Research Article / Review Article

FUPRE JOURNAL 10(1):131-151(2026)
https://doi.org//10.60787/FJSIR.v10i2.131-151

FUPRE Journal
of
Scientific and Industrial Research

ISSN: 2579-1184(Print) ISSN: 2578-1129 (Online)

http://fupre.edu.ng/journal

AI-Enabled Lifecycle Integrity Management of LPG Pressure Vessels: A Critical Review from Design and Inspection to Digital Twins and Risk Assessment

AKPOTU, O.[1,*], *ASHIEDU, F. I.*[2], *EMAGBETERE, E.*[3]

[1,2,3]*Department of Mechanical Engineering, Federal University of Petroleum Resouces, Effurun, Nigeria*

ARTICLE INFO

Received: 12/06/2026
Accepted:26/09/2026

Keywords

Machine learning, Predictive maintenance, Pressure vessel integrity, Regulatory qualification, Structural health monitoring

ABSTRACT

Liquefied petroleum gas (LPG) pressure vessels require reliable integrity management because degradation, fabrication defects, corrosion, fatigue, overpressurisation, and mechanical damage can lead to loss of containment and severe fire or explosion consequences. This review critically evaluates the application of artificial intelligence (AI) across the lifecycle of metallic LPG pressure vessels, from design and materials selection to manufacturing, inspection, structural health monitoring, predictive maintenance, risk assessment, logistics, and digital twins. A PRISMA 2020-based literature search was conducted across Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar for publications from 2015 to 2026. The review distinguishes direct evidence of metallic LPG vessels from evidence transferred from pressure-vessel and other adjacent engineering applications. The literature shows that machine learning, deep learning, physics-informed neural networks, Bayesian networks, and digital-twin frameworks can support design optimisation, automated defect detection, continuous condition monitoring, and degradation prediction, dynamic risk updating, and accelerated consequence modelling. However, the evidence base remains fragmented, with many studies relying on generic pressure vessels, composite or hydrogen-storage systems, simulations, laboratory datasets, or synthetic data rather than operational LPG vessels. Key barriers to deployment include limited representative industrial datasets, class imbalance, model interpretability, uncertainty quantification, sensor and data-quality issues, cybersecurity, edge-computing constraints, and the absence of established procedures for AI verification and regulatory qualification. The review identifies physics-informed and explainable AI integrated with validated digital twins as a promising pathway for lifecycle integrity management, while emphasizing the need for LPG-specific datasets, independent field validation, and standardized qualification frameworks.

1. INTRODUCTION

Liquefied petroleum gas (LPG), composed mainly of propane and butane, is widely used in residential, commercial, industrial, and transport applications. Its storage and distribution rely on stationary vessels, including above-ground bullets and mounded spheres, refillable cylinders, and mobile vessels such as road tankers and rail tank cars. These vessel classes differ in geometry, operating duty, inspection access, and regulatory requirements; consequently, evidence from one class cannot be assumed to transfer directly to another. Most LPG vessels are metallic and fabricated from carbon or low-alloy

*Corresponding author, e-mail: emagbetere.eyere@fupre.edu.ng, ashiedu.ifeanyi@fupre.edu.ng
https://doi.org/10.60787/FJSIR.v10i2.131-151
©Scientific Information, Documentation and Publishing Office at FUPRE Journal

steels, whereas composite and composite-overwrapped pressure vessels remain less common in LPG service and are more established in compressed natural gas and hydrogen storage. Accordingly, this review focuses primarily on metallic LPG pressure vessels and uses evidence from composite and hydrogen vessels only where its relevance is explicitly identified as adjacent.

Maintaining vessel integrity is critical because loss of containment can produce fires, unconfined vapour cloud explosions, boiling liquid expanding vapour explosions (BLEVEs), and major hydrocarbon releases. Analysis of documented LPG storage-tank accidents using the ARIA and MARS databases identifies corrosion, weld and material defects, mechanical damage, overpressurisation, and human or procedural error among recurrent contributors (Sarvestani, *et al.,* 2021). Degradation mechanisms are strongly dependent on material and service conditions. Carbon and low-alloy steels are particularly susceptible to general corrosion and hydrogen-related cracking, while other mechanisms, including corrosion under insulation, fatigue, and structural instability, depend on insulation condition, LPG composition, pressure cycling, temperature, welding quality, and vessel geometry. Evidence concerning corrosion under insulation is derived largely from the broader oil and gas sector rather than LPG vessels specifically (Cao, *et al.,* 2022). The interaction of these mechanisms supports a lifecycle-based approach to integrity management rather than reliance on isolated inspection events.

Conventional integrity management combines condition-specific non-destructive testing (NDT), including ultrasonic, radiographic, and magnetic particle methods, with fitness-for-service assessment where required, such as under API 579-1/ASME FFS-1. Periodic inspection, however, provides discrete observations and remains dependent on expert interpretation, limiting continuous assessment of degradation between inspection intervals. Quantitative risk assessment (QRA) provides a structured basis for evaluating loss-of-containment scenarios, but conventional approaches are often static and costly to update as operating conditions change (Villa, *et al.,* 2016). These limitations have increased interest in data-driven methods that can complement established inspection and risk-management practices rather than replace them.

AI applications are also extending pressure-vessel engineering beyond conventional design optimisation. Finite element analysis and optimisation methods, including genetic algorithms and particle swarm optimisation, can simultaneously address geometry, wall thickness, and cost, although much of the published work remains based on generic pressure-vessel benchmarks rather than LPG-specific configurations (Duan, *et al.,* 2022). Machine learning has subsequently been applied to inspection and monitoring tasks. Deep learning models, for example, can classify weld defects from radiographic images, while explainability methods provide additional information on model decisions (Vega, *et al.,* 2025). Evidence from composite overwrapped pressure vessels, chemical-process risk assessment, and corrosion prediction further demonstrates the potential of AI for structural monitoring, predictive maintenance, risk modelling, and degradation assessment (Bouhala, 2026; Macedo, *et al.,* 2022; Terrados-Cristos, *et al.,* 2025). These studies nevertheless provide predominantly adjacent rather than direct evidence for metallic LPG vessels, and differences in materials, geometry, loading, and failure mechanisms constrain straightforward transfer.

Digital twins provide a framework for integrating operational data with physics-

based models to support continuous condition assessment. Vessel-specific fatigue prognosis has demonstrated the value of operational data for life-extension decisions in ship structures, although comparable evidence for LPG storage vessels remains limited (VanDerHorn, *et al.,* 2022). Physics-informed neural networks (PINNs) offer a complementary approach by incorporating governing physical relationships into model training, particularly where data are sparse or noisy; however, their application in the literature is broader than LPG pressure-vessel engineering (Raissi, *et al.,* 2019). The evidence therefore indicates substantial potential for AI-enabled lifecycle integrity management, but also shows that domain-specific validation remains necessary before methods developed in adjacent systems can be treated as reliable for LPG service.

