among visibility, digital capability, environmental dynamism, and resilience (Tiwari *et al.*, 2024).

Dynamic capability reasoning further explains how organizations convert information into action. Sensing identifies demand shifts, supplier deterioration, emerging quality signals, or transportation constraints. Seizing compares response options. Reconfiguration changes suppliers, stock policies, routes, production priorities, or governance controls. Wamba *et al.* (2021) connect AI capabilities with resilience through complementary organizational resources, which supports treating AI as an embedded capability rather than an isolated technology.

Visibility Efficiency and Resilience

Supply chain visibility is the ability to observe relevant inventory, supplier, shipment, quality, demand, and location conditions across the network. Visibility does not improve performance by itself. Its value depends on whether information is timely, interpretable, and connected to a decision. Data quality is therefore foundational. Inaccurate identifiers, inconsistent units of measure, missing lead times, delayed transactions, and incomplete supplier records can produce recommendations that appear precise but are operationally wrong (Hazen *et al.*, 2014). Predictive analytics likewise requires domain knowledge and organizational processes that translate analysis into action (Waller & Fawcett, 2013).

Efficiency in a pharmaceutical setting should include forecast accuracy, order-cycle time, fill rate, inventory availability, expiry, waste, emergency procurement, transport reliability, quality deviations, and decision-response time. A policy that reduces inventory while increasing critical stockouts is not efficient in public-value terms. AI may improve efficiency by supporting demand segmentation, inventory positioning, replenishment, supplier monitoring, and exception management, but the objective function must reflect product criticality, remaining shelf life, substitution limits, and service obligations.

Resilience is the capability to prepare for disruption, absorb its effects, maintain critical service, recover operations, and learn from the event. AI can contribute through early warning, demand-supply scenarios,

supplier diversification analysis, inventory repositioning, alternative-route evaluation, and post-event learning. Baryannis *et al.* (2019) identify AI as a promising support for risk identification, assessment, and response. Ivanov and Dolgui (2020) show how digital supply-chain twins can combine data-driven and model-based analysis for disruption management. These capabilities are most useful when alerts lead to defined actions, owners, thresholds, and escalation paths.

Responsible AI Governance and Human Judgment

AI introduces model risk, automation bias, privacy exposure, cybersecurity vulnerabilities, data leakage, and dependency on vendors or infrastructure. Allocation models can also reproduce inequities if historical data or performance objectives do not reflect the needs of vulnerable facilities and patient groups. Governance is therefore part of operational design.

The National Institute of Standards and Technology (NIST, 2023) organizes AI risk management around governing, mapping, measuring, and managing risk across the lifecycle. Its generative AI profile adds concerns relating to data provenance, confabulation, information integrity, security, and human oversight (NIST, 2024). The European Union Artificial Intelligence Act applies a risk-based approach to AI obligations and reinforces the importance of documentation, transparency, monitoring, and human oversight for higher-impact applications (European Parliament and Council of the European Union, 2024).

For pharmaceutical organizations, AI governance must also align with the quality system. A model used for forecasting, allocation, anomaly detection, or supplier monitoring requires a defined intended use, data lineage, validation evidence, access control, change management, performance monitoring, user guidance, and an override process proportionate to risk. AI may flag an anomaly or prioritize an investigation, but it should not suppress a quality deviation because the predicted service benefit is large.

Human-AI collaboration links analytical output with contextual interpretation. Jarrahi (2018) argues that computational analysis and human judgment can be complementary because they address different features of organizational problems. A calibrated workflow allows the model to process data while professionals interpret ambiguity, evaluate evidence, consider ethical and regulatory consequences, and authorize action. This relationship is especially important in decisions affecting product quality, patient access, recalls, supplier qualification, or allocation equity.

Research Propositions

The reviewed literature supports six propositions. First, AI capability improves pharmaceutical supply chain efficiency and resilience when it is embedded in organizational processes. Second, visibility mediates the relationship between AI capability and operational

efficiency. Third, risk sensing and scenario analysis improve preparedness, disruption response, and recovery. Fourth, data quality and digital integration strengthen the translation of AI output into useful information. Fifth, governance quality and human-AI collaboration strengthen decision quality and responsible action. Sixth, improvements in efficiency contribute to continuity of pharmaceutical availability when quality and service constraints are maintained.

