Global Academic Journal of Economics and Business

Available online at https://www.gajrc.com
DOI: https://doi.org/10.36348/gajeb.2026.v08i06.002

OPEN ACCESS



ISSN: 2706-9001 (P)
ISSN: 2707-2584 (O)

Original Research Article

Smart Leakage Detection Systems for Enhancing Environmental Safety in Saudi Arabia's Industrial Cities under Vision 2030

Muhammad Ashfaq[1]*
[1]Independent Researcher

***Corresponding Author**
Muhammad Ashfaq
Independent Researcher

Article History
Received: 13.08.2026
Accepted: 21.10.2026
Published: 03.11.2026

Abstract: Industrial cities concentrate water, gas, petrochemical, utility, and process pipelines within operating environments where a small undetected leak can escalate into resource loss, soil or groundwater contamination, atmospheric emissions, fire risk, and prolonged service disruption. This review critically examines smart leakage detection systems as an environmental-safety capability for Saudi Arabia's industrial cities under Vision 2030. The literature is synthesized across water distribution, natural-gas and hydrocarbon pipelines, Internet of Things sensing, machine learning, and digital-twin approaches. Recent studies show a clear shift from single-sensor threshold alarms toward multivariate, data-driven and hybrid systems that combine acoustic, vibration, pressure, flow, supervisory control data, geospatial context, and physics-informed models. Yet high reported classification accuracy does not automatically translate into environmental protection because field performance is conditioned by leak rarity, weak signals, transient operations, sensor drift, corrupted telemetry, localization uncertainty, and false-alarm burden. Saudi evidence further indicates that industrial environmental monitoring must account for local meteorology, aridity, heat, dust, connectivity, and governance conditions. The review therefore proposes an integrated architecture in which robust sensing, secure edge analytics, anomaly detection, localization, digital twins, operator verification, and automated containment form a closed safety loop. It concludes that the strongest pathway for Saudi industrial cities is not a single algorithm but a validated, multisensor, risk-based system whose success is measured by detection latency, released volume avoided, localization error, alarm credibility, response time, and auditable environmental outcomes.

Keywords: Smart Leakage Detection, Industrial Cities, Saudi Arabia, Vision 2030, Pipeline Integrity, Environmental Safety, Machine Learning, Digital Twin, Iot, Anomaly Detection.

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution **4.0 International License (CC BY-NC 4.0)** which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

1. INTRODUCTION

Saudi Arabia's industrial cities contain dense networks of process piping, transmission and distribution pipelines, water systems, cooling-water loops, storage interfaces, and utility corridors. Their concentration creates economic efficiencies but also couples operational reliability to environmental safety: a leak can waste scarce water, release hydrocarbons or gases, contaminate soil, elevate local emissions, interrupt production, or create conditions for fire and explosion. The environmental relevance is not abstract. Studies of Yanbu and Jubail document

the importance of systematic monitoring of ambient pollutants in major Saudi industrial settings and show that pollutant concentrations vary with industrial activity and meteorological conditions (Al Rabadi *et al*., 2023; AlQahtani *et al*., 2024). Those studies do not attribute measured air-quality patterns to pipeline leaks, but they demonstrate why leak prevention and rapid containment should be integrated with wider environmental monitoring rather than treated only as maintenance functions.

Conventional leak management has relied on periodic inspection, mass-balance rules, pressure thresholds, operator experience, and stand-alone acoustic surveys. These methods remain useful, but they struggle with small leaks, variable demand, noisy industrial environments, transient process states, and large spatial networks. Contemporary research increasingly treats leakage as an anomaly-detection and localization problem supported by connected sensing. In water networks, deep autoencoders, noise loggers, high-frequency pressure sensing, acoustic classification, and geospatial models have been developed to identify weak or previously unreported events (Cody *et al*., 2020; Tijani *et al*., 2022; Rousso *et al*., 2023; Weyns *et al*., 2023). In pipelines, studies combined acoustic emission, negative-pressure waves, multivariate time series, unsupervised learning, and hybrid physical-data models to improve sensitivity and reduce dependence on labelled failure data (Song & Li, 2021; Kopbayev *et al*., 2022; Zuo *et al*., 2022; Miao *et al*., 2023; Rahman *et al*., 2024).

The technical direction is promising, yet the evidence base is fragmented. Water-distribution studies often provide richer operational field data and longer monitoring histories, whereas oil and gas studies more frequently rely on controlled test rigs, simulated leak scenarios, or specialized pipeline configurations. Reported metrics also differ: some studies emphasize classification accuracy or F1 score, others localization distance, identification lag, false-alarm rate, or reconstruction error. Such heterogeneity makes headline performance numbers poor proxies for environmental safety. A system that detects simulated leaks accurately but produces frequent false alarms, fails under corrupted telemetry, or cannot trigger timely isolation may provide limited protection in a live industrial city. Conversely, a moderately complex model with transparent alarm logic, stable sensor coverage, and reliable containment integration may create greater practical risk reduction.

Saudi deployment adds another layer of context. Long-range, low-power connectivity has been examined locally for water leakage monitoring, demonstrating the potential of LoRaWAN architectures while also exposing scale and communications design considerations (Alghamdi *et al*., 2022). Wider Saudi smart-city literature emphasizes the need to combine digital technologies with governance, stakeholder participation, cybersecurity, data readiness, and implementation capacity rather than assuming technology alone creates sustainable outcomes (Alamoudi *et al*., 2023; Bahreldin *et al*., 2025). For industrial cities, this implies that smart leak detection should be conceived as a socio-technical safety system linking field instrumentation, communications, analytics, control rooms, maintenance, emergency response, and environmental assurance.

This review therefore moves beyond a catalogue of algorithms. It asks how sensing modalities, artificial intelligence, digital twins, and operational response can be combined into evidence-ready leakage management for Saudi industrial environments. The analysis distinguishes detection from localization, diagnosis, containment, and post-event verification; separates laboratory promise from field readiness; and interprets technology through Saudi climatic and institutional conditions. The resulting synthesis is intended to support research design, procurement, engineering integration, and policy development without claiming that a single method is universally superior.

