Review of Applied Science and Technology

Volume: *13;* ***Issue:*** *6*
Pages: *01– 40*

Mechanical Integrity as a Pillar of Process Safety Management: An RCM Approach to Preventing Loss of Containment in Aging Oil, Gas, and Power Generation Infrastructure

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Received: *18 March 2023;* ***Revised:*** *29 April 2023;* ***Accepted:*** *29 May 2023;* ***Published:*** *02 June 2023;*

Abstract

This study examines mechanical integrity as a central pillar of process safety management by evaluating how integrated reliability, monitoring, material-assessment, and cyber-physical capabilities contribute to Loss-of-Containment Prevention Performance in aging oil, gas, pipeline, petrochemical, and power-generation infrastructure. The research addresses the problem that equipment degradation, incomplete condition information, delayed release detection, fragmented maintenance and inspection practices, and vulnerabilities in OT/ICS environments can collectively weaken containment reliability, while limited empirical evidence exists regarding how these capabilities operate together. The purpose is to determine the individual and combined effects of Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience on Loss-of-Containment Prevention Performance. A quantitative, cross-sectional, case-study-based design was employed across multiple aging industrial facility and asset cases involving pipelines, pressure vessels, storage systems, pumps, compressors, boilers, turbines, valves, and associated monitoring and control infrastructure. The purposive sample comprised reliability and mechanical-integrity engineers, maintenance and inspection specialists, corrosion and materials engineers, process and process-safety professionals, operations personnel, instrumentation and control engineers, OT/ICS specialists, asset-integrity managers, and technical supervisors. Of 320 questionnaires distributed, 302 were returned and 291 valid responses were retained, yielding a 90.9% usable response rate. Reliability coefficients ranged from .86 to .92, KMO = .901, and Bartlett's test was significant at $p < .001$. LOCPP recorded $M = 4.22$, $SD = 0.50$, followed by RCMI, $M = 4.19$, $SD = 0.54$; HRDCC, $M = 4.16$, $SD = 0.56$; MPCLA, $M = 4.13$, $SD = 0.58$; and OICSSR, $M = 4.10$, $SD = 0.60$. Correlations with LOCPP were RCMI, $r = .77$; HRDCC, $r = .74$; MPCLA, $r = .71$; and OICSSR, $r = .68$, all $p < .001$. The regression model explained 72.4% of LOCPP variance, $R^2 = .724$, adjusted $R^2 = .720$, $F(4,286) = 187.59$, $p < .001$. RCMI emerged as the strongest predictor, $\beta = .34$, followed by HRDCC, $\beta = .29$, MPCLA, $\beta = .24$, and OICSSR, $\beta = .20$. The findings support H1 through H5 and imply that stronger loss-of-containment prevention depends on coordinated mechanical reliability, timely release detection, lifecycle degradation assessment, and resilient industrial control systems rather than isolated technical interventions.

Keywords

Mechanical Integrity; Reliability-Centered Maintenance; Loss-of-Containment Prevention; Process Safety Management; OT/ICS Security

