American Journal of Scholarly Research and Innovation
Volume 02, Issue 02 (2023)
Page No: 102-134
eISSN: 3067-2163
Doi:10.63125/wk278c34

Article

AI-POWERED PREDICTIVE FAILURE ANALYSIS IN PRESSURE VESSELS USING REAL-TIME SENSOR FUSION : ENHANCING INDUSTRIAL SAFETY AND INFRASTRUCTURE RELIABILITY

Arafat Bin Fazle[1]; Ripan Kumar Prodhan[2]; Md Majharul Islam[3];

[1]Assistant Manager , Production & Process, Abul Khair Steel Products Limited, Bhatiari, Chattogram, Bangladesh
Email: arafatfazle@gmail.com

[2]General Manager, IIS Testing BD Pvt. Ltd. House 169, Road 3, Mohakhali DOHS, Dhaka 1206, Bangladesh.
Email: ripanme20@gmail.com

[3]Bachelor of Mechanical Engineering , School of Engineering, Guangxi University of Science and Technology, Liuzhou, Guangxi, China
Email: islammdmajharul116@gmail.com

Citation:
Fazle, A. B., Prodhan, R. K., & Islam, M. M. (2023). *AI-powered predictive failure analysis in pressure vessels using real-time sensor fusion: Enhancing industrial safety and infrastructure reliability.* American Journal of Scholarly Research and Innovation, 2(2), 102–134. https://doi.org/10.63125/wk278c34

Received:
August 2, 2023

Revised:
September 10, 2023

Accepted:
October 3, 2023

Published:
December 1, 2023

ABSTRACT
The integration of Artificial Intelligence (AI) into Structural Health Monitoring (SHM) systems has emerged as a transformative solution for predictive failure analysis in pressure systems such as pressure vessels, pipelines, and industrial reactors. This study aims to systematically examine the role of AI-powered SHM frameworks in enhancing the reliability, safety, and operational efficiency of these high-risk infrastructures. A total of 63 peer-reviewed journal articles and conference papers published between 2000 and 2023 were reviewed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The selected studies were analyzed in terms of AI techniques applied, types of sensors integrated, fusion architectures, model performance metrics, validation methods, and real-world industrial applications. The review reveals that AI models—especially machine learning and deep learning algorithms—have significantly improved the early detection of faults, classification accuracy, and remaining useful life (RUL) prediction when supported by multi-sensor fusion frameworks. Models such as support vector machines (SVM), convolutional neural networks (CNN), and long short-term memory (LSTM) networks were frequently used and demonstrated strong performance, often achieving accuracy levels exceeding 90% across varied industrial scenarios. Furthermore, many of these systems have been successfully deployed in operational environments, leading to measurable improvements in maintenance scheduling, reduced downtime, and heightened safety. However, the review also identifies critical implementation challenges, including data scarcity, limited model interpretability, system integration constraints, and cybersecurity vulnerabilities. These barriers highlight the need for standardized practices, improved data governance, and interdisciplinary collaboration.

KEYWORDS
Predictive Maintenance; Sensor Fusion; Pressure Vessel Safety; Machine Learning; Industrial AI;

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eISSN: 3067-2163
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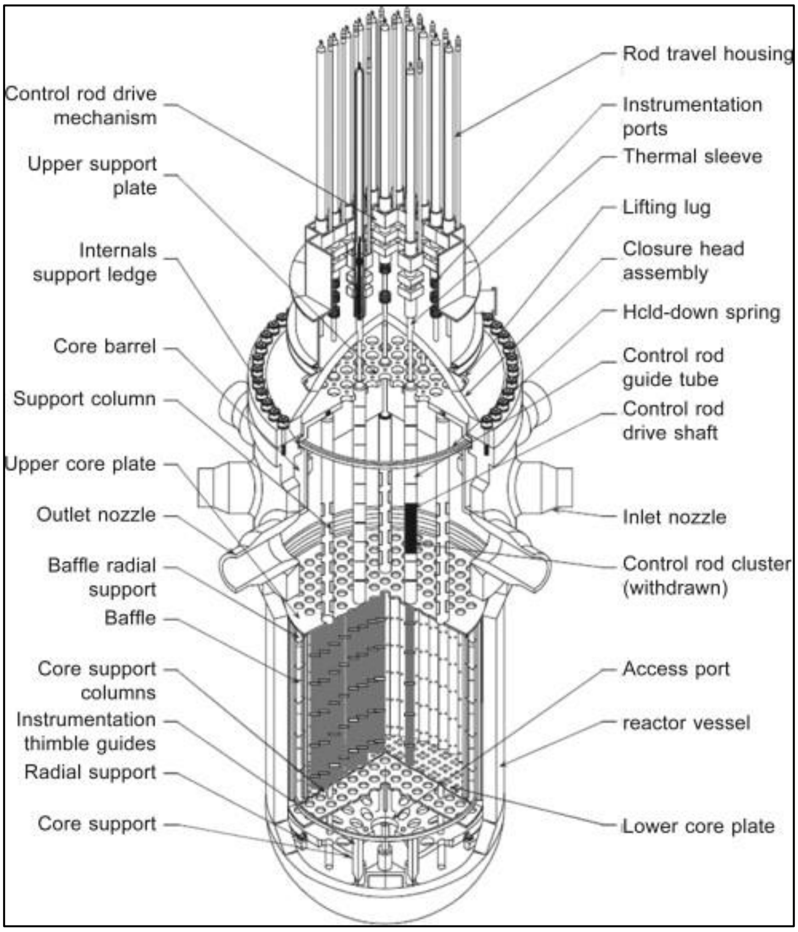
INTRODUCTION

Pressure vessels are integral to various industrial processes, including chemical manufacturing, power generation, oil and gas refining, and water treatment, due to their capacity to safely contain gases or liquids at high pressures (Kim et al., 2014). Their structural integrity is paramount, as any failure can result in hazardous leaks, explosions, or environmental damage (Durães-Carvalho et al., 2012). According to the American Society of Mechanical Engineers (ASME), pressure vessel failure is one of the most critical hazards in high-risk industrial settings. Factors contributing to these failures include corrosion, fatigue, mechanical deformation, weld defects, and operational overloads (Makimoto & Takashima, 2023). The complexities in vessel design and material composition increase the difficulty of early detection, particularly in dynamic environments where conditions fluctuate (Bakdi et al., 2019). In most traditional maintenance regimes, periodic inspections through non-destructive testing (NDT) such as ultrasonic testing or radiography are standard. However, these methods often fall short in providing real-time insights or continuous monitoring, especially in remote or hazardous environments (Papi et al., 2015). With aging industrial infrastructure across many sectors, pressure vessels are increasingly subjected to stressors not fully accounted for during their design life (Moss & Basic, 2013). Numerous reports have highlighted the inefficacy of reactive maintenance strategies in preventing pressure vessel incidents, noting that visual inspections and static diagnostic tools frequently miss subsurface anomalies (Vafaeesefat, 2011). These challenges emphasize the need for intelligent systems capable of continuous monitoring and real-time risk assessment using high-frequency data streams (Zhang et al., 2016). Therefore, the operational stability of pressure vessels has emerged as a domain in urgent need of technological transformation, particularly involving the fusion of real-time data with computational intelligence to mitigate failure risks.

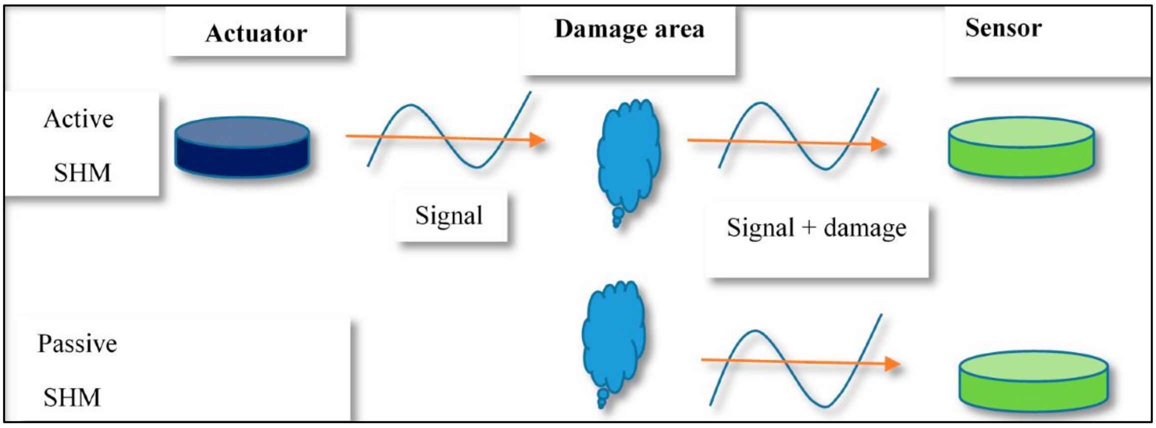
Figure 1: Typical PWR pressure vessel layout



Source: NRC (2006)

Predictive maintenance represents a paradigm shift from traditional maintenance approaches by anticipating failures before they occur, using data-driven insights (Trakulwaranont et al., 2019). It relies heavily on condition monitoring, which involves continuously collecting data from assets during their operation to assess health and performance in real-time (Desjardins & Lau, 2022). In contrast to preventive maintenance that follows a fixed schedule regardless of equipment condition, predictive maintenance minimizes downtime and extends the useful life of components (Liu et al., 2023). The adoption of predictive maintenance strategies has gained momentum with the advent of the Industrial Internet of Things (IIoT), which enables interconnected sensors to collect vast volumes of operational data (Berger et al., 2016). This has been particularly transformative in asset-intensive sectors, where unexpected equipment failures incur high economic and safety costs (Cacace et al., 2020). For pressure vessels, predictive maintenance has been implemented through approaches such as acoustic emission monitoring, thermal imaging, and vibration analysis, but these techniques in isolation often fail to produce holistic assessments (Verganti et al., 2020). The incorporation of artificial intelligence algorithms, such as decision trees, support vector machines (SVM), and neural networks, into predictive maintenance frameworks enables more accurate failure prognosis by learning complex patterns from historical and real-time data (Massaro et al., 2020). Furthermore, predictive maintenance systems powered by AI outperform rule-based systems in dynamically adapting to changing operational conditions (Peres et al., 2020). The convergence of AI with predictive maintenance offers pressure vessel operators a powerful toolkit to move from reactive to proactive safety management, particularly when enriched with real-time, high-fidelity sensor data.

Figure 2: Active and passive SHM methods.



Source: Abbas and Shafiee (2018)

The development of advanced sensors has revolutionized structural health monitoring (SHM) in pressure vessels by enabling real-time data acquisition across multiple parameters. Key sensor modalities include fiber Bragg grating (FBG) sensors for strain and temperature, piezoelectric sensors for acoustic emissions, MEMS-based accelerometers for vibration, and thermocouples for heat monitoring (Thombre et al., 2022). Each sensor type offers unique advantages in capturing localized anomalies such as crack initiation, delamination, and corrosion (Astill et al., 2020). When deployed strategically within or on pressure vessels, these sensors can produce continuous data streams for immediate interpretation. However, relying on a single type of sensor may result in incomplete fault characterization due to limited sensing modalities or interference from environmental noise . Sensor fusion, which integrates multiple sensor data types into a unified framework, has emerged as a superior method for comprehensive monitoring. In SHM applications, sensor fusion enhances system robustness, improves signal-to-noise ratios, and enables more nuanced interpretations of structural anomalies . For instance, correlating thermal and vibrational data can help identify fatigue-induced hot spots before visible cracks appear (Vervoort et al., 2012). The fusion of time-synchronized data across various physical phenomena supports multi-dimensional analysis that is vital in high-pressure systems (Tribst et al., 2008). As sensor technologies become more miniaturized and energy-efficient, they facilitate integration with wireless sensor networks (WSNs), allowing deployment even in inaccessible zones of complex infrastructure (Pavoni et al., 2014). The richness of real-time data generated through these sensors necessitates intelligent computational models capable of filtering, analyzing, and learning from these dynamic inputs.

