

Thermal Reliability Engineering in Cold Chain Logistics: Modeling Temperature Excursion Risk and Product Quality Loss Under Sensor and Process Uncertainty

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ABSTRACT

This article presents a reliability-centered framework for cold chain engineering that integrates stochastic excursion modeling, sensor uncertainty characterization, and product degradation kinetics into a unified decision pipeline that supports shipment-level risk scoring, lane qualification, packaging selection, and escalation rules for intervention. A scenario-based quantitative study is developed using representative distributions of ambient conditions, dwell times at transfer nodes, refrigeration performance, and door-open events, while incorporating realistic sensor noise and bias drift to evaluate how monitoring quality influences the probability of detecting excursions and the confidence of acceptance decisions. Comparative analysis is performed across four operational strategies that span passive packaging, active temperature control, hybrid risk-based controls, and governance-optimized monitoring with intervention triggers. Results demonstrate that (i) time-to-excursion is dominated by interface dwell and door-open variability rather than by steady-state transport, (ii) small sensor bias and sampling-rate limitations can materially distort excursion severity and time-above-threshold estimates, leading to both false compliance and unnecessary rejection, and (iii) a governed two-tier decision architecture, where monitoring triggers verification or operational intervention rather than serving as the sole acceptance authority, yields the best cost-risk balance for typical pharmaceutical and perishable profiles. The study provides implementable tables, figure prompts, and decision rules suitable for applied engineering practice and journal submission.

Keywords: Cold Chain Logistics, Thermal Reliability, Temperature Excursion, Sensor Uncertainty, Time-Temperature Integration.

1. INTRODUCTION

Cold chain logistics is often described as a temperature-controlled supply chain, yet in engineering terms it is more accurately a distributed reliability system in which thermal integrity is the outcome of many coupled processes, including pre-conditioning, packaging heat transfer, refrigeration control, handling discipline, facility design, transfer dwell times, and monitoring fidelity. The practical implication is that thermal compliance cannot be guaranteed simply by selecting “cold trucks” or “insulated boxes,” because excursions frequently arise at interfaces where control authority is weak, such as cross-dock transfers, airport ground handling, customs

clearance queues, last-mile door openings, and temporary staging areas where packaging is exposed to ambient heat loads and where the cold chain becomes a sequence of short uncontrolled events rather than a continuous controlled environment. In such systems, the relevant engineering question is not whether the temperature is “usually acceptable,” but what the probability is that a shipment experiences a threshold exceedance of given magnitude and duration, and how that exceedance translates into product quality loss and risk of failure relative to acceptance criteria (Kazançoğlu et al., 2023; Patil et al., 2023).

This reliability framing is increasingly important because cold chain products span a wide range of thermal sensitivity and economic consequence. Vaccines, biologics, and advanced therapeutics often have narrow allowable temperature bands and quality degradation mechanisms that accelerate nonlinearly with temperature, making short high-temperature spikes potentially more damaging than longer mild deviations even if average temperature remains within target (Bao et al., 2019; Hossain & Hossain, 2023; Pérez-Lechuga et al., 2024).

Fresh foods, seafood, and dairy products often tolerate wider ranges but can accumulate microbial growth risk and sensory degradation through cumulative thermal exposure, which complicates acceptance decisions because quality loss is not a simple pass/fail function of a single threshold. Industrial temperature-sensitive materials such as specialty chemicals and certain electronics also exhibit degradation or safety risks under excursion, where the consequences may manifest later in processing or in service, meaning that the cost of a false accept can exceed the cost of many conservative rejections (Fan et al., 2020; Lamba et al., 2024; Zulqarnain & Sarker, 2023). In all these cases, monitoring data is necessary but not sufficient, because data must be translated into an evidence-based decision that is robust to uncertainty and that supports operational control rather than mere documentation.