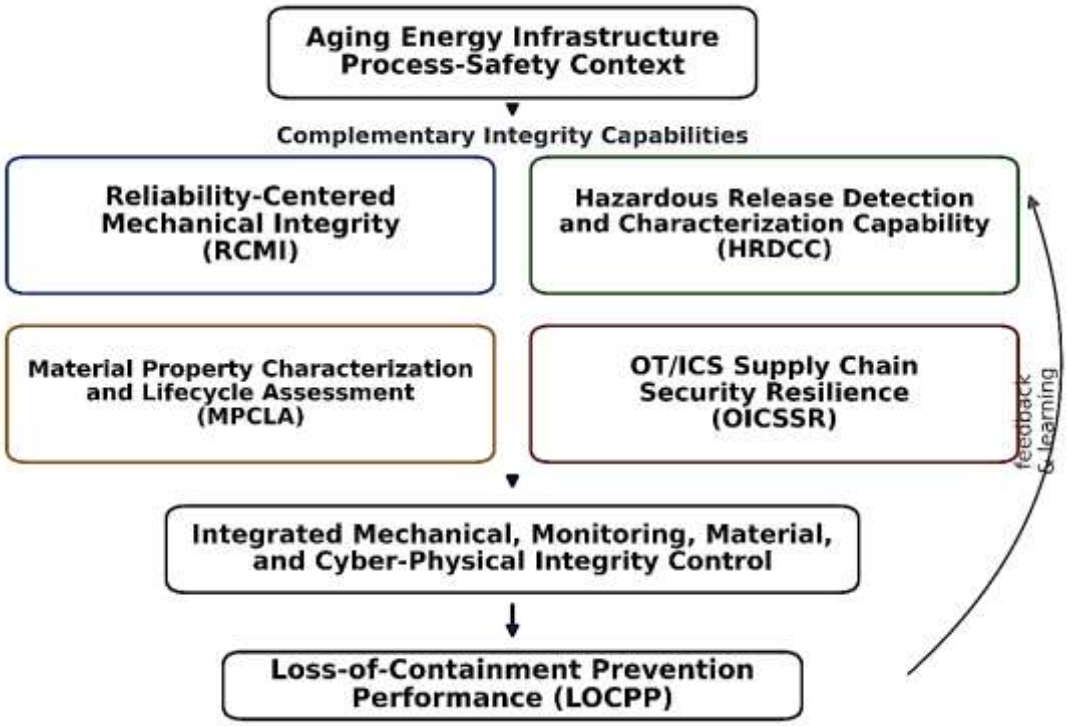
INTRODUCTION

Process safety management can be defined as the systematic identification, assessment, control, and monitoring of hazards associated with industrial processes that handle hazardous substances, while mechanical integrity refers more specifically to maintaining the physical condition, functional reliability, and containment capability of equipment throughout its operating lifecycle. Within oil, gas, petrochemical, and power-generation systems, mechanical integrity encompasses pressure vessels, piping networks, pipelines, storage systems, valves, pumps, compressors, boilers, turbines, instrumentation, protective devices, and other safety-critical assets whose degradation may initiate hazardous events. Loss of containment occurs when a substance escapes unintentionally from equipment or systems designed to confine it, ranging from minor leakage to major releases capable of producing fires, explosions, toxic exposure, environmental contamination, equipment damage, and production interruption. Internationally, prevention of loss of containment has become a fundamental process-safety concern because energy infrastructure operates under combinations of elevated pressure, high temperature, cyclic loading, vibration, mechanical stress, corrosive environments, and prolonged operating periods. Maintenance studies have demonstrated that equipment failure probability and failure consequences should be evaluated together when determining maintenance priorities in power-generation and process facilities where unexpected failures can create substantial safety and operational risks (Krishnasamy et al., 2005). Risk-based inspection research in petroleum refining has similarly demonstrated that maintenance and inspection decisions can be structured according to health, environmental, economic, and operational consequences associated with equipment deterioration (Bertolini et al., 2009). Analyses of process accidents have identified equipment malfunction, design deficiencies, inadequate hazard control, and organizational weaknesses as recurrent contributors to major industrial incidents (Kidam & Hurme, 2012; Manuel et al., 2012). Process-safety research following major industrial accidents has also emphasized the need to control low-frequency, high-consequence hazards through systematic process-safety management rather than depending exclusively on conventional occupational-safety measures (Vaughen, 2015). Mechanical-integrity failures are particularly critical because deterioration of pressure-containing equipment can reduce the ability of process systems to retain hazardous fluids, making loss of primary containment a direct precursor to fires, explosions, releases, and other severe process events (Wilson, 2022). This relationship places mechanical integrity at the center of process-safety management in aging oil, gas, and power-generation facilities where equipment condition, maintenance effectiveness, inspection quality, operating history, and degradation mechanisms collectively determine containment reliability.

Reliability-Centered Maintenance, or RCM, provides a structured maintenance philosophy for determining what must be done to ensure that physical assets continue performing their required functions within defined operating contexts. The approach evaluates asset functions, functional failures, failure modes, failure consequences, and technically appropriate maintenance activities before assigning preventive, predictive, condition-based, or corrective interventions. In aging infrastructure, this framework is particularly relevant because chronological equipment age alone does not accurately describe mechanical condition . Integrity is instead influenced by cumulative operating exposure, loading history, maintenance quality, inspection frequency, material degradation, corrosion activity, environmental conditions, and deviations from intended operating envelopes. Risk-based inspection and maintenance complement RCM by prioritizing inspection and maintenance resources according to the probability and consequences of equipment failure. Pipeline integrity research has demonstrated that inspection planning should account for corrosion growth, structural deterioration, uncertainty, and consequences associated with leakage or rupture when determining inspection intervals and maintenance priorities (Singh & Markeset, 2009). Reliability and risk concepts have also been incorporated directly into RCM frameworks for offshore oil and gas systems in which degradation mechanisms such as corrosion and erosion strongly influence maintenance decision-making (Selvik & Aven, 2011). Within power-generation environments, RCM has been applied to identify critical equipment, evaluate failure mechanisms, and prioritize maintenance activities associated with forced outages and asset reliability (Bhangu et al., 2011). Risk-based maintenance applications in petrochemical processing have similarly used failure mode and effects analysis to classify equipment

