

Risk-Based Leakage Detection and Incident Prevention in Large-Scale Saudi Industrial and Infrastructure Projects.

Abstract:

Large-scale industrial and infrastructure projects in Saudi Arabia combine extensive process piping, transmission networks, utility corridors, water systems, storage interfaces, and high-consequence facilities. Leakage in these assets can evolve from a maintenance defect into a safety, environmental, production, or reputational incident when detection is delayed or when integrity decisions are separated from consequence analysis. This review develops an integrative framework for risk-based leakage detection and incident prevention, synthesizing recent peer-reviewed work on pipeline integrity, risk-based inspection, computational leak detection, acoustic and optical sensing, machine learning, digital twins, corrosion prediction, and water-network diagnostics. The evidence indicates that no single detection technology is consistently sufficient across fluids, operating regimes, asset geometries, and leak sizes. More robust practice couples probability-of-failure models with consequence severity, detectability, sensor confidence, and lifecycle condition information. For Saudi applications, the central implication is that leak detection should be designed as a dynamic integrity-management function rather than as an isolated alarm system. The proposed framework links design assurance, commissioning baselines, multimodal monitoring, risk ranking, inspection planning, response escalation, and feedback learning. It also identifies evidence gaps in Saudi field validation, rare-event datasets, transferability under harsh environments, model uncertainty, cybersecurity, and contractor-to-operator data continuity. The review provides a technically grounded basis for project owners, engineering contractors, operators, and regulators seeking to reduce loss-of-containment risk while avoiding indiscriminate monitoring expenditure.

Keywords: risk-based inspection; leak detection; pipeline integrity; digital twin; machine learning; process safety; Saudi Arabia

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1. Introduction

Loss of containment remains one of the most consequential failure modes in industrial piping and fluid-transport infrastructure because a leak can simultaneously threaten people, the environment, asset availability, and project economics. The engineering challenge is not merely to identify a leak after it has formed. Effective prevention requires detecting deterioration early, distinguishing genuine leakage from operational transients, locating the release with sufficient confidence, and linking the signal to an action proportionate to risk. Reviews of pipeline leak detection consistently show a fragmented technology landscape in which internal computational methods, external sensors, acoustic techniques, fiber-optic approaches, visual methods, and hybrid systems exhibit different sensitivities, costs, and deployment constraints [1–4]. This fragmentation becomes more important in large projects, where one facility may contain buried water lines, hydrocarbon pipelines, process pipework, pressurized utility systems, flanged connections, tanks, and remote corridors.

Risk-based integrity management provides a useful organizing principle because it shifts attention from uniform inspection toward the assets and failure scenarios that matter most. Khan et al. describe risk-based pipeline integrity as a lifecycle activity linking inspection, maintenance, reliability, and resilience rather than a periodic compliance exercise [5]. Dynamic inspection studies similarly demonstrate that deterioration state, inspection information, and consequence can be combined to optimize intervention timing [6–10]. Such thinking is directly relevant to Saudi Arabia, where new industrial and infrastructure developments are being delivered at scale and where long asset lives require reliable handover from engineering, procurement, and construction phases into operations. The Saudi setting also creates a demanding transfer environment: high ambient temperatures, saline or aggressive service conditions in some applications, remote linear assets, high-value process units, and water-scarcity concerns can magnify the consequences of undetected leakage. These contextual factors do not make international evidence automatically transferable; they make explicit validation and uncertainty management more important.

A further limitation of conventional practice is the separation between integrity inspection and leak detection. Corrosion management, nondestructive examination, flange reliability, pressure-wave monitoring, acoustic sensing, and machine learning are frequently developed as distinct

technical domains. Yet leakage is typically the final manifestation of interacting causes. Bolted flange performance, for example, depends on gasket behavior, bolt preload, creep, thermal loading, and external loads [11], while wet-gas pipelines can experience top-of-line corrosion driven by condensation and corrosive species [12]. In multiphase systems, the flow regime itself alters leak signatures and can complicate interpretation [13]. A credible prevention strategy therefore needs both precursor knowledge and release detection.

This review addresses that integration problem. It examines how risk models, sensing technologies, data analytics, and operational decision rules can be assembled into a coherent leakage-prevention architecture for large-scale Saudi industrial and infrastructure projects. The paper does not claim that technologies validated elsewhere will perform identically in Saudi assets. Instead, it identifies the conditions under which evidence can be transferred, the points requiring local verification, and the governance mechanisms needed to convert detection capability into incident prevention.