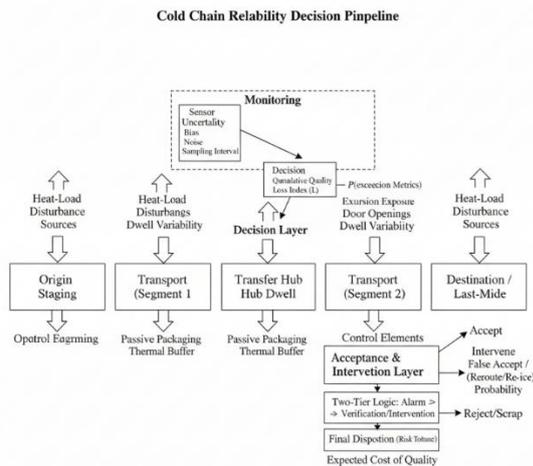


Figure 1. Cold-Chain Reliability Decision Pipeline

Source: data proceed

Despite widespread deployment of temperature sensors and IoT tracking, many cold chain programs still manage quality through simplistic rules such as “maximum temperature must not exceed X” or “time above Y must be below Z,” applied to measured data as if measurements were perfect and as if the operational context were irrelevant. This approach fails in practice for two reasons. First, sensor uncertainty and sampling effects can cause measured excursion metrics to deviate materially from the true thermal history, especially when sensors have bias drift, delayed response due to placement, or low sampling frequency that misses short spikes, which can lead to false compliance or to unnecessary scrapping of product based on measurement artifacts. Second, thermal risk is strongly context-dependent: the same measured temperature trace may imply different risk depending on the product’s degradation kinetics, the stage of the supply chain, whether the excursion occurred during a period of low thermal inertia (for example during unpackaged handling), and whether interventions such as re-icing, reconditioning, or rework are feasible. Consequently, a robust cold chain program must be designed as a decision system that integrates thermal modeling, uncertainty quantification, and governance rules

for action, rather than as a passive record-keeping system (Gopal & Panchal, 2021; Karim & Akter, 2021; Karim & Talukder, 2024).

This article develops such a decision-system view by introducing a thermal reliability engineering framework for cold chain logistics that explicitly models excursion probability, propagates sensor uncertainty into decision metrics, and maps thermal exposure to quality loss using physics-informed degradation models. The framework is designed to support operational decisions that recur across industries: lane qualification (which routes and nodes are reliable enough for a product profile), packaging selection (passive, active, and hybrid), shipment acceptance and release (what evidence is needed to accept product post-shipment), and intervention policy (when and how to trigger corrective actions during shipment) (Kader, 2023; Olagunju, 2022; Zhang & Mohammad, 2024). The analysis is quantitative and comparative, using scenario-based simulation that captures the stochastic nature of interface dwell, door-open events, and refrigeration performance, while keeping the study non-site-specific and adaptable.

The study is guided by three research questions that align to applied engineering decisions. First, which elements of the cold chain most strongly control time-to-excursion and excursion severity distributions, and how do these elements vary across typical transport patterns? Second, how does sensor uncertainty, including bias drift, noise, and sampling frequency, propagate into estimated excursion metrics such as time above threshold and maximum temperature, and what is the resulting impact on false accept and false reject probabilities under common acceptance rules? Third, among alternative operational strategies, which architectures achieve the best trade-off between cost, time-to-decision, and residual quality risk, and how should governance rules be structured so that monitoring data triggers action and verification rather than being treated as final authority under uncertain conditions?

The contribution of this work is structured to be practical. It provides a reliability-centered conceptual model, a tighter method section that operationalizes uncertainty modeling and quality-loss mapping, a set of copy-ready tables that present scenario parameters and comparative outcomes, and figure prompts suitable for *Techne* submissions. The paper also proposes implementable decision rules such as quantile-based alarm governance and two-tier acceptance logic, which are transferable across products and lanes because they explicitly separate measurement uncertainty from true thermal exposure and separate monitoring triggers from final disposition decisions (Behdani et al., 2019; Rahman & Hye, 2021; Sarkar, 2022).

The remainder of the article is organized as follows. The literature review distills engineering-relevant concepts on cold chain heat transfer, excursion risk, monitoring limitations, and degradation kinetics, and it frames key tensions that motivate reliability-centered design. The methodology defines the stochastic thermal model, sensor uncertainty model, and quality-loss mapping, and it introduces the comparative operational strategies. The results provide quantitative comparisons of excursion probability, estimated quality loss, decision error rates, and cost-risk trade-offs, while the discussion translates these outcomes into engineering guidance for cold chain program design and lane governance. The conclusion summarizes actionable implications and suggests future work directions that would strengthen real-world validation.