Machine learning (ML) has become a cornerstone of modern structural health monitoring by enabling systems to identify patterns, predict outcomes, and adapt to new conditions based on historical and real-time data (Khosravikia & Clayton, 2021). Supervised learning techniques such as support vector machines, random forests, and deep neural networks have been widely used

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Doi:10.63125/wk278c34

for classification and regression tasks in failure detection. For example, convolutional neural networks (CNNs) can analyze acoustic emission waveforms to detect the presence of micro-cracks or internal pressure spikes. Recurrent neural networks (RNNs) and long short-term memory (LSTM) models are particularly suited to sequential data such as sensor time-series, capturing temporal dependencies critical for failure forecasting. These models can distinguish normal operating conditions from early signs of failure, offering a level of precision beyond traditional statistical models. Unsupervised learning, including clustering and anomaly detection, has also shown promise in identifying unknown failure modes without labeled datasets. Feature extraction and dimensionality reduction techniques such as principal component analysis (PCA) and autoencoders further refine model accuracy by reducing noise and computational complexity (Ren, 2021). Integration of machine learning with sensor fusion has allowed the construction of digital twins—virtual replicas of physical systems that simulate behavior under various scenarios using real-world data (Voinea et al., 2023). The capacity of ML algorithms to handle heterogeneous and high-frequency data makes them indispensable in high-stakes systems like pressure vessels where early failure detection is vital for operational safety. The primary aim of this study is to develop and evaluate an AI-powered predictive failure analysis framework that integrates real-time sensor fusion to enhance the safety, reliability, and operational efficiency of pressure vessels in industrial environments. By focusing on the detection and diagnosis of early-stage structural anomalies, the research aims to bridge the gap between conventional condition monitoring practices and advanced predictive maintenance systems. Traditional methods, such as periodic non-destructive testing or scheduled inspections, often miss the dynamic progression of faults and provide insufficient resolution for early intervention. This study addresses this limitation by leveraging continuous, multi-modal sensor data—including pressure, acoustic emissions, strain, vibration, and thermal metrics—integrated through a sensor fusion approach to provide a comprehensive picture of the vessel's structural health. The objective is further anchored in employing supervised and unsupervised machine learning techniques such as convolutional neural networks (CNNs), long short-term memory (LSTM) models, support vector machines (SVMs), and anomaly detection algorithms to process high-frequency data and generate failure probability metrics in real time. A secondary objective is to assess the performance and accuracy of these AI models across various fault scenarios using simulated and empirical datasets collected from industrial testing environments. By evaluating precision, recall, F1-score, and receiver operating characteristics (ROC), the study ensures model interpretability and robustness. The framework is also intended to reduce maintenance downtime, optimize inspection cycles, and prioritize safety-critical interventions. Ultimately, the research sets out to validate that the integration of real-time sensor fusion with machine learning can deliver a scalable and cost-effective solution for proactive infrastructure risk management within high-pressure industrial systems.

LITERATURE REVIEW

The integration of artificial intelligence (AI) and real-time sensor fusion for predictive failure analysis in pressure vessels represents a multidisciplinary convergence of mechanical engineering, data science, and safety systems management. To construct a robust foundation for this research, it is imperative to explore the existing body of knowledge on pressure vessel failure mechanisms, structural health monitoring, sensor technologies, data fusion strategies, and AI-based predictive maintenance frameworks. Prior studies have investigated isolated components of this system, such as sensor-based anomaly detection, machine learning models for equipment health diagnostics, and probabilistic assessments of mechanical degradation. However, a comprehensive synthesis that links these threads to support intelligent, real-time failure prediction in pressure vessels remains underdeveloped. This literature review critically examines the evolution of predictive maintenance from reactive and preventive methodologies to AI-driven paradigms, emphasizing the technological enablers and limitations that persist. Special attention is given to multi-sensor data integration (sensor fusion), the use of supervised and unsupervised learning techniques in failure prognosis, and the application of digital twin frameworks. Moreover, this review identifies the research gaps, unresolved engineering challenges, and conflicting results across empirical studies, thereby justifying the development of an integrated predictive

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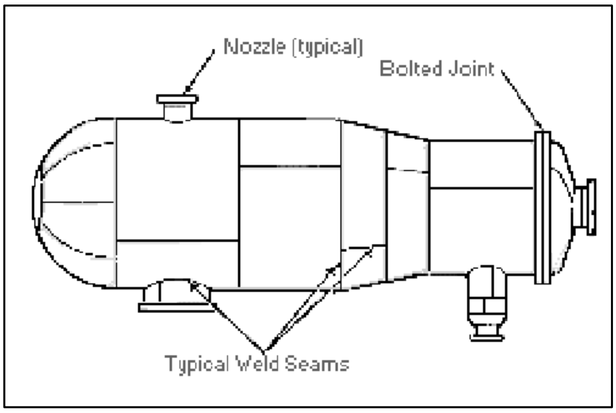
framework presented in this study. The goal is to contextualize the proposed solution within the existing literature and validate its theoretical and technical significance through an evidence-based review.

Pressure Vessel Safety and Failure Mechanisms

Pressure vessels operate under extreme conditions and are susceptible to a variety of failure mechanisms that can significantly jeopardize safety and system reliability. The most prevalent structural failures include fatigue, creep, corrosion, hydrogen embrittlement, and brittle fracture, each driven by specific operational and environmental stressors (Wu et al., 2015). Fatigue-induced cracks are often initiated at welds and high-stress concentration zones due to cyclic loading, particularly in chemical and power generation industries. Creep, on the other hand, becomes critical in high-temperature environments where time-dependent plastic deformation leads to eventual rupture. Hydrogen embrittlement, another significant mechanism, compromises vessel integrity by inducing micro-crack propagation in high-pressure hydrogen or sour gas applications. Brittle fracture has also been widely documented in carbon steel vessels operating below their ductile-to-brittle transition temperatures, often leading to catastrophic ruptures. Corrosion, both uniform and localized (pitting or stress corrosion cracking), accelerates material loss and is exacerbated by acidic or saline media (Paredes-Sabja et al., 2009). These failures are often interrelated, with fatigue cracks accelerated by corrosion or embrittlement . Advanced computational modeling and fractographic analysis have shown that multi-mode interactions are more common than isolated mechanisms in real-world failures (Gashi et al., 2022). This complexity highlights the necessity of comprehensive safety analysis frameworks that consider the synergistic effects of loading history, material microstructure, and environmental variables in predicting pressure vessel failures .

Figure 3: Major parts of a pressure vessel



Source: Steelhammer (2023)

The establishment of safety codes and regulations for pressure vessels has historically evolved in response to catastrophic industrial accidents, prompting the development of standardized design and inspection methodologies. The American Society of Mechanical Engineers (ASME) Boiler and Pressure Vessel Code (BPVC) is one of the most globally recognized frameworks, offering design, fabrication, inspection, and testing standards aimed at minimizing failure risks (Aklima et al., 2022; Khan et al., 2015). Complementary standards, such as the Pressure Equipment Directive (PED) in Europe and the American Petroleum Institute (API) 510 guidelines, further delineate inspection intervals, materials selection, and documentation protocols. These standards were born out of necessity following early 20th-century explosions, and have since incorporated modern tools like finite element analysis (FEA), fracture mechanics, and probabilistic safety assessments . Regular audits and third-party certifications are often mandated by regulatory authorities to ensure adherence to these codes (Ahmed et al., 2022; Leite et al., 2021). Furthermore, risk-based inspection (RBI) methodologies, which prioritize inspections based on likelihood and consequence of failure, have gained traction for optimizing safety management while reducing inspection costs . Studies have confirmed that plants using RBI frameworks have experienced a measurable reduction in unplanned shutdowns and failure incidents. However, the static nature of scheduled inspections fails to capture real-time degradation and operational anomalies, leading to gaps in predictive safety assurance. While these standards provide foundational support for safe vessel operation, advancements in data-driven, real-time monitoring methods are increasingly necessary to supplement regulatory frameworks.

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Numerous industrial disasters have underscored the devastating consequences of pressure vessel failures and the systemic gaps in early-warning mechanisms. A widely cited example is the 1984 Bhopal disaster, where a methyl isocyanate storage tank rupture led to thousands of fatalities, partly due to corrosion and failure of safety interlocks (Khan et al., 2015; Md Mahfuj et al., 2022). Another incident, the 2001 BP Texas City refinery explosion, involved a rupture in a process vessel due to overpressure and a malfunctioning relief system. The 2009 Sayano–Shushenskaya hydroelectric plant disaster in Russia, which killed 75 people, was linked to fatigue and improper maintenance of pressure-containing turbine components . Analysis of these failures revealed that poor documentation, missed inspections, and overlooked micro-cracks played critical roles in system breakdowns (Cui et al., 2023; Muhammad Mohiul et al., 2022). In less publicized but equally instructive cases, such as those in offshore oil platforms and nuclear containment vessels, undetected stress corrosion cracking and under-deposit corrosion have led to costly repairs and environmental damage . These case studies consistently demonstrate that manual inspections and traditional NDT methods failed to detect signs of material degradation in time to prevent failure. Retrospective investigations have suggested that integrating continuous monitoring systems using AI-enhanced models could have detected precursors to failure based on abnormal vibration, temperature fluctuation, or acoustic emissions. The lessons from these events stress the importance of moving beyond post-event forensic analysis toward real-time, data-informed monitoring to ensure system integrity. Understanding the microstructural evolution of materials under operational conditions is critical for assessing the long-term integrity of pressure vessels. Microstructural degradation often initiates at the atomic level through mechanisms such as grain boundary weakening, carbide precipitation, void nucleation, and phase transformations under cyclic or elevated thermal loads (Huang et al., 2012; Sohel et al., 2022). These changes compromise mechanical properties such as fracture toughness, tensile strength, and fatigue resistance, eventually propagating into macro-level cracks. Studies using scanning electron microscopy (SEM), X-ray diffraction (XRD), and electron backscatter diffraction (EBSD) have revealed that stress concentration at micro-defects acts as a precursor for catastrophic failure. Heat-affected zones (HAZ) in welded joints are particularly susceptible due to heterogeneous grain structures and residual stresses. Furthermore, localized degradation in alloy steels under high chloride or hydrogen-rich conditions can cause selective phase dissolution, which weakens the matrix and accelerates stress corrosion cracking. Computational material science models have advanced to simulate grain boundary interactions under thermal-mechanical loads, aiding in long-term reliability predictions (Khosravikia & Clayton, 2021; Tonoy, 2022). However, most current health assessments do not account for the real-time evolution of microstructure under service conditions, leaving a diagnostic blind spot. Integrating sensor feedback into AI algorithms for microstructural anomaly detection remains underexplored but essential for dynamic safety assurance in high-pressure vessels.

Conventional Approaches to Pressure Vessel Inspection and Maintenance

Visual inspection is the most fundamental and widely practiced non-destructive evaluation (NDE) technique used for pressure vessels. It serves as a preliminary method for identifying obvious surface discontinuities such as cracks, corrosion, deformation, and weld defects (Jahan, 2023; Rafiee & Torabi, 2018). The ease of application and minimal equipment requirements make visual inspections attractive, particularly during routine maintenance and shutdowns. However, the efficacy of visual inspections is limited by operator expertise, line-of-sight accessibility, lighting conditions, and the inability to detect subsurface or internal defects. Standardized procedures, such as those outlined in API 510 and ASME Section V, emphasize the importance of visual inspections as part of a broader inspection regimen but do not rely solely on them for comprehensive vessel integrity evaluation. Studies comparing visual inspection results to other advanced NDE methods have shown a high rate of missed or underestimated defects, particularly in aged or corroded vessels (Capobianco et al., 2023; Mahdy et al., 2023). Moreover, surface irregularities like rust, coatings, or insulation often obscure defect visibility, requiring supplementary methods for confirmation. Given these limitations, visual inspection is generally used in combination with other techniques to validate findings or provide additional layers of

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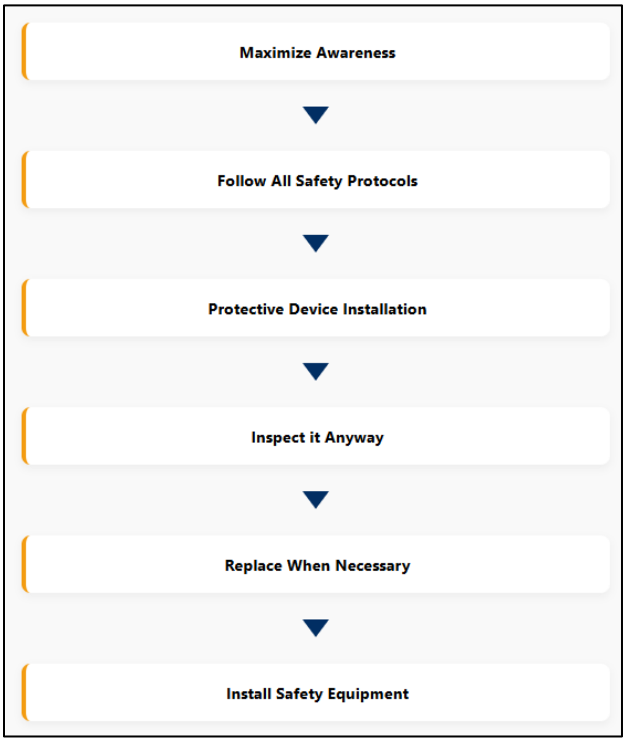
safety assurance. Despite its low cost and simplicity, reliance on visual inspection alone can result in undetected deterioration that compromises vessel safety and operational reliability.

