

Review Article

Using Immunization Cold Chain Data to Advance Predictive Maintenance: A Narrative Review with Scoping Synthesis

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Background: Immunization supply chains depend on reliable cold chain equipment to protect vaccine potency and service continuity. Most programmes rely on preventive maintenance and corrective repair, but both approaches have limitations where equipment risk, technician capacity, spare-parts availability and facility access are uneven. Predictive maintenance offers a potential third function: using routine programme data to identify early warning signs before equipment failure disrupts vaccine availability.

Methods: This narrative review with scoping synthesis mapped data sources, prediction opportunities, implementation challenges and recommendations relevant to predictive maintenance of cold chain equipment in immunization supply chains. Evidence was reviewed across immunization supply chains, cold chain maintenance, temperature monitoring, asset management, digital health, predictive maintenance, artificial intelligence, decommissioning and climate-resilient supply-chain planning.

Findings: Immunization programmes already generate multiple data streams that may support risk-based maintenance, including temperature records, alarm logs, asset registries, repair records, spare-part movement, power reliability, solar performance, stock data, facility access, technician capacity and climate-risk information. These data can support early warning for temperature excursions, likely equipment failure, spare-part demand, delayed repair, chronic poor performance, replacement need and decommissioning priority. However, implementation is constrained by incomplete records, fragmented systems, weak failure classification, limited interoperability, technician capacity gaps, unclear escalation rules and insufficient field validation.

Interpretation: Predictive maintenance should be introduced progressively, beginning with data standardization, data triangulation and simple rule-based early warnings. Advanced predictive

analytics and artificial intelligence may add value when data quality, governance and technician-confirmed validation are in place. A phased, programme-owned and equity-sensitive approach can help countries reduce downtime, protect vaccine availability and strengthen cold chain resilience.

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Introduction

Immunization programmes depend on reliable supply chains to ensure that potent vaccines are available at the right place, at the right time and under appropriate storage conditions. Cold chain equipment (CCE), including refrigerators, freezers, cold rooms, passive containers, temperature monitoring devices and energy systems, forms a critical infrastructure layer for vaccine quality and service continuity. Weak cold chain performance can expose vaccines to heat or freezing, increase wastage, disrupt sessions and reduce confidence in immunization services ^{[1][2]}.

Maintenance is central to CCE reliability. Most programmes rely on preventive maintenance, which uses planned inspection and servicing to reduce the probability of failure, and corrective or curative maintenance, which restores functionality after breakdown, temperature excursion or service interruption. Both approaches remain necessary, but both have limitations. Preventive maintenance may become calendar-based rather than risk-based, while corrective maintenance often occurs after vaccine exposure, emergency stock movement, service disruption or repeated equipment failure has already occurred ^[3].

This challenge is becoming more important as countries expand and modernize cold chain systems through solar direct-drive refrigerators, ice-lined refrigerators, cold rooms, voltage stabilizers, electronic temperature monitoring devices and remote communication systems. WHO's Performance, Quality and Safety framework includes thermometers, freeze indicators, temperature recorders, data loggers, equipment monitoring devices and alarm systems for monitoring cold chain performance ^[4]. Gavi's 2026-2030 strategy also identifies digitalisation, including artificial intelligence, improved data and evidence, as an enabler for immunization outcomes ^[5]. These developments create an opportunity to use routine programme data not only for monitoring and reporting, but also for earlier maintenance decisions.

Immunization supply chains already generate multiple data streams that could support predictive maintenance. These include temperature records, alarm logs, asset inventories, installation dates, maintenance checklists, repair records, spare-parts consumption, power interruptions, solar battery performance, vaccine stock levels, wastage reports, facility remoteness, technician travel time, supervision findings and seasonal or climate-risk information. Experience with remote temperature monitoring has shown that digital temperature data can improve visibility into cold chain performance and help identify poorly performing refrigerators ^[6]. However, temperature data alone are insufficient. Repeated alarms may reflect equipment failure, unstable power, poor loading practice, frequent door opening, weak staff response or delayed technician access.

Predictive maintenance should therefore be understood as a data-to-decision approach rather than as an artificial intelligence intervention alone. It can begin with better data quality and simple rule-based risk flags, progress toward condition-based maintenance, and later incorporate validated predictive analytics where data systems and maintenance feedback loops are mature. This approach aligns with wider immunization supply-chain strengthening efforts, including resource centres for technical capacity and data use ^[7], planned decommissioning and safe disposal of obsolete CCE ^[8], improved visibility of cold-chain waste streams ^[9], and low-carbon, climate-resilient supply-chain planning ^[10].

