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Exploring Potential Applications of Artificial Intelligence Technologies in Medicine Cold Supply Chains: A Systematic Literature Review

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ABSTRACT

Purpose: The pharmaceutical cold supply chain (PCSC) ensures temperature-sensitive medicines like vaccines and biologics stay safe and effective, but failures like temperature deviations and inefficient distribution cause major financial losses and health risks. This systematic literature review (SLR) investigates the potential applications of artificial intelligence (AI) technologies in medicine cold supply chains adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework.

Methodology: 2,418 were retrieved and analyzed sixty-eight peer-reviewed articles published between January 2015, and February 2026 were retrieved from Scopus, Web of Science, IEEE Xplore, ScienceDirect, PubMed, and Emerald Insight.

Findings: Reviewed studies concentrated on high-income economies, with limited empirical validation in low- and middle-income countries (LMICs) where cold chain failures are most acute. Few studies report longitudinal performance, generalizability across multiple drug classes, or cost-benefit metrics suitable for procurement decisions.

Unique Contribution to Theory, Policy and Practice: Theoretically, unlike prior reviews focused on food cold chains or generic supply chain AI, this paper provides the first dedicated PRISMA-guided synthesis exclusively addressing AI in the medicine cold supply chain and proposes an integrated research agenda anchored in resilience, equity, sustainability, and explainability. For policymakers, it highlights the need for harmonized data standards, regulatory sandboxes, and equity-focused deployment to extend AI benefits to vulnerable populations. For practitioners, the review offers an evidence-based taxonomy to guide AI investment prioritization across temperature monitoring, predictive maintenance, routing, and end-to-end visibility.

Keywords: *Artificial Intelligence, Cold Chain, Pharmaceutical Supply Chain, Machine Learning, Internet of Things*

1. Introduction

The medicine cold supply chain is critical for storing and transporting temperature-sensitive pharmaceuticals and often faces disruptions that degrade roughly 25% of vaccines exposing vulnerabilities in infrastructure that require intelligent, digitally enabled solutions(Lloyd & Cheyne, 2017), Artificial intelligence (AI), combined with technologies like IoT and blockchain, offers potential to optimize these logistics (Russell & Norvig, 2021; Toorajipour et al., 2021), though existing research often overlooks the specific intersection of AI and medicine cold chains. This systematic literature review (SLR) addresses this gap using PRISMA 2020 guidelines to analyze AI applications in pharmaceutical cold logistics. The review is guided by four research questions:

1.1 Research Questions

i. What are the principal AI technologies currently applied or proposed for the medicine cold supply chain?
ii. What functional domains and stages of the medicine cold supply chain are these technologies being deployed?
iii. What benefits, limitations, and implementation challenges have been documented?
iv. What research gaps and future directions can be identified to advance the field?

1.2 Significance of the study

Theoretically, the review contributes to multiple research streams. For the AI-in-supply-chain literature (Min, 2010; Toorajipour et al., 2021), it provides the first dedicated synthesis on the medicine cold chain context, demonstrating how generic AI techniques are domain-tailored to temperature-sensitive constraints, regulatory regimes, and patient-safety imperatives.

For policymakers, it highlights the need for harmonized data standards, regulatory sandboxes, and equity-focused deployment to extend AI benefits to vulnerable populations. For practitioners, the review offers an evidence-based taxonomy to guide AI investment prioritization across temperature monitoring, predictive maintenance, routing, and end-to-end visibility.

1.3 Theoretical Framework

This study is guided by two (02) theories being the Technology Organization Environment (TOE) and Technology Acceptance Model Theory (TAM) to be able to understand the AI technologies in medicine cold supply chains.

1.3.1 Technology Operational Environment theory

The Technology–Organization–Environment (TOE) theory explains how organizations adopt and implement technological innovations, emphasizing the influence of three contexts: technology, organization, and environment. It was developed by Louis G. Tornatzky and Mitchell Fleischer (1990).