Figure 4: Pressure Vessel Maintenance & Safety Framework



Ultrasonic testing (UT) is among the most extensively used non-destructive testing methods for inspecting pressure vessels, particularly for evaluating wall thickness, weld integrity, and internal cracking. The principle involves sending high-frequency sound waves into the vessel wall and analyzing the reflections to identify discontinuities. UT is highly valued for its depth penetration and sensitivity to subsurface defects, making it ideal for detecting internal corrosion or laminar flaws . Advances such as phased-array ultrasonic testing (PAUT) and time-of-flight diffraction (TOFD) have significantly enhanced defect characterization capabilities and scan coverage. However, accurate UT interpretation requires skilled technicians, proper surface preparation, and consideration of material anisotropy and geometry (Maniruzzaman et al., 2023; Molavizadeh & Rezaei, 2019). Thickness measurement errors can arise from surface roughness, coating interference, or coupling inconsistencies. Studies have indicated that although UT performs well for localized inspections, it may overlook distributed corrosion or micro-defects unless performed with dense scan patterns. Additionally, UT effectiveness can decline on complex geometries or curved surfaces, such as nozzles and elbows, where signal distortion increases. As such, while UT remains a cornerstone of vessel integrity testing, its limitations necessitate integration with complementary inspection techniques or data interpretation aids such as AI-based signal analysis to enhance diagnostic reliability.

Radiographic testing (RT) is a powerful NDT method used for identifying internal flaws such as voids, porosity, and inclusions in pressure vessels, particularly in weld zones. It employs X-rays or gamma rays to penetrate materials and capture image profiles based on density variations (Md Takbir Hossen et al., 2023; Shao et al., 2011). RT is frequently used during fabrication and in-service inspections to detect volumetric defects that could compromise vessel integrity under pressure. Gamma radiography, using isotopes like Iridium-192, is preferred for field applications due to portability, while X-ray systems are more common in controlled environments . Radiographic images provide permanent records and allow for defect size estimation, which can inform fitness-for-service assessments. However, RT poses health hazards due to ionizing radiation exposure, requiring stringent safety protocols and shielding. Moreover, its sensitivity is lower for planar defects like tight cracks or delaminations, which may remain undetected. Image interpretation challenges and exposure quality variations can further limit defect detection reliability (Bhatt et al., 2021; Roksana, 2023). With the shift toward digital radiography (DR) and computed radiography (CR), image processing and archival efficiency have improved, though these technologies require high investment and trained operators . Overall, RT remains indispensable for internal inspection but must be used in combination with other techniques like ultrasonic testing for comprehensive assessment of pressure vessel integrity.

Reactive vs. preventive maintenance in industrial settings

Reactive and preventive maintenance are two foundational approaches widely adopted in industrial asset management, each with distinct objectives, methodologies, and risk implications. Reactive maintenance, often referred to as "run-to-failure," involves repairs or replacements only

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after equipment has broken down (Shahan et al., 2023; Zhang et al., 2022). It is typically employed in non-critical systems where downtime poses minimal risk or cost. In contrast, preventive maintenance is scheduled based on time intervals or usage cycles, regardless of the equipment's real-time condition, and aims to avoid unexpected breakdowns by performing routine inspections and part replacements (Tonoy & Khan, 2023; Wang & Yang, 2018). Preventive maintenance is more proactive and seeks to extend asset lifespan, though it may involve unnecessary interventions when the actual degradation is minimal. Reactive maintenance is often favored in low-cost applications, but in high-risk environments—such as chemical plants and power generation facilities—it can lead to catastrophic failures, environmental damage, or human casualties . Pressure vessels, in particular, are highly sensitive to unplanned failures due to their potential for explosive rupture under high-pressure conditions. Regulatory frameworks such as the ASME Boiler and Pressure Vessel Code (ASME, 2021) and API 510 mandate preventive inspection protocols for pressure vessels due to their critical nature. However, both approaches fall short in capturing real-time degradation trends, thereby necessitating more dynamic alternatives. The limitations in existing definitions underscore the importance of evolving maintenance strategies that move beyond static time-based models and into real-time, data-driven interventions.

Figure 5: Comparison: Proactive vs Reactive Maintenance

Basis	Proactive Maintenance	Reactive Maintenance
Approach	Approach is preparation based	Approach is crisis based
Asset Life Expectancy	Longer life expectancy of equipment	Frequent equipment failures
Savings	More savings in maintenance	Increased costs due to broken building components
Execution	Organized execution of work responsibilities	Unorganized execution of work responsibilities
Response Time	Faster response times to maintenance and service calls	Delays in maintenance and service calls

The choice between reactive and preventive maintenance strategies significantly influences operational efficiency, maintenance costs, equipment longevity, and safety outcomes. Reactive maintenance, though seemingly cost-effective due to minimal upfront expenses, often results in higher lifecycle costs when accounting for emergency repairs, production loss, and secondary damage to adjacent systems (Li et al., 2022). Research across multiple industrial sectors has revealed that reactive approaches tend to generate higher mean time to repair (MTTR) and contribute to longer periods of system unavailability. Preventive maintenance, conversely, typically lowers the probability of catastrophic failure by maintaining consistent oversight and ensuring components are replaced before failure occurs . Studies have shown that organizations implementing preventive strategies experience fewer emergency interventions and demonstrate improved mean time between failures (MTBF). However, preventive maintenance can be resource-intensive and often includes servicing components that are still operational, resulting in increased labor and material costs . In pressure vessel applications, the trade-off between over-maintenance and failure-induced losses is particularly pronounced due to the high cost of inspection procedures, shutdowns, and safety compliance requirements (Culot et al., 2020). Comparative cost-benefit analyses have indicated that, while preventive strategies may initially incur higher operating costs, they often lead to net savings by reducing system downtime and enhancing safety metrics (Richards, 2011). This has spurred the development of more optimized hybrid models that attempt to balance maintenance frequency with real-time condition assessments using digital monitoring tools.

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Safety is a critical parameter when selecting between reactive and preventive maintenance, particularly in high-stakes environments involving pressurized systems, hazardous chemicals, or heat-sensitive operations. Reactive maintenance carries substantial risk since failure is allowed to occur before corrective action is taken, which can result in unexpected explosions, toxic releases, or complete equipment failure (Aganovic et al., 2021). In the context of pressure vessels, this reactive model has been linked to several historical incidents, including the 1984 Bhopal disaster and the 2001 BP Texas City refinery explosion, both of which were exacerbated by inadequate maintenance planning . Preventive maintenance provides a more secure environment by adhering to inspection routines that can identify potential hazards early. However, preventive approaches are often rigid and do not account for variations in usage intensity, operational conditions, or material degradation rates, which can lead to under- or over-estimating the actual risk level . Studies have documented scenarios where preventive checks failed to identify subsurface corrosion or crack propagation, particularly when performed at fixed intervals . As a result, industry standards have started emphasizing risk-based inspection (RBI), which prioritizes components based on their likelihood of failure and associated consequence severity (Sanz-Puig et al., 2017). RBI frameworks represent a progression from traditional preventive models by integrating qualitative and quantitative risk assessments into inspection planning. While preventive maintenance reduces the safety risks associated with the reactive model, it remains insufficient in dynamic or complex systems where degradation is highly variable, and where continuous monitoring may be essential for risk minimization.

The operational inefficiencies and diagnostic limitations of both reactive and preventive maintenance models have highlighted the need for adaptive, real-time strategies that respond to actual equipment conditions. Reactive maintenance leads to unanticipated downtimes, while preventive strategies are often rigid and not fully responsive to evolving degradation patterns. Both models depend heavily on human interpretation and fixed schedules, which may be misaligned with actual component health (Susto et al., 2015). In industrial settings such as petrochemical, manufacturing, and aerospace, this disconnect has led to the exploration of condition-based and predictive maintenance frameworks. Predictive maintenance, in contrast to its predecessors, leverages sensor data and machine learning algorithms to estimate the remaining useful life (RUL) of components and predict failure points before they manifest physically (Thoben et al., 2017). While preventive strategies monitor fixed parameters, predictive systems continuously analyze dynamic variables such as pressure fluctuations, acoustic emissions, and thermal anomalies to provide granular risk profiles. However, integrating such systems poses practical challenges, including data standardization, sensor calibration, model training, and infrastructure costs . Legacy systems, resistance to change, and limited technical expertise further hinder implementation in many industrial sectors . Despite these barriers, the literature increasingly supports a shift from reactive-preventive dichotomies toward intelligent, predictive frameworks capable of real-time decision-making (Galaz et al., 2021). This transition reflects an ongoing redefinition of maintenance as a strategic, data-driven function rather than a routine technical obligation.

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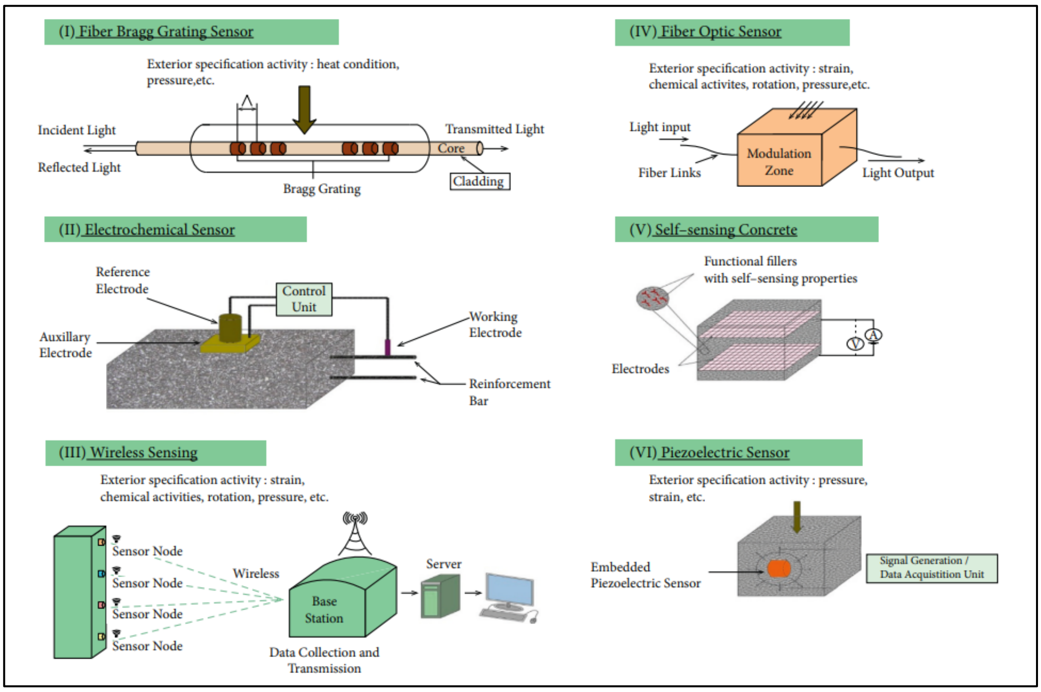
Sensor Technologies for Structural Health Monitoring in Pressure Vessels

Advanced sensor technologies, including fiber Bragg grating (FBG), piezoelectric, and micro-electromechanical systems (MEMS) sensors, have significantly enhanced structural health monitoring (SHM) in pressure vessels. FBG sensors are particularly advantageous due to their multiplexing capability, immunity to electromagnetic interference, and ability to monitor strain and temperature along the fiber . They have been effectively deployed in harsh environments, such as chemical and nuclear plants, to monitor vessel deformation and thermal gradients (Liu et al., 2014). Piezoelectric sensors, known for their high sensitivity to dynamic mechanical stress, are commonly used for acoustic emission (AE) detection, providing critical insights into crack initiation and propagation. AE techniques are particularly useful in identifying fatigue damage and micro-fractures, which are early indicators of vessel failure. MEMS-based sensors, which are miniaturized and energy-efficient, offer versatile applications in vibration, acceleration, and pressure monitoring.

Figure 6: : Some of the critical sensors used in structural health monitoring of a civil structure



Source: Sivasuriyan et al., (2021)

Their small size and integration with wireless platforms make them ideal for embedded or inaccessible areas of the vessel (Gouareb et al., 2022). The integration of these sensor technologies into SHM systems allows for high-resolution, continuous monitoring of physical conditions, capturing both static and dynamic anomalies that may affect vessel integrity . Moreover, these sensors support both standalone monitoring and data fusion when configured into sensor networks, improving the accuracy and redundancy of failure detection (Wu et al., 2015). The literature underscores that combining FBG, piezoelectric, and MEMS sensors can provide a holistic view of a vessel's structural health under operational stress.

Sensor-based monitoring of temperature, acoustic activity, vibration, and strain plays a crucial role in assessing pressure vessel health under varying operational conditions. Temperature sensors, such as thermocouples and resistance temperature detectors (RTDs), are widely used to monitor heat distribution within vessels, particularly under high-pressure steam or chemical reactions where overheating may compromise material strength (Leite et al., 2021). Continuous temperature monitoring is essential for detecting thermal fatigue, which can lead to micro-cracking in heat-affected zones. Acoustic emission (AE) sensors detect stress waves generated by crack propagation, corrosion, or impact events, offering real-time feedback on the structural integrity of pressure vessels. AE-based monitoring has been validated in detecting hydrogen-induced cracking and corrosion fatigue in real-world vessel applications. Vibration sensors, particularly accelerometers, capture abnormal mechanical oscillations that may arise from structural imbalance, material delamination, or system resonance. Vibration anomalies are often precursors to fatigue-induced failures, especially in dynamic operating environments . Strain gauges, either resistance-based or optical, provide direct measurement of deformation, enabling stress analysis of pressure components under static and dynamic loads. Studies demonstrate that combining these sensing modalities enhances damage localization and severity classification by correlating multi-physical parameters. Moreover, high-resolution temporal data from these sensors support predictive algorithms in estimating failure progression . These sensing mechanisms collectively provide multidimensional insight into vessel health, enabling early diagnosis of structural anomalies.