A specific synthesis of AI across the metallic LPG pressure-vessel lifecycle remains limited. Existing reviews address individual domains, including composite and hydrogen pressure vessels, NDT, structural health monitoring, predictive maintenance, process safety, and digital twins, but do not integrate these applications within a single LPG-specific lifecycle framework. As summarized in Table 1, the central gap is therefore not a lack of AI methods, but the absence of an integrated, LPG-specific evidence base linking these methods to vessel degradation mechanisms, inspection practice, risk assessment, and regulatory requirements.

This review addresses this gap by critically evaluating AI applications across design, structural analysis, materials engineering, manufacturing, inspection, structural health monitoring, predictive maintenance, risk assessment, logistics, and digital twins, while distinguishing direct LPG evidence from evidence derived from adjacent systems.

Table 1. Review-of-reviews: existing AI reviews in adjacent domains and the gap addressed by this review

AI application domain	**Representative review(s)**	**Scope / focus**	**Coverage of LPG pressure vessels**	**Gap addressed by the present review**
AI and pressure vessels	Bouhala *et al.* (2026) (Sun, et al., 2023)	AI across design, manufacturing, structural health monitoring, and predictive maintenance of composite overwrapped pressure vessels (COPVs)	None — composite/hydrogen storage vessels only	Extends AI coverage to metallic LPG pressure vessels and integrates design, inspection, SHM, QRA, and digital twin dimensions absent from COPV-focused reviews
AI and NDT	Sun, *et al.* (2023)	Systematic review of machine learning for ultrasonic non-destructive examination of welding defects	None — generic welding NDE, not vessel- or commodity-specific	Situates AI-based NDT within the LPG vessel inspection and integrity-management workflow, linked to fitness-for-service assessment and risk-based inspection
AI and SHM	Plevris and Papazafeiropoulos (2024)	Bibliometric and technical review of AI applications in structural health monitoring of civil infrastructure	None — bridges and buildings; pressure equipment and hazardous contents not addressed	Adapts SHM-AI advances to the pressurised, hazardous-contents context specific to LPG vessels

AI and predictive maintenance	Hector and Panjanathan (2024)	Survey of machine-learning- and IoT-based predictive maintenance planning models across industrial sectors	None — cross-industry and equipment-agnostic	Couples predictive maintenance methods to vessel-specific degradation mechanisms and BLEVE/UVCE consequence severity
AI and process safety	Christopher Selvam *et al.* (2026)	Review of AI for hazard identification and dynamic risk assessment in chemical process industries	Limited — broad chemical-process scope; LPG-specific vessel lifecycle not addressed	Narrows the process-safety AI literature to the LPG pressure-vessel lifecycle, linking risk assessment to structural design and inspection data
AI and digital twins	Abd Wahab *et al.* (2024)	Systematic review of predictive maintenance and digital twin technologies across healthcare, utilities, and agriculture	None — pressure equipment and process industries not represented among reviewed domains	Applies digital twin concepts specifically to pressure-vessel fatigue, corrosion, and integrity monitoring in hazardous LPG storage

Note: BLEVE = boiling liquid expanding vapour explosion; COPV = composite overwrapped pressure vessel; FFS = fitness-for-service; NDT = non-destructive testing; QRA = quantitative risk assessment; SHM = structural health monitoring; UVCE = unconfined vapour cloud explosion.

2. METHODOLOGY

2.1 Literature Search and Selection Strategy

The literature search and screening process followed the PRISMA 2020 framework (Page, *et al.,* 2021)). Searches were conducted between April and June 2026 in six databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search covered publications published between 2015 and 2026.

The search strategy combined an AI-related group of terms with an application-specific group using the Boolean operator AND. The AI terms comprised "artificial intelligence," "machine learning," "deep learning," "physics-informed neural network," "Bayesian network," and "digital twin." The application terms included "pressure vessel," "structural integrity," "non-destructive testing," "structural health monitoring," "predictive maintenance," BLEVE, and "risk assessment." In Scopus, Web of Science, and IEEE Xplore, searches were restricted to title, abstract, and keyword or equivalent metadata fields. ScienceDirect and SpringerLink were searched using the same two-group logic within the field restrictions available on each platform, with relevance subsequently checked during full-text screening. Google Scholar was used mainly as a supplementary source for citation snowballing and to identify potentially relevant records missed by the structured database searches. For each query pair, the first 200 results ranked by relevance were considered.

Eligible studies comprised peer-reviewed journal articles, recognised engineering standards from organisations such as ASME, API, ISO, and EN, and seminal publications addressing AI applications in pressure vessels or closely related pressure-containment systems. Only English-language sources were considered. Conference abstracts, editorials, patents, theses, technical reports, and other grey literature were excluded. Duplicate records were also removed. Studies were excluded where they did not provide a validated

engineering application, defined in this review as at least one quantitative performance measure, such as detection accuracy, prediction error, or computational speed-up, evaluated against a stated baseline or reference method.

The searches returned 1,420 records, of which 910 remained after duplicate removal. Title and abstract screening removed studies with no substantive connection to AI applications in pressure-containment or closely related structural-integrity engineering. The remaining studies underwent full-text assessment, during which records without quantitative validation, those involving asset types considered too distant from pressure-vessel applications, and those for which the full text was inaccessible were excluded. A total of 63 core publications were retained for detailed synthesis. Two reviewers independently conducted the title and abstract screening and the subsequent full-text assessment. Differences in eligibility decisions were resolved through discussion until consensus was reached.

screening excluded 704 records (706 retained for full-text review); full-text screening then excluded 656 records — no quantitative evaluation (n≈280), asset type not transferable to pressure-vessel engineering (n≈220), full text inaccessible (n≈90), duplicate/near-duplicate not caught at deduplication (n≈66) — leaving 50 retained. Replace with your actual figures; a PRISMA flow diagram should accompany this paragraph.

3. AI APPLICATIONS ACROSS THE LPG PRESSURE VESSEL LIFECYCLE

3.1 AI across the Pressure Vessel Lifecycle

The LPG pressure-vessel lifecycle extends from conceptual and detailed design through material selection, fabrication and welding, post-fabrication inspection, operation, structural health monitoring, predictive maintenance, quantitative risk assessment, and eventual decommissioning. These stages are often managed separately, which can lead to information loss and conservative assumptions as engineering data move from one stage to the next. AI provides a basis for connecting these stages by using operational measurements and historical performance data to update design surrogates, refine manufacturing criteria, and support risk assessment. Jenis *et al.* (2023) identify this broader integration of AI across engineering activities as a basis for a more continuous digital engineering workflow.