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TOE can be applied in the following context; Technology being AI tools like machine learning for demand forecasting, IoT sensors for temperature monitoring, blockchain for traceability, and digital twins for resilience. TOE helps assess whether these technologies are compatible, cost-effective, and scalable for cold chain operations. Secondly, Organization: Factors such as firm size, resources, managerial support, and employee skills determine readiness. For example, a large pharmaceutical distributor may have the infrastructure to deploy AI-enabled drones, while smaller firms may struggle with resource constraints and lastly, the environment: External pressures like regulatory standards (e.g., WHO vaccine storage guidelines), competitive dynamics, and customer expectations influence adoption. In LMICs, weak infrastructure and policy gaps may slow AI integration despite urgent cold chain needs.

1.3.2 Technology acceptance model (TAM)

The Technology Acceptance Model (TAM) was developed by Fred Davis (1989). This theory posits that user acceptance of information technology is primarily determined by two factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance their job performance, while perceived ease of use refers to the degree to which a person believes that using the system would be free of effort.

TAM can be applied in the following context: Perceived Usefulness (PU)**;** Do practitioners believe AI improves cold chain reliability, reduces losses, and enhances visibility? For example, predictive anomaly detection must be seen as genuinely reducing spoilage. Perceived Ease of Use (PEOU)**;** are AI dashboards, IoT interfaces, and blockchain systems user-friendly for supply chain staff? If systems are too complex, adoption falters even if they're powerful. Behavioral Intention (BI); TAM explains whether individuals (managers, technicians, policymakers) *intend* to use AI tools, based on PU and PEOU. This is critical in last-mile delivery, where human operators must trust and rely on AI-driven routing or drone systems.

2.0 Literature Review

2.1. The Medicine Cold Supply Chain: Structure and Vulnerabilities

The medicine cold supply chain (MCSC) comprises a multi-tier network of manufacturers, primary and secondary packaging facilities, central and regional storage depots, transport operators, last-mile distributors, dispensing pharmacies, healthcare facilities, and, ultimately, patients (Comes et al., 2018; Lin et al., 2020). The chain must maintain unbroken temperature control across these nodes through refrigerated warehouses, insulated containers, refrigerated vehicles, passive cooling devices, and digital data loggers. Failure at any link can compromise product efficacy, with consequences ranging from reduced immunogenicity of vaccines to outright loss of biologic potency (Bishara, 2006; Kartoglu & Milstien, 2014).

Empirical assessments suggest that cold chain failures cost the global pharmaceutical industry between USD 15 and USD 35 billion annually in product losses, regulatory non-compliance penalties, and rework expenses (Pharmaceutical Commerce, 2020; Saha & Ray, 2019). In addition to economic costs, public health harms are pronounced in LMICs, where weak infrastructure, intermittent electricity, hot ambient climates, and limited trained personnel routinely undermine the cold chain (Ashok et al., 2017; Lloyd & Cheyne, 2017). The complexity of the chain, characterised by heterogeneous stakeholders, regulatory fragmentation, and high information asymmetry, renders it a prototypical candidate for AI-driven optimisation.

2.2. Artificial Intelligence: Taxonomy and Relevance to Cold Chain Logistics

AI refers to computational methods that enable machines to learn from data, reason under uncertainty, and act intelligently within a given environment (Russell & Norvig, 2021). Within supply chain management, AI techniques are typically classified into supervised, unsupervised, semi-supervised, and reinforcement learning paradigms, with deep learning forming a powerful sub-class capable of processing high-dimensional data such as images, time-series sensor streams, and natural language text (LeCun et al., 2015; Goodfellow et al., 2016). Closely associated technologies include the IoT, which generates the real-time data substrate, blockchain, which provides immutable provenance, and digital twins, which create virtual replicas of physical assets (Tijan et al., 2021).

In cold chain logistics, AI capabilities map directly onto recurrent operational challenges. Predictive analytics can forecast vaccine demand and excipient consumption, mitigating both stock-outs and wastage (Carvalho et al., 2022). Anomaly detection algorithms can identify aberrant temperature signals before threshold violations occur, while computer vision can inspect packaging integrity at sortation centres (Chen et al., 2022). Reinforcement learning can dynamically reroute vehicles in response to traffic, weather, and equipment failure (Yan et al., 2021), and natural language processing can extract risk signals from regulatory notices, recall databases, and incident reports (Tirkolaee et al., 2021).