MATERIALS AND METHODS

Study Design

The study used an integrative review and framework-synthesis design. This design was selected because the research problem spans supply chain management, pharmaceutical quality, public administration, information systems, organizational theory, and AI governance. The purpose was to combine complementary forms of evidence, identify recurring mechanisms and conditions, and construct a coherent administrative model. The unit of analysis was the relationship among AI capability, decision mechanisms, enabling conditions, and pharmaceutical supply chain outcomes.

Evidence Base and Selection Criteria

Source identification followed purposive, theory-driven sampling. The evidence base contained 24 sources published between 1955 and 2026: 17 peer-reviewed scholarly works and seven authoritative standards,

regulatory instruments, or guidance documents. Foundational theory was retained where it explained bounded rationality, information processing, or organizational decision making. Recent review and empirical studies were retained where they addressed AI applications, predictive analytics, visibility, risk, resilience, pharmaceutical supply-chain conditions, or human-AI collaboration. Authoritative documents were included where they defined quality, distribution, traceability, AI governance, or risk-management requirements relevant to controlled pharmaceutical decisions.

Sources were eligible when they met three conditions: they had a traceable scholarly or institutional origin; they addressed at least one construct in the research model; and they contributed evidence about a mechanism, outcome, enabling condition, or control. Sources used only for broad technology description, unsupported commercial claims, or applications without decision or governance relevance were not treated as evidence. The mix of scholarly and authoritative sources allowed operational relationships to be considered together with quality, accountability, and public-value requirements. Two E-Palli articles were included as adjacent-sector evidence because they address AI-supported forecasting and resilience, and smart-logistics technologies and efficiency. Their U.S. retail and food-and-beverage settings inform the mechanisms but do not establish outcomes in pharmaceutical supply chains.

Table 1: Evidence base used in the integrative review

Evidence category	Number	Main analytical contribution
	8	Forecasting, visibility, pharmaceutical reliability, digital capability, and operational mechanisms
Standards, regulatory instruments, and official guidance	7	Quality risk management, distribution, traceability, AI governance, oversight, and accountability
Total	24	Integrated operational and governance evidence

Data Extraction and Synthesis

Each source was examined against a common analytical matrix. The matrix recorded the study context, relevant AI capability, decision mechanism, operational outcome, enabling condition, implementation risk, and administrative implication. Capabilities included forecasting, anomaly detection, optimization, natural-language processing, sensor analytics, and scenario analysis. Mechanisms included visibility, risk sensing, information quality, and decision comparison. Outcomes included efficiency, resilience, continuity, response speed, quality coordination, and availability. Enabling conditions included data quality, digital integration, governance, human oversight, validation, and organizational learning. The analysis proceeded in four stages. First, statements relevant to the research questions were coded into the matrix. Second, codes were grouped into recurring themes and compared across scholarly and authoritative evidence. Third, relationships were mapped to bounded rationality, organizational information processing, and dynamic capability reasoning. Fourth, the model was

refined by checking whether each proposed relationship had an identifiable mechanism, an operational implication, and a corresponding control. Apparent benefits were considered together with failure conditions so that the model would not equate technological sophistication with organizational value.

Framework Development and Analytical Integrity

Framework development used explanation building rather than statistical aggregation because the sources differed in method, context, and outcome measures. Convergent evidence was identified when different sources supported the same mechanism or condition. Differences were retained where they changed interpretation. For example, forecasting accuracy was treated as an input to a decision rather than a complete measure of performance, and visibility was treated as useful only when connected to action. The final model was checked against pharmaceutical quality and public-administration requirements to ensure that cost or speed did not override quality, traceability, continuity, or accountability.

RESULTS AND DISCUSSION

Overview of Findings

The synthesis yielded five findings. They explain how AI capability can influence pharmaceutical supply

chain outcomes and why the same technology can produce different results across organizations. Table 2 summarizes the findings, their evidence base, and their implications