2. Aim of the Study

The study aims to critically synthesize recent peer-reviewed evidence on smart leakage detection and translate it into an implementation framework for enhancing environmental safety in Saudi Arabia's industrial cities. The focus is on how sensing, communications, machine learning, digital twins, and automated response can jointly reduce the time, uncertainty, and environmental consequences associated with leaks in water, gas, and hydrocarbon pipeline systems.

3. Research Objectives

1. To compare the sensing and analytical mechanisms used for detecting and localizing leaks across water, gas, and hydrocarbon pipeline networks.
2. To evaluate how recent machine-learning, semi-supervised, generative, and digital-twin methods address scarce labels, weak signals, operational transients, and corrupted data.
3. To identify the environmental-safety performance measures that are more decision-relevant than algorithmic accuracy alone.
4. To examine the transferability of international evidence to Saudi industrial-city conditions, including heat, dust, aridity,

network scale, and digital-infrastructure requirements.
5. To develop research, managerial, and policy priorities for evidence-based deployment under Vision 2030.

4. Research Questions

1. Which sensing and analytics combinations provide the most credible foundations for early detection and localization across heterogeneous industrial pipeline systems?
2. What methodological weaknesses currently limit the translation of high-performing leak-detection models from experiments to continuous field operation?
3. How should environmental-safety outcomes be measured when evaluating smart leakage detection in Saudi industrial cities?
4. Which architecture, governance, and validation practices are required to align smart leakage detection with Saudi digital-transformation and sustainability objectives?

5. REVIEW METHODOLOGY

A structured integrative review was used because the topic spans civil water infrastructure, process safety, oil and gas pipelines, artificial intelligence, communications, and Saudi smart-city research. The review protocol defined the evidence domains before synthesis rather than treating all leak-detection papers as directly comparable. Primary indexing targets were Scopus and Web of Science Core Collection, while article discovery and metadata checking were supported through publisher databases and platforms including ScienceDirect, SpringerLink, Taylor & Francis, ASCE Library, Oxford Academic, and MDPI. Crossref and publisher DOI records were used for bibliographic verification. The search window was January 2020 through December 2025, with emphasis on 2022-2025 research while retaining a small number of 2020-2021 studies that established relevant deep-learning, acoustic, and negative-pressure-wave methods.

Search strings combined leak terminology with infrastructure, sensing, analytics, and Saudi-context terms. Representative combinations included "leak detection" AND pipeline AND machine learning; "water distribution" AND acoustic AND leak; gas pipeline AND anomaly detection; pipeline AND digital twin AND leakage; SCADA AND leak localization; IoT AND water leakage AND Saudi Arabia; and industrial city AND Saudi Arabia AND environmental monitoring. Related terms such as vibration, pressure transient, negative pressure wave, autoencoder, contrastive learning, generative model, sensor fusion, localization, and environmental safety were iteratively added when relevant studies identified adjacent technical mechanisms.

Eligibility required peer-reviewed journal publication, a resolvable DOI, substantive relevance to leakage detection or the Saudi deployment context, and sufficient methodological detail to support critical interpretation. Empirical detection studies had to describe the sensing input, analytical method, and validation setting. Review papers were retained when they synthesized method classes or pipeline-failure evidence. Saudi-context studies were eligible when they informed connectivity, industrial environmental monitoring, smart-city governance, or digital-twin readiness even if they did not test industrial pipeline leaks directly. Conference papers, theses, trade articles, vendor brochures, non-peer-reviewed reports, papers without verifiable bibliographic details, and studies focused on unrelated structural defects were excluded. No article-screening counts are reported because the review did not use a prospectively registered exhaustive-search design and inventing numerical flow statistics would overstate reproducibility.

Screening proceeded through relevance checks at title, abstract, and full-text or publisher-record level, followed by duplicate removal and DOI verification. Quality appraisal was qualitative and mechanism-oriented. Each study was examined for data provenance; realism of the leak scenario; distinction between training and independent validation; handling of operational variability; treatment of class imbalance; reporting of false alarms or detection lag; localization capability; and clarity about limitations. Field studies and experiments using real operational signals were interpreted as stronger evidence for deployment than purely simulated demonstrations, but simulation-based studies remained valuable where they explored transient conditions, rare events, or digital-twin behavior that is difficult to reproduce safely at full scale.

The final evidence set contains exactly the 30 verified peer-reviewed references listed in this manuscript. Synthesis was thematic rather than meta-analytic because sensor modalities, leak sizes, pipe materials, fluids, network topologies, sampling frequencies, and outcome metrics were too heterogeneous for defensible statistical pooling. Evidence was organized into four linked themes: sensing and communications; data-driven detection and localization; physics-informed and digital-twin integration; and environmental-safety deployment in Saudi industrial cities. Within each theme, findings were compared by mechanism, validation realism, and operational limitations. The synthesis then mapped technical capabilities to an environmental-

safety chain comprising detection, confirmation, localization, isolation, response, and verification.

This approach has two methodological safeguards. First, reported accuracy values are not compared as if they were generated under equivalent conditions. A high result on a controlled test rig is treated differently from performance in a noisy operational network. Second, Saudi-context evidence is used to calibrate deployment requirements rather than to claim that technologies validated abroad will reproduce the same performance locally. These safeguards reflect the central methodological premise of the review: transferability depends on boundary conditions, not only on model architecture.