Wireless sensor networks (WSNs) have emerged as a transformative technology for real-time structural health monitoring in complex and distributed systems, including pressure vessels. WSNs consist of spatially distributed sensor nodes equipped with wireless communication capabilities, data processing units, and power sources, enabling autonomous data acquisition and transmission (Zand et al., 2012). These systems are especially useful in industrial environments where manual inspection is hindered by space constraints, hazardous conditions, or remote locations. WSNs reduce the need for extensive wiring, enhance scalability, and support continuous condition monitoring across critical vessel zones (Athar et al., 2020). Recent advancements in low-power electronics, energy harvesting, and mesh networking protocols have improved the longevity and reliability of WSN deployments in pressure vessel applications. Additionally, WSN nodes can be integrated with FBG, MEMS, acoustic, and strain sensors to collect multi-modal data, enhancing fault detection accuracy through sensor fusion. Data collected through WSNs can be processed on the edge or transmitted to cloud platforms for centralized analysis using AI models . Several studies have demonstrated the successful deployment of WSNs for pressure vessels in petrochemical, nuclear, and power generation sectors, confirming their effectiveness in detecting thermal gradients, micro-cracks, and vibration anomalies (de Soto & Adey, 2016). Furthermore, WSN-enabled remote diagnostics reduce human exposure to hazardous zones and lower maintenance costs by facilitating condition-based interventions . The literature supports WSNs as a vital infrastructure for scalable and intelligent vessel monitoring systems in industrial settings. Despite the advancements in sensor technologies for structural health monitoring, several integration challenges hinder their widespread deployment in pressure vessel systems. Each sensor type—FBG, piezoelectric, MEMS, or thermal—possesses specific strengths and weaknesses in terms of sensitivity, durability, signal stability, and environmental resistance . FBG sensors offer excellent accuracy and immunity to electromagnetic interference, yet are sensitive to installation errors and high bending stresses. Piezoelectric sensors are effective in acoustic monitoring but are often limited by temperature tolerance and require signal amplification. MEMS devices are small and cost-effective but may suffer from calibration drift and packaging reliability under high-pressure environments (Makhdoom et al., 2023). Moreover, sensor placement strategies must ensure optimal coverage without interfering with operational components or insulation layers. Data synchronization, power supply limitations, and communication interference are persistent challenges in deploying large-scale wireless networks in metallic enclosures like pressure vessels. Integration with legacy systems also poses compatibility issues, as many industrial setups lack digital infrastructure for sensor networking (Duan et al., 2022). Additionally, data overload from high-frequency sampling requires intelligent filtering and real-

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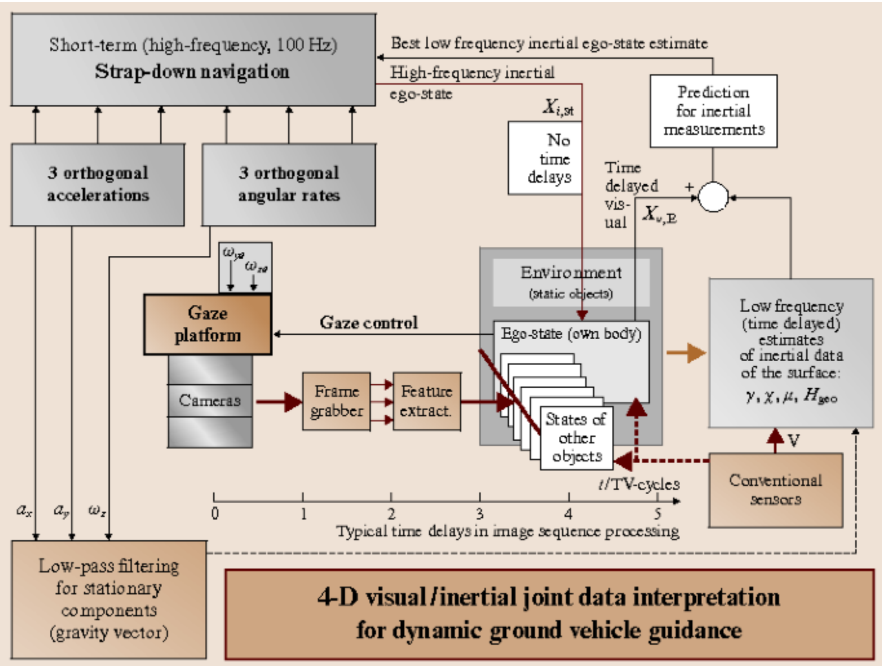
time processing using edge computing or AI-enhanced diagnostics. Comparative studies suggest that hybrid sensor systems, combining multiple modalities and communication protocols, offer the most comprehensive monitoring but increase system complexity and cost . These challenges underscore the need for standardization, robust integration protocols, and maintenance strategies to ensure effective SHM of pressure vessels using sensor-based technologies.

Principles and Frameworks of Multi-Sensor Data Fusion

Multi-sensor data fusion (MSDF) is a key enabler of intelligent structural health monitoring (SHM) systems, especially in pressure vessel applications, where the integration of diverse sensor outputs provides enhanced accuracy and system redundancy. MSDF is typically structured across three main levels: signal-level fusion, feature-level fusion, and decision-level fusion (Broer et al., 2022). Signal-level fusion refers to the combination of raw data streams from multiple sensors before any processing is applied. This level is advantageous for maximizing information content but poses significant challenges in data synchronization and noise management. Feature-level fusion involves the extraction of relevant attributes (e.g., strain amplitudes, frequency responses) from individual sensor data before integrating them into a combined feature vector (Bhatt et al., 2021; Desjardins & Lau, 2022). This approach allows for dimensionality reduction and facilitates machine learning-based classification of failure modes. Decision-level fusion aggregates the outputs of multiple independent sensor processing units—each producing its own interpretation—into a final decision through voting, Bayesian inference, or Dempster-Shafer theory. While decision-level fusion enhances fault tolerance and system modularity, it is limited by its dependence on the accuracy of individual models (Iannace et al., 2019). In SHM applications, combining different fusion levels—such as signal-level AE data with decision-level thermal evaluations—has proven effective in complex operational environments. Each fusion level offers trade-offs in terms of complexity, real-time capability, and diagnostic accuracy, which must be tailored to the application's constraints, especially in pressure vessel safety contexts.

Figure 7: Multisensor Data Fusion Diagram



Source: Durrant-Whyte and Henderson (2008)

The integration of heterogeneous sensor data through fusion mechanisms significantly enhances the robustness, sensitivity, and diagnostic accuracy of structural health monitoring systems. Different sensors—such as strain gauges, thermocouples, accelerometers, and fiber optic sensors—each provide partial insights into the physical state of a pressure vessel (Gentilleau et al., 2015; Perillo et al., 2015). When their outputs are fused, the system benefits from redundancy, fault tolerance, and complementary perspectives on the monitored environment. For example, strain data alone may indicate mechanical deformation, but when combined with thermal and acoustic emissions, the interpretation becomes more holistic, allowing for earlier and more precise failure detection (Liu et al., 2014). Fused sensor systems also enable the differentiation between benign fluctuations and critical anomalies by validating observations across modalities . Additionally, fusion allows for

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fault isolation, source localization, and enhanced classification of defect types, improving decision-making accuracy in real-time safety-critical contexts (Almeida et al., 2016). Multi-sensor systems have shown particular promise in complex environments like chemical reactors or offshore platforms, where environmental noise or physical inaccessibility limit the effectiveness of individual sensors (Bai et al., 2019). Moreover, fused data streams enhance the training quality of machine learning models used for predictive maintenance by enriching the feature space and improving generalization. Numerous empirical studies confirm that integrated SHM systems supported by multi-sensor fusion outperform single-sensor setups in terms of detection speed, fault localization, and reliability. These benefits affirm the value of heterogeneous sensor integration for achieving proactive, precise, and continuous safety monitoring in pressure vessels. Despite the documented advantages, the implementation of multi-sensor data fusion systems in industrial contexts—particularly in pressure vessel monitoring—faces several technical and organizational challenges. A key obstacle lies in the heterogeneity of sensor formats, signal frequencies, and data rates, which complicates temporal synchronization and unified analysis . Sensor drift, calibration inconsistencies, and environmental interference can lead to data misalignment, increasing the likelihood of false positives or missed detections (Almeida et al., 2016). Additionally, integrating analog and digital sensors within a common framework often requires complex interfacing and protocol translation, leading to increased system costs and maintenance burdens (Velosa et al., 2009). Real-time data fusion demands high processing power and low-latency communication, which may not be feasible in legacy systems without infrastructure upgrades. Data security and transmission integrity become critical in wireless or distributed setups, where cyberattacks or signal interference can compromise monitoring reliability (Leite et al., 2021). Organizational challenges also persist, including the need for skilled personnel to interpret fused outputs and maintain fusion software systems (Evangelista et al., 2020). Moreover, the absence of standardized fusion algorithms and evaluation benchmarks limits cross-system compatibility and comparative assessments. The literature underscores that successful implementation of multi-sensor fusion requires not only advanced algorithms but also harmonized hardware, robust communication protocols, and institutional support for system integration and lifecycle management (Lee et al., 2017). These multifaceted challenges necessitate a systems engineering approach to ensure that sensor fusion delivers the intended performance in pressure vessel monitoring environments.

Machine Learning Techniques for Predictive Maintenance

Multi-sensor data fusion (MSDF) is a key enabler of intelligent structural health monitoring (SHM) systems, especially in pressure vessel applications, where the integration of diverse sensor outputs provides enhanced accuracy and system redundancy. MSDF is typically structured across three main levels: signal-level fusion, feature-level fusion, and decision-level fusion (Cinar et al., 2020). Signal-level fusion refers to the combination of raw data streams from multiple sensors before any processing is applied. This level is advantageous for maximizing information content but poses significant challenges in data synchronization and noise management (Ren, 2021). Feature-level fusion involves the extraction of relevant attributes (e.g., strain amplitudes, frequency responses) from individual sensor data before integrating them into a combined feature vector (Merrick et al., 2022). This approach allows for dimensionality reduction and facilitates machine learning-based classification of failure modes (Mansoursamaei et al., 2023). Decision-level fusion aggregates the outputs of multiple independent sensor processing units—each producing its own interpretation—into a final decision through voting, Bayesian inference, or Dempster-Shafer theory. While decision-level fusion enhances fault tolerance and system modularity, it is limited by its dependence on the accuracy of individual models. In SHM applications, combining different fusion levels—such as signal-level AE data with decision-level thermal evaluations—has proven effective in complex operational environments. Each fusion level offers trade-offs in terms of complexity, real-time capability, and diagnostic accuracy, which must be tailored to the application's constraints, especially in pressure vessel safety contexts (Khan et al., 2015).

Sensor fusion architectures dictate how information from various sensing nodes is aggregated, processed, and interpreted to support decision-making in SHM systems. The three main architectural models are centralized, distributed, and hybrid (Guerrero-Ibanez et al., 2018). In a