This narrative review with scoping synthesis aims to map available data sources within immunization cold chain systems, identify maintenance-related risks that could be predicted from these data, and examine operational challenges and recommendations for advancing predictive maintenance of CCE in immunization supply chains.

Methods

Review design

This narrative review with scoping synthesis mapped available data sources, potential prediction targets and implementation considerations for predictive maintenance of cold chain equipment in immunization supply chains. The synthesis was informed by scoping-review principles, including the mapping of key concepts, evidence sources and knowledge gaps, but was not designed as a formal PRISMA-ScR review ^{[11][12]}. This design was selected because the topic spans immunization supply chains, cold chain equipment maintenance, temperature monitoring, digital health, artificial intelligence, asset management, equipment lifecycle management and health-system resilience.

Review question

The review was guided by the following question: What data sources are available within immunization cold chain systems, what maintenance-related risks could be predicted from these data, and what operational challenges and recommendations are relevant for advancing predictive maintenance of cold chain equipment?

Evidence sources and search approach

Evidence was identified from peer-reviewed literature, review articles, implementation studies, technical reports, normative guidance, policy documents and selected early-stage publications directly relevant to the review question. Sources were searched across PubMed/MEDLINE, Scopus, Web of Science, Google Scholar and institutional websites, including WHO, UNICEF, Gavi, PATH, JSI and other immunization supply-chain partners. Search terms combined concepts related to vaccines and immunization supply chains with cold chain equipment, maintenance, digital monitoring and predictive analytics. Core terms included “vaccine cold chain”, “immunization supply chain”, “cold chain equipment”, “preventive maintenance”, “corrective maintenance”, “curative maintenance”, “remote temperature monitoring”, “temperature data logger”, “equipment monitoring device”, “predictive maintenance”, “condition-based maintenance”, “machine learning”, “artificial intelligence”, “asset management”, “spare parts”, “decommissioning”, “waste”, “climate resilience” and “low-carbon supply chain”.

Eligibility criteria

Sources were considered eligible if they addressed at least one of the following domains: immunization supply chains, vaccine cold chain equipment, cold chain maintenance, remote or electronic temperature monitoring, asset management, spare-parts management, predictive maintenance, condition-based maintenance, artificial intelligence, machine learning, digital health, cold chain waste, equipment decommissioning, climate resilience or low-carbon immunization systems. Sources were included when they described data sources, maintenance practices, prediction opportunities, digital monitoring tools, equipment performance, operational risks or decision-making processes relevant to cold chain equipment maintenance. Literature from industrial systems, healthcare technology and building systems was used only where it provided transferable concepts for predictive maintenance and was not treated as direct immunization evidence.

Data extraction and synthesis

Information was extracted around six domains: data source, data tool or system, prediction target, maintenance decision supported by the prediction, implementation challenge and relevance to immunization programme resilience. Evidence was grouped into temperature and equipment-performance data, asset and lifecycle data, maintenance and repair data, spare-parts and procurement data, power and energy data, vaccine stock and wastage data, facility and geographic data, supervision and workforce data, and climate or environmental risk data. Findings were synthesized narratively and organized into a data-to-decision framework that emphasized practical programme action rather than algorithmic performance alone.

Methodological limitations

This review maps data sources and potential prediction pathways but does not estimate the diagnostic accuracy, cost-effectiveness or operational impact of predictive maintenance models. The evidence base includes heterogeneous sources, and immunization-specific studies on artificial intelligence-enabled predictive maintenance remain limited. Some relevant evidence comes from technical guidance, programme experience, early-stage publications and transferable predictive-maintenance literature from other sectors. The findings should therefore be interpreted as an implementation-oriented synthesis and framework, not as proof that predictive maintenance has already been validated across immunization cold chain systems.

Results

Data sources for predictive maintenance in immunization cold chain systems

The reviewed evidence and guidance indicate that predictive maintenance for cold chain equipment should be built from multiple routine immunization supply-chain data streams rather than from temperature monitoring data alone ^{[3][4][6][13]}. Temperature data provide the most direct signal of equipment performance and vaccine storage risk, but prediction becomes more operationally useful when combined with asset information, maintenance history, spare-parts movement, power reliability, vaccine stock data, facility context, technician capacity and environmental risk. Table 1 maps key data domains, generic data sources, prediction targets and programme value.