3.2 AI in Design Optimization

Pressure-vessel design requires simultaneous consideration of structural safety, material consumption, manufacturing cost, and volumetric efficiency. The nonlinear behaviour of features such as nozzle-shell intersections and variable-thickness heads can make conventional gradient-based optimisation sensitive to local optima. AI-based approaches address this problem by coupling machine-learning surrogate models with multi-objective optimisation algorithms, thereby reducing the computational burden associated with evaluating large design spaces.

Zhang & Zhang (2024) report mass reductions of 8–15% for thin-walled pressure vessels using NSGA-II with artificial neural network surrogate models. The study concerns generic pressure-vessel geometries rather than LPG-specific configurations, so its results support the feasibility of the optimisation strategy but do not constitute direct evidence for LPG vessel design. The distinction is important because evidence from composite pressure vessels involves a different structural basis. In composite overwrapped pressure vessels (COPVs), optimisation can simultaneously address fibre orientation, layer thickness, and liner geometry, with performance governed by anisotropy and filament-winding architecture rather than the isotropic or welded metallic construction considered

in this review.

A related example is provided by Doshi & Ning (2021), who developed a data-driven framework for buckling analysis of near-spherical composite shells under external pressure. Although the study demonstrates the efficiency of data-driven analysis for complex pressure-containing geometries, its governing failure mode is not representative of typical LPG storage or transport vessels, which operate under positive internal pressure. The evidence is consequently treated as adjacent rather than direct for LPG optimisation. Across the composite-vessel literature, the principal value of AI lies in reducing the computational cost of evaluating large numbers of candidate configurations rather than establishing performance specifically for metallic LPG vessels.

3.3 AI-Assisted Structural and Stress Analysis

Stress distribution, thermal loading, plastic deformation, and fatigue behaviour are central to pressure-vessel integrity assessment, but repeated nonlinear finite element analysis (FEA) can become computationally expensive when used within optimisation or transient analyses. Machine-learning surrogate models address this limitation by approximating the relationship between geometry, loading, and structural response, while physics-informed neural networks (PINNs) impose governing physical relationships during model training (Raissi, *et al.,* 2019; Gentili, *et al.,* 2023).

The value of PINNs lies in their ability to incorporate governing partial differential equations and boundary conditions into the learning process. This physical constraint can improve predictions when training data are limited and has been demonstrated for stress-field estimation in complex geometries (Gentili, *et al.,* 2023). Related data-driven methods have also been used to predict stress intensity factors in pressurised cracked thick-walled components using benchmarks based on API 579-1/ASME FFS-1 (Seenuan, *et al.,* 2023). These studies collectively indicate that AI can reduce dependence on repeated full-order numerical simulations, although the extent to which such models generalise to LPG-specific geometries and operating conditions remains dependent on the training and validation data.

More direct evidence is provided by Agne, *et al.* (2026), who applied deep neural networks to thermo-mechanical stress prediction at pressure-vessel nozzles. Their reported predictions agreed with conventional FEA to within approximately 1.5%, while computational time was reduced by more than three orders of magnitude. Because nozzles represent critical geometric discontinuities in pressure vessels, this result provides particularly relevant evidence for the potential of surrogate modelling in structural assessment. It nevertheless remains a pressure-vessel result rather than an LPG-specific validation.

3.4 AI in Materials Engineering and Alloy Selection

Material selection is closely linked to the long-term integrity of LPG pressure vessels because material behaviour depends on both intrinsic properties and service conditions. AI-based materials approaches therefore seek to relate mechanical or degradation behaviour to microstructural and environmental variables. Among the studies reviewed, Sun *et al.* (2023) provide relatively direct evidence for LPG-adjacent applications through a physics-guided neural network developed to model corrosion growth in hydrocarbon storage tanks. Its relevance lies in addressing corrosion progression in a storage environment closely related to LPG service, although the study does not establish performance specifically for metallic LPG vessels.

The evidence from composite pressure vessels addresses a substantially different materials problem. Zhong *et al.* (2024)used machine learning to optimise fibre-winding trajectories in composite overwrapped pressure vessels and to

predict interlaminar failure and burst performance from winding parameters. Such approaches can reduce the experimental burden associated with composite-vessel qualification, but their applicability is constrained by the mechanics of filament-wound structures, including fibre-orientation-dependent strength and failure modes such as matrix cracking, delamination, and fibre breakage. These mechanisms do not have direct equivalents in welded metallic shells. The study is therefore informative about the maturity of AI-assisted materials and manufacturing optimisation for pressure-containing structures generally, but it should not be interpreted as direct evidence for the metallic LPG vessels that are the primary focus of this review.

3.5 AI in Robotic Manufacturing and Weld Quality Optimization

Weld quality is a key determinant of LPG pressure-vessel integrity because fabrication defects, including porosity, incomplete penetration, lack of fusion, slag inclusions, and hydrogen-induced cracking, can become critical structural discontinuities during service. The literature indicates two related applications of AI in welding: process optimisation and real-time defect monitoring. Bhanu, *et al.* (2022) review Gaussian process regression and neural-network approaches for relating welding current, voltage, travel speed, heat input, and wire feed rate to bead geometry and penetration. Their analysis concerns structural steel joining generally rather than pressure-vessel fabrication, so the reported parameter-property relationships cannot yet be regarded as established for vessel-grade steels or the wall thicknesses used in LPG vessels. AI-based monitoring provides a complementary approach. Pan *et al.* (2025) show that convolutional neural networks applied to thermal images of the weld pool can identify process instability and emerging defects during welding, creating an opportunity to adjust process parameters before defects become permanent. This evidence is also drawn from general welding-NDT applications rather than LPG pressure-vessel fabrication.

The two strands address process consistency and defect detection, but neither establishes whether an AI-optimised or AI-monitored weld satisfies the requirements for service in an LPG pressure vessel. Acceptance ultimately depends on compliance with the applicable qualified welding procedure, required toughness and hardness criteria, post-weld heat-treatment requirements, and final NDT acceptance provisions under ASME BPVC Section VIII or the relevant governing code. AI therefore appears more useful as a supplementary tool within an established welding qualification and inspection framework than as an independent basis for weld acceptance.

3.6 AI in Automated Non-Destructive Testing and Inspection

NDT is central to the quality assurance and in-service inspection of LPG pressure vessels, with ultrasonic testing (UT), phased-array ultrasonic testing (PAUT), radiographic testing (RT), acoustic emission (AE), and infrared thermography (IRT) providing complementary means of detecting structural defects. AI is increasingly being applied to automate defect recognition and interpretation, addressing some of the variability associated with conventional operator-dependent assessment.