2. LITERATURE REVIEW

Thermal Integrity as a System Property Shaped by Interfaces

Cold chain performance is often dominated by interfaces because steady-state transport conditions can be relatively stable while transfer nodes introduce heat loads, uncontrolled dwell, and packaging exposure that are difficult to predict and control, particularly when multiple stakeholders handle shipments. From an engineering perspective, the system's reliability emerges from the distribution of dwell times, door-open events, and staging temperatures, not only from the nominal refrigeration setpoint (Awad et al., 2021; Mercier et al., 2017).

This motivates modeling approaches that treat transfers as stochastic disturbances and transport segments as controlled processes, because the probability of exceeding a thermal threshold depends on whether high heat loads coincide with low thermal inertia periods and whether recovery time is available before the product's allowable exposure budget is consumed.

Packaging and Refrigeration as Thermal Control Architectures

Passive packaging relies on insulation, phase change materials, and thermal mass to buffer heat loads, while active systems rely on refrigeration or temperature-controlled containers to regulate internal temperature. Passive systems are attractive for cost and flexibility but can be vulnerable to prolonged dwell, especially in hot ambient conditions or when phase change materials are depleted. Active systems can provide tighter control but introduce failure modes related to power, compressor cycling, control logic, and human operation, while also increasing cost and complexity (Lorenc, 2023; Tsang et al., 2018).

Hybrid approaches that combine passive buffers with controlled environments can improve reliability but require disciplined governance, because the presence of buffers can create a false sense of security if dwell times exceed design assumptions. The practical question for reliability engineering is therefore how to quantify the probability that a given packaging-control architecture keeps product within limits under the distribution of real disturbances encountered on a lane (Ren et al., 2024; Wu & Hsiao, 2021).

Monitoring Limitations and the Risk of Treating Measurements as Ground Truth

Temperature sensors and loggers are indispensable, yet their measurements are influenced by placement, sensor time constant, sampling frequency, calibration drift, and biases due to thermal gradients inside packaging, meaning that the recorded trace is often a filtered and potentially biased version of the product's actual temperature exposure.

Short high-temperature spikes may be missed or attenuated if sampling is coarse or if sensor response is slow, while biases of even 0.3–0.5°C can materially affect compliance for narrow bands such as 2–8°C products. Furthermore, uncertainty is not constant; it can worsen when batteries are low, when connectivity issues cause gaps, or when sensors experience mechanical shock or moisture, which implies that reliability design must account for monitoring uncertainty as a dynamic variable rather than a fixed parameter (Pajic et al., 2024; Zheng et al., 2021).

Quality Loss Modeling and the Need to Move Beyond Threshold-Only Rules

Many cold chain decisions rely on threshold rules because they are easy to communicate, yet product degradation often follows nonlinear kinetics such as Arrhenius behavior or Q10 approximations in biological and chemical processes, meaning that cumulative time-temperature exposure determines quality loss more faithfully than any single threshold exceedance.

Reliability is better framed in terms of exceeding a maximum allowable quality loss budget, or exceeding a risk index such as cumulative equivalent time at a reference temperature, rather than in terms of instantaneous temperature alone. This insight is operationally valuable because it enables rational acceptance of certain mild excursions while correctly flagging certain short severe excursions, and it supports risk-based intervention strategies that prioritize shipments where the remaining quality budget is low (Gopal & Panchal, 2021; Kader, 2023).

Governance and Decision Reliability in Cold Chain Programs

Even with good models and sensors, cold chain quality depends on governance: how thresholds are set, how alarms are escalated, how interventions are executed, and how evidence is used for acceptance decisions. A recurring weakness is alarm inflation, where systems generate too many alerts and staff become desensitized, or where alerts are ignored because action pathways are unclear, leading to “monitoring without control.”