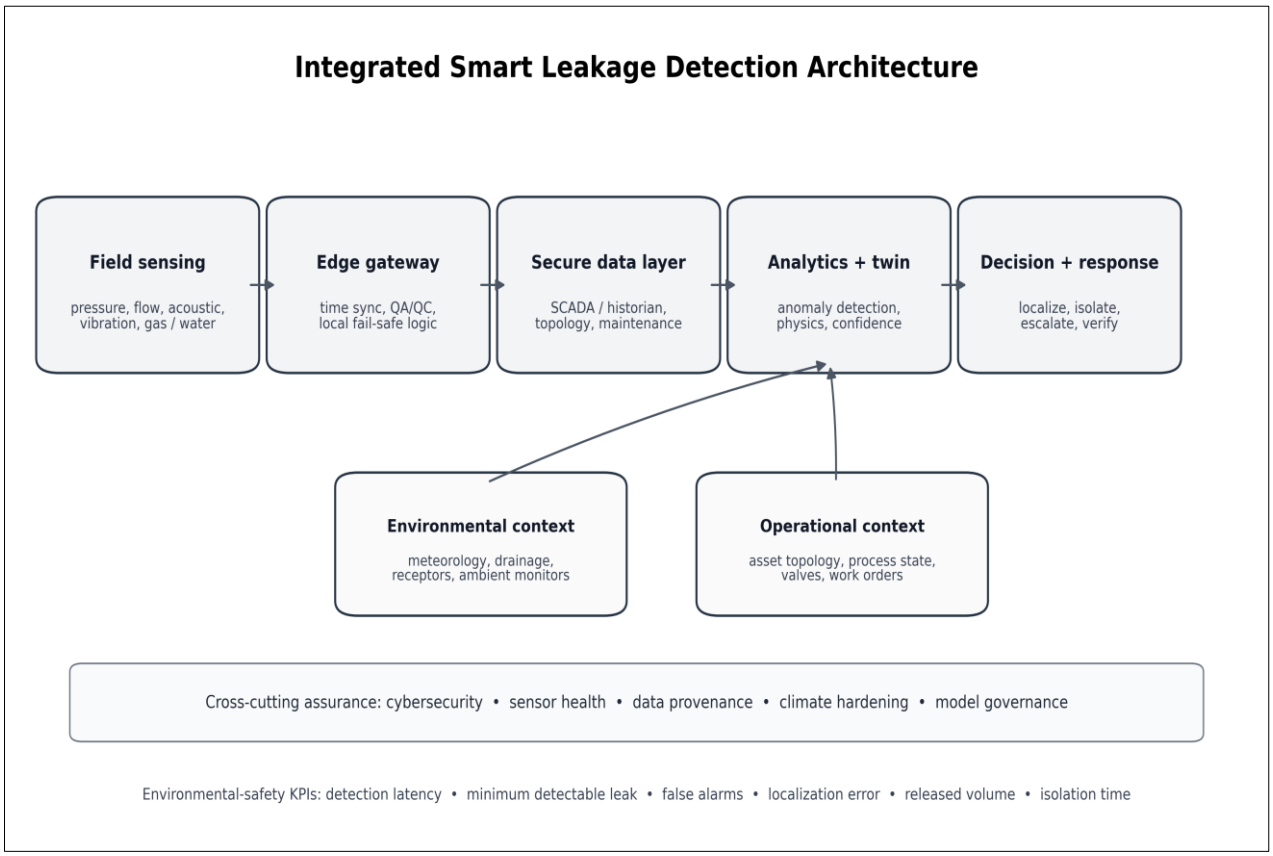


Figure 1: Integrated architecture linking field sensing, secure data handling, analytics and digital twins to localization, response and environmental verification. Cross-cutting assurance and consequence-oriented KPIs convert a technical detection stack into an environmental-safety system.

6. Thematic Literature Review and Critical Analysis

6.1 Sensing, Communications, and Observability

Leak detection begins with observability. Acoustic and vibration sensors are attractive because escaping fluid generates characteristic energy, but signal quality depends on pipe material, burial conditions, sensor distance, flow noise, pressure, and background machinery. Cody *et al.,* (2020) showed that hydroacoustic spectrograms combined with a deep autoencoder can expose small anomalies, while Tijani *et al.,* (2022) demonstrated that feature processing can improve the usefulness of noise-logger data collected from real water networks. Vanijjirattikhan *et al*., (2022) further connected acoustic classification with cloud-based data management and field use, illustrating that practical value arises from the whole acquisition-to-decision workflow rather than the classifier alone. Field localization work using MEMS accelerometers also shows that performance degrades with sensor-to-leak distance, making placement density an engineering variable rather than a minor implementation detail (Liu *et al*., 2024c).

Pressure and flow data provide complementary system-level information. In water networks, high-frequency pressure monitoring can support anomaly detection and hydraulic interpretation; Rousso *et al*., (2023) found that real smart-water applications increasingly use permanent pressure and acoustic sensors but remain difficult to benchmark because case descriptions and performance measures are not standardized. Multivariate SCADA data can exploit relationships among pressure, flow, and time. Tornyeviadzi and Seidu (2023a) used a one-dimensional convolutional autoencoder with multivariate SCADA signals, while

Tornyeviadzi *et al*., (2023b) applied a bidirectional LSTM autoencoder to night-flow analysis. Such methods are relevant to industrial utilities because they can learn normal operating structure without requiring a large archive of labelled leaks. However, their reliability depends on stable instrumentation, trustworthy timestamps, and explicit handling of maintenance, valve operations, production changes, and sensor replacement.

Communications determine whether sensing becomes continuous situational awareness. The Saudi LoRaWAN study by Alghamdi *et al*., (2022) supports the feasibility of low-power wide-area connectivity for distributed water monitoring, but its housing-complex setting should not be generalized directly to hazardous industrial zones. Industrial adoption requires intrinsically safe hardware where applicable, radio-frequency surveys, redundancy, cybersecurity controls, and defined behavior when connectivity is degraded. Consequently, network coverage should be treated as a safety requirement with measured packet loss, latency, availability, clock synchronization, and failover performance.