Data domain	Key data inputs	Data source/tool	Prediction target or early-warning signal	Action triggered and programme value
Temperature and equipment performance	Temperature excursions, recovery time, repeated alarms, unresolved alarms	Temperature monitoring tools, 30-day recorders, data loggers, equipment monitoring systems, remote temperature monitoring devices	Future hot or cold excursion risk; unstable equipment performance; equipment needing urgent follow-up	Enables early corrective action before vaccine exposure, stock movement or service disruption
Asset and lifecycle information	Equipment age, model, make, installation date, energy source, PQS status, warranty status, replacement history	Cold chain inventory, asset registry, procurement record, warranty database, equipment management information system	Failure risk by age, model or technology type; repair-versus-replace signal; decommissioning priority	Supports replacement planning, warranty escalation, procurement decisions and lifecycle management
Maintenance, repair and spare-parts history	Preventive maintenance status, missed visits, breakdown history, repeat repairs, repair cost, spare-parts use, stock-outs and lead time	Maintenance logbook, digital checklist, service ticket, technician report, spare-parts inventory, procurement record	Equipment likely to fail; chronic poor performance; model-specific weak points; future spare-part demand	Prioritizes technician visits, reduces repeated repair cycles, supports spare-part pre-positioning and informs supplier feedback
Power and energy reliability	Power cuts, voltage fluctuation, generator use, stabilizer faults, solar panel condition, battery age, autonomy hours	Facility power log, stabilizer record, solar refrigerator checklist, battery log, energy assessment	Power-related temperature instability; solar or battery underperformance	Guides backup power planning, stabilizer deployment, solar servicing and off-grid facility protection

Data domain	Key data inputs	Data source/tool	Prediction target or early-warning signal	Action triggered and programme value
User practice and service operations	Door opening pattern, overloading, stock arrival days, ice-pack handling, temperature-recording quality, staff skills	User checklist, supportive supervision tool, equipment-use observation, EVM-style assessment	User-practice-related excursions; data-quality risk; recording or response problems	Prevents unnecessary technician dispatch and targets training, workflow correction and supervision
Vaccine stock and wastage risk	Stock volume, stock value, session load, campaign period, wastage, discarded doses, VVM change, excursion investigation findings	Stock ledger, eLMIS, vaccine utilization dashboard, campaign microplan, wastage report, stock adjustment record	Consequence of equipment failure; facilities or equipment repeatedly associated with vaccine loss	Prioritizes high-consequence facilities and links maintenance performance with vaccine availability and wastage reduction
Facility access, workforce and equity	Facility type, catchment population, remoteness, road access, technician travel time, technician workload, transport and fuel availability	Master facility list, GIS tool, district microplan, technician roster, work-order system, fleet record	Delayed repair risk; maintenance backlog; hard-to-reach facilities at risk of service disruption	Supports technician routing, equitable prioritization and continuity of services in remote areas
Climate and environmental risk	Ambient temperature, heat, flooding, dust, humidity, seasonal access constraints	Weather data, climate-risk map, facility environmental assessment, emergency preparedness plan	Seasonal or climate-related equipment stress	Improves preparedness for heat, floods, storms, dust-prone environments and climate-sensitive disruption

Table 1. Data domains, prediction targets and programme value for predictive maintenance of cold chain equipment in immunization supply chains

The mapping shows that predictive maintenance is not a single-technology intervention. It is a structured use of programme data to identify risk earlier and connect that risk to action. The most immediate opportunities are likely to come from rule-based risk flags using existing data: repeated temperature excursions, delayed recovery, missed preventive maintenance, repeated repairs, high spare-part consumption, unstable power and difficult technician access. More advanced predictive analytics or artificial intelligence may become useful where these data are digitized, linked to unique equipment identifiers and validated against technician-confirmed failures.

From data signals to predictive maintenance decisions

Table 1 shows that predictive maintenance in immunization cold chain systems should be developed as a progressive data-to-decision pathway. The first step is to improve the visibility and completeness of existing data, including temperature trends, asset history, maintenance records, repair findings, spare-part movement, power reliability, stock risk, facility access and environmental conditions. The second step is to convert these data into simple and explainable risk flags, such as repeated excursions, delayed temperature recovery, missed preventive maintenance, repeated repairs, high spare-part consumption, unstable power or difficult technician access.