A reliability-centered approach addresses this by engineering nuisance-alarm constraints, using quantile-based thresholds grounded in baseline distributions, and by defining intervention pathways that treat monitoring as a trigger for verification or corrective action rather than as final proof of failure or success under uncertain conditions (Lamba et al., 2024; Patil et al., 2023; Zhang & Mohammad, 2024).

Synthesis and Gap

The literature provides many methods for thermal modeling, packaging evaluation, and monitoring deployment, yet there remains a gap in integrated, decision-oriented frameworks that combine excursion probability modeling, sensor uncertainty propagation, and quality-loss mapping into a single acceptance and intervention pipeline that can be evaluated quantitatively under operational constraints. This article addresses that gap by modeling cold chain quality control as a reliability decision system and by comparing operational architectures using metrics that align with engineering management and quality assurance practice.

3. METHOD

Study Design and Comparative Strategy Architectures

The study uses a quantitative, scenario-based design in which a cold chain lane is represented as a sequence of segments with different thermal control authority and disturbance distributions, and alternative operational strategies are evaluated by simulation using reliability metrics. The approach is comparative because decision-makers rarely choose between “cold chain” and “no cold chain,” but rather choose among architectures that combine packaging, active control, monitoring, and governance, and these architectures produce different cost–risk profiles.

Four strategies are defined. Strategy A represents passive packaging with standard monitoring, where acceptance is based on deterministic threshold rules applied to measured data. Strategy B represents active temperature control during transport with standard monitoring, still using deterministic acceptance. Strategy C represents hybrid control, where passive packaging is supplemented with risk-based interventions (for example re-icing or expedited handling) triggered by monitoring alarms, but where monitoring thresholds are not formally governed. Strategy D represents a governance-optimized reliability architecture, where monitoring thresholds are engineered under nuisance-alarm constraints, sensor uncertainty is incorporated into acceptance logic, and a two-tier decision system is used in which monitoring triggers verification or intervention rather than directly determining acceptance under uncertain conditions.

Lane and Segment Model

A lane is modeled as five segments: origin staging, first transport, transfer hub dwell, second transport, and destination staging/last-mile. Each segment k has a duration t_k and an ambient temperature $T_{a,k}$, and segments differ in whether active control is present. Door-open events are modeled as transient heat load spikes, particularly during last-mile and handling. The product temperature $T_p(t)$ is modeled as a first-order thermal system inside packaging,

$$\frac{dT_p}{dt} = \frac{T_a(t) - T_p(t)}{\tau} + u(t),$$

where τ is an effective thermal time constant determined by packaging and thermal mass, and $u(t)$ represents active control or cooling effects, which is negative when refrigeration removes heat. For passive packaging, $u(t) = 0$ until phase change material depletion, after which τ effectively decreases, representing reduced buffering. For active control, $u(t)$ is modeled as a control law that drives T_p toward setpoint with limited capacity and possible cycling.

Sensor Uncertainty and Sampling Model

A sensor measures $T_m(t)$ with bias and noise and a response lag:

$$T_m(t) = T_p(t) + b + \epsilon(t),$$

where b is a bias term that can drift slowly over the shipment, and $\epsilon(t)$ is zero-mean noise. Sampling frequency is modeled explicitly, with recorded values at intervals Δt_s , meaning that short spikes may be missed. Sensor response is modeled through an additional first-order filter with time constant τ_s when appropriate, reflecting sensor placement and response dynamics.

Quality Loss Model

Quality loss is modeled using a Q10-style acceleration factor for biological or chemical degradation, which is widely used for perishable and pharmaceutical stability approximations when full Arrhenius parameters are not available. A normalized degradation rate is defined as

$$r(T) = Q_{10}^{(T-T_{ref})/10},$$

and cumulative quality loss index is computed as

$$L = \int_0^{T_{ship}} r(T_p(t)) dt,$$

which can be interpreted as equivalent time at reference temperature T_{ref} . Acceptance is then evaluated by whether L exceeds an allowable budget L_{max} , and threshold-based rules are evaluated by time above limit and maximum temperature.