2. Aim of the Study

The study aims to develop a critical, evidence-based framework for integrating risk assessment, leakage detection, integrity inspection, and incident-prevention decisions across the lifecycle of large-scale Saudi industrial and infrastructure projects. The emphasis is on how heterogeneous evidence can support practical prioritization: which assets require intensive monitoring, which detection combinations are technically defensible, when inspection should be advanced, and how alarms should trigger proportionate operational action.

3. Research Objectives

The review pursues five distinct objectives.

First, it classifies the principal leakage mechanisms, precursors, and consequence pathways relevant to complex piping and pipeline assets.

Second, it compares internal, external, acoustic, optical, model-based, and machine-learning detection approaches against operational needs rather than laboratory accuracy alone.

Third, it examines how risk-based inspection and dynamic integrity models can prioritize surveillance and intervention.

Fourth, it develops a lifecycle architecture connecting engineering data, commissioning baselines, online monitoring, inspection, and emergency response.

Fifth, it identifies research, managerial, and policy requirements for reliable adaptation of the evidence to Saudi projects.

4. Research Questions

Five questions guide the synthesis.

RQ1: Which technical and operational factors most strongly shape leakage probability and consequence in large industrial and infrastructure systems?

RQ2: What are the comparative strengths and limitations of contemporary leak detection technologies under realistic operating variability?

RQ3: How can risk-based inspection, condition prediction, and leak monitoring be combined into a dynamic prioritization process?

RQ4: What data, governance, and lifecycle controls are required to convert detection outputs into effective incident prevention?

RQ5: Which evidence gaps must be resolved before broad deployment in Saudi industrial and infrastructure projects?

5. Review Methodology

A structured integrative review design was adopted because the topic spans process safety, pipeline engineering, civil infrastructure, sensing, machine learning, and asset integrity. The method was designed to compare heterogeneous study types without converting laboratory performance, simulation results, and field evidence into a false common metric. The attached reference paper was used only to inform the expected scholarly organization and level of methodological transparency; none of its wording, datasets, results, or analytical conclusions were used as substantive evidence in this review.

The search architecture targeted peer-reviewed journal literature indexed in Scopus or Web of Science and retrievable through major publisher and disciplinary platforms. Search pathways covered ScienceDirect, ASCE Library, MDPI journal platforms, and other publisher records, while bibliographic verification was performed against publisher metadata and DOI records. Search strings combined terms such as “pipeline leak detection,” “loss of containment,” “risk-based inspection,” “pipeline integrity management,” “dynamic Bayesian network,” “acoustic emission,” “negative pressure wave,” “optical gas imaging,” “wireless sensor network,” “digital twin,” “machine learning leak detection,” “corrosion prediction,” “water distribution leak,” and “incident prevention.” Saudi Arabia, arid environment, industrial project, infrastructure, oil and gas, water, and utility terms were used as contextual modifiers rather than as mandatory filters because a Saudi-only search would exclude important transferable engineering evidence.

The primary publication window was 2020–2025, selected to capture contemporary sensing, analytics, and dynamic risk methods. Earlier work was considered only when necessary to interpret a technique, but it was not needed in the final evidence set. Eligible studies were peer-reviewed journal articles or reviews with direct relevance to leakage detection, localization, precursor deterioration, risk-based inspection, or data-driven integrity decisions. Studies were excluded when they concerned unrelated fault diagnosis, lacked sufficient methodological information, were conference-only outputs, theses, patents, vendor literature, standards without peer review, or duplicated substantially the evidence of a more complete journal publication. Because the retrieval environment did not provide a single auditable export spanning all platforms, the review deliberately does not report invented identification, deduplication, or screening counts.

Quality assessment was qualitative and domain-sensitive. Each candidate source was examined for clarity of asset and fluid context, validity of experimental or simulation design, transparency of features and performance measures, realism of operating conditions, treatment of uncertainty, and relevance to deployment decisions. Field data and validated industrial case studies were weighted more heavily when discussing implementation, while controlled experiments and simulation studies were used primarily to explain mechanisms or algorithmic capability. Review papers were used to establish method families and unresolved limitations, not to inflate evidence through double counting. DOI, year, journal, title, and authorship metadata for the 30 included

references were checked against publisher or Crossref-linked records before manuscript preparation.