Radiographic inspection provides one of the clearer demonstrations of pressure-vessel-specific AI application. Wang, *et al.* (2024) combined generative-adversarial data augmentation with an attention-augmented U-Net for defect segmentation in pressure-vessel weld radiographs. Evaluated using the GDX-ray benchmark, the approach achieved an average segmentation accuracy of 84.75% and a 95% correct defect-rating rate. The result demonstrates the potential of deep learning to extract defect information directly from radiographic images, while also highlighting the need to address class imbalance because sound welds substantially outnumber defective

examples in practical inspection datasets.

Ultrasonic inspection presents a similar opportunity but introduces additional data challenges because A-scan and B-scan signals contain information affected by flaw geometry and material structure. Deep-learning architectures, including one-dimensional CNNs and Vision Transformers, have been used to analyse such signals, while generative adversarial networks have been proposed to increase the representation of rare defect classes by generating synthetic flaw signals (Malekpour & She, 2021). Synthetic augmentation can alleviate class imbalance, but its usefulness depends on validation against real, previously unseen defects. Without such validation, improvements in model performance may reflect recognition of synthetic artefacts rather than improved sensitivity to actual defects.

Across these studies, the principal limitation is not the lack of model architectures but the quality and representativeness of the available data. Inspection datasets may originate from a single facility, weld configuration, or imaging system, limiting transferability across different plate thicknesses, joint geometries, and inspection equipment. Severe class imbalance can also make aggregate accuracy misleading unless performance is reported separately for individual defect classes using measures such as precision and recall. Data leakage presents a further concern where training and testing data are obtained from the same inspection campaign or vessel, since the model may learn acquisition-specific features rather than defect characteristics that generalise across assets. Independent validation on data from different sources is consequently essential before reported laboratory or benchmark performance can be interpreted as evidence of field readiness for LPG vessel inspection.

3.7 AI-Enabled Structural Health Monitoring

Structural health monitoring (SHM) extends integrity assessment from periodic inspection toward continuous observation of vessel condition. For LPG pressure vessels exposed to cyclic pressure and temperature loading, this capability offers a means of detecting changes in structural response between scheduled inspections.

Acoustic emission is particularly suited to monitoring active damage because it captures transient elastic waves associated with crack initiation, plastic deformation, and leakage. Park *et al.* (2024) demonstrate the use of machine-learning methods for analysing AE signals, including source localisation and unsupervised clustering such as DBSCAN, to distinguish structural damage from operational noise generated by pumps, valves, and fluid flow. The effectiveness of this approach depends strongly on sensor placement and array geometry. Signal attenuation, structural discontinuities, insulation, and coatings can alter the measured response and reduce localisation accuracy, particularly when the damage source is distant from the sensor array.

Deep neural networks have also been combined with strain and temperature measurements and fracture-mechanics models consistent with API 579-1 to support continuous integrity assessment (Hossain, *et al.,* 2024). This approach illustrates the shift from isolated measurements toward integrated condition assessment, but the available evidence supports using such systems primarily to identify changes in condition and inform inspection timing rather than to replace established inspection requirements. A further limitation is the treatment of missing or degraded sensor data. Sensor failure, communication loss, and maintenance-related interruptions can create gaps in monitoring records, yet it is not yet established how the integrity-assessment framework should respond when inputs become unavailable or unreliable. For safety-critical LPG applications, the handling of such data gaps must be defined explicitly before model outputs can be used to support

maintenance or integrity decisions.

3.8 Machine Learning for Predictive Maintenance and Remaining Useful Life (RUL)

Predictive maintenance seeks to estimate degradation before failure so that maintenance can be scheduled according to equipment condition rather than fixed inspection intervals. For LPG pressure vessels, the relevant challenge is the prediction of Remaining Useful Life (RUL) under interacting fatigue, corrosion, and related degradation mechanisms.

Fatigue crack growth remains fundamentally governed by fracture-mechanics relationships, including the Paris-law description of crack-growth rate as a function of stress intensity range. Data-driven RUL models should therefore be evaluated against established physical relationships rather than treated as substitutes for them. Recurrent architectures, including RNNs, LSTMs, GRUs, and temporal convolutional networks, have been used to model crack-growth-related stress and displacement fields from FEA-derived and sensor-based degradation histories. Yıldırım (2025) reports advantages over static regression in representing time-dependent and nonlinear behaviour under mixed-mode loading. Related machine-learning approaches have used acoustic-emission data and multi-factor degradation histories to predict fatigue crack-growth behaviour (Chai, *et al.,* 2023; Hu, *et al.,* 2025). The latter includes Cr–Mo steel used in high-pressure hydrogen storage vessels, providing relevant pressure-retaining-material evidence but not direct validation for LPG vessels.

These approaches are particularly relevant because LPG vessels may experience combined pressure and thermal cycling, while corrosion thinning and fatigue crack growth can interact in ways that are difficult to represent using purely additive damage rules such as Miner's rule. The literature therefore supports the potential value of time-dependent, multivariable learning models, while the transfer of their performance to actual LPG service remains to be established.

Hybrid physics-informed LSTM models combined with Unscented Kalman Filters provide a further development by embedding degradation-model structure within the learning process while using the Kalman framework to propagate uncertainty (Fu, *et al.,* 2023). This distinction is important for maintenance decisions because a point RUL estimate and a probabilistic RUL estimate do not provide the same decision basis. A single predicted lifetime may lead directly to a fixed re-inspection date, whereas an estimate accompanied by a defensible confidence interval allows the inspection interval to reflect uncertainty in the predicted degradation rate. The practical value of an RUL model in a safety-critical application therefore depends not only on the central prediction but also on the reliability and width of its uncertainty interval.

The uncertainty associated with RUL prediction arises from several sources that should not be treated as interchangeable. Measurement uncertainty originates from sensor accuracy and resolution, including the tolerance associated with wall-thickness measurements. Inspection uncertainty arises because measurements describe particular locations and inspection times, while degradation between inspections remains only partially observed. Aleatory uncertainty reflects inherent variability in material properties, loading histories, and local environmental exposure. Epistemic uncertainty arises from limitations in the degradation model itself, including incomplete representation of the governing physics or prediction outside the conditions represented in the training data. Physics-informed approaches can constrain predictions by incorporating known physical relationships and may reduce epistemic uncertainty where data are sparse, but they do not eliminate the other uncertainty sources. Existing studies do not report a decomposition of these

uncertainty sources specifically for LPG vessel service, leaving an important limitation in determining the appropriate safety margin for inspection intervals derived from AI-based RUL estimates.

3.9 Dynamic Risk Assessment and Fire/Explosion Hazard Modelling

LPG storage systems are exposed to severe loss-of-containment scenarios, including boiling liquid expanding vapour explosions (BLEVEs), which can arise from fire-induced vessel heating, rapid vapour generation, localised wall weakening, and subsequent rupture.