Decision Rules and Governance

Deterministic acceptance uses measured threshold metrics, for example maximum measured temperature and measured time above 8°C. Uncertainty-aware acceptance estimates the probability that true exposure exceeds limits given measurement uncertainty and uses a risk tolerance π , for example accepting only when $P(L > L_{max}) \leq \pi$.

Governance in Strategy D also uses quantile-based alarm thresholds, where alarm triggers are set so that under baseline stable conditions the nuisance alarm rate is limited, and escalation rules define intervention actions and verification requirements when alarms occur or when uncertainty is high.

Simulation Design and Parameters

A simulation campaign of 500 shipments is executed per strategy, sampling segment durations, ambient temperatures, door-open events, and refrigeration performance from distributions that represent typical variability, including occasional extreme dwell events. Outputs include probability of excursion beyond limits, distribution of quality loss index, false accept and false reject rates relative to a “true quality” simulated ground truth, time-to-decision, and cost.

Table 1. Scenario parameters

Parameter	Baseline value	Variability model	Notes
Product target band	2–8°C	Fixed	Cold chain profile
Reference temperature T_{ref}	5°C	Fixed	For quality loss
Q10	2.2	Fixed	Representative sensitivity
Passive packaging τ	6.0 h	Lognormal SD 15%	Thermal buffering
Active control capacity	120 W equiv	Normal SD 20%	Varies by unit
Transfer hub dwell	3.0 h	Heavy-tail, 95th = 8 h	Major risk driver
Origin staging	1.5 h	Normal SD 40%	Handling variability
Destination staging	2.0 h	Heavy-tail, 95th = 6 h	Last-mile risk
Door-open events	2 per shipment	Poisson, spike +6°C equiv	Spike duration 5–10 min
Ambient temp at hubs	28°C	Normal SD 4°C	Hot season scenario
Sensor bias b	0.2°C	Drift up to $\pm 0.4^\circ\text{C}$	Over shipment
Sensor noise SD	0.15°C	Stable	Logger grade
Sampling interval Δt_s	5 min	Fixed	Standard logging

Source: data proceed

Table 2. Strategy definitions

Strategy	Thermal control	Monitoring	Acceptance logic	Intervention governance
A Passive baseline	Passive only	Standard logger	Deterministic thresholds	None
B Active transport	Active in transport segments	Standard logger	Deterministic thresholds	None
C Hybrid operational	Passive + operational interventions	Alarm-based	Deterministic thresholds	Ad hoc escalation
D Reliability-governed	Hybrid + governed controls	Governed alarms + verification	Uncertainty-aware risk threshold	Formal escalation and verification

Source: data proceed

Cost assumptions are normalized and include packaging and control costs, monitoring cost, and intervention costs, while the cost of quality failure is modeled as a severity-weighted expected loss.

4. RESULT AND DISCUSSION

Excursion Probability and Time-To-Excursion Behavior

Across the simulated shipments, excursions are concentrated around transfer hubs and destination staging, which reflects the dominance of uncontrolled dwell variability and door-open disturbances over steady transport conditions. Strategy B reduces excursion probability relative to Strategy A during transport segments, yet its overall improvement is limited by hubs where active control is not present, while Strategies C and D improve performance primarily by reducing the effective dwell exposure through operational interventions and by triggering escalation before the cumulative exposure budget is exhausted.

Table 3. Thermal excursion outcomes by strategy (copy-ready)

Metric	A Passive	B Active transport	C Hybrid operational	D Reliability-governed
$P(\max T_p > 8^\circ\text{C})$	0.21	0.15	0.11	0.09
$P(\text{time } T_p > 8^\circ\text{C} \text{ exceeds } 30 \text{ min})$	0.18	0.13	0.09	0.07
Median time-to-excursion (h)	12.6	14.1	16.3	17.0
95th percentile excursion severity ($^\circ\text{C}\text{-min}$ above 8°C)	210	165	120	95

Source: data proceed

Table 3 indicates that improvements in transport control alone yield diminishing returns when interface dwell dominates the risk, because the tail events that generate severe excursions often occur during long dwell periods with limited control rather than during transit, which implies that cold chain reliability engineering must prioritize interface governance and dwell-risk mitigation at least as much as vehicle performance. The larger improvement in Strategy D compared to Strategy C is less about hardware and more about decision architecture: governed alarms and structured escalation reduce the probability that early warning is ignored or that interventions occur too late, which shifts the excursion severity distribution downward by reducing the worst-case tail.