according to failure severity and maintenance priority (Wang et al., 2012). Preventive-maintenance scheduling models for generating facilities have shown that maintenance timing can be directly connected with generating-unit reliability and system availability (Perez-Canto & Rubio-Romero, 2013). Oil and gas research has further indicated that successful RCM implementation depends on technical capabilities, organizational arrangements, maintenance information, decision-support practices, and management commitment rather than maintenance scheduling alone (Zeinalnezhad et al., 2020). Integrity-management research also identifies inspection, defect characterization, degradation prediction, maintenance planning, and risk-based intervention as interconnected lifecycle activities for maintaining pipeline containment performance (Xie & Tian, 2018). Mechanical integrity can therefore be examined through an RCM perspective in which maintenance decisions are driven by equipment criticality, failure mechanisms, degradation evidence, risk exposure, and the continuing capability of safety-critical assets to perform their intended containment functions.

Figure 1: Integrated Mechanical Integrity Overview for Loss-of-Containment Prevention



Hazardous-release detection and characterization represent another fundamental dimension of mechanical-integrity management because containment preservation requires both prevention of degradation and reliable recognition of abnormal conditions when a barrier begins to fail. Hazardous-release detection refers to identifying the unintended escape of gases, liquids, or multiphase process materials, while release characterization concerns determining the location, magnitude, duration, physical signature, progression, or other measurable attributes of the release. Within oil, gas, and power-generation infrastructure, detection systems may use pressure measurements, flow monitoring, mass or volume balancing, transient modeling, acoustic signals, vibration analysis, optical-fiber sensing, infrared technologies, supervisory control data, and computational signal-processing methods. Dynamic pipeline models have demonstrated that pressure and flow information can be integrated through state-estimation techniques to identify leakage under steady and transient operating conditions (Reddy et al., 2011). Acoustic leakage research has shown that the escape of pressurized gas produces distinctive pressure disturbances and acoustic signatures that can be analyzed to identify leakage and estimate release location (Meng et al., 2012). Signal-processing and pattern-recognition methods have also been applied to improve gas-pipeline leak detection by separating leak-generated acoustic characteristics from background operational noise (Xu et al., 2013).

Optical-fiber sensing technologies have extended monitoring capability by identifying vibration and frequency characteristics associated with pipeline leakage across monitored sections (Png et al., 2018). Broader assessments of pipeline monitoring technologies have classified leak-detection systems according to sensing principles, sensitivity, localization accuracy, monitoring range, operational conditions, and technological limitations (Adegboye et al., 2019). Reviews of oil and gas pipeline leakage detection have additionally differentiated hardware-based and computational techniques, including acoustic methods, optical systems, pressure monitoring, SCADA-assisted analysis, and transient-model approaches (Lu et al., 2020). Experimental gas-pipeline research has further demonstrated that acoustic-wave decomposition and signal-processing techniques can support leakage identification and localization under controlled operating conditions (Lukonge et al., 2021). These findings show that hazardous-release detection should not be represented merely by the availability of sensors. A meaningful detection and characterization capability incorporates measurement coverage, signal quality, detection sensitivity, localization accuracy, diagnostic reliability, alarm effectiveness, information processing, and the organization's capacity to identify containment abnormalities before they develop into more severe process-safety events.