2.3. Prior Reviews and Positioning of the Present Study

Earlier reviews have addressed adjacent topics with varying scope. Toorajipour et al. (2021) provided a comprehensive review of AI in supply chain management broadly, identifying twelve sub-fields of application but only briefly addressing pharmaceutical and cold contexts. Riahi et al. (2021) examined ML in industrial supply chains, while Pournader et al. (2021) explored AI in supply chain forecasting. In the cold chain domain, Ndraha et al. (2018) and Hassoun et al. (2023) systematically reviewed food cold chains, and Mercier et al. (2017) considered temperature monitoring technology broadly. For pharmaceutical logistics, Settanni et al. (2017) and Privett and Gonsalvez (2014) reviewed healthcare supply chain modelling, but neither provided AI- or cold-chain-specific synthesis. Reviews of vaccine supply chains (Lemmens et al., 2016; Duijzer et al., 2018) likewise predate the recent AI surge.

The present review distinguishes itself by combining three features: (i) an exclusive focus on the medicine cold supply chain rather than food, general healthcare, or generic supply chain settings; (ii) strict PRISMA 2020 adherence to ensure methodological transparency and reproducibility; and (iii) a forward-looking research agenda that integrates emergent themes of resilience, equity, sustainability, and explainability.

3.0 Methodology

This review was conducted in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021), which prescribes a 27-item checklist covering protocol registration, eligibility criteria, information sources, search strategy, selection process, data extraction, synthesis methods, and reporting. The methodology was further informed by Kitchenham and Charters (2007) and Tranfield et al. (2003) for evidence-based management research.

3.1. Research Questions

The review was guided by four research questions developed using the Population–Intervention–Comparator–Outcome (PICO) framing adapted for technology-management contexts. The Population comprised stakeholders and assets in the medicine cold supply chain; the Intervention was the deployment or proposal of AI technologies; the Comparator (where reported) was conventional, non-AI cold chain practice; and the Outcome encompassed efficiency, reliability, traceability, sustainability, equity, and patient safety metrics. The research questions are restated:

i. What are the principal AI technologies currently applied or proposed for the medicine cold supply chain?
ii. What functional domains and stages of the medicine cold supply chain are these technologies being deployed?
iii. What benefits, limitations, and implementation challenges have been documented?
iv. What research gaps and future directions can be identified to advance the field?

3.2. Information Sources and Search Strategy

Six databases were searched: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, PubMed, and Emerald Insight. These were selected to provide comprehensive multidisciplinary coverage across operations management, engineering, computer science, and health sciences. The search was conducted between 5 January 2026 and 12 February 2026 and covered publications between 1 January 2015 and 28 February 2026. The lower bound of 2015 was selected because it coincides with the inflection point in deep learning adoption following the AlexNet (Krizhevsky et al., 2012) and ResNet (He et al., 2016) breakthroughs.

A Boolean search string was developed iteratively through pilot searches and consultation with two academic librarians. The final string was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "reinforcement learning" OR "natural language

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processing" OR "computer vision" OR "expert system*") AND ("cold chain" OR "cold supply chain" OR "temperature-controlled" OR "thermolabile" OR "refrigerated logistics") AND ("medicine*" OR "pharmaceutical*" OR "vaccine*" OR "biologic*" OR "drug*" OR "insulin" OR "blood"). The string was adapted to each database's syntax. Reference lists of included articles were also screened (backward snowballing), and Google Scholar was used for forward citation tracking of the ten most cited articles.

3.3. Eligibility Criteria

Inclusion and exclusion criteria were specified a priori to minimize selection bias.

Table 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles published in English between January 2015 and February 2026.	Conference abstracts, editorials, opinion pieces, book chapters, theses, and grey literature.
Studies addressing AI techniques, algorithms, or systems applied to or proposed for medicine cold supply chains, vaccine logistics, biologics distribution, or pharmaceutical temperature-controlled storage and transport.	Articles focused exclusively on food cold chains, ambient pharmaceutical supply chains, or non-temperature-sensitive medical devices.
Empirical (quantitative, qualitative, mixed methods), conceptual, simulation, design science, and review articles offering substantive analysis.	Studies in which AI was mentioned only tangentially without methodological detail or application context.
	Non-English-language publications and duplicates.