The third step is condition-based maintenance, where technician visits are prioritized according to observed equipment performance and operational risk rather than calendar schedules alone. For example, a refrigerator with repeated alarms, delayed recovery and previous repair history may require earlier technical follow-up than equipment that is only due for routine inspection. Similarly, repeated use of a specific spare part in one model may indicate a model-specific weakness and support warranty claims, supplier feedback, procurement review or decommissioning decisions.

The fourth step is predictive analytics or artificial intelligence, where linked datasets are used to estimate future risk of equipment failure, spare-part demand, delayed repair or vaccine exposure. This stage requires stronger data quality, unique equipment identifiers, reliable maintenance records and validation against technician-confirmed failures. Predictive maintenance should therefore complement preventive

and corrective maintenance by adding a risk-based function that helps programmes act earlier and use limited maintenance resources more efficiently.

Implementation challenges

The transition to predictive maintenance will depend on the readiness of immunization programmes to collect, link, interpret and act on cold chain data. Table 2 summarizes key implementation challenges and practical mitigation options.

Challenge domain	How the challenge appears	Implication for predictive maintenance	Practical mitigation option
Data quality and standardization	Incomplete temperature records, missing installation dates, weak repair documentation and non-standard failure descriptions	Prediction becomes unreliable if equipment condition and failure history are poorly recorded	Define a minimum CCE data package and standard failure categories
Data fragmentation and interoperability	Temperature tools, asset registries, eLMIS, supervision tools, repair records and procurement data are often separate	Programmes cannot link repeated excursions, repairs, spare-part use and wastage to the same equipment	Use unique equipment identifiers and define interoperability requirements for digital tools
Maintenance feedback loop	Technician findings are not routinely entered back into programme databases	Predicted risks cannot be validated against confirmed technical failures	Require technician-confirmed diagnosis, action taken, spare part used and repair outcome in each service record
Technician and response capacity	Few trained technicians may cover large areas with limited transport, fuel and tools	Even accurate predictions may not lead to timely action	Use risk scores to prioritize visits, bundle routes and align spare parts before dispatch
Governance and ownership	Data may be managed by vendors, partners or different programme units	Predictive maintenance may remain a project activity rather than a national system function	Assign national responsibility for CCE data governance, review meetings and escalation rules
Financing and lifecycle planning	Maintenance, spare parts, connectivity, technician transport and decommissioning are often underfunded	Risk identification may not translate into corrective action	Include predictive maintenance requirements in EPI budgets, cMYPs, Gavi support and service contracts
Equity and climate risk	Remote, off-grid or climate-exposed facilities may have weaker data visibility and slower repair access	Predictive systems may under-detect risks in facilities with the highest vulnerability	Combine digital signals with manual records, supervision findings, remoteness, power

Challenge domain	How the challenge appears	Implication for predictive maintenance	Practical mitigation option
			reliability and climate-risk data

Table 2. Implementation challenges for predictive maintenance of cold chain equipment

These challenges indicate that predictive maintenance should be introduced in phases. Programmes can begin with a limited set of high-value indicators: repeated temperature excursions, delayed recovery, repeated repairs, missed preventive maintenance, unstable power and difficult technician access. Advanced predictive analytics or artificial intelligence should be considered only after basic data quality, equipment identification, maintenance documentation and technician feedback loops are functional.

Discussion

This review suggests that predictive maintenance for immunization cold chain equipment is best understood as a phased data-to-decision approach rather than as a fully automated artificial intelligence intervention. Immunization-specific evidence currently supports the value of temperature monitoring, equipment visibility, maintenance systems and structured data review [\[3\]\[4\]\[6\]\[13\]](#). Evidence from industrial systems, prognostics and health management, medical equipment and HVAC systems provides transferable concepts, including condition monitoring, fault detection, anomaly detection, machine learning and risk-based maintenance prioritization [\[14\]\[15\]\[16\]\[17\]\[18\]\[19\]](#). However, these concepts should be adapted cautiously because vaccine cold chain systems operate within public health programmes, not controlled industrial environments.