Material property characterization and lifecycle assessment provide the physical and engineering basis for evaluating whether aging assets can continue performing their required containment functions under actual operating conditions. Material property characterization concerns assessment of the mechanical, metallurgical, physical, chemical, and degradation-related properties that determine how process equipment responds to pressure, temperature, vibration, stress, corrosive media, cyclic loading, and prolonged environmental exposure. Lifecycle assessment within mechanical-integrity management involves evaluating equipment condition through inspection results, defect characteristics, degradation rates, remaining strength, fitness-for-service assessments, residual life calculations, and repair or replacement criteria. Corrosion is one of the most significant degradation mechanisms affecting oil and gas infrastructure because general wall loss, localized pitting, corrosion under insulation, and related damage can reduce pressure-retaining capacity and increase susceptibility to leakage or rupture. Probabilistic corrosion research has demonstrated that corrosion depth and corrosion-growth rate are important determinants of remaining service life and pipeline failure probability (Li et al., 2009). Investigations of pipeline failures in corrosive environments have further connected corrosion damage with fatigue, hydrogen-related deterioration, stress corrosion cracking, and reductions in structural capacity (Ossai et al., 2015). External-corrosion management consequently depends on inspection and monitoring systems capable of evaluating coating defects, corrosion activity, cathodic-protection effectiveness, and other conditions influencing buried pipeline deterioration (Varela et al., 2015). Protective coatings also contribute to lifecycle integrity because coating degradation, adhesion loss, disbondment, shielding behavior, and interaction with cathodic protection influence long-term corrosion resistance (Thompson & Saithala, 2016). Stress corrosion cracking represents another critical aging mechanism in which electrochemical conditions, tensile stress, cyclic loading, coating condition, and crack propagation interact to threaten the integrity of pressure-containing systems (Chen, 2016). In-line inspection studies have therefore combined magnetic-flux leakage, ultrasonic inspection, corrosion-growth modeling, and repeated measurements to estimate deterioration and support maintenance decisions (Vanaei et al., 2017). Pipeline integrity research has further linked defect identification, degradation prediction, inspection planning, and risk-based intervention as related elements of lifecycle mechanical-integrity management (Xie & Tian, 2018). Fitness-for-service assessment extends this process by integrating measured flaws, wall loss, fracture mechanics, fatigue behavior, material characteristics, and inspection accuracy when determining whether damaged assets remain suitable for continued operation (Reda et al., 2022). Material characterization and lifecycle information therefore provide the evidence required to understand how aging mechanisms influence containment reliability across the operational life of oil, gas, and power-generation assets.

The increasing dependence of mechanical-integrity and process-safety activities on operational technology introduces an additional cyber-physical dimension to containment management. Operational technology refers to hardware and software used to monitor, automate, and control

physical industrial processes, while industrial control systems include supervisory control and data acquisition systems, distributed control systems, programmable logic controllers, safety-related control devices, sensors, actuators, industrial networks, engineering workstations, and associated communication infrastructure. These systems provide the technological pathways through which operators observe process conditions, detect abnormalities, receive alarms, adjust operating parameters, control valves and equipment, and initiate protective responses. Research on SCADA systems has documented the movement of industrial control environments from comparatively isolated architectures toward interconnected communication infrastructures, increasing cybersecurity concerns alongside conventional requirements for reliability and availability (Gao et al., 2014). Studies of industrial control cybersecurity management have similarly identified increasing exposure associated with network connectivity, remote access, software dependence, and interaction between information technology and operational technology environments (Knowles et al., 2015). Safety and cybersecurity are closely connected in industrial control environments because disruption or manipulation of control functions can change physical process states and interfere with safety-related actions (Kriaa et al., 2015). Industrial cyber-resilience research has also shown that common-cause vulnerabilities, controller compromise, and communications disruption can affect the continuing operation of critical physical processes (Chaves et al., 2017). Broader ICS security research identifies vulnerability assessment, network segmentation, authentication, access control, intrusion detection, risk assessment, secure architecture, and system monitoring as central elements of industrial cybersecurity management (Asghar et al., 2019; Bhamare et al., 2020). The supply-chain dimension extends these concerns to equipment manufacturers, software providers, third-party integrators, firmware suppliers, remote service providers, and other external dependencies that contribute components or services to OT environments. Research on critical-infrastructure supply chains has identified significant variation in the way organizations define, assess, and manage cybersecurity risks originating from suppliers and external technology dependencies (Topping et al., 2021). ICT supply-chain studies also emphasize hardware integrity, software integrity, component provenance, supplier relationships, lifecycle security, and trusted information exchange within interconnected technological ecosystems (Masip-Bruin et al., 2021). Industrial-control incident research further demonstrates that effective detection, response, containment, restoration, and recovery processes are important for preserving industrial operations when cybersecurity events affect control environments (Staves et al., 2022). Within aging oil, gas, and power-generation infrastructure, these technological dependencies connect mechanical integrity with the reliability and security of monitoring, control, sensing, diagnostic, and protective systems used to identify equipment degradation and maintain containment performance.