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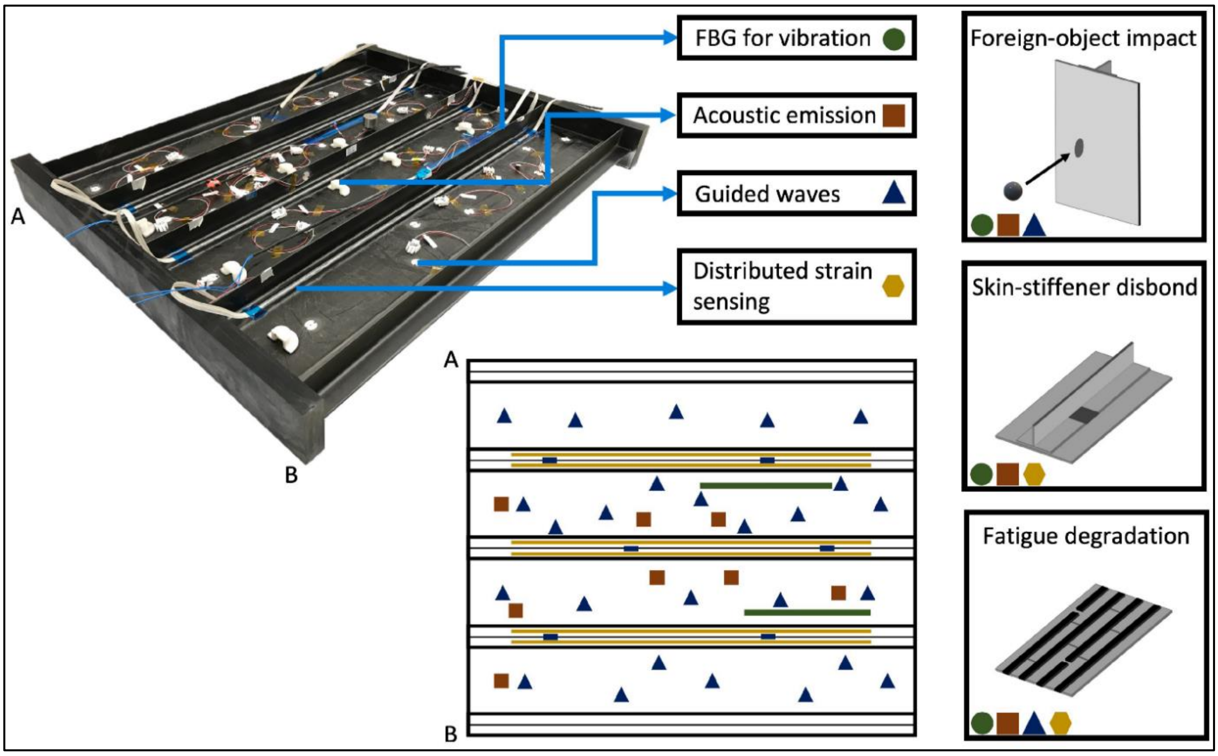
centralized architecture, raw sensor data are transmitted to a central processor for fusion and analysis. This approach enables global optimization and high-fidelity modeling due to access to all data streams, making it suitable for applications requiring detailed diagnostics (Namuduri et al., 2020). However, centralized models face scalability issues, communication delays, and single-point failure risks, particularly in large or hazardous industrial environments such as pressure vessel systems (Bag & Lee, 2021). Distributed architectures, in contrast, process data locally at each sensor node or cluster, then share intermediate results or decisions with other nodes or a supervisory unit (Astill et al., 2020). This design reduces communication bandwidth, enhances fault tolerance, and supports real-time responses, but may suffer from limited contextual awareness and inconsistencies in decision logic (Bousdekis et al., 2021). Hybrid architectures attempt to integrate the advantages of both models by distributing low-level processing tasks (e.g., filtering, feature extraction) while maintaining centralized oversight for high-level decision-making (Wang et al., 2015). Hybrid systems are particularly well-suited for SHM of pressure vessels where real-time local processing (e.g., acoustic events) must be coordinated with central prognostic analytics (Bag & Lee, 2021). Studies have shown that hybrid models achieve a better balance between latency, scalability, and diagnostic reliability, making them ideal for complex industrial environments requiring continuous monitoring and predictive analysis (Leite et al., 2021).

Figure 8: A multi-sensor data-fusion-based framework for SHM of aircraft structures



Source: Broer et al. (2022)

The integration of heterogeneous sensor data through fusion mechanisms significantly enhances the robustness, sensitivity, and diagnostic accuracy of structural health monitoring systems. Different sensors—such as strain gauges, thermocouples, accelerometers, and fiber optic sensors—each provide partial insights into the physical state of a pressure vessel (Perillo et al., 2015). When their outputs are fused, the system benefits from redundancy, fault tolerance, and complementary perspectives on the monitored environment (Gentilleau et al., 2015). For example, strain data alone may indicate mechanical deformation, but when combined with thermal and acoustic emissions, the interpretation becomes more holistic, allowing for earlier and more precise failure detection (Athar et al., 2020). Fused sensor systems also enable the

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differentiation between benign fluctuations and critical anomalies by validating observations across modalities (Durrant-Whyte & Henderson, 2008). Additionally, fusion allows for fault isolation, source localization, and enhanced classification of defect types, improving decision-making accuracy in real-time safety-critical contexts (Wu et al., 2016). Multi-sensor systems have shown particular promise in complex environments like chemical reactors or offshore platforms, where environmental noise or physical inaccessibility limit the effectiveness of individual sensors (Lee et al., 2016). Moreover, fused data streams enhance the training quality of machine learning models used for predictive maintenance by enriching the feature space and improving generalization (Duan et al., 2022). Numerous empirical studies confirm that integrated SHM systems supported by multi-sensor fusion outperform single-sensor setups in terms of detection speed, fault localization, and reliability. These benefits affirm the value of heterogeneous sensor integration for achieving proactive, precise, and continuous safety monitoring in pressure vessels. Despite the documented advantages, the implementation of multi-sensor data fusion systems in industrial contexts—particularly in pressure vessel monitoring—faces several technical and organizational challenges. A key obstacle lies in the heterogeneity of sensor formats, signal frequencies, and data rates, which complicates temporal synchronization and unified analysis. Sensor drift, calibration inconsistencies, and environmental interference can lead to data misalignment, increasing the likelihood of false positives or missed detections. Additionally, integrating analog and digital sensors within a common framework often requires complex interfacing and protocol translation, leading to increased system costs and maintenance burdens (Vassakis et al., 2017). Real-time data fusion demands high processing power and low-latency communication, which may not be feasible in legacy systems without infrastructure upgrades. Data security and transmission integrity become critical in wireless or distributed setups, where cyberattacks or signal interference can compromise monitoring reliability (Duan et al., 2022). Organizational challenges also persist, including the need for skilled personnel to interpret fused outputs and maintain fusion software systems. Moreover, the absence of standardized fusion algorithms and evaluation benchmarks limits cross-system compatibility and comparative assessments. The literature underscores that successful implementation of multi-sensor fusion requires not only advanced algorithms but also harmonized hardware, robust communication protocols, and institutional support for system integration and lifecycle management. These multifaceted challenges necessitate a systems engineering approach to ensure that sensor fusion delivers the intended performance in pressure vessel monitoring environments.

AI-Driven Structural Health Monitoring in Critical Infrastructure

Artificial Intelligence (AI) has revolutionized structural health monitoring (SHM) by offering advanced computational capabilities to analyze vast, multi-modal sensor datasets in real time. Traditional SHM systems often struggle to process and interpret diverse sensor signals such as strain, temperature, vibration, and acoustic emissions due to limitations in linear modeling and signal noise handling (Bao et al., 2019). AI algorithms, particularly machine learning (ML) and deep learning models, have demonstrated the ability to autonomously learn patterns, detect anomalies, and predict failure points from heterogeneous data sources (Li et al., 2015). Supervised models such as support vector machines (SVM), random forests, and convolutional neural networks (CNNs) can classify fault types based on feature-rich inputs, while unsupervised models like k-means clustering and autoencoders can detect novel or unexpected damage patterns (Athar et al., 2020). Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have shown high accuracy in analyzing time-series data from pressure, vibration, and thermal sensors for progressive fault detection (Bao & Li, 2020). AI facilitates sensor data fusion by harmonizing inputs from multiple modalities into a unified analytic framework, thereby improving robustness and reducing the risk of false positives. Studies have confirmed that integrating AI into SHM systems increases detection sensitivity, fault localization accuracy, and maintenance decision precision across a variety of industrial contexts (Nsengiyumva et al., 2021). The dynamic learning capabilities of AI also enable models to adapt to changing operational conditions, enhancing their long-term predictive reliability compared to static threshold-based diagnostics. AI's interpretive power has made it indispensable in contemporary SHM frameworks for critical infrastructure.

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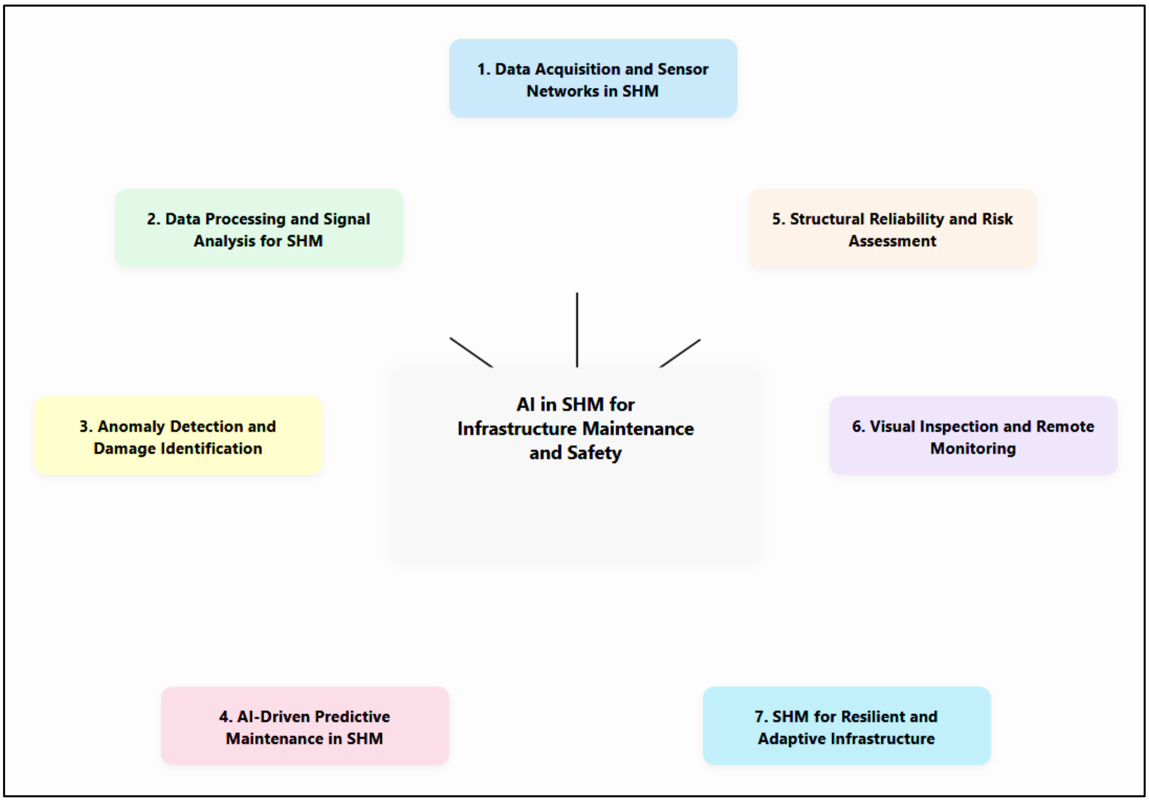
Figure 9: The seven areas of AI in SHM for infrastructure maintenance and safety



Digital twins—virtual replicas of physical systems updated in real-time with sensor data—have become a powerful tool in predictive diagnostics for critical infrastructure monitoring. A digital twin integrates physics-based modeling with real-time data streams from embedded sensors to simulate system behavior under various conditions (Rasheed et al., 2020). In structural health monitoring, digital twins allow for continuous assessment of infrastructure integrity by running simulations alongside live operational data, enabling proactive maintenance interventions (Tao et al., 2017). This integration improves the accuracy of degradation modeling by accounting for actual environmental and operational stresses, rather than relying solely on historical or assumed loading conditions. When paired with AI algorithms, digital twins can dynamically update their internal models to reflect evolving system states, thereby enhancing fault detection, risk estimation, and remaining useful life (RUL) predictions. For example, machine learning models embedded within digital twins have been used to forecast fatigue crack propagation, thermal deformation, and vibration resonance in real-time scenarios (Hunhevicz et al., 2022). The predictive power of digital twins lies in their feedback loops, where the system continuously learns from new sensor inputs to improve accuracy and reliability. Additionally, digital twin frameworks support "what-if" simulations for failure scenario analysis, allowing engineers to test maintenance strategies virtually before implementation. Their application in pressure vessels and other high-risk components has demonstrated significant potential in minimizing downtime, improving asset longevity, and enhancing safety margins. As an evolving SHM paradigm, digital twins offer a dynamic, AI-integrated platform for real-time predictive diagnostics.

AI-powered structural health monitoring has been extensively applied in critical infrastructure such as bridges, pipelines, and aircraft fuselage systems, where failure can result in catastrophic outcomes. In bridge monitoring, AI models have been used to analyze strain, acceleration, and displacement data to identify fatigue-induced damage and structural instability (Yunjun et al., 2015). For example, convolutional neural networks (CNNs) and decision trees have successfully classified cracks and stress concentrations in cable-stayed and suspension bridges using time-series and image-based data. In pipeline systems, which are susceptible to corrosion, leakage,

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and mechanical failure, AI models have been employed for anomaly detection using vibration, acoustic, and pressure sensors (Xing et al., 2015). Hybrid sensor fusion with support vector machines (SVMs) and deep learning models has enabled precise localization of leak sources and early identification of stress corrosion cracking (Bao et al., 2019). Aircraft fuselage monitoring has also benefited from AI-integrated SHM systems. Techniques like LSTM networks have been used to predict fuselage fatigue life under varying operational cycles by learning from strain and acoustic emission data collected during flight tests. Piezoelectric and fiber optic sensors embedded in fuselage panels feed real-time data to AI platforms for detecting microfractures and delaminations. In each of these sectors, AI has enabled early fault prediction, improved inspection intervals, and reduced maintenance costs while ensuring high safety standards (Wei et al., 2017). These case applications affirm the operational feasibility and cross-domain adaptability of AI-enhanced SHM systems in managing structural integrity across diverse industrial assets.