Synthesis proceeded in four stages. First, evidence was coded into failure drivers, detection mechanisms, decision models, and operational controls. Second, studies were compared according to what they detect: an incipient defect, a physical leak signal, a process imbalance, or a consequence indicator. Third, the evidence was mapped onto a risk logic in which probability of failure and consequence of failure are modified by detectability, data confidence, and response time. Fourth, findings were translated into a Saudi project lifecycle perspective covering design, construction, commissioning, operations, integrity management, and emergency response. Figure 1 represents this synthesis logic. The approach supports critical transfer of evidence while acknowledging that performance demonstrated in one fluid, pipe material, climate, or test rig cannot be assumed to reproduce unchanged in another.

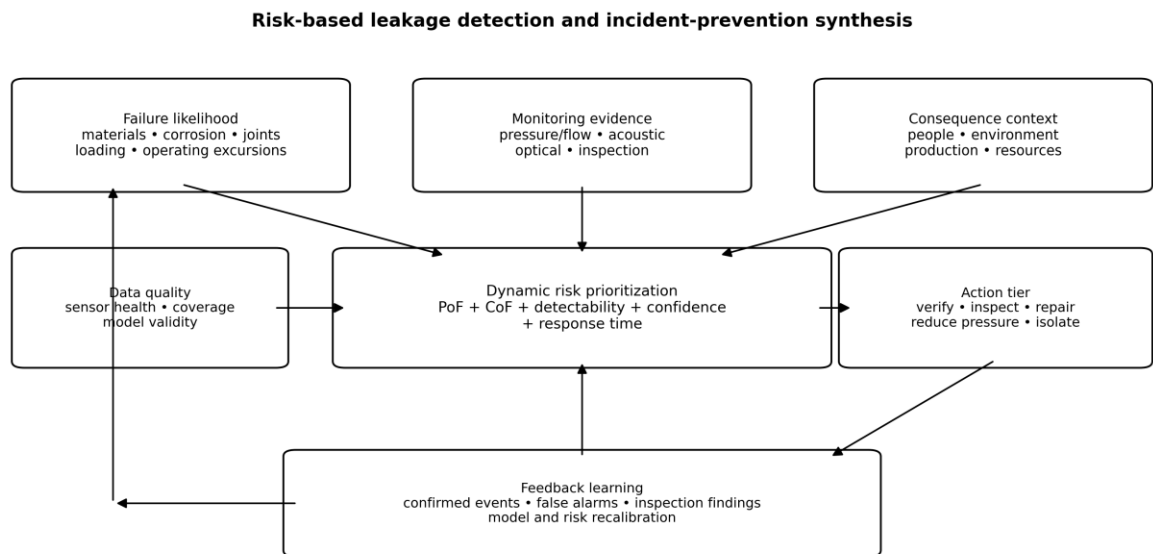


Figure 1. Risk-based leakage detection and incident-prevention synthesis linking failure drivers, monitoring evidence, consequence, uncertainty, response, and feedback learning.

6. Thematic Literature Review and Critical Analysis

6.1 From leak detection to risk-based loss-of-containment control

The literature increasingly supports treating leakage as a risk-control problem rather than a sensor-selection problem. Conventional leak detection reviews compare technologies by sensitivity, location accuracy, cost, and response time [1–4], whereas risk-based integrity research asks when failure is most likely, what its consequences would be, and which intervention yields the greatest risk reduction [5–10]. These perspectives are complementary. A highly sensitive detector installed on a low-consequence line may generate less value than a moderately sensitive, redundant system on a high-consequence segment. Conversely, a risk model without timely condition or leak information can become static and insensitive to emerging degradation.

Dynamic Bayesian approaches illustrate how inspection data can update failure probability as corrosion or combined defects evolve [6,7,10]. Risk-based maintenance models further connect degradation trajectories to intervention timing [8], while fatigue-oriented inspection planning shows the importance of loading cycles and defect geometry [9]. The practical lesson is that the “risk” attached to leakage should not be reduced to a fixed matrix score. It should be a living estimate informed by design margin, age, material, service chemistry, inspection history, operating excursions, joint density, accessibility, detectability, and consequence receptors. For Saudi mega-projects, this implies that sensor deployment density and alarm logic should be justified by segment-level risk and updated as operating evidence accumulates.