Table 2: Principal findings of the framework synthesis

Finding	Evidence-based interpretation	Administrative implication
AI operates as an organizational capability	Value arises from the combination of analytical tools, data, skills, processes, and decision rights	Evaluate the complete decision system rather than model accuracy alone
Visibility connects analytics with efficiency	Timely and reliable information improves planning, coordination, and exception management	Integrate supply, inventory, quality, and logistics data before scaling automation
Risk sensing and scenario analysis strengthen resilience	Early warning and alternative evaluation improve preparation and response when alerts trigger action	Link signals to thresholds, owners, playbooks, and escalation
Governance and human-AI collaboration determine decision quality	Validation, explanation, review, and override controls shape trust and responsible use	Apply controls in proportion to the impact of the decision
Pharmaceutical constraints must be embedded in design	Quality, traceability, criticality, shelf life, and patient availability change acceptable choices	Define objectives and constraints with quality and public-value stakeholders

AI Value Is Produced by the Decision System

The first finding is that AI should be evaluated as an organizational capability rather than as a stand-alone model. Supply-chain reviews identify many technical applications, but their operational value depends on integration with business processes (Pournader *et al.*, 2021; Toorajipour *et al.*, 2021). Bounded rationality explains the contribution: AI expands the information that managers can process, while managers retain responsibility for objectives, trade-offs, and action (Simon, 1955). Dynamic capability reasoning adds that sensing produces value only when organizations can seize and reconfigure resources. This finding clarifies why predictive accuracy is an incomplete success measure. A forecast may be statistically better but operationally irrelevant if it arrives after the purchasing deadline, uses inconsistent product identifiers, ignores constrained capacity, or cannot be translated into an approved order. Likewise, an alert may be accurate but ineffective if no one owns the response. AI capability therefore includes data access, analytical competence, workflow integration, user interpretation, and management authority.

The finding is consistent with Wamba *et al.* (2021), who connect AI capability with resilience through complementary organizational resources. It extends that reasoning to pharmaceutical administration by adding quality, availability, and patient-protection constraints. The practical unit of analysis becomes the path from data to recommendation, review, action, and outcome.

Visibility and Data Quality Connect Analytics With Efficiency

The second finding is that visibility and information quality carry much of the relationship between AI capability and

efficiency. AI can combine orders, inventory, supplier performance, production capacity, shipment status, quality events, and external signals. This processing can reduce information latency and expose dependencies that separate functional reports do not show. Tiwari *et al.* (2024) support the role of visibility in healthcare supply-chain resilience, while Hazen *et al.* (2014) show that data quality is a foundational condition for predictive analytics. Dauda (2026) similarly identifies data quality and organizational maturity as conditions for AI-supported forecasting in food and beverage supply chains.

The relationship is conditional. More data do not necessarily create more visibility. Data must be accurate, complete, timely, consistent, and interpretable. A stock record without batch, shelf-life, location, quarantine, or quality status can misstate usable inventory. A supplier score without data provenance can create false confidence. Digital integration must therefore connect ERP, warehouse, procurement, manufacturing, quality, transport, and regulatory information using common definitions and controlled access.

Efficiency also requires a balanced outcome model. Forecast accuracy, fill rate, inventory days, order-cycle time, expiry, waste, emergency procurement, quality deviations, and response time should be assessed together. Carbonneau *et al.* (2008) demonstrate the potential of machine-learning forecasting, and Waller and Fawcett (2013) explain the broader role of data science in supply-chain decisions. The present synthesis shows why these capabilities should not be optimized around cost alone. A lower inventory level that increases essential-medicine stockouts transfers risk rather than improving the system. Sheikh *et al.* (2025) also assess machine-learning forecasts in relation to inventory optimization, service

reliability, and cost efficiency in U.S. retail supply chains. This adjacent-sector analysis supports evaluating models against operational measures, not forecast accuracy alone.

Risk Sensing and Scenario Analysis Strengthen Resilience

The third finding is that resilience depends on the combination of early detection and governed response. AI can classify regulatory notices, detect unusual supplier or shipment behavior, identify temperature patterns, and estimate disruption exposure. Baryannis *et al.* (2019) place AI across risk identification, assessment, and response. Jaberidoost *et al.* (2013) demonstrate the multidimensional nature of pharmaceutical supply-chain risk, and Tucker and Daskin (2022) show that network configuration and recovery speed influence shortage performance.

Risk sensing becomes useful when the organization defines thresholds, evidence requirements, accountable owners, and response playbooks. An alert should lead to a controlled decision such as supplier review, inventory repositioning, quality investigation, route change, or contingency activation. Without this link, a larger number of alerts can create noise and reduce attention to material risks.