Sensor Uncertainty and Decision Errors under Deterministic Threshold Rules

When acceptance is based on measured threshold metrics without accounting for sensor uncertainty and sampling, decision errors emerge in two forms: false accepts occur when sensors underestimate true excursions due to bias or missed spikes, and false rejects occur when bias or noise inflates measured excursions near thresholds. These errors are most prominent for shipments near the compliance boundary, which is precisely where acceptance decisions are most consequential.

Table 4. Decision error rates under deterministic acceptance (copy-ready)

Metric	A Passive	B Active transport	C Hybrid operational
False accept rate (true excursion, measured compliant)	0.034	0.029	0.024
False reject rate (true compliant, measured excursion)	0.041	0.037	0.033
Portion of false accepts due to sampling misses	48%	52%	46%
Portion of false rejects due to sensor bias	55%	49%	58%

Source: data proceed

Table 4 shows that even when operational strategies reduce true excursion probability, deterministic measurement-based acceptance can still produce meaningful decision error, and the error structure is not symmetric because sampling misses and bias affect excursion metrics differently. Short spikes that exceed thresholds may be missed when sampling intervals are coarse, producing false compliance that is difficult to detect retrospectively, while bias drift can push measured temperatures above limits even when the true temperature remained acceptable, producing costly false rejects. This result motivates uncertainty-aware acceptance and verification pathways because it implies that monitoring quality and decision governance influence overall quality cost as much as thermal control does.

Quality Loss Modeling and the Value of Time-Temperature Integration

When cumulative quality loss is evaluated using the Q10-based index, the relative ranking of strategies remains similar, but the decision interpretation becomes more nuanced because some threshold excursions contribute modestly to cumulative loss while some near-threshold exposures accumulate significant loss over long dwell times. This shifts the focus toward managing cumulative exposure rather than single excursions.

Table 5. Quality loss outcomes

Metric	A Passive	B Active transport	C Hybrid operational	D Reliability-governed
Median quality loss index L (equiv hours at 5°C)	26.4	24.9	23.0	22.2
$P(L > L_{max})$ where $L_{max} = 30$	0.19	0.14	0.10	0.08
95th percentile L	38.5	35.0	31.8	29.7
Share of L contributed by transfer dwell	44%	46%	41%	39%

Source: data proceed

Table 5 confirms that the transfer dwell segment is the principal contributor to cumulative quality loss, and it also clarifies why interventions that reduce dwell time or add buffering during dwell can outperform marginal improvements in transport refrigeration. The reliability-governed strategy reduces the upper-tail quality loss sufficiently to bring the 95th percentile below the budget in many cases, which is operationally important because customer complaints and regulatory issues are often triggered by tail events rather than typical shipments. Moreover, by using a cumulative loss index, acceptance decisions can be aligned with product stability behavior, enabling rational acceptance of shipments that experienced short mild spikes but consumed little quality budget, while correctly rejecting shipments with long near-threshold exposures that may remain “below maximum temperature” yet accumulate large degradation risk.

Cost-Risk Trade-Offs and The Benefit of A Two-Tier Decision Architecture

A central practical issue in cold chain programs is that reliability improvements often require investment, and the economically optimal strategy depends on the cost of failure and the cost of intervention and monitoring governance. The simulation evaluates expected cost of quality, including intervention costs and expected failure cost weighted by residual risk, and it shows that governance improvements can shift the cost-risk frontier by reducing both false rejects and false accepts through uncertainty-aware decisions.