1.1 Background of the Study

Mechanical integrity has become a central component of process safety management in industries where equipment failure can lead to hazardous releases, fire, explosion, toxic exposure, environmental damage, production interruption, and major economic loss. In aging oil, gas, and power-generation infrastructure, this concern is especially significant because the physical condition of pipelines, pressure vessels, storage tanks, boilers, turbines, valves, pumps, compressors, and associated control systems changes progressively throughout the operating lifecycle. Long-term exposure to corrosion, erosion, fatigue, vibration, thermal cycling, pressure fluctuations, stress corrosion cracking, embrittlement, creep, coating deterioration, and changing operating environments can reduce equipment reliability and weaken the barriers designed to maintain primary containment. Conventional time-based maintenance approaches may not always identify which assets require immediate intervention because equipment age alone does not provide sufficient information about actual degradation or failure probability. Reliability-Centered Maintenance provides a more structured basis for identifying critical equipment functions, potential failure modes, failure consequences, inspection requirements, condition-monitoring priorities, and maintenance actions according to risk and reliability considerations. Within this approach, mechanical integrity becomes a continuous process involving inspection, maintenance, degradation assessment, condition monitoring, integrity verification, and risk-based intervention. The effectiveness of mechanical integrity also increasingly depends on technologies that detect and characterize hazardous releases, evaluate material condition

and remaining service life, and support operational decision-making through industrial control systems. Modern oil, gas, and power facilities rely heavily on sensors, supervisory control and data acquisition systems, distributed control systems, programmable logic controllers, digital instrumentation, industrial communication networks, and other operational technologies to observe equipment condition and process behavior. Consequently, weaknesses in OT/ICS hardware, software, firmware, vendor services, or supply-chain components can interfere with monitoring, alarms, diagnostics, control actions, and safety-related responses. These interconnected physical and digital conditions establish the need to examine mechanical integrity as an integrated process-safety capability in which Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience contribute collectively to Loss-of-Containment Prevention Performance in aging critical energy infrastructure.

Problem Statement

Aging oil, gas, and power-generation infrastructure faces a persistent process-safety problem because equipment deterioration, maintenance deficiencies, incomplete condition information, delayed leak detection, and weaknesses in industrial control environments can collectively increase the likelihood of loss-of-containment events. Many facilities continue to operate pipelines, vessels, rotating machinery, boilers, storage systems, and associated safety-critical equipment for extended periods under demanding service conditions. These assets may experience corrosion, erosion, wall thinning, cracking, fatigue, thermal degradation, coating failure, vibration, and other forms of deterioration that are not always captured effectively by fixed maintenance schedules or isolated inspection activities. A further problem is that mechanical integrity is frequently managed through separate technical functions. Maintenance teams may concentrate on equipment reliability, inspection teams may focus on physical defects, process-safety personnel may focus on hazard control, and OT/ICS teams may concentrate on cybersecurity and control-system availability. Such separation can create gaps between degradation detection, release identification, material assessment, maintenance prioritization, digital monitoring, and containment protection. Hazardous releases may also develop rapidly when early-warning systems lack sufficient sensitivity, localization capability, diagnostic accuracy, or integration with maintenance decisions. Similarly, material-condition information may not be translated consistently into lifecycle interventions, replacement priorities, or Reliability-Centered Maintenance strategies. The dependence of modern facilities on digital monitoring and control adds another concern because vulnerabilities in industrial control systems, sensors, software, firmware, communication networks, and third-party supply chains can reduce the trustworthiness or availability of information required for safe operation. The central research problem is therefore the limited empirical understanding of how these physical, maintenance, monitoring, material, and cyber-physical capabilities work together to strengthen loss-of-containment prevention. A quantitative examination is required to determine the individual and combined influence of Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience on Loss-of-Containment Prevention Performance in aging oil, gas, and power-generation environments.