Scenario analysis complements sensing because managers rarely know which disruption will occur. Digital-twin and simulation approaches allow decision makers to compare supplier loss, demand surge, production downtime, route interruption, or regulatory hold before committing scarce resources (Ivanov & Dolgui, 2020). The result should be expressed as a range of consequences and assumptions rather than a single certain answer. This reduces false precision and helps decision makers compare service, cost, quality, and recovery trade-offs.

Chen *et al.* (2023) show how IoT and blockchain-enabled visibility can support pharmaceutical resilience. The synthesis indicates that sensor and traceability systems require calibration, access control, data provenance, and exception procedures. An immutable record does not guarantee that the original observation was correct. Resilience therefore depends on reliable evidence and response capability, not on the presence of a technology label.

Governance and Human AI Collaboration Determine Decision Quality

The fourth finding is that governance and human-AI collaboration are productive capabilities. NIST's AI risk-management guidance emphasizes lifecycle governance, measurement, and risk treatment (NIST, 2023, 2024). The European Union's risk-based regulatory approach reinforces documentation, monitoring, transparency, and human oversight for consequential applications (European Parliament and Council of the European Union, 2024). These principles align with ISO 31000's emphasis on integrated and iterative risk management (ISO, 2018).

The pharmaceutical quality system adds a stricter operational context. ICH Q9(R1) requires risk decisions

to be grounded in scientific knowledge and patient protection, with effort and documentation proportionate to risk (ICH, 2023). WHO distribution guidance and FDA traceability requirements reinforce controlled handling and verifiable records (FDA, 2025; WHO, 2010). AI-supported recommendations must therefore have a defined intended use, an accountable owner, validated performance, change control, version history, monitoring thresholds, user guidance, and an incident process.

Human review is most important where ambiguity and consequence are high. Jarrahi (2018) explains that computational and human intelligence are complementary. A model can compare patterns and alternatives, while a professional interprets context, challenges assumptions, evaluates stakeholder consequences, and authorizes action. The appropriate design is calibrated rather than uniformly manual or automatic. Low-impact tasks may permit automated processing with monitoring. Decisions affecting product quality, patient availability, supplier qualification, recall, or allocation equity require explicit professional approval and escalation.

Trust should likewise be calibrated. Users need enough explanation to understand the drivers, assumptions, uncertainty, and limits of a recommendation. They also need the ability to record an override and its reason. Override rates, model drift, false positives, false negatives, incidents, and outcome differences across facilities or patient groups are therefore governance indicators as well as technical measures.

Pharmaceutical and Public Administration Constraints Shape Acceptable Use

The fifth finding is that pharmaceutical and public-value constraints must be designed into the model. Demand forecasting should account for product criticality, intermittent use, epidemiological signals, tenders, seasonality, and known supply constraints. Inventory optimization should consider shelf life, cold-chain conditions, substitution, service obligations, and the consequences of shortage. Supplier risk sensing should distinguish evidence of risk from a conclusion about misconduct. Quality monitoring can prioritize investigation but cannot authorize release outside validated processes.

Public administrators must also consider distributional consequences. A purchasing rule that minimizes average cost may disadvantage remote facilities or products with low commercial volume. Allocation and shortage models should therefore respect essential-medicine priorities, minimum service levels, emergency reserves, transparency duties, and equity across facilities. This extends the model from business performance to public value.

Figure 1 integrates the five findings. AI capability affects outcomes through visibility, risk sensing, scenario analysis, and decision quality. Data quality, digital integration, governance, and human-AI collaboration enable each pathway. Pharmaceutical quality and public-value requirements constrain the full decision process.