Leakage prevention also depends on precursor mechanisms. Flanged joints can lose sealing capability through preload relaxation, gasket nonlinearity, thermal effects, and external loading [11]. Corrosion mechanisms can be strongly conditioned by phase behavior and local chemistry [12], and multiphase flow changes the hydraulic signature available to computational detection [13]. These mechanisms argue for a combined integrity model: defect-development evidence should influence leak-monitoring expectations, and abnormal leak signals should in turn accelerate inspection of plausible failure locations. Table 1 summarizes this relationship across major technology families.

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189 **Table 1. Comparative evidence layers for risk-based leakage detection and prevention.**

Evidence family	Primary observation	Principal strength	Key limitation	Risk-based role
Internal/computational [1–4,13,25,29]	Pressure, flow, mass balance, transient response	Long-segment coverage using process instrumentation	Model mismatch, meter error, transients, micro-leak threshold	Continuous detection and localization evidence; supports rapid escalation
Acoustic/vibration [14–17,20,24]	Leak-induced sound, vibration, time delay	Sensitive local evidence; useful for pinpointing	Noise, attenuation, mounting, supports and geometry create domain shift	Independent confirmation and targeted high-risk monitoring
Optical gas imaging [18]	Visible infrared plume characteristics	Non-contact screening and classification for accessible gas sources	Line-of-sight, weather, contrast and release-rate dependence	Verification and consequence-oriented screening of exposed sources
Integrity precursors/NDE [11,12,27,28]	Joint sealing state, corrosion, defect morphology	Can act before through-wall leakage occurs	Periodic access; inference from defect to future release remains uncertain	Updates PoF and advances inspection/repair before loss of containment
Hybrid/digital-twin	Fused condition,	Combines	Requires data	Portfolio prioritization,

Evidence family	Primary observation	Principal strength	Key limitation	Risk-based role
risk layer [5–10,26,30]	operating and consequence evidence	complementary evidence and can update priorities dynamically	governance, model maintenance and transparent uncertainty	inspection timing and decision support

190 6.2 Detection technologies: complementary evidence rather than a universal solution

191 Internal computational methods infer leakage from pressure, flow, mass balance, or transient
192 behavior. They can cover long assets with instrumentation already present, but their performance
193 depends on model fidelity, meter quality, process stability, and the distinguishability of leaks
194 from legitimate transients [1–4]. Pressure-wave methods can provide rapid localization, yet their
195 effectiveness varies with leak size, sensor spacing, wave attenuation, noise, and operating state
196 [29]. Model-based Bayesian updating can improve robustness by acknowledging parameter
197 uncertainty rather than treating the pipeline model as exact [25]. In multiphase service, however,
198 flow-regime complexity and uncertain fluid properties can erode the assumptions underlying
199 simple mass-balance or pressure-response models [3,4,13].

200 External sensing provides different evidence. Wireless vibration or accelerometer networks can
201 identify leak-induced signatures close to the pipe wall; Spandonidis et al. demonstrated deep-
202 learning approaches using wireless sensor data in noisy industrial conditions [14]. Acoustic
203 cross-correlation can support detection and localization, but low signal-to-noise ratios and
204 propagation effects challenge time-delay estimation [15]. Yao et al. addressed background noise
205 and limited effective features through acoustic feature reconstruction [16], while Siddique et al.
206 combined time-frequency representations with deep learning to improve classification [17].
207 These studies show the benefit of feature engineering and representation learning, but their
208 reported accuracy should not be interpreted as a guaranteed plant-wide performance level.
209 Industrial noise spectra, mounting conditions, pipe supports, insulation, branch geometry, and
210 unseen leak modes can create substantial domain shift.

211 Optical monitoring adds another layer. Infrared video can detect methane plumes without
212 contacting the pipe and can support automated classification; VideoGasNet demonstrated that

temporal information can extend optical gas imaging beyond binary visual inspection [18]. Optical methods are valuable for accessible gas-release sources, but performance can depend on viewing geometry, background, meteorology, temperature contrast, and leak rate. They are therefore better viewed as complementary confirmation or screening tools than as a universal substitute for internal monitoring.

Water-network research offers transferable lessons because it has extensively tested acoustic, hydraulic, and machine-learning strategies under distributed infrastructure conditions. Comparative surveys identify the same core trade-off between physical interpretability, sensor density, data requirements, and false-alarm exposure [19]. Time-frequency convolutional methods have been applied to leakage acoustics [20]; transient-flow models combined with machine learning exploit high-frequency hydraulic responses [21]; simulation-driven frameworks can support multiple-leak localization [22]; tree-based models have been evaluated against on-site signals [23]; and cloud-supported AI systems have been field tested for acoustic leak pinpointing [24]. These studies are not direct substitutes for hydrocarbon or process-piping validation, but they demonstrate that deployability depends on calibration, field noise, operator workflow, and data management as much as on algorithm choice.