Table 1: Comparative synthesis of smart leakage-detection technology classes and Saudi industrial-city implications

Technology / evidence stream	Operational value	Critical limitation	Saudi industrial-city implication
Acoustic / vibration	Sensitive local signatures; useful for pinpointing and confirmation	Attenuation and interference from flow, machinery, burial, pipe material and sensor distance	Use condition-based sensor spacing and site-specific noise baselines; combine with pressure/flow evidence
Pressure / flow / SCADA	Continuous system-level observability; compatible with installed instrumentation	Process transients and valve or production changes can mimic leakage	Model operating states explicitly; synchronize tags and maintain event logs for interpretation
IoT / LPWAN connectivity	Extends monitoring to distributed assets with low-power devices	Packet loss, latency, coverage gaps, hazardous-area requirements and cyber exposure	Treat communications availability and degraded-mode behavior as safety acceptance criteria
Semi-supervised / unsupervised AI	Uses abundant normal data when labelled leaks are rare	Threshold selection, drift and benign anomalies can increase false alarms	Validate by season, operating mode and independent sites; govern alarm thresholds and retraining
Generative / contrastive learning	Improves representation where labelled data are scarce	Synthetic or augmented data can reproduce artifacts rather than physical variability	Require leakage-physics checks and out-of-distribution validation before operational credit
Digital twin / hybrid physics-AI	Adds physical consistency, scenario testing and consequence context	Calibration error and model drift can create false confidence	Maintain calibration, sensor-health estimation and auditable model versions; use twins for scenario and isolation planning

6.2 Machine Learning For Detection, Localization, and Scarce Labels

The strongest recent trend is a shift from fixed thresholds toward representation learning and anomaly detection. Leak data are inherently scarce because utilities and operators seek to prevent failures, and intentional full-scale releases are costly or unsafe. Semi-supervised methods therefore have a structural advantage: they can learn normal behavior and flag deviations. Tornyeviadzi *et al*., (2023c) compared multiple semi-supervised anomaly-detection methods and showed that algorithm choice interacts with uncertainty and evaluation criteria. In gas pipelines, Zuo *et al*., (2022) similarly developed a semi-supervised multivariate time-series method, while Miao *et al.,* (2023) used unsupervised learning with stress perception. These studies collectively support a practical principle for Saudi facilities: normal-operation data are abundant, but leak labels are rare, so deployment strategies should prioritize robust normal-state modelling and carefully governed alarm thresholds.

Deep learning can increase sensitivity, but its apparent sophistication can conceal data weaknesses. Liu *et al*., (2024a) used a generative model to enrich acoustic leak data, and Wu *et al*., (2024) examined data augmentation from a data-centric perspective. Liu *et al*., (2024b) showed how contrastive learning can improve detection when

labelled signals are limited. The common contribution is not simply higher classification performance; it is a response to limited and unbalanced failure data. Yet synthetic or augmented samples must preserve physically meaningful variation. If generated signals reproduce training artifacts rather than leak physics, they can increase confidence without increasing field robustness. Independent pipeline, season, pressure-regime, and site validation are therefore more important than random train-test splits from the same acquisition campaign.

Gas-pipeline literature makes the challenge of weak signals especially clear. Song and Li (2021) used convolutional learning with acoustic emission under internal flow noise, and Ning *et al*., (2021) combined spectrum enhancement with convolutional analysis. Ye *et al*., (2024) targeted weak leakage using negative-pressure-wave data and feature enhancement in realistic urban environments. These studies show why preprocessing and feature representation matter when leakage signatures are close to background variability. However, an industrial city introduces additional confounders such as compressor starts, pump changes, control-valve movement, road vibration, construction, and neighboring process units. A model that is not trained or stress-tested against these benign disturbances may convert ordinary operations into persistent alarms.

Localization is a separate requirement from detection. Environmental response improves when crews know which segment, corridor, or valve zone to isolate. Weyns *et al*., (2023) combined autoencoders with geographic information to localize water-network anomalies, showing the value of connecting time-series analytics to network topology. Vibroacoustic field experiments by Liu *et al*., (2024c) likewise demonstrate that localization error depends on distance and measurement conditions. In industrial settings, geospatial topology should include pipe class, fluid, pressure, isolation valves, drainage pathways, sensitive receptors, and access constraints. This allows an alarm to be translated into a response plan rather than a generic warning.

6.3 Physics-Informed Analytics and Digital Twins

Purely data-driven models can struggle when operating states move outside the training distribution. Physics-informed and digital-twin approaches seek to reduce this fragility by representing expected pressure, flow, inventory, or transient behavior. Wang *et al*., (2023) combined digital-twin modelling with machine learning for gas-pipeline leakage identification, linking physical and virtual states and using the twin as part of an alarm and response process. Rahman *et al*., (2024) reviewed mechanistic, computational-fluid-dynamics, machine-learning, and digital-twin methods and argued for greater integration among them. For Saudi industrial cities, this hybrid direction is especially relevant because assets may operate across wide throughput ranges and because simulated scenarios can safely cover rare leak sizes and locations.

Transient operation is a critical test of hybrid methods. A pressure drop caused by a legitimate production change can resemble a leak if the algorithm assumes steady state. Kim *et al*., (2024) integrated dynamic modelling and machine learning specifically for transient gas-pipeline conditions, while Tian *et al*., (2021) combined signal fitting and an extreme learning machine for low-pressure gas distribution. These studies illustrate two complementary strategies: model the process dynamics explicitly, or extract features designed to distinguish abnormal transients from expected operating changes. Neither eliminates the need for field validation. Simulated scenarios can systematically vary leak size and location, but real instrumentation introduces bias, drift, communication gaps, undocumented operator actions, and simultaneous disturbances.

Data corruption is another reason to favor hybrid architectures. Zhang *et al*., (2024) addressed natural-gas leak detection under corrupted data using twin robust autoencoders, highlighting the need to distinguish sensor quality problems from process anomalies. This issue is central in hot, dusty, saline, or vibration-intensive environments where instrument degradation can create false patterns. A practical digital twin should therefore estimate not only pipeline state but also data quality, sensor health, and confidence. Alarms should carry uncertainty and evidence provenance rather than a binary leak/no-leak label alone.