The main implication is that countries should first improve the usability of existing cold chain data before investing in complex predictive algorithms. Temperature excursions, delayed recovery, repeated alarms, missed preventive maintenance, repeat repairs, spare-part consumption, unstable power and difficult technician access can be converted into simple early-warning rules. These rules are easier to explain, validate and act upon than black-box models, particularly where data quality and technician feedback loops remain weak.

A second implication is that predictive maintenance can strengthen cold chain equipment lifecycle management. Linked repair, spare-part, warranty and procurement data can help identify chronically failing equipment, recurring component problems, model-specific weaknesses and inefficient assets. This can support supplier feedback, warranty claims, post-market surveillance, replacement planning and safe decommissioning ^{[8][9]}. In this sense, predictive maintenance is not only a repair function; it is also an asset-management and procurement-improvement function.

A third implication is that predictive maintenance may contribute to climate resilience and sustainability. Cold chain equipment in remote, off-grid, flood-prone, dusty or heat-stressed settings may face higher risk of performance instability and delayed repair. Combining equipment performance data with power reliability, geographic access and climate-risk information can help programmes prioritize maintenance resources where disruption would have the greatest effect on vaccine availability ^{[10][20]}.

The most important risk is over-implementation before system readiness. Predictive tools may generate false alarms, miss failures or lose user trust if data are incomplete, fragmented or poorly classified. Before advanced analytics are scaled, programmes should ensure unique equipment identifiers, minimum data standards, failure-category coding, technician-confirmed diagnosis and clear escalation rules. Predictive maintenance should therefore complement preventive and corrective maintenance. Its added value is to identify elevated risk earlier and direct limited resources toward the equipment, facilities and districts where timely action is most likely to protect vaccine availability.

Recommendations

Predictive maintenance should be introduced as a phased immunization supply-chain strengthening approach rather than as a stand-alone artificial intelligence intervention. Table 3 summarizes priority actions for countries, partners and implementers.

Recommendation area	Priority action	Expected programme value
Data quality and standardization	Define a minimum CCE data package covering equipment identity, location, model, installation date, maintenance status, repair history, spare-part use and temperature-event history	Creates a reliable foundation for risk-based maintenance decisions
Data triangulation	Link temperature data with asset records, repair reports, spare-part movement, stock data, power reliability, facility access and climate-risk information	Provides a more complete risk picture than any single data source
Algorithm development and validation	Start with simple rule-based triggers before developing predictive models; validate any model against technician-confirmed failures	Reduces false alarms, improves trust and supports safer use of advanced analytics ^{[20][14][17]}
Capacity building and workflow integration	Train EPI managers, cold-chain technicians and logisticians to interpret risk signals, document faults and act on maintenance alerts	Converts data visibility into timely corrective action
Governance, financing and lifecycle planning	Assign national ownership for CCE data governance and include maintenance, spare parts, connectivity, technician transport, warranty management and decommissioning in programme budgets and Gavi 6.0 applications	Supports sustainable CCE performance and reduces dependence on emergency repair ^{[5][21]}
Equity and climate resilience	Combine digital data with manual records, supervision findings, remoteness, power reliability and climate-risk data	Helps ensure that remote, off-grid and climate-exposed facilities are not missed

Table 3. High-level recommendations for advancing predictive maintenance of cold chain equipment

A practical implementation pathway would begin with data standardization and data triangulation, followed by simple escalation rules for repeated excursions, delayed recovery, repeated repairs, missed preventive maintenance, unstable power and difficult technician access. Predictive algorithms and

artificial intelligence should be introduced only after unique equipment identification, maintenance documentation, technician feedback loops and governance systems are functional.

Conclusion

Predictive maintenance offers a practical opportunity to strengthen immunization cold chain resilience, but it should be implemented as an evolution of existing preventive and corrective maintenance systems. Immunization programmes already generate data that may help anticipate CCE failure, including temperature trends, asset history, repair records, spare-part movement, power reliability, stock risk, facility access and environmental conditions. The immediate priority is to improve data quality, triangulate existing data sources and apply simple risk-based triggers for technician response, spare-part planning, warranty escalation, replacement and decommissioning decisions. Advanced predictive analytics and artificial intelligence may add value when data quality, governance and field validation are strong. A phased, programme-owned and equity-sensitive approach can help countries act earlier, reduce downtime, protect vaccine availability and improve lifecycle management of cold chain equipment.

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