6.3 Machine learning, digital twins, and the problem of trustworthy generalization

Machine learning can extract weak patterns from multivariate or high-dimensional signals, yet leakage is a rare-event domain where the most consequential classes are often the least represented. Recent reviews conclude that model performance is constrained by limited real leak data, class imbalance, inconsistent benchmarks, and transferability between laboratory and field conditions [30]. The risk is not only false negatives. Excessive false positives can normalize alarms, encourage bypassing, or increase unnecessary field verification. For safety-critical use, a model therefore needs calibrated uncertainty, interpretable features where possible, and explicit fallback behavior when input data depart from the training distribution.

A more defensible direction is hybridization. Bayesian model updating combines physical pipeline behavior with uncertain measurements [25]. Data-driven digital twins can learn normal operational behavior and update representations over the asset lifecycle [26]. Theory-guided machine learning for pitting-corrosion depth embeds engineering knowledge into feature construction rather than relying solely on statistical correlation [27]. Deep learning applied to

magnetic flux leakage inspection likewise shows potential for defect characterization while also raising interpretability and data-augmentation questions [28]. Together, these studies support an architecture in which physics, inspection, and data-driven models constrain one another.

For large Saudi projects, the digital twin should not be conceived as a visualization layer detached from integrity decisions. Its value lies in maintaining traceability from tag and line number to design conditions, material specification, joint history, inspection measurements, sensor health, operating envelope, anomaly history, and consequence context. Leak analytics can then be tested against a consistent asset state. Figure 2 presents a closed-loop lifecycle in which baseline information established during design and commissioning becomes the reference for monitoring, anomaly assessment, intervention, and model updating. This is particularly important when assets are delivered by multiple contractors and operated for decades after project completion.

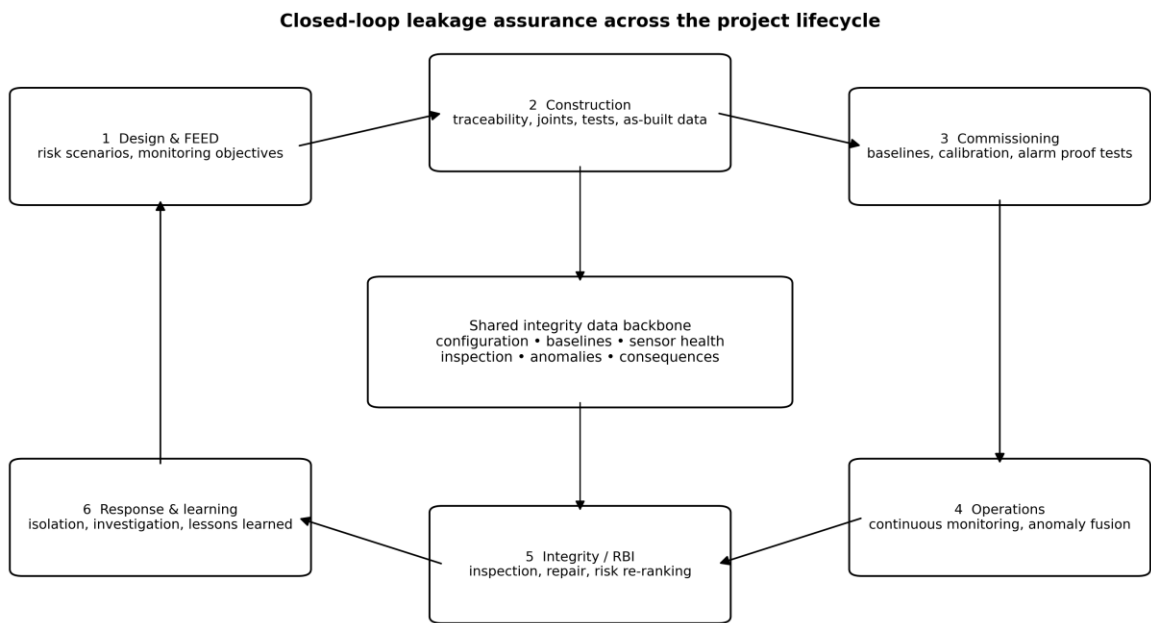


Figure 2. Closed-loop leakage assurance across design, construction, commissioning, operations, risk-based inspection, response, and organizational learning.