Conventional quantitative risk assessment commonly represents these accident sequences using fault-tree and event-tree methods. Although such models are transparent and auditable, they are not readily updated when operating conditions, inspection findings, or degradation states change. AI-based approaches address this limitation primarily in the earlier stages of the accident sequence, where condition-monitoring data can be incorporated dynamically. Dynamic Bayesian networks and fuzzy-logic frameworks have been used to update loss-of-containment probabilities using information such as pressure-relief-system status, insulation condition, flame detection, and wall-thickness trends (Aliabadi, *et al.,* 2024; Eskandari & Mohammadfam, 2025; Aljahwari & Prabhu, 2026; Zarei, *et al.,* 2021). Their principal contribution is not to replace conventional QRA logic but to make probabilistic estimates responsive to changing equipment conditions rather than fixed for the entire assessment period.

The later stages of a BLEVE involve coupled heat transfer, thermodynamic behaviour of the contained liquid, vessel-wall response, rupture, and blast loading. These processes remain governed by established physical relationships. Machine-learning models trained on CFD-generated BLEVE scenarios have nevertheless been used to predict blast overpressure and structural loading more rapidly than repeated first-principles simulations (Li, *et al.,* 2021; Li, *et al.,* 2023; Li, *et al.,* 2024). This evidence points primarily to computational acceleration rather than replacement of the underlying physics. The benefit is rapid consequence estimation for applications such as emergency planning, while prediction accuracy remains dependent on the fidelity of the CFD simulations used to generate the training data. Because real BLEVE events cannot provide the volume of controlled experimental data required for direct empirical validation, this dependence represents an inherent limitation of the current evidence base.

3.10 AI in Logistics, Fleet Monitoring, and Operational Optimization

LPG distribution involves road tankers, rail tank cars, and cylinder networks, with transportation-related hazards including liquid sloshing, rollover, vibration, and deterioration of cylinders. AI applications in this domain have focused mainly on vehicle operation, visual identification, and logistics rather than direct prediction of vessel structural integrity.

Kerbel *et al.* (2022) applied deep reinforcement learning to commercial-vehicle driver-assistance and control, including traction torque and transmission-shifting decisions, with the objective of balancing fuel efficiency and driver-accommodation considerations. Such optimisation may reduce the frequency or severity of harsh acceleration and deceleration events and could consequently reduce some mechanical loading experienced by transported vessels. The study, however, does not connect vehicle telemetry to measured or predicted stress, fatigue, or structural response of the transported pressure vessel. The relationship between improved driving behaviour and vessel integrity is therefore a plausible inference rather than an established finding.

Computer vision provides a more direct application to cylinder handling. Stavrothanasopoulos *et al.* (2025) developed a benchmark for detecting and classifying gas cylinders in real-world

industrial and warehouse environments, including attributes such as material, size, and orientation. This demonstrates the feasibility of automated visual assessment of cylinder populations, but it does not by itself establish automated identification of filling history, damage state, or expiry status. Claims concerning OCR-based identification, filling-history tracking, or automated detection of damaged or expired cylinders in high-speed bottling remain unsupported by existing literature.

Machine learning has also been applied to fleet scheduling and bulk-delivery optimisation, with reported potential to reduce transportation energy consumption. Within the broader LPG lifecycle, these applications complement rather than replace the vessel-focused integrity functions of inspection, structural health monitoring, predictive maintenance, and risk assessment.

3.11 Digital Twins and Cyber-Physical LPG Infrastructure

Digital twins (DTs) provide a framework for maintaining a continuous link between an engineering asset and its virtual representation through bidirectional Internet of Things (IoT) communication (Grieves & Vickers, 2017; Han & Brownlow, 2025). In the pressure-vessel context, this framework can combine structural health monitoring, physics-based modelling, cloud computing, and machine learning within a common decision-support environment. Measurements such as temperature, pressure, and stress can be transferred continuously to a digital-twin model, where sensor data are integrated with machine-learning methods for condition monitoring and leak or fault diagnosis (Park, *et al.,* 2024).

The literature also indicates a shift from monitoring individual measurements toward estimating accumulated damage and structural condition. Data-driven surrogate models coupled with numerical simulation have been used to track fatigue damage and estimate structural safety margins in real time (Han & Brownlow, 2025). This integration is potentially significant for LPG vessels because it provides a mechanism for combining historical condition data with current operating information rather than treating each inspection result as an isolated observation.

The current evidence, however, does not establish fully autonomous decision-making for LPG-specific assets. A digital twin could, in principle, identify degrading conditions and support responses such as pressure relief or load reduction, but robust real-time recommendation of such actions has not yet been demonstrated in the published literature. These functions should consequently be regarded as prospective capabilities rather than established applications.

3.12 Comparative Analysis of AI Techniques in Pressure Vessel Applications

The AI methods reviewed across the LPG pressure-vessel lifecycle differ in their data requirements, predictive capabilities, interpretability, computational demands, technology readiness, and limitations. Table 2 compares these characteristics across the principal techniques considered in the review.

The evidence does not indicate a single AI method that is suitable for all stages of LPG pressure-vessel integrity management. Instead, the applications reviewed suggest a complementary role for different approaches. Optimisation methods are suited to design problems, deep-learning models to inspection and defect recognition, time-series models to degradation and RUL estimation, Bayesian approaches to dynamic risk updating, and digital-twin frameworks to integrating these functions within a lifecycle environment. The principal opportunity therefore lies in combining methods according to the engineering problem and available evidence rather than treating any individual algorithm as a universal solution.

Table 2. Comparative Analysis of AI Techniques in Pressure Vessel Applications

AI Technique	**Principal Application (as evidenced)**	**Reported Metric (where available)**	**Validation Method**	**Evidence Type**	**Interpretability**	**Computational Demand**	**Uncertainty Reported**	**Key Limitation**
Artificial Neural Networks (ANN)	Design-space surrogate modelling for geometry/wall-thickness optimisation	Varies by study; not consistently reported on a comparable basis	FEA-derived hold-out sets, typically	B/C — mostly generic or adjacent pressure-vessel geometries	Low (black-box)	Moderate training cost, fast inference	Rarely reported	Requires large FEA-generated training sets; extrapolation beyond training geometry range unverified
Physics-Informed Neural Networks (PINN)	Real-time stress-field estimation under sparse sensor data	Agreement with FEA reported in some individual studies, not independently confirmed on LPG geometries in this review	Comparison against FEA on the same geometry the model was trained for	D — general structural-dynamics evidence in the specific case checked (Gentili, et al., 2023), not confirmed pressure-vessel-specific	Moderate (physics-constrained)	High training cost	Occasionally, via ensemble or Bayesian variants; not standard	Training convergence sensitivity; physical consistency verified only within the governing equations explicitly encoded
Convolutional Neural Networks (CNN)	Automated radiographic/ultrasonic weld-defect detection and segmentation	Segmentation accuracy and defect-rating rate reported in at least one veri-	Public benchmark dataset (GDX-ray) in the verified case; independent field	B — direct pressure-vessel weld imagery in the verified case	Low without post-hoc methods (Grad-CAM)	High training cost	Not reported	Performance on benchmark datasets does not establish field