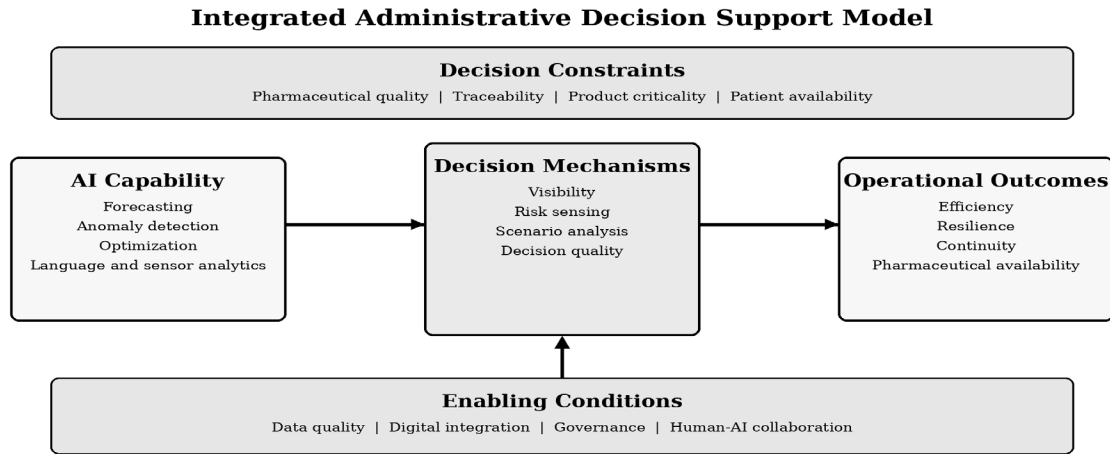


Figure 1 : Integrated AI-enabled administrative decision-support model

Table 3: Propositions derived from the integrative review

Code	Proposition
P1	AI capability positively influences pharmaceutical supply chain efficiency and resilience when embedded in organizational processes.
P2	Supply chain visibility mediates the relationship between AI capability and operational efficiency.
P3	Risk sensing and scenario analysis improve disruption preparedness, response speed, and recovery capability.
P4	Data quality and digital integration strengthen the relationship between AI capability and visibility.
P5	Governance quality and human-AI collaboration strengthen decision quality and responsible risk management.
P6	Supply chain efficiency supports continuity of pharmaceutical availability when quality and service constraints are maintained.

Implementation Implications

Implementation should begin with a decision problem rather than a technology purchase. The organization should identify a high-impact decision, establish a baseline, map the required data and workflow, define ownership, and select a proportionate analytical method. A pilot should compare the AI-supported process with a credible baseline and record errors as well as improvements. Scaling should follow only when intended use, validation, security, quality controls, training, and

monitoring are established.

Performance measurement should include model, process, and outcome indicators. Model indicators include accuracy, calibration, false positives, false negatives, and drift. Process indicators include time from signal to decision, review completion, override rate, and escalation compliance. Outcome indicators include forecast error, fill rate, critical-product availability, stockouts, expiry, emergency procurement, supplier on-time delivery, quality deviations, temperature excursions, and recovery

Table 4: Administrative roadmap for controlled AI implementation

Stage	Primary action	Evidence of completion
Data foundation	Standardize product, supplier, location, batch, quality, and transaction data	Data ownership, lineage, access control, and quality monitoring
Assisted analytics	Pilot forecasting, anomaly detection, or supplier monitoring	Baseline comparison, trained users, and documented review
Integrated decision support	Connect operational, quality, procurement, and logistics systems	Cross-functional workflow, assigned owners, and escalation rules
Resilience orchestration	Use scenario analysis and controlled optimization for disruptions	Tested contingency plans and recovery measures
Adaptive governance	Monitor performance, drift, incidents, reliance, and outcomes	Review calendar, change control, and documented learning

time. Reviewing all three levels prevents a technically strong model from being credited for an operational result it did not produce.

Limitations and Research Directions

The integrative design combines heterogeneous evidence and supports explanation building, but it does not estimate a pooled effect size. The evidence base was selected for conceptual and sector relevance rather than exhaustive coverage of every AI technique or pharmaceutical market. Regulatory expectations and AI methods also continue to evolve, so specific controls require review within the applicable jurisdiction and intended use.

The framework can be examined across pharmaceutical manufacturers, distributors, hospitals, pharmacies, logistics providers, and public procurement authorities. Longitudinal, case-based, and quasi-experimental designs can evaluate changes before and after implementation. Organizational studies can also compare AI-supported and conventional decisions using operational records. The measurement instrument in Appendix A provides a structured basis for assessing the model's constructs alongside objective indicators.

CONCLUSION

Artificial intelligence can strengthen pharmaceutical supply chain efficiency and resilience when it is embedded in an accountable administrative decision system. Its contribution lies in expanding information-processing capacity, identifying risk signals, comparing alternatives, and supporting coordinated response. The review shows that analytical capability does not act directly or uniformly. Visibility, risk sensing, scenario analysis, and decision quality explain how AI influences operational outcomes, while data quality, digital integration, governance, and human judgment determine whether that influence is reliable.