6.4 Converting detection into incident prevention

Detection prevents incidents only when it is connected to decision rules. A useful risk-based workflow separates four questions: Is the signal credible? What failure scenario is plausible? What is the current consequence if the leak is real? What action is justified now? The first requires sensor diagnostics, data-quality checks, and corroboration across independent channels. The second links the alarm to mechanisms such as corrosion, joint relaxation, mechanical damage, hydraulic transient, or instrumentation error. The third evaluates people, environment, production, water loss, ignition potential, and escalation pathways. The fourth selects responses ranging from intensified monitoring and field verification to pressure reduction, isolation, shutdown, or emergency response.

This logic discourages two weak practices: treating every alarm identically and delaying action until perfect localization is achieved. High-consequence systems may require conservative action under uncertainty, while low-consequence anomalies can be verified without unnecessary shutdown. Similarly, precursor inspection should be risk-triggered. A rising corrosion prediction, repeated transient anomalies, or degrading sensor trend can advance inspection even before a confirmed leak appears. The objective is not maximum data collection; it is minimum residual risk for a justified lifecycle cost.

Table 2 translates this principle into project stages. During design, risk assessment should determine monitoring requirements and instrumentation provisions. Construction should preserve material, weld, flange, and test traceability. Commissioning should create clean baselines and prove alarm-response paths. Operations should combine online detection with risk-based inspection and management of change. Emergency planning should specify isolation boundaries, escalation thresholds, communications, and post-incident learning. This integration is the distinguishing feature of a risk-based leakage program: the detection system becomes one control within a broader barrier strategy rather than an independent technology package.

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294 **Table 2. Lifecycle controls for a risk-based leakage assurance program.**

Lifecycle stage	Leakage-assurance activity	Required evidence	Risk-based decision	Verification indicator
Design / FEED	Define credible release scenarios, critical segments, monitoring objectives and isolation philosophy	P&IDs, line list, materials, design envelope, consequence receptors	Allocate sensor coverage and barrier strength by scenario risk	Requirements traceable to hazards and testable acceptance criteria
Construction	Preserve weld, flange, material, burial and test traceability	As-built records, torque/weld/NDE data, deviations, redlines	Escalate defects or incomplete records before concealment/startup	Complete asset history tied to tag/line/location
Commissioning	Establish clean baselines and prove alarm-response chain	Hydro/pneumatic test results, calibration, normal transients,	Set thresholds and confirm response authority	Demonstrated detection, communication and isolation path

Lifecycle stage	Leakage-assurance activity	Required evidence	Risk-based decision	Verification indicator
		cause-and-effect tests		
Operations	Fuse process, acoustic, optical and condition data; monitor sensor health	Historian data, alarms, sensor diagnostics, operating envelope	Verify, monitor, reduce pressure, inspect or isolate according to current risk	Latency, false-alarm burden, availability and closure time tracked
Integrity / maintenance	Update PoF from inspection and degradation evidence; optimize intervention	ILI/NDE results, corrosion growth, joint findings, repair history	Advance or defer inspection/repair using documented risk tolerance	Risk reduction and residual uncertainty recorded
Emergency / learning	Control release, investigate causes and feed evidence back	Isolation timeline, event labels, consequence data, root-cause findings	Revise models, thresholds, procedures and criticality	Lessons implemented and effectiveness re-tested

295 6.5 Performance assurance and decision thresholds

296 A risk-based program also requires a more disciplined definition of performance than overall
297 detection accuracy. Accuracy can be misleading when non-leak periods dominate the dataset,
298 because a model can appear strong while missing rare hazardous events. Deployment criteria
299 should therefore include sensitivity at defined leak sizes, specificity during known operational
300 transients, time to detection, location uncertainty, sensor uptime, probability of missed detection,
301 and the operational cost of false alarms. These measures should be stratified by risk class and
302 operating regime. For example, a high-consequence gas segment may justify a lower alarm

threshold and faster confirmatory action than a low-consequence utility header, even if the lower threshold increases nuisance alarms.