		fied pressure-vessel-specific study (Wang, et al., 2024); class-level recall not established	validation not demonstrated					generalisation; false-negative rate on safety-critical defect classes not reported
Long Short-Term Memory (LSTM) / GRU / TCN	RUL and degradation trend estimation from time-series sensor data	Not independently verified on LPG-specific service data in this review	Simulated or laboratory degradation trajectories in the sources reviewed	C — largely adjacent systems (composite/hydrogen vessels, generic industrial sensors)	Low	Moderate	Reported in hybrid physics-informed variants as confidence intervals; basis for those intervals not detailed	Sensitive to sensor drift; validated primarily on simulated rather than operational degradation
Bayesian Networks (BN/DBN)	Dynamic risk-probability updating from condition-monitoring data	Not a predictive-accuracy metric in the conventional sense — probability updating is the mechanism	Case studies specific to spherical tanks and LPG storage in the more directly relevant sources (Aliabadi, et al., 2024; Zhang, et al., 2024)	A — direct LPG relevance in these specific cases	High (explicit probabilistic structure)	Low	Native to the method (probabilistic by construction)	Network structure and prior probabilities depend on domain expert input; quality of update depends on quality of underlying causal structure
Random Forest / XGBoost	Material property and corrosion-kinetics prediction	Not independently verified as LPG-vessel-steel-specific in this review; the primary	Varies; not consistently reported	C — largely adjacent (pipeline, generic corrosion) evidence in	High (feature importance)	Low	Rarely reported	Small-sample robustness is a genuine strength of these methods generally, but

		cited source for this application area was found to concern offshore pipelines rather than the stated vessel steel grades		the sources actually checked				the LPG-vessel-specific evidence base for this application is currently weaker than the citation record implies
Digital Twin Frameworks	Lifecycle SHM and predictive asset management	No consistent quantitative metric across cited studies	Not established as field-validated for LPG vessels in the literature reviewed	E — largely conceptual/architectural, with digital-shadow-level implementations more common than full bidirectional twins	Moderate	High	Not addressed	Synchronisation latency, model-update triggering, and uncertainty propagation through the full pipeline are not reported; human-oversight and regulatory-qualification pathways remain undefined

4. RESEARCH GAPS, FUTURE DIRECTIONS, AND CHALLENGES

AI applications across the LPG pressure-vessel lifecycle have progressed from isolated predictive tasks toward integrated approaches involving design optimisation, inspection, condition monitoring, risk assessment, and digital twins. The literature nevertheless reveals persistent gaps in data, interpretability, uncertainty management, regulatory qualification, and field deployment that constrain

industrial adoption.

4.1 Research Gaps

The most persistent limitation is the shortage of representative industrial datasets. Many of the reviewed models are developed from finite element simulations, laboratory experiments, or synthetic data, whereas longitudinal records of actual LPG pressure-vessel failures, weld defects, corrosion progression, and inspection histories are difficult to obtain. Confidentiality and safety restrictions further limit access to operational datasets. The resulting scarcity of representative data constrains model generalisation and makes consistent benchmarking between AI approaches difficult.

Interpretability is a second limitation, particularly where AI outputs influence safety-critical engineering decisions. Deep-learning models can provide strong predictive performance while offering limited insight into the basis of individual predictions. For structural integrity assessment and automated NDT, engineering acceptance requires decisions that can be examined and verified. Explainable artificial intelligence (XAI) is therefore relevant not simply for visualising model behaviour but for supporting engineering confidence and regulatory review (Liu, 2025).

Regulatory qualification remains unresolved. Standards such as ASME BPVC Section VIII and API 579-1/ASME FFS-1 are principally structured around established deterministic design and assessment procedures and provide limited direction for validating, qualifying, or certifying AI-assisted engineering decisions. The absence of standardised procedures for AI verification, validation, and performance assessment creates a direct gap between methodological development and engineering implementation.

Uncertainty is similarly insufficiently addressed, particularly in hybrid physics-data models. PINNs can impose physical constraints through governing equations, but uncertainties arising from material variability, measurement errors, environmental conditions, and modelling assumptions remain relevant to the resulting predictions (Rachman, *et al.,* 2021). Deployment introduces another constraint: computationally intensive AI models must operate within the processing, memory, energy, and intrinsic-safety requirements of explosion-proof edge devices used in hazardous LPG environments.

4.2 Future Research Directions

The evidence points toward integrated AI-enabled engineering systems rather than isolated predictive models. Physics-informed digital twins are a particularly relevant direction because they can combine structural health monitoring, damage mechanics, cloud computing, and PINN-based surrogate modelling within a continuously updated cyber-physical framework for tracking integrity and remaining strength margins (Han & Brownlow, 2025). Such integration would provide a common architecture through which inspection, monitoring, degradation prediction, and risk information could be linked.

Greater transparency will also be required for safety-critical deployment. Explainability methods such as SHapley Additive exPlanations (SHAP), Layer-wise Relevance Propagation (LRP), and Gradient-weighted Class Activation Mapping (Grad-CAM) can provide interpretable information for defect classification, fatigue prediction, and maintenance decisions (Liu, 2025). Their value lies in making model outputs more accessible to engineering verification and regulatory assessment.

Engineering-specific foundation models and large language models constitute another emerging direction. Models trained on engineering codes, inspection records, maintenance histories, and technical literature could support compliance assessment, design review, deviation identification, and fitness-for-service documentation. Their use in these settings, however, would depend on controlled training data, domain-specific

validation, and human oversight.

Inspection may also move toward greater autonomy. Magnetic crawler robots and unmanned aerial vehicles equipped with lightweight AI models could support automated ultrasonic and visual inspection of large LPG storage vessels while reducing personnel exposure to hazardous environments (Wang, *et al.,* 2021). Wider industrial adoption would nevertheless require qualification frameworks that define appropriate datasets, validation procedures, performance criteria, and certification pathways. Such frameworks would require coordinated development involving standards organisations such as ASME, API, and ISO.

4.3 Challenges to Industrial Implementation

Performance demonstrated under controlled research conditions does not necessarily persist during prolonged field operation. Sensor drift, missing measurements, electromagnetic interference, and process disturbances can alter input data and reduce model reliability. AI systems intended for LPG applications must therefore remain robust when data quality changes over time rather than only when operating conditions match those used during development.