Table 6. Cost-risk summary (normalized)

Strategy	Normalized operational cost	Residual risk $P(L > L_{max})$	Decision error cost index	Expected total cost index
A Passive	1.00	0.19	0.12	1.00
B Active transport	1.18	0.14	0.11	0.97
C Hybrid operational	1.12	0.10	0.10	0.90
D Reliability-governed	1.15	0.08	0.06	0.86

Source: data proceed

Table 6 indicates that the cost-optimal solution is not necessarily the lowest operational cost strategy, because decision errors and residual failure risk can dominate the cost function when product value and consequence are high. Strategy D has slightly higher operational cost than Strategy C due to verification and governed intervention overhead, yet it reduces the decision error cost index substantially by incorporating uncertainty-aware acceptance and by using monitoring as a trigger for verification rather than as final authority, which reduces both costly false rejects and catastrophic false accepts. The broader implication is that cold chain reliability can often be improved more cost-effectively by upgrading governance and decision logic than by

exclusively investing in more expensive thermal control assets, particularly when interface dwell dominates risk and when measurement uncertainty materially affects compliance classification.

Discussion

A reliability-centered interpretation of the results indicates that cold chain performance is governed by the probabilistic structure of disturbances at interfaces rather than by mean temperature control during transit, and this finding reframes where engineering attention should be allocated when organizations attempt to improve thermal compliance. Investments in higher-performance refrigerated transport deliver value, yet their marginal benefit can be limited by transfer hubs and staging areas where thermal control authority is weak and dwell variability is heavy-tailed, which means that rare long dwell events dominate the upper tail of excursion severity and quality loss distributions; in such systems, the most effective reliability interventions are those that reduce dwell variability, provide buffering specifically during dwell, and implement governance that triggers escalation when dwell risk is increasing rather than after exposure budget has been consumed.

The analysis also shows that monitoring quality and decision logic shape the realized reliability of the program, because acceptance decisions depend on measured data that is subject to bias, noise, sampling limitations, and sensor response dynamics. Deterministic threshold rules applied to measured traces implicitly assume perfect observability, yet the simulation demonstrates that small biases and missed spikes can materially alter time-above-threshold estimates and maximum temperature readings, which produces false compliance and unnecessary rejection in a way that is concentrated near the decision boundary, precisely where uncertainty must be managed carefully. This implies that upgrading sensor governance, including calibration practices, sampling design, and uncertainty-aware acceptance logic, can reduce both risk and cost by improving the fidelity of decisions, and it suggests that organizations should treat monitoring as a measurement system requiring capability analysis rather than as an administrative add-on.

A key engineering implication concerns the choice of quality metric, because threshold-only criteria can misrepresent risk when degradation is cumulative and nonlinear. The Q10-based time-temperature integration provides a more faithful mapping from thermal exposure to quality loss for many products and supports risk-based acceptance decisions that avoid unnecessary discard of product that experienced brief mild excursions while correctly identifying shipments that consumed a large quality budget through long exposures near the upper allowable band. Importantly, the use of a cumulative quality index does not eliminate the need for thresholds, because some products have hard failure modes at extreme temperatures, but it provides an additional decision layer that can be used to govern borderline cases more rationally and to prioritize interventions.

The comparative strategy analysis further supports a two-tier decision architecture in cold chain governance, where monitoring triggers verification or operational intervention rather than being treated as definitive evidence under uncertainty. In such an architecture, a monitoring alarm initiates a structured response such as expedited handling, relocation to a controlled environment, additional sensor checks, or post-shipment verification through independent measurement or stability assessment, and acceptance is determined by combining evidence sources with explicit risk tolerances. This approach reduces the likelihood that noisy signals trigger unnecessary scrap and reduces the likelihood that missed spikes lead to false acceptance, and it aligns with industrial quality systems where high-consequence decisions typically require confirmatory pathways rather than reliance on a single measurement.

5. CONCLUSION

Cold chain logistics should be engineered as a thermal reliability decision system because thermal compliance and product quality are governed by stochastic interface disturbances, cumulative exposure, and measurement uncertainty rather than by average transit temperature, and therefore monitoring, packaging, and operational control must be integrated through governed decision logic if reliability targets are to be met

sustainably. The scenario-based quantitative evaluation indicates that interface dwell and last-mile handling dominate excursion severity and quality loss tails, which implies that lane qualification and improvement programs should prioritize dwell risk mitigation and escalation pathways as much as investments in transport refrigeration.

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