1.3 Purpose and Objectives of the Study

The purpose of this study is to quantitatively examine the extent to which integrated mechanical-integrity capabilities contribute to the prevention of loss of containment in aging oil, gas, and power-generation infrastructure. The study focuses on Reliability-Centered Mechanical Integrity as the principal maintenance and asset-integrity capability while also examining Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience as complementary determinants of containment performance. The first objective is to evaluate whether Reliability-Centered Mechanical Integrity improves Loss-of-Containment Prevention Performance by strengthening failure-mode identification, asset criticality assessment, condition-based maintenance, risk-based intervention, inspection prioritization, and maintenance decision quality. The second objective is to determine the relationship between Hazardous Release Detection and Characterization Capability and Loss-of-Containment Prevention Performance by examining the effectiveness of sensing, monitoring,

localization, abnormal-condition identification, alarm generation, and release characterization. The third objective is to assess the influence of Material Property Characterization and Lifecycle Assessment on containment performance through the evaluation of degradation mechanisms, material condition, inspection findings, corrosion behavior, remaining strength, remaining service life, and fitness-for-service information. The fourth objective is to examine whether OT/ICS Supply Chain Security Resilience contributes to containment protection by supporting the availability, integrity, reliability, and trustworthiness of industrial monitoring and control technologies. The fifth objective is to determine the combined predictive power of these four independent variables in explaining variations in Loss-of-Containment Prevention Performance. Through a quantitative, cross-sectional, case-study-based design, the study will use structured Likert-scale measurements, descriptive statistics, reliability and validity assessment, Pearson correlation analysis, and multiple regression modeling to test these relationships. The objectives are therefore structured to measure both the independent contribution of each capability and their collective role within an integrated mechanical-integrity and process-safety context.

1.4 Significance of the Research

i. Process Safety Significance: The study is significant to process safety because it examines loss-of-containment prevention through an integrated mechanical-integrity perspective rather than treating maintenance, inspection, hazardous-release detection, material degradation, and OT/ICS security as independent concerns. This provides a clearer basis for understanding the factors associated with containment reliability in aging hazardous-process infrastructure.

ii. Mechanical Integrity and Maintenance Significance: The research is significant to reliability engineers, mechanical-integrity specialists, inspection teams, maintenance managers, and asset owners because it evaluates whether RCM-oriented practices are statistically associated with stronger containment performance. The findings can help clarify the relative importance of failure-mode analysis, criticality assessment, condition monitoring, risk-based inspection, preventive maintenance, and lifecycle intervention.

iii. Hazardous-Release Management Significance: The study gives specific attention to the organizational capability to detect and characterize releases. This is important because monitoring effectiveness depends not only on the presence of sensors but also on detection accuracy, localization, alarm quality, data interpretation, and integration with operational responses.

iv. Material and Lifecycle Significance: The study is relevant to corrosion engineers, material specialists, inspection personnel, and lifecycle managers because it connects material-condition knowledge directly with process-safety performance. It examines how degradation assessment, remaining-life information, defect characterization, and fitness-for-service understanding relate to loss-of-containment prevention.

v. OT/ICS Security Significance: The research adds a cyber-physical dimension by examining the reliability and security of the industrial technologies used to monitor and control safety-critical processes. It recognizes that compromised, unavailable, or untrustworthy OT/ICS components can interfere with the information and control functions required for maintaining mechanical integrity.

vi. Empirical Significance: The study provides a quantitative framework in which the individual and combined relationships among RCMI, HRDCC, MPCLA, OICSSR, and LOCPP can be tested using descriptive statistics, correlation analysis, and regression modeling. This allows the research to move beyond conceptual discussion and provide measurable evidence regarding the determinants of containment-prevention performance.

2. LITERATURE REVIEW

The literature on mechanical integrity and process safety spans several technical and managerial domains that are directly relevant to the prevention of loss of containment in aging oil, gas, and power-generation infrastructure. Mechanical integrity research generally focuses on the ability of equipment and systems to continue performing their intended functions safely throughout their operating lifecycle, while Reliability-Centered Maintenance provides a structured method for identifying critical functions, failure modes, failure consequences, and appropriate maintenance actions. Within hazardous-process industries, this literature is closely connected with risk-based inspection, condition monitoring, predictive maintenance, asset criticality assessment, and equipment-reliability