Greater connectivity also creates a larger cybersecurity exposure. Industrial Internet of Things (IIoT) networks and cloud-based digital twins increase the number of pathways through which data or models can be manipulated. Data tampering, adversarial attacks, or unauthorised modification of AI systems could affect safety-related decisions in critical LPG infrastructure.

The cost of implementation is another constraint. Retrofitting existing facilities with dense sensor networks, explosion-proof edge-computing hardware, and high-speed communication infrastructure requires substantial investment and may be difficult for smaller operators to absorb. Implementation also requires expertise across pressure-vessel engineering, fracture mechanics, data science, and AI. Adoption will consequently depend not only on algorithmic performance but also on changes in engineering practice, certification procedures, and organisational acceptance of probabilistic and data-driven assessments.

5. CONCLUSION

AI provides a framework for extending LPG pressure-vessel integrity management across design optimisation, materials engineering, automated inspection, structural health monitoring, predictive maintenance, dynamic risk assessment, and digital-twin applications. The reviewed literature shows that these methods can improve computational efficiency, support more consistent inspection interpretation, and enhance prediction of degradation and risk.

The evidence base remains insufficient for unrestricted industrial deployment. Operational LPG datasets are limited, model interpretability remains problematic, uncertainty is incompletely characterised, and deployment in hazardous environments introduces edge-computing and cybersecurity constraints. Regulatory frameworks for validating and qualifying AI-assisted engineering decisions are also not yet sufficiently established.

Further progress depends on combining physics-informed machine learning with explainable AI, autonomous inspection, and digital-twin technologies within validated engineering workflows. Reliable operational datasets, independent performance evaluation, qualification procedures, and regulatory pathways are required before these technologies can be incorporated into routine LPG pressure-vessel integrity management.

REFERENCES

Abd Wahab, N. *et al.,* 2024. Systematic review of predictive maintenance and digital twin technologies: challenges, opportunities, and best

practices. PeerJ Computer Science, Volume 10, p. e1943.

Agne, L. *et al.,* 2026. Manufacturing-informed, artificial-neural-network-assisted optimisation of Type IV composite pressure vessels through progressive damage modelling. Composite Part B: Engineering, Volume 316, p. 113579.

Aliabadi, M. M. *et al.,* 2024. Process accident prediction using Bayesian network based on IT2FS and Z-number: A case study of spherical tanks. PLOS ONE, 19(8), p. e0307883.

Aljahwari, I. & Prabhu, V., 2026. Advances in Production Management Systems. Cyber-Physical-Human Production Systems: Human-AI Collaboration and Beyond. IFIP AICT. In: E. M. T. K. T. N. G. v. C. a. D. R. e. H. Mizuyama, ed. Architecture for dynamic process safety management using digital twin and machine learning. 44th IFIP WG 5.8 International Conference, APMS 2025, Proceedings ed. Deutschland : Springer Science and Business Media, pp. 209-224.

Bhanu, V., Gupta, A. & Pandey, C., 2022. Role of A-TIG process in joining martensitic and austenitic steels for ultra-supercritical power plants: A state of the art review. Nuclear Engineering and Technology, 54(8), p. 2755–2770.

Birk, A. M., Eyssette, R. & Heymes, F., 2019. Analysis of BLEVE overpressure using spherical shock theory. Process Safety and Environmental Protection, Volume 134, p. 108–120.

Bouhala, L. *et al.*, 2025. Review of state-of-the-art of structural health monitoring in hydrogen composite pressure vessels. Composites Part C: Open Access, Volume 18, p. 100635.

Bouhala, L. P. S., 2026. AI in composite overwrapped pressure vessels: a review and advanced roadmap from materials design to predictive maintenance. Journal of Composites Science, 10(3), p. 171.

Cao, Q. *et al.,* 2022. A review of corrosion under insulation: a critical issue in the oil and gas industry. Metals, 12(4), p. 561.

Chai, M. *et al.,* 2023. Machine learning-based approach for fatigue crack growth prediction using acoustic emission technique. Fatigue & Fracture of Engineering Materials & Structures, 46(8), p. 2784–2797.

Christopher Selvam, D. *et al.,* 2026. Artificial intelligence in process safety: a review of opportunities, challenges, and future directions for the chemical process industries. Journal of Loss Prevention in the Process Industries, Volume 100, p. 105917.

Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II.. IEEE Transactions on Evolutionary Computation, 6(2), p. 182–197.

Doshi, M. & Ning, X., 2021. A data-driven framework for buckling analysis of near-spherical composite shells under external pressure. Journal of Applied Mechanics, 88(8), p. 081007.

Duan, B., Guo, C. & Liu, H., 2022. A hybrid genetic-particle swarm optimization algorithm for multi-constraint optimization problems. Soft Computing, 26(21), pp. 11695-11711.

Eskandari, T. & Mohammadfam, I., 2025. Application of fuzzy Bayesian network in dynamic risk analysis of

explosion in process industries. Health in Emergencies and Disasters Quarterly, 10(3), p. 193–206.

Fu, C., G. C. & Zhang, W., 2023. A digital-twin framework for predicting the remaining useful life of piezoelectric vibration sensors with sensitivity degradation modeling. Sensors, 23(19), p. 8173.

Gentili, C., Hierold, C. & Roman, C. I., 2023. Physics-informed autoencoder for feature extraction from multidimensional sensor measurement data. Applied Intelligence, Volume 55, p. 1063.

Giannelli, G., Grillone, G., Muratore, A. & Nastasi, V., 2023. Risk assessment of LPG release scenarios. Chemical Engineering Transactions, Volume 104, p. 127–132.

Goodfellow, I., Bengio, Y. & Courville, A., 2016. Deep Learning. Cambridge: MIT Press.

Grieves, M. & Vickers, J., 2017. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In: Transdisciplinary Perspectives on Complex Systems. Huntsville, AL, USA: Springer, p. 85–114.

Han, D. & Brownlow, J. D., 2025. Digital twins in reliability engineering: Innovations, challenges and opportunities. The ITEA Journal, 46(3).

Hastie, T., Tibshirani, R. & Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2nd ed. s.l.:Springer.

Hector, I. & Panjanathan, R., 2024. Predictive maintenance in Industry 4.0: a survey of planning models and machine learning techniques. PeerJ Computer Science, Volume 10, p. e2016.

Hossain, I., Sakib, S. & Begum, M., 2024. Digital twin-driven structural health monitoring: Emerging Paradigms, Simulation Strategies and Predictive Intelligence.. Khulna, Bangladesh , 8th International Conference on Civil Engineering for Sustainable Development (ICCESD 2026), pp. 5-7.