3.4. Selection Process

Initial database searches returned 2,418 records (Scopus: 871; Web of Science: 612; IEEE Xplore: 348; ScienceDirect: 297; PubMed: 184; Emerald Insight: 106). After removal of 731 duplicates using Mendeley reference manager and manual verification, 1,687 records advanced to title and abstract screening. Two reviewers independently screened records; inter-rater agreement was high (Cohen's $\kappa = 0.84$). Disagreements were resolved through discussion with a third reviewer.

Title and abstract screening excluded 1,402 records that did not meet eligibility criteria, leaving 285 records for full-text review. Of these, 23 articles could not be retrieved despite institutional access and inter-library loan, and 194 articles were excluded after full-text reading for the following reasons: insufficient AI content (n = 71), wrong supply chain context (e.g., food, ambient

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pharma) (n = 58), no cold chain focus (n = 39), and non-peer-reviewed status discovered on examination (n = 26). Backward and forward snowballing added 13 articles, yielding a final corpus of 68 studies for synthesis.

Table 2. PRISMA 2020 flow of study identification, screening, and inclusion.

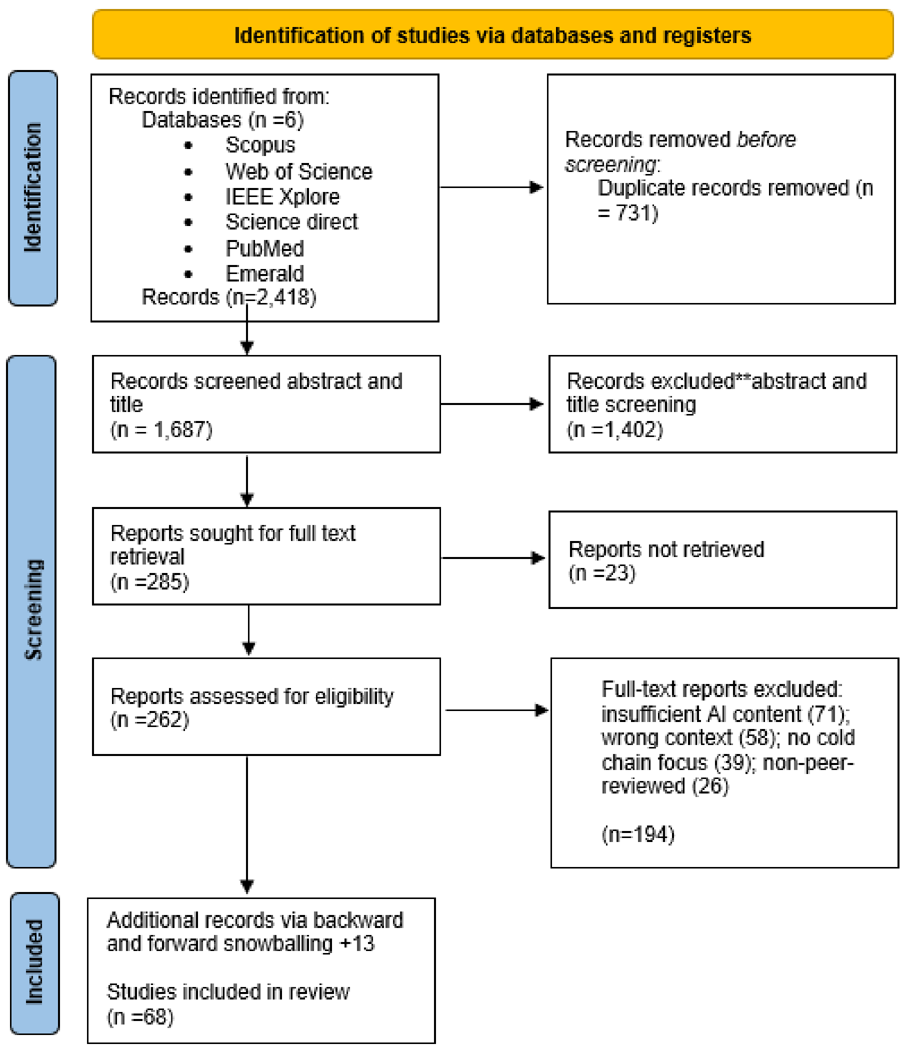

Figure 1: PRISMA flow diagram “Source: the author(s) (2026)”