Thresholds should also be linked to response capacity. Detecting a small anomaly has limited preventive value if isolation valves cannot be operated promptly, field access is delayed, or the responsible team does not receive contextual information. Alarm design should therefore incorporate escalation time, available isolation boundaries, estimated release progression, and the confidence of independent evidence. A useful decision record captures the raw anomaly, corroborating indicators, current risk rank, responsible authority, required response time, action taken, and final event label. Over time, these records create the operational evidence needed to recalibrate models and demonstrate that monitoring is actually reducing risk. This emphasis on end-to-end performance is particularly important on complex Saudi projects, where technical systems may cross organizational interfaces between EPC contractors, specialist vendors, asset owners, and operating companies.

7. Discussion

The synthesis indicates that the main technical problem is not choosing between model-based, acoustic, optical, or machine-learning detection. It is deciding how much confidence each evidence stream deserves under a particular failure scenario. The literature consistently favors complementarity: reviews highlight hybrid systems [1–4], risk models benefit from time-varying inspection evidence [6–10], and recent analytics increasingly combine physical knowledge with data-driven inference [25–30]. A Saudi implementation should therefore organize monitoring around risk scenarios, not vendor product categories.

Three design principles follow. First, probability and consequence must be separated analytically before being recombined. A frequently leaking low-pressure utility line and a rarely failing high-consequence hydrocarbon segment can require very different controls even if both generate similar sensor anomalies. Second, detectability should be treated as an explicit risk modifier. Buried assets, multiphase flow, inaccessible joints, and low-rate chronic leaks can remain hazardous precisely because conventional signals are weak [3,4]. Third, uncertainty must be visible to decision-makers. A binary “leak/no leak” output can hide sensor degradation,

extrapolation beyond training data, or model mismatch. Confidence bands, data-quality flags, and corroboration status are operationally more useful.

The resulting framework also changes project governance. Engineering contractors must deliver more than drawings and instrument lists; they must preserve structured integrity data and baseline conditions that operators can reuse. Operators must maintain sensor health, model configuration, anomaly labels, and inspection feedback. Asset integrity, process control, HSE, maintenance, and cybersecurity teams need shared escalation logic because leak detection increasingly depends on networked sensing and analytics. Regulators and owners, meanwhile, can evaluate performance through measurable outcomes such as minimum detectable leak under defined conditions, detection latency, localization error, false-alarm burden, sensor availability, inspection closure time, and demonstrated response readiness. These metrics are more meaningful than requiring a specific technology irrespective of context.

A fourth principle is that leakage assurance should be engineered for degradation of the monitoring system itself. Sensors drift, communications fail, process historians contain gaps, and analytical models become stale when operating conditions change. A risk register should therefore include detection-system failure modes alongside pipe or equipment failure modes. When monitoring confidence falls below an accepted level, the compensating action may be temporary inspection, additional portable sensing, reduced operating envelope, or expedited repair of the monitoring channel. This creates a barrier-management view in which the health of the detection barrier is visible rather than assumed.

8. Research Gaps and Future Research

Five gaps are especially important. First, Saudi-specific field evidence remains limited relative to the scale and diversity of the infrastructure to which these technologies may be applied. Future studies should report controlled releases or validated historical events across representative fluids, materials, temperatures, burial conditions, and facility layouts rather than assuming transfer from laboratory rigs. Second, rare-event datasets need governance frameworks that allow anonymized cross-project learning without exposing sensitive operating information. Shared benchmark datasets should include normal transients, sensor faults, maintenance activities, and ambiguous events, not only clean leak/no-leak labels.

Third, research should quantify domain shift. Models trained on one pipe diameter, fluid, noise environment, or sensor installation should be tested prospectively on different assets, with uncertainty calibration and abstention mechanisms when confidence is low. Fourth, lifecycle digital twins require stronger evidence that updating models with operational data improves safety decisions rather than merely improving prediction metrics. Comparative studies should measure avoided incidents, inspection efficiency, false-alarm burden, and response time. Fifth, cybersecurity and data integrity deserve direct treatment. A risk-based leak system that depends on connected sensors, edge devices, historians, and cloud analytics must be resilient to missing, delayed, corrupted, or manipulated data.

Future research should therefore favor multi-site field validation, physics-informed learning, multimodal sensor fusion, explainable risk models, and human-in-the-loop decision experiments. Saudi universities, project owners, industrial cities, utilities, and operators could add particular value by developing locally representative validation protocols and by publishing de-identified performance evidence that distinguishes true field capability from laboratory potential.