management. A second body of literature concerns hazardous-release detection and characterization, including pressure and flow monitoring, acoustic sensing, optical-fiber systems, process-data analysis, leak localization, signal processing, alarm systems, and other methods used to identify abnormal releases from pipelines and process equipment. A third research stream addresses material degradation and lifecycle assessment, including corrosion, fatigue, creep, cracking, erosion, coating failure, nondestructive examination, fitness-for-service assessment, remaining-life estimation, and structural-integrity evaluation. These studies explain how material condition and degradation mechanisms influence the continuing ability of assets to maintain primary containment. A fourth literature stream concerns OT/ICS security and cyber-physical reliability, covering industrial control systems, SCADA, distributed control systems, programmable logic controllers, industrial sensors, networks, vendor dependencies, firmware, remote access, software integrity, and technology supply chains. These areas have become closely associated with process safety because industrial monitoring, alarms, diagnostics, and protective actions depend increasingly on digital systems. The present literature review therefore integrates these research domains around one central issue: the ability of aging energy infrastructure to prevent loss of containment through coordinated mechanical integrity, RCM, hazardous-release detection, material and lifecycle assessment, and resilient OT/ICS technologies. The review is organized to establish the theoretical and empirical basis of the study variables, identify relationships among the constructs, and support development of the conceptual framework and research hypotheses.

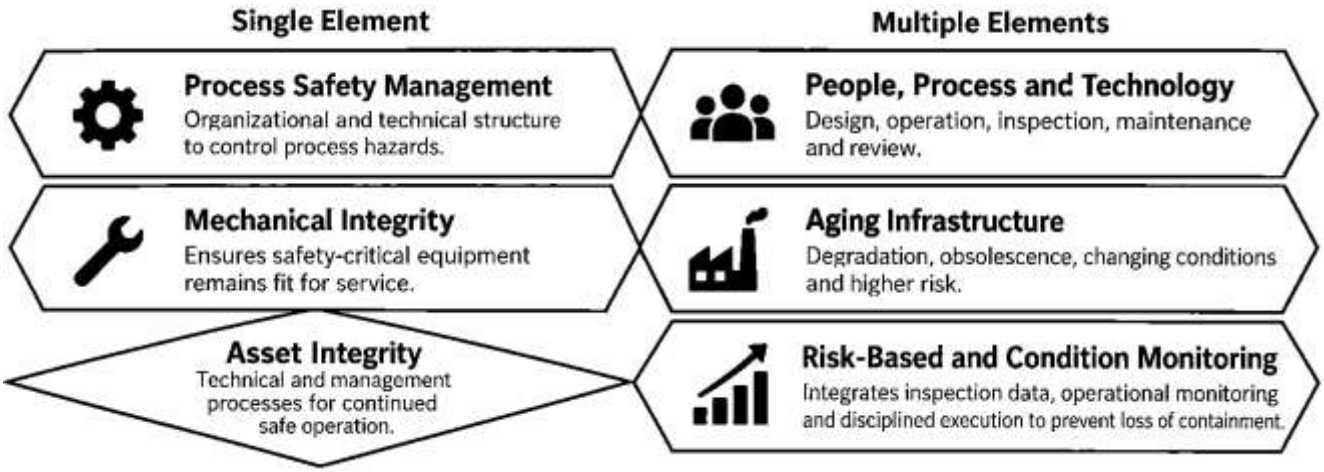
Process Safety Management and Mechanical Integrity in Aging Industrial Infrastructure

Process Safety Management (PSM) and mechanical integrity are closely connected disciplines in hazardous industries because both are concerned with maintaining control over process hazards before equipment failure develops into a major accident. PSM provides the organizational and technical structure through which hazardous processes are designed, operated, inspected, maintained, and reviewed, whereas mechanical integrity focuses on ensuring that safety-critical equipment remains capable of performing its intended function throughout its service life. In aging oil, gas, and power-generation infrastructure, this relationship becomes particularly important because pressure vessels, pipelines, storage tanks, boilers, heat exchangers, pumps, compressors, valves, and associated protective systems may remain in operation for decades under changing mechanical, thermal, chemical, and environmental conditions. Asset integrity is therefore not limited to the physical condition of equipment; it also includes the management processes required to identify degradation, verify fitness for service, control operating limits, maintain documentation, and coordinate inspection and maintenance activities. Research on asset integrity management has emphasized the importance of mapping technical and organizational interfaces so that gaps and overlaps between engineering, operations, inspection, and maintenance functions do not weaken integrity assurance (Rahim et al., 2010). This is particularly relevant to mature facilities where equipment modifications, changing feedstocks, deferred maintenance, obsolescence, and accumulated degradation can alter the original risk profile. A strong mechanical-integrity program must consequently maintain an accurate understanding of the condition of safety-critical assets and ensure that inspection, testing, preventive maintenance, repair, and replacement activities are based on credible technical information. Within the broader PSM system, asset integrity and reliability have been identified as major contributors to incident prevention because construction quality, testing, inspection, maintenance, and human factors collectively influence the frequency of process-safety events (Sattari et al., 2022). Mechanical integrity therefore functions as an operational barrier that links equipment condition with process-hazard control.