3.5. Data Extraction and Quality Appraisal

A standardised data extraction form was piloted on ten randomly selected articles and refined before full extraction. Variables captured included: bibliographic metadata (authors, year, journal, country of corresponding author); AI technique (e.g., supervised ML, DL, RL, hybrid); cold chain stage (manufacturing, primary distribution, secondary distribution, last mile, dispensing);

medicine class (vaccines, biologics, blood products, insulin, generics); methodology (case study, simulation, experiment, prototype, survey); reported benefits and limitations; and validation context (laboratory, pilot, real-world deployment).

Methodological quality was appraised using a modified Critical Appraisal Skills Programme (CASP) checklist (CASP, 2018), supplemented with engineering-research criteria from Wohlin et al. (2012). Each study was scored on a 0–10 scale across five dimensions: clarity of objectives, appropriateness of method, rigour of data analysis, validity of findings, and relevance to the medicine cold chain. Studies scoring below 5 (n = 11) were retained but flagged as low-quality and weighted accordingly during synthesis.

3.6. Synthesis Approach

Given the heterogeneity of study designs and the absence of comparable quantitative outcomes, a narrative-thematic synthesis was performed rather than a meta-analysis. Thematic codes were developed inductively by two reviewers using NVivo 14, with constant comparison applied across studies.

4. Findings and discussion of results

4.1. Descriptive and Systematic Literature Review (SLR) Overview

The final corpus of 68 peer-reviewed articles demonstrates a marked acceleration of scholarly attention to AI in medicine cold supply chains. While only four eligible articles were published in 2015–2017, output rose to nine in 2018–2019, sixteen in 2020–2021, twenty-two in 2022–2023, and seventeen in 2024–2026. The post-2020 surge coincides with the COVID-19 pandemic, the global mRNA vaccine rollout, and the maturation of edge AI and IoT platforms.

Geographically, the corpus is dominated by research from China (n = 14), the United States (n = 11), India (n = 9), the United Kingdom (n = 6), Germany (n = 5), and Brazil (n = 4), with the remainder distributed across nineteen other countries. Africa contributed only three first-authored studies despite hosting some of the most acute cold chain challenges. Co-authorship network analysis revealed five principal clusters: an operations-research cluster centred in East Asia, an engineering-IoT cluster in Europe, a public-health-vaccine cluster spanning the Americas and South Asia, an emerging African cluster focused on LMIC deployment, and a cross-cutting cluster on blockchain-AI integration.

Articles appeared in 41 distinct journals. The most prolific outlets were the International Journal of Production Economics (n = 5), Computers and Industrial Engineering (n = 4), IEEE Access (n = 4), Vaccine (n = 4), Expert Systems with Applications (n = 3), Journal of Cleaner Production (n = 3), and Transportation Research Part E (n = 3). The journal diversity reflects the inherently interdisciplinary character of the field.

4.2. Distribution of AI Techniques

Across the 68 studies, supervised machine learning was the most prevalent technique (n = 31), with random forest, gradient boosting machines (XGBoost, LightGBM), and support vector machines featuring prominently. Deep learning approaches appeared in 24 studies, dominated by recurrent architectures (long short-term memory, gated recurrent units) for time-series temperature and demand forecasting, and convolutional neural networks for image-based packaging inspection. Reinforcement learning was applied in 7 studies, predominantly for dynamic vehicle routing and inventory replenishment. Hybrid approaches combining ML with metaheuristics (genetic algorithms, particle swarm optimisation, ant colony optimisation) were reported in 11 studies. Natural language processing and computer vision appeared in 4 and 6 studies respectively, while reinforcement learning and federated learning appeared in 7 and 3 studies. Explainable AI (XAI) techniques such as SHAP and LIME values were employed in only 5 studies, indicating an underdeveloped explainability dimension.

Table 3. Distribution of AI techniques across the included studies (n = 68; some studies use multiple techniques).