Machine-learning reviews in oil and gas reinforce this caution. Al-Sabaeei *et al*., (2023) found growing use of advanced learning methods for pipeline-failure prediction but also emphasized data reliability and methodological challenges. The implication is that a digital twin is not a substitute for instrumentation discipline. Its value emerges when calibrated models, governed telemetry, maintenance history, and analytics create a consistent representation of the asset. In environmental-safety terms, the twin should support scenario testing, minimum-detectable-leak analysis, isolation planning, and post-event reconstruction, not merely visualization.

6.4 From Algorithmic Performance to Environmental Safety in Saudi Industrial Cities

The environmental objective changes how performance should be defined. Classification accuracy is useful, but environmental harm is more directly related to how long a leak persists, how much material is released, where it migrates, whether ignition or toxic exposure occurs, and how quickly the correct isolation action is taken. Accordingly, evaluation should include detection latency, minimum detectable leak rate, false-alarm frequency, missed-event rate, localization error, communication availability, time to operator confirmation, time to isolation, estimated released volume, and completeness of post-event verification. These measures create a chain from analytical performance to avoided environmental consequence.

Saudi industrial conditions make context-sensitive baselines essential. Yanbu air-quality research shows that pollutant interpretation depends on industrial activity and meteorology (Al Rabadi *et al*., 2023), while the Jubail study demonstrates the use of sustained multi-station monitoring and the influence of meteorological conditions on measured gaseous pollutants (AlQahtani *et al*., 2024). A leak-detection platform should therefore exchange data with environmental monitoring systems where appropriate. Wind direction, temperature, humidity, and ambient hydrocarbon measurements can strengthen consequence assessment after a gas or volatile-organic-compound alarm, while drainage and groundwater information can support liquid-spill response. The goal is not to make ambient monitors primary leak sensors, but to use them as independent evidence within a broader safety picture.

The Saudi smart-city literature also argues against technology-only implementation. Alamoudi *et al*., (2023) emphasize stakeholder and governance dimensions in smart sustainable cities, and Bahreldin *et al*., (2025) identify digital twins and advanced digital technologies as promising while noting challenges around data security and infrastructure readiness. Translated to industrial leak detection, this means that ownership of sensors, data, alarm acceptance, isolation authority, maintenance, model updates, and audit records must be explicit. Without such governance, even technically strong systems can fail at the handoff between detection and response.

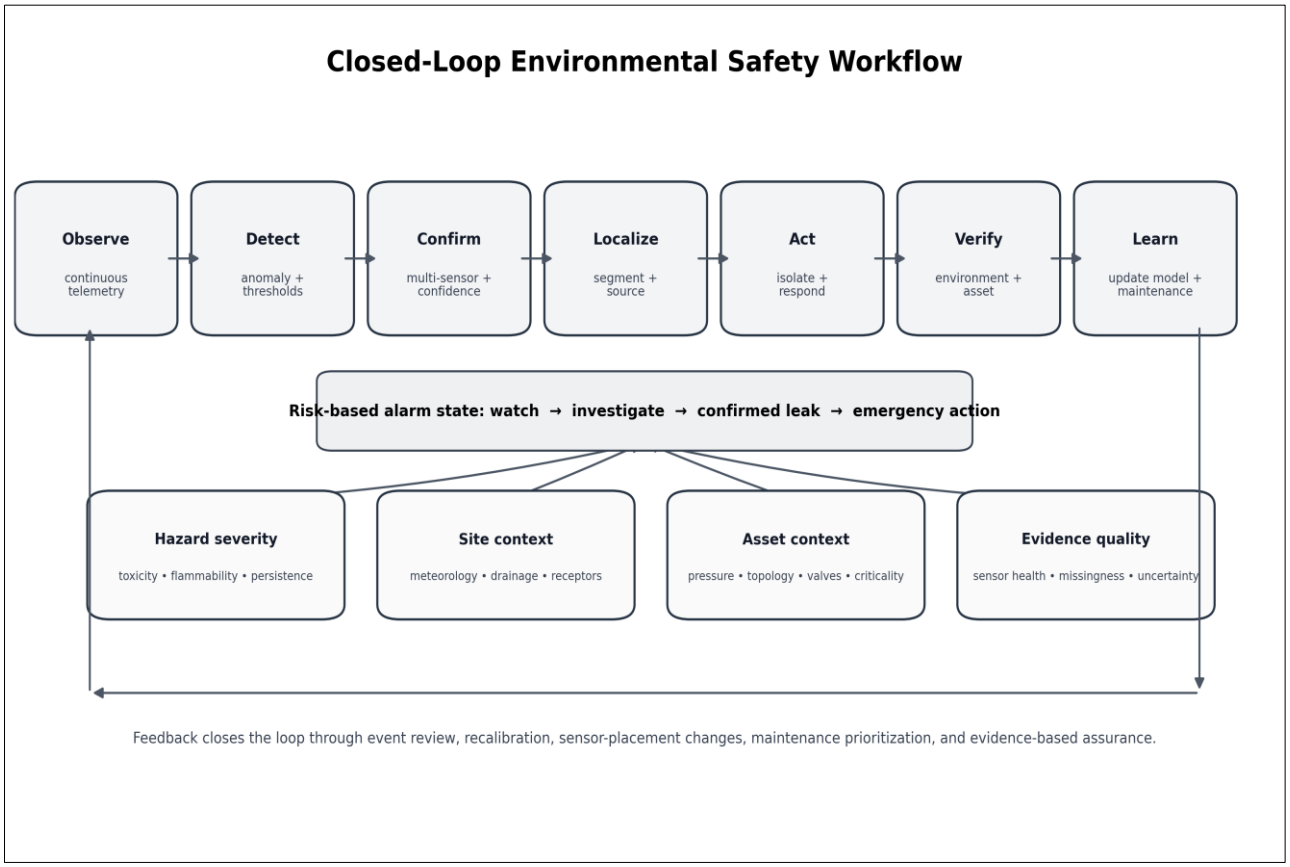


Figure 2. Closed-loop environmental-safety workflow. Detection is treated as one stage within a risk-based sequence that incorporates evidence quality, hazard severity, site context, response, environmental verification and learning.