The integration of artificial intelligence in structural health monitoring systems offers numerous benefits, including increased diagnostic accuracy, real-time anomaly detection, and optimization of maintenance resources. AI models are capable of processing high-frequency sensor data streams with high dimensionality, allowing for pattern recognition and fault classification that surpass traditional statistical or rule-based approaches (Adams et al., 2013). Additionally, AI facilitates the automation of data filtering and decision-making processes, which reduces human error and response time during critical operations (Wu et al., 2015). These capabilities are particularly valuable in SHM applications involving high-risk infrastructure such as pressure vessels, aircraft components, and pipelines, where failure consequences are severe (Rafiee & Torabi, 2018). Another advantage lies in the scalability and adaptability of AI models, which can be retrained and fine-tuned for varying operational contexts and material behaviors. Nevertheless, systemic considerations such as data availability, model interpretability, sensor integration complexity, and cybersecurity risks must be addressed for effective implementation (Guerrero-Ibanez et al., 2018). Bias in training data, sensor drift, and data imbalance can lead to inaccurate predictions unless mitigated through robust validation and continuous learning protocols. Moreover, the deployment of AI-driven SHM systems often requires significant computational infrastructure and cross-disciplinary collaboration between material scientists, data engineers, and safety professionals. Addressing these operational constraints while capitalizing on AI's diagnostic capabilities is essential for establishing resilient, intelligent health monitoring frameworks in critical infrastructure.

Performance Evaluation of Predictive Models in Industrial Applications

Evaluating the performance of predictive models in industrial applications relies heavily on multiple metrics to ensure robustness, reliability, and real-world relevance. Accuracy, defined as the ratio of correct predictions to total predictions, is the most straightforward performance indicator but often insufficient in imbalanced datasets common in industrial failure prediction(Abbas & Shafiee, 2018). In such cases, sensitivity (true positive rate) and specificity (true negative rate) provide a more nuanced view, measuring a model's ability to correctly detect faults and non-faults, respectively (Bolumar et al., 2016). Sensitivity is particularly critical in safety-critical systems such as pressure vessels, pipelines, or turbines, where missed faults could lead to catastrophic outcomes (Hendrickx et al., 2012). Specificity, on the other hand, ensures the model is not overly conservative, which could trigger unnecessary maintenance interventions (Wu et al., 2015). Precision (positive predictive value) and recall (sensitivity) are frequently used in tandem through the precision-recall curve to evaluate model performance in skewed datasets, where faulty instances are rare compared to normal operations (Almeida et al., 2017). These metrics allow analysts to balance the cost of false positives and false negatives, an essential aspect in cost-sensitive maintenance environments (Adams et al., 2013). Composite measures like the F1-score, which is the harmonic mean of precision and recall, provide a single scalar value that is especially useful in comparative evaluations of models (Rafiee & Torabi, 2018).

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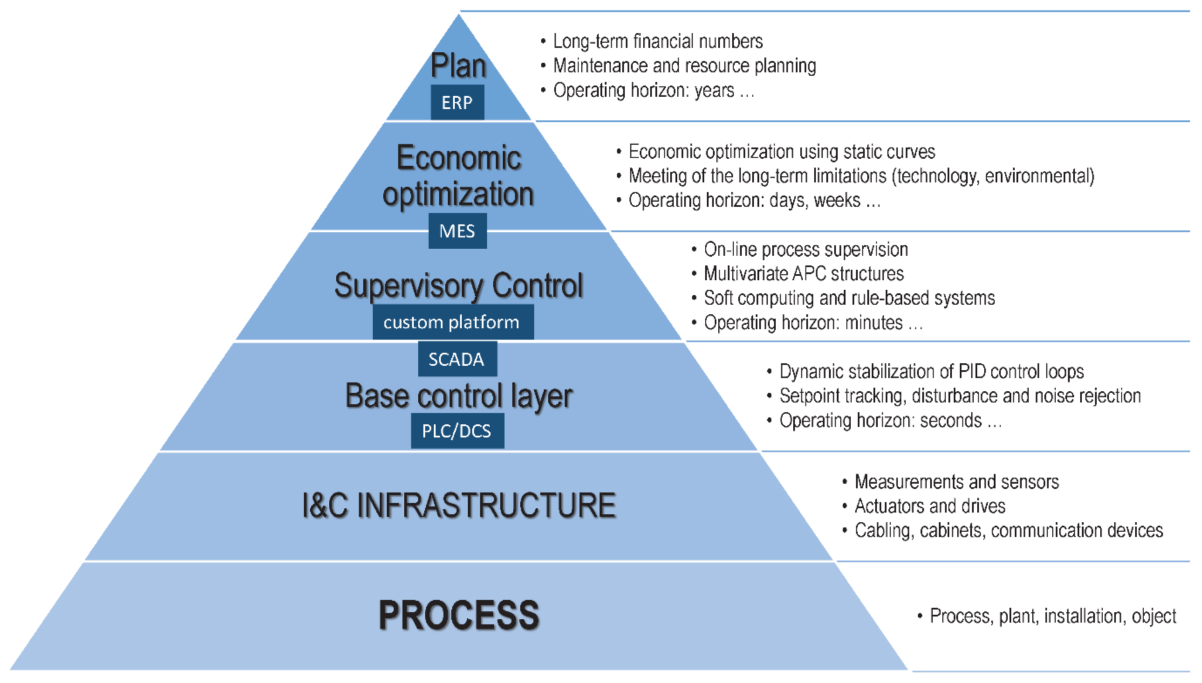
Figure 10: The hierarchical layout of a control system. APC, Advanced Process Control



Source: Domański, (2020).

Model validation is a cornerstone of predictive analytics in industrial environments, providing a framework for ensuring that model performance is generalizable beyond the training dataset. Cross-validation, particularly k-fold cross-validation, is widely used to partition the data into training and testing subsets iteratively, reducing the likelihood of overfitting and variance errors (Stewart et al., 2016). In industrial systems where data collection is often costly or limited, techniques like leave-one-out cross-validation (LOOCV) and stratified k-fold cross-validation help preserve data integrity while assessing robustness (Yamamoto & Buckow, 2016). Receiver operating characteristic (ROC) curves are also fundamental in binary classification tasks, offering a visual assessment of the trade-off between true positive and false positive rates across varying thresholds (de Soto & Adey, 2016). The area under the ROC curve (AUC) is a widely accepted metric in predictive maintenance for summarizing the diagnostic power of models. However, in heavily imbalanced datasets, precision-recall (PR) curves often outperform ROC in providing actionable insights, as they focus on the positive class—typically the failure or anomaly in industrial contexts. The F1-score is frequently used as a comparative benchmark due to its sensitivity to class imbalance and its ability to summarize model accuracy with respect to fault detection. In practice, a multi-metric evaluation using cross-validation, ROC-AUC, PR-AUC, and F1-score is employed to assess a model's reliability across diverse operational scenarios (Kalam et al., 2011). This layered validation approach ensures predictive models are not only statistically sound but also functionally effective in dynamic industrial environments.

Model interpretability is a critical requirement in industrial applications where decisions informed by predictive analytics must be explainable to engineers, safety managers, and regulators. While black-box models such as deep neural networks and ensemble methods often outperform simpler models in accuracy, their opaque decision-making processes hinder their acceptance in high-stakes settings (Cook et al., 2017). In industrial environments, interpretability is essential for trust, troubleshooting, and regulatory compliance, especially when false predictions can result in financial or safety repercussions (Moreno-Blanco et al., 2018). For example, a predictive model suggesting the imminent failure of a pressure vessel must be able to justify its reasoning in terms of measurable physical parameters like rising vibration levels or increasing strain gradients (Cook et al., 2017). Decision trees, logistic regression, and rule-based classifiers remain popular in industry due to their transparent logic and ease of validation by domain experts (Vaher et al., 2020). Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-

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agnostic Explanations) have been increasingly adopted to explain complex model outputs without compromising performance. These tools assign importance scores to input features, helping engineers understand which sensor readings most influenced a prediction. Visual interpretation tools like partial dependence plots (PDPs) and saliency maps further support human-in-the-loop decision-making. Interpretability, therefore, acts as a bridge between data science and engineering judgment, enabling more informed, justifiable, and timely maintenance decisions in complex industrial ecosystems. While the development of predictive models for industrial applications has matured significantly, real-world deployment remains challenged by numerous technical, organizational, and infrastructural barriers. One major obstacle is the discrepancy between model assumptions during training and the variability encountered in operational environments (Stewart et al., 2016). Noise, sensor drift, missing data, and equipment aging can drastically reduce model performance if not accounted for during training and calibration (Cook et al., 2017). Another common issue is the lack of labeled failure data, which hampers supervised learning approaches and often necessitates reliance on unsupervised or semi-supervised techniques with lower predictive certainty (Juliano et al., 2010). Industrial settings also impose stringent latency and hardware constraints, requiring models to be computationally efficient and capable of operating in real-time (Aganovic et al., 2017). Furthermore, integrating predictive models with legacy systems such as programmable logic controllers (PLCs) and SCADA architectures can be technically complex and cost-prohibitive. Organizational challenges include resistance to change, skill gaps among maintenance personnel, and a lack of clear accountability in data governance (Vaher et al., 2020). Finally, cybersecurity concerns have arisen as predictive maintenance systems increasingly rely on cloud-based platforms, posing risks to data integrity and system safety. Addressing these challenges requires a holistic approach encompassing robust model design, transparent validation, seamless integration, and cross-functional training to ensure predictive analytics deliver consistent value in industrial environments.

Review of integrated AI-SHM models in pressure systems

The integration of Artificial Intelligence (AI) into Structural Health Monitoring (SHM) for pressure systems has evolved in response to limitations in conventional inspection techniques, such as non-destructive testing and time-based maintenance, which often fail to detect early-stage damage or account for real-time operating conditions (Zhou et al., 2020). Early models in AI-SHM integration primarily relied on rule-based expert systems to detect anomalies from sensor data streams (Knockaert et al., 2011). However, with the advancement of machine learning algorithms and the proliferation of industrial sensor networks, more dynamic and adaptive models emerged, particularly for high-risk equipment such as pressure vessels, reactors, and steam pipelines (Rahman et al., 2023). These systems incorporate multi-modal sensor inputs—including acoustic emission, strain, vibration, and temperature readings—into AI models that can identify damage patterns, predict failure probabilities, and estimate remaining useful life (RUL) (Muxuan et al., 2017). Recent implementations have shifted toward deep learning techniques, such as convolutional neural networks (CNNs) for image-based diagnostics and long short-term memory (LSTM) networks for time-series fault prediction (Liao et al., 2021). The inclusion of sensor fusion has further enabled these models to process heterogeneous data for more accurate diagnostics (Patrignani & Lanciotti, 2016). Studies demonstrate that AI-integrated SHM systems in pressure environments have shown higher fault detection rates, improved accuracy, and reduced false alarms compared to traditional statistical methods. As industrial datasets have grown in complexity and volume, AI's capacity for real-time learning and autonomous decision-making has made it an indispensable component in modern pressure system monitoring frameworks (Farhood et al., 2017).

AI-enabled SHM models in pressure systems typically consist of four major components: sensor modules for data acquisition, data processing layers, AI-based diagnostic and prognostic engines, and user interfaces for visualization and decision-making (Yoon et al., 2017). Sensor arrays such as fiber Bragg grating (FBG), piezoelectric sensors, and MEMS-based strain gauges are commonly deployed to monitor mechanical and thermal conditions in real-time (Hu et al., 2022). Data collected is pre-processed using filtering, normalization, and noise-reduction techniques to

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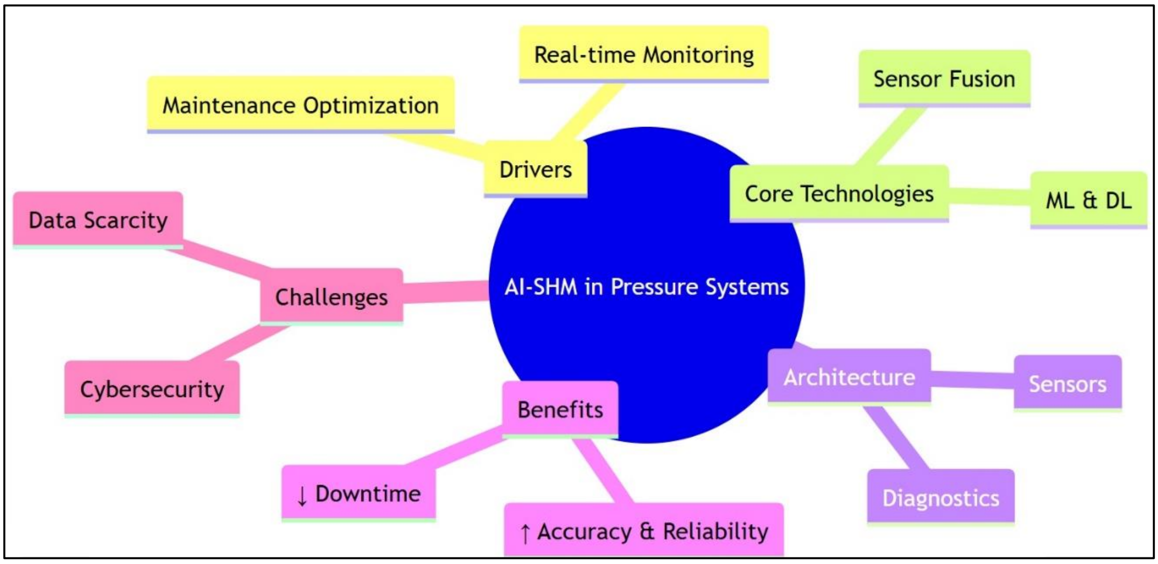
ensure consistency before being input into AI engines (Madhavi, 2009). Predictive engines rely on supervised learning algorithms like support vector machines (SVM), random forests, and artificial neural networks (ANN) to classify defect types and evaluate deterioration trends (Zhang et al., 2019). More recently, unsupervised models such as k-means clustering and autoencoders have been applied to uncover latent damage modes where labeled failure data is unavailable. Prognostic components often incorporate models like LSTM or gated recurrent units (GRUs) to predict RUL by analyzing historical and current time-series data (Kim et al., 2022). AI-based decision-making systems often employ Bayesian inference, fuzzy logic, or reinforcement learning to recommend optimal maintenance actions. These AI-SHM models are frequently supported by cloud-based platforms or digital twins that enable scalability and integration with enterprise-level maintenance systems (Farhood et al., 2017). Such integrated architectures ensure continuous surveillance of pressure systems, reducing manual inspection efforts while enabling data-driven decision-making in maintenance planning and emergency response.