9. Practical, Managerial and Policy Implications

For project owners, the immediate implication is to specify leakage assurance during front-end engineering rather than purchasing detection after construction. High-risk segments should have defined detection objectives, sensor-access provisions, isolation capability, data architecture, and acceptance tests before startup. Procurement specifications should state performance under defined operating conditions and require evidence for detection latency, localization, false alarms, and sensor diagnostics. Redundancy should be risk-justified: independent physical principles are preferable when a single common cause could defeat several similar sensors.

For managers and operators, governance should connect alarm handling with integrity work management. Each significant anomaly should generate a traceable decision: corroborate, inspect, reduce pressure, repair, isolate, or continue under defined controls. Inspection findings should update risk models, while confirmed leaks and false alarms should be labeled and returned to analytics teams. Contractor handover must include machine-readable line lists, material and joint records, pressure-test results, sensor configuration, calibration history, and

baseline signatures. Without this continuity, advanced analytics can begin operations with incomplete context.

Policy should remain performance-based and risk-sensitive. Owners or regulators can require documented leakage-management plans, auditable risk ranking, periodic proof testing, management-of-change controls, competency requirements, and post-event learning without prescribing one sensing technology. For environmentally sensitive or high-consequence services, requirements can increase in proportion to potential harm. Consistent data definitions across major projects would also support benchmarking and learning while preserving confidentiality. The objective is a governance system in which technology performance, engineering judgment, and accountable response are demonstrably connected.

A practical maturity model can help organizations sequence investment. Early maturity focuses on asset register quality, criticality ranking, alarm ownership, and reliable baseline instrumentation. Intermediate maturity adds targeted sensor fusion, standardized event labeling, and risk-linked inspection. Advanced maturity introduces continuously updated probabilistic models, digital twins, automated confidence scoring, and portfolio-level optimization. Progression should be conditional on demonstrated data quality and workforce capability, not on the availability of new software alone. This progression makes investment decisions auditable, allowing owners to compare safety benefit, readiness, and lifecycle cost transparently.

10. Limitations

This review is limited by heterogeneity in the underlying literature. Studies use different fluids, pipe scales, leak sizes, sensor arrangements, performance metrics, and validation settings, preventing a defensible pooled accuracy estimate. Much of the machine-learning literature relies on laboratory, simulated, or curated datasets, so reported classification performance may overstate field generalizability. Saudi-specific peer-reviewed field studies are comparatively sparse; accordingly, the Saudi framework presented here is an evidence-informed transfer model, not proof of performance in a particular Saudi facility. The review also does not replace asset-specific quantitative risk assessment, hazard studies, code compliance, or vendor qualification. Finally, the absence of a single cross-platform bibliographic export means that no article-flow counts are reported; this was a deliberate choice to avoid fabricated screening statistics.

11. Conclusion

Risk-based leakage detection is most effective when it is embedded within lifecycle integrity management. The reviewed evidence shows that leak detection technologies differ in what they observe and where they fail: computational methods depend on hydraulic or process-model fidelity; acoustic methods are sensitive to propagation and noise; optical systems depend on visibility and release conditions; and machine-learning models depend on representative data and controlled generalization. Risk-based inspection contributes the missing prioritization logic by connecting deterioration state and uncertainty to consequence and intervention timing.

For large-scale Saudi industrial and infrastructure projects, a defensible strategy is therefore layered. Design establishes risk scenarios, monitoring objectives, isolation philosophy, and data requirements. Construction and commissioning preserve traceability and create verified baselines. Operations combine multimodal detection with sensor-health monitoring, dynamic risk updating, and targeted inspection. Confirmed events and near misses then feed back into models, procedures, and asset priorities. This closed loop turns detection from a reactive alarm function into an incident-prevention capability.

The central research need is credible local validation. Field evidence should test minimum detectable leaks, false-alarm behavior, localization, model uncertainty, environmental robustness, and response effectiveness under representative Saudi conditions. Until such evidence is mature, hybrid architectures and transparent uncertainty are preferable to claims of universal algorithmic superiority. The most reliable outcome is not the system that generates the most alarms, but the system that identifies meaningful loss-of-containment risk early enough for a justified action to prevent escalation. Implementation should therefore begin with asset criticality and verified baseline data, then expand only when added sensing or analytics demonstrates measurable decision value. This sequence reduces technology-driven complexity, preserves engineering accountability, and creates a basis for comparing performance across projects, contractors, and operating organizations over time.

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