7. DISCUSSION

The literature indicates that smart leakage detection is becoming a layered capability rather than a single instrument. Acoustic and vibration sensing can expose local signatures; pressure, flow, and SCADA data capture system behavior; geospatial models support localization; machine learning handles nonlinear and multivariate patterns; and digital twins provide physics-based context. The critical design question is therefore not which algorithm is universally best, but how these layers can corroborate one another under real operating conditions. Kammoun *et al*., (2022) show the breadth of artificial-intelligence approaches available for water networks, while the gas-pipeline literature demonstrates similarly diverse acoustic, pressure-wave, unsupervised, and hybrid methods. The diversity supports sensor fusion but also warns against procurement based on a single benchmark score.

A useful distinction is between analytical sensitivity and operational credibility. Sensitivity concerns whether the model recognizes weak leakage. Credibility concerns whether personnel can trust the alarm, understand its evidence, identify the affected segment, and act safely. False positives consume inspection resources and can cause alarm fatigue; false negatives prolong releases. The appropriate threshold therefore depends on fluid hazard, pipe location, environmental receptor, isolation complexity, and consequence severity. High-hazard hydrocarbon lines may justify more conservative thresholds and multisensor confirmation than noncritical water services, while scarce-water systems may prioritize persistent small-leak detection even where immediate safety consequences are low.

The evidence also exposes a transferability gap. Several water studies include real-network signals, but their pipe materials, hydraulic regimes, and leak consequences differ from those of petrochemical infrastructure. Gas studies increasingly address realistic noise, transient conditions, and weak leaks, yet many remain bounded to specific experimental configurations. Saudi industrial-city programs should therefore use the international literature to select mechanisms, not to import performance claims. Commissioning should create site-specific baselines and deliberately test changes in pressure, flow, temperature, operating mode, sensor failure, communications loss, and representative benign disturbances.

A practical synthesis of the evidence favors staged multisensor confirmation. Continuous pressure and flow analytics can provide broad surveillance, acoustic or vibration channels can increase confidence near suspected segments, and topology-aware localization can restrict the search area before isolation. This sequence is preferable to indiscriminate sensor density because it links instrumentation cost to decision value. It also creates redundancy: a pressure anomaly unsupported by acoustic evidence may indicate a normal process transient, while an acoustic signature without inventory imbalance may justify inspection rather than immediate shutdown. Digital twins can arbitrate between these signals by testing whether the observed combination is physically consistent with a leak scenario. Importantly, confirmation logic should remain risk sensitive. For toxic, flammable, or environmentally persistent fluids, waiting for multiple channels could delay a necessary protective action; therefore, single-channel alarms may still trigger precautionary escalation when consequence models indicate high potential harm. The architecture should consequently support graded alarm states, from anomaly watch to confirmed leak and emergency isolation, with each transition tied to explicit evidence and authority. This design also improves learning after events because operators can compare which sensors changed first, which model generated the earliest useful warning, and which evidence ultimately confirmed the leak. Over time, such event records can support recalibration, sensor-placement changes, and maintenance prioritization. In this sense, smart leakage detection is best treated as a continuously improving assurance process, not a static model installed at commissioning. A parallel environmental record should capture weather, drainage, receptor proximity, and cleanup observations so that detection performance can be connected to consequence reduction during audits and design reviews.

A second gap concerns environmental verification. Most technical papers stop at detection or localization. For Vision 2030-aligned sustainability management, the more important question is whether smart detection measurably reduces unaccounted water, hydrocarbon release duration, contaminated media, emergency-response time, or other verified environmental burdens. This requires linking control-room data with maintenance work orders, isolation timestamps, spill records, environmental samples, and root-cause findings. Such integration turns a predictive model into an auditable risk-reduction system.

8. Research Gaps and Future Research

Four gaps deserve priority. First, standardized field-validation protocols are lacking. Future studies should report leak size relative to normal flow, pipe material and diameter, pressure regime, sensor spacing, background disturbances, sampling frequency, detection latency, false alarms

per operating period, localization error, and independent validation conditions. This would make results more comparable than accuracy alone.

Second, Saudi-specific benchmark datasets are needed. These should contain long-duration normal operations, planned hydraulic or process transients, sensor faults, communications gaps, and safely engineered leak experiments across representative water, gas, and industrial utility assets. Privacy and infrastructure-security constraints can be addressed through controlled data enclaves, feature-level sharing, or federated learning rather than unrestricted raw-data release.

Third, research should connect detection to consequence-aware automation. Digital twins could estimate released inventory and forecast migration, while rule-based safety logic determines when automated isolation is permissible and when human confirmation is required. Field trials should evaluate the entire detect-localize-decide-isolate-verify sequence, including degraded-mode behavior.

Fourth, lifecycle model governance remains underdeveloped. Future work should define drift detection, recalibration intervals, sensor-health diagnostics, retraining approval, version control, explainability requirements, and rollback procedures. Models should be challenged against heat, dust, corrosion, seasonal demand, maintenance interventions, and changing production patterns so that performance remains stable after commissioning.

9. Practical, Managerial, and Policy Implications

For operators, the recommended deployment unit is a risk-ranked pipeline zone rather than an undifferentiated citywide platform. High-consequence corridors should receive redundant sensing, edge processing, precise valve mapping, environmental receptor data, and tested isolation logic. Lower-consequence utilities can use wider-area anomaly screening followed by portable confirmation. This tiered design controls cost while matching assurance to consequence.

For managers, procurement specifications should require measurable safety outcomes, open interfaces, data ownership, time synchronization, cybersecurity controls, model documentation, maintenance obligations, and independent acceptance testing. Vendors should demonstrate performance under site-representative transients and data loss rather than only present laboratory accuracy. Alarm governance should define who validates, escalates, isolates, records, and closes each event.