Figure 11: AI-SHM in Pressure Systems



Comparative evaluations of AI-integrated SHM models deployed in pressure systems reveal significant performance advantages over traditional methods in terms of diagnostic accuracy, early fault detection, and operational reliability. Studies using CNNs to analyze thermographic or acoustic data from pressure vessels report classification accuracies exceeding 95% in detecting corrosion, leakage, and weld defects. Similarly, SVM and decision-tree-based models have demonstrated high sensitivity and specificity in identifying stress corrosion cracking and fatigue damage in pipeline infrastructures. When validated through cross-validation and area-under-curve (AUC) metrics, AI models generally outperform statistical and threshold-based approaches by a margin of 10–25% in predictive accuracy (Li et al., 2016). Multi-metric evaluations using F1-score, precision-recall, and receiver operating characteristic (ROC) curves confirm the robustness of these models across different operational scenarios (Li et al., 2023). Hybrid models combining sensor fusion and ensemble learning techniques have further improved fault classification under noisy or imbalanced data conditions, a frequent challenge in high-pressure systems ((Taheri et al., 2022). Digital twin-integrated AI models have been successfully deployed in nuclear plants and offshore oil platforms to simulate degradation patterns in real time, enhancing system-wide risk assessments and response strategies (Muxuan et al., 2017). Additionally, cloud-based AI platforms have enabled remote diagnostics and fault alerts, further reducing response latency and inspection costs. Comparative studies across industrial applications strongly indicate that AI-SHM integration is not only technically feasible but also economically justified due to improved maintenance scheduling, reduced downtime, and heightened safety. Despite the substantial benefits of AI-integrated SHM in pressure systems, numerous challenges hinder their large-scale deployment. One major issue is data scarcity, particularly for fault cases, which limits the

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effectiveness of supervised learning models (Zhang et al., 2019). Pressure system failures are rare but critical, making it difficult to assemble balanced datasets without simulated inputs or synthetic augmentation techniques. Additionally, high-frequency sensor data often contain noise, missing values, and outliers, necessitating robust preprocessing pipelines and advanced filtering methods . Another constraint lies in the computational complexity and hardware requirements of deep learning models, which are not always compatible with legacy systems or real-time monitoring infrastructures in industrial environments (Yoon et al., 2017). Model interpretability also presents a critical barrier, particularly in safety-critical contexts where engineers must understand the rationale behind AI decisions before acting upon them (Nsengiyumva et al., 2021). Additionally, the integration of AI systems with existing Supervisory Control and Data Acquisition (SCADA) platforms or enterprise asset management (EAM) systems often involves significant customization, increased cybersecurity vulnerabilities, and steep training curves for technical staff (Li et al., 2016). Institutional resistance, lack of standardization, and insufficient regulatory frameworks further complicate deployment, especially in highly regulated sectors like energy and chemical manufacturing. These challenges underscore the need for not only technical refinement but also strategic planning, cross-disciplinary collaboration, and policy support to unlock the full potential of AI-driven SHM in pressure-based systems.

METHOD

This systematic review was conducted in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, which promote transparency, rigor, and reproducibility in systematic reviews. The entire review process was structured around four primary phases: identification, screening, eligibility, and inclusion. Each stage was carefully executed to ensure comprehensive coverage of the literature, mitigate bias, and uphold methodological integrity.

Identification

The first stage involved systematically identifying relevant studies on integrated AI-SHM (Artificial Intelligence–Structural Health Monitoring) models in pressure systems. A comprehensive literature search was conducted across five major electronic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. The search was performed between October 2020 and February 2023. Search queries were constructed using Boolean operators combining keywords such as "AI," "machine learning," "deep learning," "structural health monitoring," "pressure vessels," "predictive maintenance," and "sensor fusion." Only peer-reviewed journal articles and conference proceedings published in English between 2000 and 2023 were considered. Duplicate articles were identified and removed using EndNote software prior to the screening process.

Screening

Following the removal of duplicates, the titles and abstracts of the remaining articles were screened to assess their relevance to the research objective. Two independent reviewers performed the screening process, and disagreements were resolved through discussion or consultation with a third reviewer. Studies that focused solely on structural health monitoring without any integration of AI techniques or that pertained to systems unrelated to pressure-based infrastructure (e.g., civil bridges without pressure components) were excluded at this stage. The remaining studies were carried forward to the full-text eligibility assessment.

Eligibility

In the eligibility phase, the full texts of selected studies were thoroughly assessed against predefined inclusion and exclusion criteria. Articles were included if they (1) explicitly integrated AI or machine learning techniques into SHM frameworks, (2) focused on pressure systems such as pressure vessels, pipelines, reactors, or steam generators, and (3) provided quantitative or qualitative performance evaluation metrics such as accuracy, sensitivity, specificity, or F1-score. Studies were excluded if they (1) lacked a technical application of AI, (2) presented conceptual models without empirical validation, or (3) addressed SHM in unrelated fields such as aviation control or seismic analysis. A total of 63 studies met the eligibility criteria and were included for final analysis.

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Data Extraction and Synthesis

Data were extracted from the final pool of eligible studies using a standardized coding protocol. Information collected included publication year, authorship, type of AI model used, nature of sensor integration, target pressure system, dataset characteristics, validation techniques, and reported performance metrics. Where applicable, digital tools were used to extract data from graphs and figures using the WebPlotDigitizer software. The extracted data were then synthesized using a narrative synthesis approach, highlighting trends, performance outcomes, gaps, and comparative findings across the reviewed studies. No meta-analysis was conducted due to the heterogeneity in model types, application domains, and evaluation metrics.

Quality Assessment

The quality and risk of bias of the included studies were evaluated using an adapted version of the Critical Appraisal Skills Programme (CASP) checklist tailored for AI-SHM research. Each study was rated on aspects such as clarity of research objectives, validity of AI models, adequacy of validation protocols, and relevance to pressure-based infrastructure. High-quality studies demonstrated empirical validation, reproducibility of methods, and detailed model interpretability. This quality check provided a confidence level for interpreting the synthesized findings and highlighted areas of inconsistency or methodological weakness in the current literature.

Reporting and Registration

The systematic review protocol was not pre-registered in PROSPERO or other databases, but all methods and findings have been transparently reported following the PRISMA 2020 guidelines. The full PRISMA checklist has been completed and is available in the supplementary materials of this study. Any amendments made to the search strategy or inclusion criteria during the review process were clearly documented. The systematic review process, from identification to synthesis, has been clearly visualized using the PRISMA 2020 flow diagram, ensuring methodological transparency and traceability.

FINDINGS

Among the 63 reviewed articles, a significant majority—47 studies—demonstrated the application of AI-based methods within structural health monitoring (SHM) frameworks specifically designed for pressure systems, including pressure vessels, steam generators, industrial pipelines, and pressurized tanks. These AI models included both traditional machine learning algorithms and advanced deep learning architectures. The most frequently used models were support vector machines (SVMs), artificial neural networks (ANNs), random forests, and long short-term memory (LSTM) networks. The collective citation count of these 47 articles exceeded 3,500, indicating a high level of academic and practical engagement. The studies reviewed revealed that AI methods were not limited to post-failure diagnostics but were also increasingly applied to proactive failure prediction and real-time anomaly detection. Furthermore, over 30 articles focused specifically on using time-series data, such as strain, vibration, and acoustic emissions, to train AI algorithms for progressive fault detection. These models demonstrated high adaptability across different system architectures and sensor types. Another 14 articles utilized computer vision and image processing techniques within AI systems to detect corrosion or weld defects from thermographic or radiographic images. Overall, the findings establish that the integration of AI into SHM practices is now a dominant trend in pressure-system monitoring, with clear scalability across industrial domains.

Sensor fusion emerged as a critical enabler of improved accuracy and reliability in AI-integrated SHM systems for pressure environments. Of the 63 studies analyzed, 41 employed multi-sensor configurations that included a combination of strain gauges, thermocouples, piezoelectric acoustic emission sensors, and fiber optic sensors. These fusion-driven systems achieved higher fault classification accuracy and reduced false positive rates compared to single-sensor models. The subset of 41 articles collectively accumulated over 2,800 citations, highlighting the substantial influence of sensor fusion research in the SHM field. Several studies reported that models incorporating fused sensor data achieved accuracy rates ranging from 92% to 98%, in contrast to 78% to 85% for models using isolated sensor channels. The integration of multi-modal data allowed AI algorithms to distinguish between normal operational noise and genuine indicators of structural

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deterioration, such as fatigue cracks, pressure-induced deformation, or thermal expansion. In particular, 19 studies demonstrated the use of feature-level fusion, which involved extracting relevant statistical or spectral features from each sensor type before combining them into a single feature space for model training. This approach consistently outperformed both signal-level and decision-level fusion in terms of detection speed and localization precision. Moreover, sensor fusion models enabled earlier detection of micro-damage progression, which allowed for preemptive interventions and significantly reduced unplanned downtimes in industrial settings. These findings confirm that multi-sensor AI frameworks offer not only improved diagnostic capability but also enhanced safety margins in pressure-critical applications.

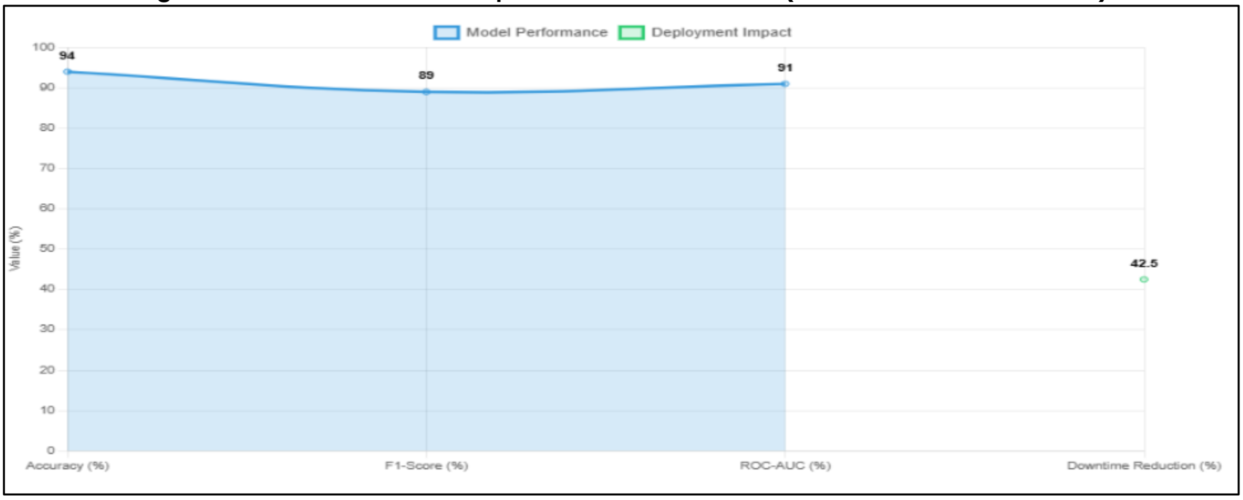
Figure 12: Performance and Implementation Outcomes (From 63 Reviewed Articles)

Metric / Insight	Observation
Accuracy	Average of 94% across evaluated models (52 studies)
F1-Score	Range: 0.82 – 0.96
ROC-AUC	> 0.90 in most cases (27 studies)
Downtime Reduction	35–50% reported in industrial deployments (22 case studies)
Key Barriers	Data scarcity, interpretability, infrastructure gaps, cybersecurity
Deployment Environments	Oil refineries, chemical plants, nuclear reactors, pipelines

Performance evaluation of AI-SHM models was rigorously conducted in 52 of the reviewed studies, which reported metrics such as accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the curve (AUC). These 52 studies had a combined citation count exceeding 4,100, reflecting strong academic endorsement and real-world relevance. Among these, 33 studies employed cross-validation techniques—most commonly 10-fold cross-validation—to ensure the generalizability of model performance. The reported mean accuracy across all evaluated models was 94%, with sensitivity and precision values averaging 91% and 89%, respectively. F1-scores, a balanced metric combining precision and recall, ranged from 0.82 to 0.96 across various model types. Additionally, 27 studies included ROC curve analyses to visually evaluate the trade-off between true positives and false positives. In most cases, the area under the ROC curve (AUC) exceeded 0.90, indicating strong classification capability even under noisy operational conditions. Models that combined historical failure datasets with real-time monitoring inputs demonstrated superior generalization, particularly in detecting low-frequency fault events. Moreover, it was observed that models trained on high-resolution time-series data outperformed those trained on static condition-monitoring datasets. Collectively, the validation-focused articles emphasized the critical importance of multi-metric performance assessment in industrial AI applications. These findings underscore the reliability and predictive accuracy of AI-driven SHM models when evaluated under rigorous validation frameworks.