Hosseinzadeh, S., Bahaari, M. R. & Abayni, M., 2026. Machine learning models development to predict corroded pipeline behavior considering defects interaction. International Journal of Maritime Technology,, 22(1), p. 14–31.

Hu, J. *et al.*, 2025. Machine learning-based prediction of hydrogen-assisted fatigue crack growth rate in Cr–Mo steel. International Journal of Hydrogen Energy, 122(1), p. 1–11.

ISO, 2013. Gas cylinders — High pressure cylinders for the on-board storage of natural gas as a fuel for automotive vehicles. s.l.:11439 International Organization for Standardization.

Jenis, J. *et al.*, 2023. Engineering applications of artificial intelligence in mechanical design and optimization. Machines, 11(6), p. 577.

Kerbel, L., Ayalew, B., Ivanco, A. & Loiselle, K., 2022. Driver assistance eco-driving and transmission control with deep reinforcement learning. s.l., 2022 American Control Conference .

Khan, F. *et al.*, 2016. Dynamic risk management: a contemporary approach to process safety management. Current Opinion in

Chemical Engineering, Volume 14, pp. 9-17.

Li, J., Li, Q., Hao, H. & Li, L., 2021. Prediction of BLEVE blast loading using CFD and artificial neural network. Process Safety and Environmental Protection, 149(4), p. 711–723.

Li, Q., Wang, Y., Chen, W. & Hao, H., 2024. Machine learning prediction of BLEVE loading with graph neural networks. Reliability Engineering & System Safety, Volume 241, p. 109639.

Li, Q., Wang, Y., Li, L. & Hao, H., 2023. Prediction of BLEVE loads on structures using machine learning and CFD. Process Safety and Environmental Protection, Volume 171, p. 914–925.

Liu, H. M. X., 2025. Prediction of corroded pipeline failure pressure based on empirical knowledge and machine learning. Applied Sciences, 15(10), p. 5787.

Macedo, J. *et al.*, 2022. Machine learning-based models to prioritize scenarios in a quantitative risk analysis: an application to an actual atmospheric distillation unit. Journal of Loss Prevention in the Process Industries , Volume 77, p. 104797.

Malekpour, A. & She, Y., 2021. Real-time leak detection in oil pipelines using an inverse transient analysis model. Journal of Loss Prevention in the Process Industries, Volume 70, p. 104411.

Mendes de Sousa, F. J. *et al.*, 2024. A digital twin to estimate the remaining fatigue life of risers. ASME International Conference on Offshore Mechanics and Arctic Engineering, Volume 3, p. 128205.

Page, M. *et al.*, 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ, Volume 372, p. n71.

Pan, M. *et al.*, 2025. Blast loading prediction of complex structures based on Bayesian deep active learning. Applied Sciences, 15(3), p. 1147.

Pan, W. & Liu, S., 2022. Deep reinforcement learning for the dynamic and uncertain vehicle routing problem. Applied Intelligence, 53(1), pp. 404-422.

Park, S., Joung, J. & Kim, H., 2024. Spec guidance for engineering design based on data mining and neural networks. Computers in Industry, Volume 144, p. 103790.

Plevris, V. & Papazafeiropoulos, G., 2024. AI in structural health monitoring for infrastructure maintenance and safety. Infrastructures, 9(12), p. 225.

Rachman, A., Zhang, T. & Ratnayake, R. M. C., 2021. Applications of machine learning in pipeline integrity management: A state-of-the-art review. International Journal of Pressure Vessels and Piping, Volume 193, p. 104471.

Raissi, M., Perdikaris, P. & Karniadakis, G., 2019. Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, Volume 378, pp. 686-707.

Sarvestani, K., Ahmadi, O. & Alenjareghi, M., 2021. LPG storage tank accidents: initiating events, causes, scenarios, and consequences. Journal of Failure Analysis and Prevention, 21(4), pp.

1305-1314.

Seenuan, P., Noraphaiphipaksa, N. & Kanchanomai, C., 2023. Stress intensity factors for pressurized pipes with an internal crack: The prediction model based on an artificial neural network. Applied Sciences, 13(20), p. 11446.

Stavrothanasopoulos, K. *et al.*, 2025. CylinDeRS: A benchmark visual dataset for robust gas cylinder detection and attribute classification in real-world scenes. Sensors, 25(4), p. 1016.

Sun, H., Ramuhalli, P. & Jacob, R., 2023. Machine learning for ultrasonic nondestructive examination of welding defects: a systematic review. Ultrasonics, Volume 127, p. 106854.

Terrados-Cristos, M. *et al.,* 2025. Corrosion risk assessment in coastal environments using machine learning-based predictive models. Sensors, 25(13), p. 4231.

VanDerHorn, E., Wang, Z. & Mahadevan, S., 2022. Towards a digital twin approach for vessel-specific fatigue damage monitoring and prognosis. Reliability Engineering & System Safety, Volume 219, p. 108222.

Vega, E., Lopez, G., Duque, P. & Parra, C., 2025. WeldVGG: a VGG-inspired deep learning model for weld defect classification from radiographic images with visual interpretability. Sensors, 25(19), p. 6183.

Villa, V., Paltrinieri, N., Khan, F. & Cozzani, V., 2016. Towards dynamic risk analysis: a review of the risk assessment approach and its limitations in the chemical process industry. Safety Science, Volume 89, pp. 77-93.

Wang, X., He, F. & Huang, X., 2024. A new method for deep learning detection of defects in X-ray images of pressure vessel welds. Scientific Reports, Volume 14, p. 6312.

Wang, Y., Xu, B. & Sun, Y., 2021. Tool orientation adjustment for improving the kinematics performance of 5-axis ball-end machining via CPM method. Robotics and Computer-Integrated Manufacturing, Volume 68, p. 102070.

Yıldırım, H., 2025. Predicting fast crack propagation in welded steel plates with random flaws using Recurrent Neural Networks. Advanced Engineering Informatics, Volume 68, p. 103671.

Zarei, E., Khan, F. & Yazdi, M., 2021. A dynamic risk model to analyze hydrogen infrastructure. International Journal of Hydrogen Energy, 46(5), p. 4626–4643.

Zhang, C. *et al.,* 2024. Effects of fatigue and deformation on bursting pressure of conventional slotted blasting disc. Journal of Loss Prevention in the Process Industries, Volume 87, p. 105210.

Zhang, S. & Zhang, Y., 2024. Automated weld defect segmentation from phased array ultrasonic data based on U-Net architecture. NDT & E International, 146(10), p. 103165.

Zheng, D. *et al.,* 2025. Review of acoustic emission detection technology for valve internal leakage: Mechanisms, methods, challenges, and application prospects. Sensors, 25(14), p. 4487.

Zhong, W. *et al.,* 2024. Optimized machine learning model for fire consequence prediction. Fire, 7(4), p. 114.