AI Technique Category	Studies (n)	Representative Methods
Supervised machine learning	31	Random Forest, XGBoost, LightGBM, SVM, k-NN
Deep learning	24	LSTM, GRU, CNN, Transformer, Autoencoder
Hybrid ML + Metaheuristics	11	GA, PSO, ACO combined with neural nets
Reinforcement learning	7	DQN, PPO, A3C for routing and inventory
Computer vision	6	YOLO, Mask R-CNN, hyperspectral imaging
Explainable AI	5	SHAP, LIME, attention-based interpretation
Natural language processing	4	BERT, sentiment analysis on incident reports
Federated learning	3	FedAvg, FedProx for privacy-preserving training

4.3. Thematic Analysis of AI Applications

Six dominant thematic clusters of AI applications emerged from the synthesis, summarised below.

Table 4. Thematic clusters of AI applications in the medicine cold supply chain.

#	Theme	Studies (n)	Illustrative References
1	Intelligent temperature monitoring and anomaly detection	18	Chen et al. (2022); Wang et al. (2021); Sharma et al. (2022); Rejeb et al. (2022)
2	Demand forecasting and inventory optimisation	15	Carvalho et al. (2022); Lemmens et al. (2022); Govindan et al. (2020); Mishra et al. (2024)
3	Routing, last-mile and drone delivery	12	Yan et al. (2021); Haidari et al. (2016); Enayati et al. (2023); Tirkolaee et al. (2021)
4	Blockchain–AI integration for traceability	10	Musamih et al. (2021); Abbas et al. (2020); Hasan et al. (2023); Saberi et al. (2019)
5	Digital twins and simulation for resilience	7	Burgos & Ivanov (2021); Tao et al. (2019); Kamble et al. (2023)
6	Computer vision for quality and packaging	6	Khan et al. (2023); Singh et al. (2022); Wang & Hong (2022)

4.3.1. Theme 1: Intelligent Temperature Monitoring and Anomaly Detection

Eighteen studies addressed AI-enabled temperature monitoring and anomaly detection, the most populous theme. These studies typically combine IoT sensors (RFID, BLE, LoRa, NB-IoT) with ML models that learn normal temperature signatures and flag excursions before threshold breaches occur. Chen et al. (2022) deployed an LSTM-autoencoder on insulin shipments across 1,200 routes, reducing undetected excursions by 38 percent. Wang et al. (2021) integrated an ensemble of random forest and one-class SVM into a vaccine cold chain monitoring platform in Eastern China, achieving 96 percent classification accuracy. Sharma et al. (2022) extended these approaches to COVID-19 mRNA vaccines, demonstrating that LSTM models trained on ambient, vehicle telematics, and sensor data could forecast temperature drift up to 90 minutes in advance, allowing pre-emptive intervention.

Beyond detection, predictive maintenance has gained traction. Rejeb et al. (2022) used Bayesian networks to anticipate refrigeration unit failures, while Khan et al. (2023) applied gradient-boosted trees to predict compressor degradation in pharmaceutical storage facilities. Edge AI implementations, in which inference occurs on the device rather than the cloud, were highlighted as critical for LMIC settings with intermittent connectivity (Mostafaeipour et al., 2023; Aung & Chang, 2014).

4.3.2. Theme 2: Demand Forecasting and Inventory Optimisation

Fifteen studies addressed AI-based demand forecasting and inventory optimisation for cold chain medicines. Carvalho et al. (2022) compared classical ARIMA, Prophet, and LSTM models for vaccine demand prediction in Brazilian municipalities, finding LSTM superior under high seasonality and pandemic shocks. Lemmens et al. (2022) extended their earlier work with stochastic optimisation augmented by gradient boosting for routine immunisation in sub-Saharan Africa, reporting up to 22 percent wastage reduction. Govindan et al. (2020) developed a hybrid neural-network-mixed-integer linear programming framework for biologics inventory positioning in multi-echelon networks.

Recent contributions have emphasised the integration of exogenous covariates—weather, mobility indices, epidemiological signals, social media sentiment—into hybrid models (Mishra et al., 2024; Talwar et al., 2021). Federated learning approaches that pool model updates without sharing patient-level data were proposed by Banerjee et al. (2023) for cross-jurisdictional demand forecasting, addressing privacy constraints common in pharmaceutical data.