For public and industrial-city authorities, policy can encourage interoperable environmental-safety data without prescribing one algorithm. Common KPI definitions, auditable incident timestamps, standardized metadata, and minimum validation requirements would support benchmarking across industrial zones. Vision 2030-oriented digitalization is best served when digital twins and AI are tied to verifiable resource conservation, pollution prevention, resilience, and accountable operations rather than technology deployment counts alone.

Table 2: Minimum assurance framework for operational deployment and acceptance

Assurance domain	Minimum acceptance evidence	Decision KPI	Accountable function
Sensing and placement	Coverage study, sensor-health checks, documented spacing and calibration	Availability; drift; minimum detectable leak	Instrumentation / reliability
Data and communications	Time synchronization, missing-data rules, cyber controls, failover test	Latency; packet loss; data completeness	OT / SCADA / cybersecurity
Analytics and model governance	Independent validation, false-alarm analysis, version control, rollback and drift monitoring	Detection lag; missed events; false alarms per period	Data / process engineering
Localization and topology	Validated network model, valve mapping, GIS linkage and access constraints	Localization error; correct isolation zone	Asset integrity / maintenance
Response integration	Alarm ownership, escalation matrix, tested isolation and degraded-mode procedure	Time to confirmation; time to isolation	Operations / emergency response
Environmental verification	Weather and receptor context, release estimate, cleanup or sampling record, post-event closure	Released volume; affected media; closure time	Environment / HSE

10. Limitations

This review is integrative rather than exhaustive and does not claim complete coverage of every leak-detection publication. The 30-reference corpus privileges recent, DOI-verified, peer-reviewed work and may underrepresent proprietary industrial

deployments whose performance data are not public. Cross-study comparison is constrained by heterogeneous fluids, sensors, pipelines, datasets, and metrics. Saudi evidence on industrial environmental conditions is stronger than Saudi peer-reviewed evidence on full-scale intelligent pipeline leakage systems, so several implementation conclusions are reasoned transferability propositions that require local validation.

11. CONCLUSION

Smart leakage detection can materially strengthen environmental safety in Saudi Arabia's industrial cities when it is engineered as an end-to-end risk-control system rather than purchased as an isolated AI feature. Recent research supports acoustic, vibration, pressure, flow, SCADA, geospatial, semi-supervised, generative, contrastive, and digital-twin approaches, but no method removes the need for reliable instrumentation and field validation. The most defensible architecture combines complementary sensors, secure communications, edge and central analytics, physics-informed context, localization, operator verification, containment, and post-event environmental confirmation.

For Saudi deployment, success should be judged by credible alarms and reduced consequence: faster detection, smaller released volume, better localization, shorter isolation time, fewer false alarms, and auditable environmental outcomes. Heat, dust, aridity, industrial noise, transient operations, connectivity resilience, cybersecurity, and institutional responsibilities must be designed into the system from the beginning. Under these conditions, smart leakage detection can become a measurable component of resource efficiency, pollution prevention, industrial resilience, and evidence-based digital transformation under Vision 2030.

REFERENCES

- Al Rabadi, S. J., Al-Zboon, K., Albkoor Alrawashdeh, K., & Al-Samrraie, L. (2023). Assessment of ambient air quality in heavy industrial localities: A case study of Yanbu industrial city. Environmental Monitoring and Assessment, 195(6), 683. https://doi.org/10.1007/s10661-023-11267-w
- Al-Sabaeei, A. M., Alhussian, H., Abdulkadir, S. J., & Jagadeesh, A. (2023). Prediction of oil and gas pipeline failures through machine learning approaches: A systematic review. Energy Reports, 10, 1313-1338. https://doi.org/10.1016/j.egyr.2023.08.009
- Alghamdi, A. M., Khairullah, E. F., & Al Mojamed, M. M. (2022). LoRaWAN performance analysis for a water monitoring and leakage detection system in a housing complex. Sensors, 22(19), 7188. https://doi.org/10.3390/s22197188
- Alamoudi, A. K., Abidoye, R. B., & Lam, T. Y. M. (2023). Implementing smart sustainable cities in Saudi Arabia: A framework for citizens' participation towards Saudi Vision 2030. Sustainability, 15(8), 6648. https://doi.org/10.3390/su15086648
- AlQahtani, A. I., Salama, K. F., Alwadei, M. M., Aljassim, M. T., Alsaif, A. S., Al-Warthan, M., & AlMulla, A. A. (2024). Air quality levels in the industrial city of Jubail, Saudi Arabia. Frontiers in Environmental Engineering, 3, 1483568. https://doi.org/10.3389/fenve.2024.1483568
- Bahreldin, I., Samir, H., Maddah, R., Hammad, H., & Hegazy, I. (2025). Leveraging advanced digital technologies for smart city development in Saudi Arabia: Opportunities, challenges, and strategic pathways. International Journal of Low-Carbon Technologies, 20, 834-847. https://doi.org/10.1093/ijlct/ctaf044
- Cody, R. A., Tolson, B. A., & Orchard, J. (2020). Detecting leaks in water distribution pipes using a deep autoencoder and hydroacoustic spectrograms. Journal of Computing in Civil Engineering, 34(2), 04020001. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000881
- Kammoun, M., Kammoun, A., & Abid, M. (2022). Leak detection methods in water distribution networks: A comparative survey on artificial intelligence applications. Journal of Pipeline Systems Engineering and Practice, 13(3). https://doi.org/10.1061/(ASCE)PS.1949-1204.0000646
- Kim, J., Han, S., Kim, D., & Lee, Y. (2024). Gas pipeline leak detection by integrating dynamic modeling and machine learning under the transient state. Energies, 17(21), 5517. https://doi.org/10.3390/en17215517
- Kopbayev, A., Khan, F., Yang, M., & Halim, S. Z. (2022). Gas leakage detection using spatial and temporal neural network model. Process Safety and Environmental Protection, 160, 968-975. https://doi.org/10.1016/j.psep.2022.03.002
- Liu, R., Zayed, T., & Xiao, R. (2024a). Advanced acoustic leak detection in water distribution networks using integrated generative model. Water Research, 254, 121434. https://doi.org/10.1016/j.watres.2024.121434
- Liu, R., Zayed, T., & Xiao, R. (2024b). Contrastive learning method for leak detection in water distribution networks. npj Clean Water, 7, 118. https://doi.org/10.1038/s41545-024-00406-6
- Liu, R., Tariq, S., Tijani, I. A., Fares, A., Bakhtawar, B., Fan, H., Zhang, R., & Zayed, T. (2024c). Data-driven approaches for vibroacoustic localization of leaks in water distribution networks.