The pharmaceutical context changes the meaning of efficiency. Cost and inventory reductions must be assessed together with quality, expiry, traceability, critical-product availability, and continuity of care. Models that ignore these conditions can optimize a local measure while increasing system-wide risk. Quality and public-value requirements should therefore be encoded in objectives, constraints, approval rules, and monitoring indicators from the beginning.

The resulting model provides a practical sequence for adoption. Organizations should define the decision and its owner, establish reliable data and a measurable baseline, design the human workflow, validate the model for its intended use, pilot it under controlled conditions, and monitor operational and quality outcomes. Higher-impact decisions require stronger evidence, explanation, approval, and escalation. Continuous learning should translate model performance, overrides, incidents, and disruption experience into updated procedures, training, data definitions, and controls.

The study contributes a sector-specific framework that

connects AI capability with supply-chain outcomes without separating technology from administration. Its central conclusion is that responsible AI adoption is the design of a governed decision process linking information, professional judgment, quality requirements, operational action, and public value. This approach allows pharmaceutical organizations and public authorities to pursue efficiency while protecting resilience, accountability, and the continuity of medicines on which patients and communities depend.

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APPENDIX A MEASUREMENT INSTRUMENT

The instrument operationalizes the constructs in Figure 1 for organizational assessment. Respondents rate each statement on a five-point scale: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree. Organizational applications should follow the relevant approval, consent, confidentiality, and data-protection requirements.

Professional and Organizational Information

- Organization type: pharmaceutical manufacturer; distributor; hospital or health system; pharmacy; public procurement authority; logistics provider; other.
- Professional function: supply chain; procurement; quality; manufacturing; regulatory affairs; information systems; finance; public administration; other.
- Years of relevant experience: less than 5; 5-10; 11-15; more than 15.
- Supply-chain digital maturity: limited; developing; integrated; advanced.
- Experience with AI-supported tools: none; pilot use; regular use in one function; integrated use across functions.

AI Capability

1. The organization uses analytical models to support pharmaceutical supply-chain decisions.
2. AI tools identify patterns in demand, inventory, supplier, or logistics data.
3. AI outputs are integrated into operational planning and workflows.
4. AI-supported tools are evaluated against relevant business or quality baselines.
5. Employees receive guidance on the appropriate use and limitations of AI recommendations.

Data Quality and Digital Integration

6. Product, supplier, location, batch, and inventory data are accurately and consistently defined.
7. Relevant supply-chain data are available in time for operational decisions.
8. Data errors and missing values are identified and corrected through established procedures.
9. Supply-chain, procurement, quality, warehouse, and logistics systems exchange information effectively.
10. The organization can trace the source, transformation, and use of important data.

Visibility and Risk Sensing

11. Managers can identify the status and location of critical products and shipments.
12. The organization can identify supplier or logistics problems before they become major disruptions.
13. AI-supported alerts help prioritize operational risks according to likelihood and impact.
14. Risk information is shared across procurement, quality, operations, and senior management.
15. The organization can identify interdependencies among demand, inventory, suppliers, production, and distribution.

Scenario Analysis and Decision Quality

16. Managers can compare alternative responses to a potential disruption before acting.
17. AI-supported analysis shows assumptions, uncertainty, trade-offs, and expected consequences.
18. Decision makers can override an AI recommendation when professional judgment or quality

requirements justify it.

19. The organization records important decisions, reasons, approvals, and follow-up outcomes.

20. AI-supported information improves the timeliness and quality of supply-chain decisions.

Governance and Human AI Collaboration

21. AI use cases have clearly assigned owners and decision responsibilities.

22. Models are reviewed for accuracy, security, explainability, and fitness for intended use.

23. High-impact pharmaceutical decisions require appropriate human approval.

24. Employees understand when AI recommendations should be questioned or escalated.

25. The organization monitors AI incidents, model drift, bias, and unintended consequences.

Efficiency Resilience and Availability

26. AI-supported planning has reduced avoidable delays, rework, or emergency interventions.

27. The organization manages inventory levels while limiting stockouts, expiry, and waste.

28. The organization can respond quickly when supplier, transport, production, or demand conditions change.

29. The supply chain can maintain critical pharmaceutical availability during disruptions.

30. AI-supported decisions improve the organization's ability to learn from operational events.