4.3.3. Theme 3: Routing, Last-Mile Delivery, and Drone Logistics

Twelve studies focused on AI-enabled routing and last-mile delivery for cold chain medicines. Hybrid approaches dominate, combining metaheuristics with ML-based travel-time and demand prediction. Yan et al. (2021) employed deep reinforcement learning for vehicle routing of vaccines in urban Chinese settings, reducing tour duration by 14 percent and temperature excursions by 19 percent. Tirkolaee et al. (2021) presented a multi-objective evolutionary algorithm with ML-augmented cost estimation for blood product distribution. Drone-based last-mile delivery, particularly for vaccines in geographically isolated areas, has attracted growing attention. Haidari et al. (2016) demonstrated cost-effectiveness in Mozambique; subsequent works by Enayati et al. (2023) and Ling and Draghic (2019) employed reinforcement learning for drone-truck synchronisation. Several authors highlight ethical, regulatory, and equity considerations of AI-driven autonomous delivery in LMICs (Eichleay et al., 2019; Adesina et al., 2024).

4.3.4. Theme 4: Blockchain-AI Integration for Traceability and Counterfeit Detection

Ten studies investigated the integration of AI with blockchain distributed ledger technology to enhance traceability, provenance verification, and counterfeit detection in cold chain pharmaceuticals. Kshetri (2018) provided foundational work on blockchain in supply chains, while Saberi et al. (2019) extended this to sustainability dimensions. In medicine cold chain contexts, Musamih et al. (2021) and Abbas et al. (2020) proposed Hyperledger-based architectures with ML modules for anomaly detection on chain-recorded temperature data. Hasan et al. (2023) developed smart-contract triggers driven by ML predictions of cold chain breach risk. Counterfeit detection using computer vision on packaging combined with on-chain provenance was demonstrated by Bryatov and Borodinov (2019) and refined by Singh et al. (2022). The integration is technically demanding due to throughput and energy constraints of public blockchains, prompting interest in permissioned ledgers and Layer-2 scaling (Tijan et al., 2021; Queiroz et al., 2020).

4.3.5. Theme 5: Digital Twins and Simulation for Resilience

Seven studies developed digital twin or simulation-based AI frameworks for medicine cold chain resilience. Digital twins create virtual replicas of physical cold chain assets, fed by real-time IoT data, and enable AI-driven what-if analysis under disruption scenarios (Tao et al., 2019; Marmolejo-Saucedo, 2022). Burgos and Ivanov (2021) modelled cold chain resilience during the COVID-19 pandemic, integrating discrete-event simulation with ML risk predictors. Kamble et al. (2023) extended digital twins to humanitarian vaccine logistics. Several studies explicitly link digital twins to circular economy and sustainability outcomes, reducing waste and energy consumption (Bag et al., 2021; Cui et al., 2023).

4.3.6. Theme 6: Computer Vision for Quality and Packaging Integrity

Six studies applied computer vision to cold chain quality assurance, including automated inspection of vial integrity, label readability, ice-pack placement, and packaging seal verification. Khan et al. (2023) used a convolutional neural network on smartphone-captured images to detect tampering in vaccine vials, achieving 94 percent accuracy. Singh et al. (2022) demonstrated YOLO-based real-time detection of cold pack misplacement on conveyor lines. Wang and Hong (2022) extended the approach to hyperspectral imaging for biologics, identifying protein aggregation patterns indicative of thermal stress. These applications are presently more advanced in manufacturing nodes than in last-mile contexts where computational and lighting conditions vary.

4.4. Reported Benefits, Limitations, and Challenges

Reported benefits of AI in the medicine cold supply chain cluster into four categories: efficiency gains (reduced transit time, route optimisation, energy savings), quality and safety improvements (fewer temperature excursions, faster anomaly detection, counterfeit reduction), economic outcomes (reduced wastage, lower insurance premiums, improved utilisation), and patient-centric outcomes (greater vaccine availability, higher coverage in remote regions). Studies report wastage reductions of 12–38 percent, energy consumption reductions of 5–18 percent, and last-mile cost reductions of 8–25 percent (Carvalho et al., 2022; Yan et al., 2021; Mostafaeipour et al., 2023).