Environmental Processes, 11(1), 14. https://doi.org/10.1007/s40710-024-00682-x

- Miao, X., Zhao, H., & Xiang, Z. (2023). Leakage detection in natural gas pipeline based on unsupervised learning and stress perception. Process Safety and Environmental Protection, 170, 76-88. https://doi.org/10.1016/j.psep.2022.12.001
- Ning, F., Cheng, Z., Meng, D., Duan, S., & Wei, J. (2021). Enhanced spectrum convolutional neural architecture: An intelligent leak detection method for gas pipeline. Process Safety and Environmental Protection, 146, 726-735. https://doi.org/10.1016/j.psep.2020.12.011
- Rahman, M. A., Barooah, A., Khan, M. S., Hassan, R., Hassan, I., Sleiti, A. K., Hamilton, M., & Rezaei Gomari, S. (2024). Single and multiphase flow leak detection in onshore/offshore pipelines and subsurface sequestration sites: An overview. Journal of Loss Prevention in the Process Industries, 90, 105327. https://doi.org/10.1016/j.jlp.2024.105327
- Rousso, B. Z., Lambert, M., & Gong, J. (2023). Smart water networks: A systematic review of applications using high-frequency pressure and acoustic sensors in real water distribution systems. Journal of Cleaner Production, 410, 137193. https://doi.org/10.1016/j.jclepro.2023.137193
- Song, Y., & Li, S. (2021). Gas leak detection in galvanised steel pipe with internal flow noise using convolutional neural network. Process Safety and Environmental Protection, 146, 736-744. https://doi.org/10.1016/j.psep.2020.11.053
- Tian, X., Jiao, W., Liu, T., Ren, L., & Song, B. (2021). Leakage detection of low-pressure gas distribution pipeline system based on linear fitting and extreme learning machine. International Journal of Pressure Vessels and Piping, 194, 104553. https://doi.org/10.1016/j.ijpvp.2021.104553
- Tijani, I. A., Abdelmageed, S., Fares, A., Fan, K. H., Hu, Z. Y., & Zayed, T. (2022). Improving the leak detection efficiency in water distribution networks using noise loggers. Science of the Total Environment, 821, 153530. https://doi.org/10.1016/j.scitotenv.2022.153530
- Tornyeviadzi, H. M., & Seidu, R. (2023a). Leakage detection in water distribution networks via 1D CNN deep autoencoder for multivariate SCADA data. Engineering Applications of Artificial Intelligence, 122, 106062. https://doi.org/10.1016/j.engappai.2023.106062
- Tornyeviadzi, H. M., Mohammed, H., & Seidu, R. (2023b). Robust night flow analysis in water distribution networks: A BiLSTM deep autoencoder approach. Advanced Engineering Informatics, 58, 102135. https://doi.org/10.1016/j.aei.2023.102135
- Tornyeviadzi, H. M., Mohammed, H., & Seidu, R. (2023c). Semi-supervised anomaly detection methods for leakage identification in water distribution networks: A comparative study. Machine Learning with Applications, 14, 100501. https://doi.org/10.1016/j.mlwa.2023.100501
- Vanijjirattikhan, R., Khomsay, S., Kitbutrawat, N., Khomsay, K., Supakchukul, U., Udomsuk, S., Suwatthikul, J., Oumtrakul, N., & Anusart, K. (2022). AI-based acoustic leak detection in water distribution systems. Results in Engineering, 15, 100557. https://doi.org/10.1016/j.rineng.2022.100557
- Wang, D., Shi, S., Lu, J., Hu, Z., & Chen, J. (2023). Research on gas pipeline leakage model identification driven by digital twin. Systems Science & Control Engineering, 11(1), 2180687. https://doi.org/10.1080/21642583.2023.2180687
- Weyns, M., Mazaeva, G., Vaes, G., Vancoillie, F., De Turck, F., Van Hoecke, S., & Ongenae, F. (2023). Leak localization in water distribution networks using GIS-enhanced autoencoders. Urban Water Journal, 20(7), 859-881. https://doi.org/10.1080/1573062X.2023.2216191
- Wu, Y., Ma, X., Guo, G., Jia, T., Huang, Y., Liu, S., Fan, J., & Wu, X. (2024). Advancing deep learning-based acoustic leak detection methods towards application for water distribution systems from a data-centric perspective. Water Research, 261, 121999. https://doi.org/10.1016/j.watres.2024.121999
- Ye, L., Wang, C., Zhou, X., Qin, Z., & Yu, C. (2024). EMDet: An entropy blending and multi-link parallel feature enhancement detection model for gas pipeline weak leakage detection. Process Safety and Environmental Protection, 186, 1580-1592. https://doi.org/10.1016/j.psep.2024.03.030
- Zhang, H., Zuo, Z., Li, Z., Ma, L., Liang, S., Lu, Q., & Zhou, H. (2024). Leak detection for natural gas gathering pipelines under corrupted data via assembling twin robust autoencoders. Process Safety and Environmental Protection, 188, 492-513. https://doi.org/10.1016/j.psep.2024.05.112
- Zuo, Z., Ma, L., Liang, S., Liang, J., Zhang, H., & Liu, T. (2022). A semi-supervised leakage detection method driven by multivariate time series for natural gas gathering pipeline. Process Safety and Environmental Protection, 164, 468-478. https://doi.org/10.1016/j.psep.2022.06.036.