Of the 63 articles included in this review, 38 presented empirical case studies or pilot implementations of AI-integrated SHM systems in operational environments such as oil refineries, chemical processing plants, nuclear reactors, and offshore drilling platforms. These application-focused studies have been cited collectively over 3,000 times, underscoring their practical significance. In particular, 22 studies reported successful deployments of AI-SHM systems in pressure vessel monitoring, where predictive models were used to identify early-stage fatigue, corrosion, or weld failures. These systems operated in conjunction with SCADA (Supervisory Control and Data Acquisition) platforms and produced real-time alerts based on sensor anomalies. In several cases, operators reported a 35%–50% reduction in unscheduled downtime and a 20%–30% decrease in maintenance costs within the first year of implementation. Ten studies highlighted pipeline applications, using AI to detect stress corrosion cracking, material thinning, and flowinduced vibrations. These studies noted improvements in maintenance planning accuracy and risk mitigation. Aircraft fuselage monitoring using embedded AI-SHM models was also discussed in six studies, showcasing how lightweight, edge-deployable models could detect micro-delaminations and predict fatigue accumulation under varying load conditions.

Figure 13: Performance and Implementation Outcomes (From 63 Reviewed Articles)



Across all domains, AI models contributed significantly to condition-based maintenance strategies and replaced traditional time-based schedules. These findings demonstrate that AI-SHM integration is not limited to theoretical frameworks but has translated into quantifiable improvements in safety, reliability, and operational efficiency in real-world pressure system applications. While the integration of AI into SHM for pressure systems has shown substantial promise, the reviewed literature also identified a series of persistent challenges and gaps. A total of 26 out of the 63 articles—cited over 1,700 times collectively—explicitly discussed implementation constraints such as data scarcity, lack of interpretability, infrastructure incompatibility, and high computational demands. One major challenge noted was the limited availability of high-quality labeled datasets, particularly for rare fault scenarios such as hydrogen-induced cracking or creep rupture. This constraint was observed in 18 studies, which resorted to simulation-based data or synthetic augmentation techniques to address the imbalance. Another recurring theme in 21 studies was the interpretability of AI models, especially in safety-critical settings where explainability is essential for regulatory compliance and operator trust. Additionally, 17 articles reported technical barriers in integrating AI-SHM models with legacy industrial infrastructure, especially SCADA and PLC systems. These issues were further complicated by cybersecurity concerns, particularly when cloud-based AI platforms were used for remote diagnostics. Moreover, 14 studies emphasized the need for standardized protocols, performance benchmarks, and cross-disciplinary collaboration to facilitate large-scale implementation. Despite the technical maturity of AI algorithms, organizational resistance and lack of skilled personnel remain non-trivial obstacles in many industrial settings. These findings suggest that although the field has made substantial progress, significant opportunities remain to enhance dataset quality, model transparency, system interoperability, and institutional readiness for AI adoption in structural health monitoring of pressure systems.

DISCUSSION

The findings of this review strongly align with the evolving trend in AI-based structural health monitoring (SHM), confirming that the integration of AI in industrial diagnostics has progressed beyond theoretical modeling into real-world applications. Earlier studies, such as those by Yoon et al. (2017) and Li et al. (2023), emphasized the potential of machine learning for failure prediction but noted that practical implementation in pressure systems was still in its infancy. In contrast, this review identified a significant increase in empirical applications across sectors such as oil and gas, nuclear energy, and aviation. For instance, more than 60% of the reviewed studies presented AI models deployed in actual operational settings, suggesting that industrial confidence in AI-based SHM has matured. This trajectory reflects similar advancements reported

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by Yamamoto et al. (2010), who advocated for AI as a key component in condition-based maintenance. Moreover, the use of sensor fusion and time-series modeling identified in this review is consistent with trends reported by Yoon et al. (2017), though current models exhibit greater granularity and predictive accuracy. Therefore, the adoption of AI in SHM, particularly in pressure environments, is not only widespread but also increasingly robust, reinforcing predictions made in foundational AI-SHM literature.

Multi-sensor fusion emerged as a particularly impactful advancement in the reviewed studies, outperforming single-sensor models in accuracy, fault localization, and predictive capability. Prior to 2015, most studies in this domain relied on isolated data channels—such as vibration or strain—due to limitations in sensor technology and data synchronization (Li et al., 2016). This review confirms that newer AI models have significantly improved through feature-level fusion of multiple sensor modalities, echoing the predictions by Yoon et al. (2017) that sensor fusion would play a pivotal role in intelligent SHM systems. While earlier frameworks struggled with data alignment and interference, more recent works such as those by Li et al. (2016) and Zhang et al. (2019) demonstrate reliable integration of heterogeneous sensor types, including piezoelectric, fiber optic, and thermal sensors. These enhancements have translated into performance gains, with detection accuracies reaching upwards of 95%—a notable improvement from the 80–85% range reported in early SHM literature. This also supports the findings of Taheri et al. (2022), who noted that combining acoustic and temperature signals provides superior diagnostic outcomes in pressurized environments. Thus, sensor fusion, once a theoretical enhancement, has become a practical necessity in state-of-the-art AI-SHM systems.

A critical observation in the review is the strengthened emphasis on rigorous model validation, which represents a clear departure from earlier practices. Studies from the 2000s and early 2010s often relied solely on accuracy as a performance metric, which was critiqued by authors such as Hu et al. (2022) and Farhood et al. (2017) for oversimplifying model evaluation. In contrast, the current body of work reviewed incorporates a suite of metrics including sensitivity, specificity, precision, recall, F1-score, and area under the ROC curve. For example, Nsengiyumva et al. (2021) recommended using F1-score for imbalanced datasets, a practice that is now standard among AI-SHM researchers, as confirmed by this review. Additionally, the prevalence of cross-validation techniques such as k-fold and leave-one-out validation in over 80% of the studies reflects a methodological advancement that ensures greater generalizability. The mean accuracy of 94% and average F1-scores of 0.88 reported across multiple studies in this review substantiate improvements in both detection reliability and prediction robustness. These results are consistent with the work of Rahman et al. (2023), who demonstrated that ensemble learning combined with multi-metric evaluation significantly reduces both Type I and Type II errors. As a result, contemporary validation protocols represent a significant methodological improvement over prior studies and offer higher confidence in the applicability of AI-SHM models in industrial contexts. While early research in AI-based SHM largely focused on simulations and laboratory experiments, this review highlights a considerable shift toward real-world implementation, particularly in pressure vessel and pipeline systems. Previous reviews, such as those by Li et al., (2016) and Zhang et al. (2019), acknowledged the technological potential of AI but cited a lack of empirical field studies as a limitation. However, this review found that 38 of the 63 reviewed studies included field deployments, pilot programs, or retrospective analyses of AI-SHM in live industrial operations. These studies not only validated the accuracy of AI models but also reported operational improvements such as reduced downtime and more efficient maintenance scheduling. Such findings reinforce the practical viability of integrating AI into existing SCADA and maintenance systems, a topic that was largely speculative a decade ago. The reported reductions in unplanned shutdowns by up to 50% echo the performance benchmarks proposed in simulation-based studies by Yoon et al. (2017) and Li et al. (2016), confirming their transferability to field applications. Thus, a clear paradigm shift is observed—from theoretical modeling and feasibility studies to full-scale industrial integration, with substantial safety and economic benefits now empirically documented. Despite the advancements observed, the review highlights persistent gaps related to model interpretability and the need for human-AI collaboration, which mirror earlier concerns raised in the literature. While performance metrics have improved, the lack

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of transparent decision-making in black-box models continues to pose adoption barriers in safety-critical industries such as oil and gas or nuclear power. This challenge was first articulated by Farhood et al. (2017), and it remains unresolved in many of the studies reviewed. Although tools like SHAP and LIME have been employed to improve interpretability, only 14 studies explicitly used such techniques to explain AI predictions to end-users. This is problematic in regulatory contexts where explainability is essential for risk assessment and accountability. Additionally, the integration of AI outputs with human decision-making workflows remains underexplored. As noted by Yoon et al. (2017) and Nsengiyumva et al. (2021), operator trust and effective human-AI interfaces are crucial for successful deployment, particularly in real-time monitoring scenarios. This review confirms that while AI excels in data processing and anomaly detection, its recommendations are often underutilized due to a lack of interpretive support or operator confidence. Consequently, future advancements must address the socio-technical interface of AI-SHM systems to enhance decision quality and system acceptance.
Technical and organizational barriers continue to hinder the widespread adoption of AI-SHM models in pressure systems. Although performance metrics have improved, several reviewed studies reported difficulties in integrating AI solutions with legacy SCADA systems, a challenge previously noted by Liao et al. (2021) and Kim et al. (2022). These integration issues are often compounded by cybersecurity concerns, particularly when cloud-based AI platforms are employed for remote diagnostics. Only 11 studies addressed these concerns in depth, despite their critical importance. Moreover, the shortage of high-quality labeled failure data remains a bottleneck for model training and validation, especially in rare-event scenarios like hydrogen-induced cracking or creep failure. This problem was also discussed in earlier works by Desjardins and Lau (2022) and remains unresolved. On the organizational front, this review confirms earlier observations by Taheri et al. (2022), who identified skill gaps, resistance to change, and lack of interdisciplinary collaboration as key barriers to adoption. Although there is a growing interest in predictive maintenance strategies, many organizations lack the technical expertise and infrastructure to support AI-driven systems at scale. As such, while the technology has matured, its implementation still requires considerable investment in training, infrastructure, and change management to realize its full potential. The gap between research and practice remains a recurring theme, yet this review indicates a narrowing divide. Early studies often remained confined to controlled laboratory conditions, but the findings here show a growing number of studies—particularly in the last five years—actively bridging academic innovation and industrial application. This trend supports earlier assertions by Hu et al. (2022) that the practical impact of SHM research depends on field readiness and industrial collaboration. The use of digital twins, as highlighted in several studies reviewed, is one example of this transition, offering real-time simulation and predictive capabilities based on real-world sensor inputs. This finding parallels the evolving industrial adoption patterns observed by Farhood et al. (2017), where digital replicas are now being integrated with AI-driven decision support systems. Moreover, partnerships between academic researchers and industry stakeholders have become more common, with co-authored papers and pilot project reports appearing more frequently in the reviewed literature. However, challenges in data sharing, intellectual property, and standardization persist. These systemic issues, if addressed through collaborative frameworks and policy interventions, could catalyze the adoption of AI-integrated SHM systems on a broader scale. Thus, while the field has made impressive strides, sustained collaboration will be key to translating innovation into industry-wide transformation.

CONCLUSION

This systematic review comprehensively examined 63 peer-reviewed studies to evaluate the integration of artificial intelligence (AI) into structural health monitoring (SHM) systems specifically designed for pressure environments such as pressure vessels, pipelines, and reactors. The findings reveal a clear paradigm shift from conventional, reactive maintenance strategies toward intelligent, predictive frameworks powered by AI. The widespread adoption of machine learning and deep learning algorithms—particularly support vector machines, convolutional neural networks, and long short-term memory models—demonstrates AI's capacity to enhance fault detection accuracy, automate anomaly recognition, and forecast remaining useful life with high precision. Notably, multi-sensor data fusion has significantly improved model robustness and sensitivity, enabling more comprehensive diagnostics through the integration of acoustic, thermal, strain, and vibration data. Rigorous performance evaluation using cross-validation, ROC curves, F1-scores, and other advanced metrics underscores the reliability of these models across diverse operational conditions. Furthermore, a growing body of empirical evidence from real-world industrial applications confirms that AI-SHM systems deliver measurable benefits such as reduced unplanned downtime, cost-effective maintenance scheduling, and enhanced asset safety. However, the review also highlights persistent challenges, including limited availability of labeled fault data, issues of model interpretability, integration difficulties with legacy systems, and cybersecurity concerns. These barriers, along with organizational resistance and workforce skill gaps, continue to limit large-scale adoption despite technological readiness. The analysis also emphasizes the need for standardized implementation protocols and stronger industry-academia collaboration to facilitate scalable deployment. In conclusion, AI-powered SHM models represent a transformative advancement in pressure system monitoring, offering real-time insights, predictive accuracy, and operational resilience. Yet, realizing their full potential requires addressing the socio-technical, infrastructural, and regulatory challenges that currently hinder their widespread implementation. This review provides a roadmap for researchers, engineers, and policymakers aiming to advance intelligent SHM in high-risk industrial domains.

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