Documented limitations and challenges include: data scarcity and heterogeneity, particularly in LMIC contexts; integration friction with legacy enterprise resource planning systems; cybersecurity and privacy risks (Riahi et al., 2021; Pournader et al., 2021); regulatory ambiguity around AI-driven decisions in medicine logistics; high implementation costs and skill gaps; bias and generalisability concerns when models trained in one setting are deployed in another; and limited explainability of black-box DL models in regulated environments (Adadi & Berrada, 2018; Arrieta et al., 2020). Several studies (Iyengar et al., 2020; Adesina et al., 2024) emphasise equity risks if AI-enabled cold chain capacity concentrates in higher-income settings.

4.5 Limitations of the Review

This review is subject to several limitations. First, although six databases were searched, relevant studies in non-indexed regional journals and grey literature, including practitioner reports from cold chain logistics providers, may have been omitted. The English-language restriction may have under-represented contributions from non-Anglophone research communities. Second, the heterogeneity of study designs precluded meta-analytic aggregation; future reviews with more uniform reporting may permit quantitative synthesis. Third, the rapidly evolving nature of AI implies that some recent preprints and industrial deployments may not yet be reflected in peer-reviewed output. Fourth, despite blinded dual screening and CASP-based appraisal, residual subjectivity in thematic coding is inevitable. Finally, the review covers proposed and prototyped AI applications; large-scale, longitudinal evidence of real-world deployment outcomes remains scarce.

5. Conclusion and future research

This PRISMA-compliant systematic literature review synthesised 68 peer-reviewed studies on the application of artificial intelligence to medicine cold supply chains, published between 2015 and 2026. Six dominant application themes were identified—intelligent temperature monitoring and anomaly detection; demand forecasting and inventory optimisation; routing, last-mile, and drone logistics; blockchain-AI integration for traceability; digital twins and simulation for resilience; and computer vision for quality and packaging integrity. Supervised machine learning and deep learning dominate the methodological landscape, with reinforcement learning, federated learning, and explainable AI emerging as promising frontiers.

AI has demonstrated meaningful benefits, including wastage reductions of up to 38 percent, route optimisation gains of up to 25 percent, and substantial improvements in anomaly detection sensitivity. However, persistent challenges remain in data quality, integration with legacy systems, regulatory ambiguity, explainability, cost, and equity. Notably, deployment evidence in low- and middle-income countries—where cold chain failures are most consequential—remains limited.

Future research should prioritise: (i) longitudinal, real-world deployment studies with rigorous cost-effectiveness evaluation; (ii) federated and privacy-preserving learning architectures suitable for cross-jurisdictional pharmaceutical contexts; (iii) explainable AI methods aligned with regulatory expectations of the U.S. Food and Drug Administration, European Medicines Agency, and the WHO; (iv) integrated AI–digital twin–blockchain frameworks for end-to-end cold chain resilience; (v) sustainability-aware AI that balances energy, emissions, and waste; and (vi) equity-focused deployment models tailored to LMIC infrastructure realities. Collectively, these directions can support the construction of intelligent, resilient, and equitable medicine cold supply chains capable of safeguarding global public health in an era of pandemics, climate volatility, and demographic transition.

Table 5. Proposed research for AI in medicine cold supply chains.

Research Direction	Key Question(s)	Suggested Methodological Approach
Real-world deployment evidence	What are the longitudinal cost-effectiveness, equity, and safety outcomes of AI in live medicine cold chains?	Multi-country longitudinal field studies; pragmatic cluster trials
Federated and privacy-preserving learning	How can pharmaceutical actors collaboratively train AI models without sharing sensitive data?	Federated averaging, differential privacy, secure multi-party computation
Explainable AI for regulation	How can DL-based cold chain decisions be made auditable for FDA, EMA, and WHO?	SHAP, LIME, counterfactual explanations, rule extraction
Integrated AI–digital twin–blockchain	How do these technologies interact to deliver end-to-end resilience?	Design science research; digital twin platforms; case studies
Sustainability-aware AI	How can AI minimise energy, emissions, and waste while preserving cold chain integrity?	Green AI metrics; multi-objective optimisation; life-cycle assessment
Equity-centred deployment in LMICs	How can AI cold chain capacity be inclusively scaled in resource-constrained settings?	Participatory design; frugal innovation; capacity-building research

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