The management of aging industrial infrastructure requires a lifecycle perspective because equipment deterioration occurs gradually and may remain hidden until an inspection, monitoring activity, process deviation, or failure reveals the underlying damage. Mechanical integrity programs must therefore distinguish between calendar age and actual condition, since components of the same age may have very different levels of remaining strength depending on materials, service environment, loading history, corrosion mechanisms, maintenance quality, operating excursions, and prior repairs. This condition-based perspective places inspection and maintenance within a broader asset-integrity framework that combines design integrity, operational integrity, and technical integrity. Performance-

based asset-integrity management has been described as a means of linking the physical condition of assets with organizational, environmental, societal, and economic performance, highlighting the need for balanced decisions rather than isolated maintenance actions (Ratnayake & Markeset, 2012). For oil, gas, and power-generation facilities, this means that integrity decisions should consider the consequences of pressure-boundary failure, equipment criticality, available degradation data, inspection confidence, maintenance history, operating envelopes, and the effectiveness of protective barriers. Aging plants also face additional complications from equipment obsolescence, unavailable spare parts, legacy design assumptions, undocumented modifications, reduced accessibility for inspection, and incomplete historical records. These conditions can make it difficult to determine whether an asset remains fit for continued operation or requires repair, replacement, derating, or more frequent surveillance. Mechanical integrity must therefore be treated as a continuous management process rather than a periodic inspection exercise. The process includes identifying safety-critical equipment, defining performance requirements, selecting inspection and testing methods, evaluating degradation, recording defects, assessing remaining capability, controlling temporary repairs, and verifying that corrective actions are completed. The reliability of these activities determines whether developing weaknesses are recognized while adequate safety margins still exist, which is especially important in facilities where prolonged service has progressively changed the physical and operational condition of process equipment.

Figure 2: Process Safety Management and Mechanical Integrity Framework for Aging Industrial Infrastructure



Aging infrastructure also increases the importance of integrating mechanical integrity with real-time operational awareness and disciplined execution of process-safety requirements. Traditional integrity programs often rely on periodic inspection intervals, but hazardous process systems may experience rapid changes in operating conditions, corrosion rates, vibration, pressure, temperature, or loading between scheduled inspections. Offshore and remotely operated facilities illustrate this challenge because equipment may operate in severe environments while inspection access is limited and the consequences of delayed intervention can be substantial. Research on offshore process-system integrity has therefore emphasized the value of combining risk-based integrity management with condition monitoring so that changes in system health can be recognized more continuously rather than only during scheduled inspection campaigns (Khan et al., 2016). This approach reinforces the role of mechanical integrity as a dynamic element of PSM in which inspection findings, operating data, alarms, maintenance information, and degradation knowledge are used together to judge whether equipment remains within acceptable integrity limits. The effectiveness of such systems, however, also depends on operational discipline. Formal procedures, inspection programs, maintenance plans, and technical standards cannot protect containment when required activities are inconsistently executed, abnormal conditions are normalized, corrective actions remain open, or deviations are not investigated. Loss-of-containment research has shown that weaknesses in operational discipline can contribute directly to

process incidents when personnel and organizations fail to apply established PSM requirements consistently in everyday operations (Vaughen & Klein, 2011). Mechanical integrity in aging oil, gas, and power-generation infrastructure must consequently be understood as both a technical and managerial control system. It requires reliable equipment information, competent inspection and maintenance, defined operating limits, timely corrective action, and disciplined adherence to integrity-related requirements. These interconnected elements form the process-safety foundation through which organizations attempt to prevent degradation from progressing into leakage, rupture, equipment failure, and other forms of loss of containment.

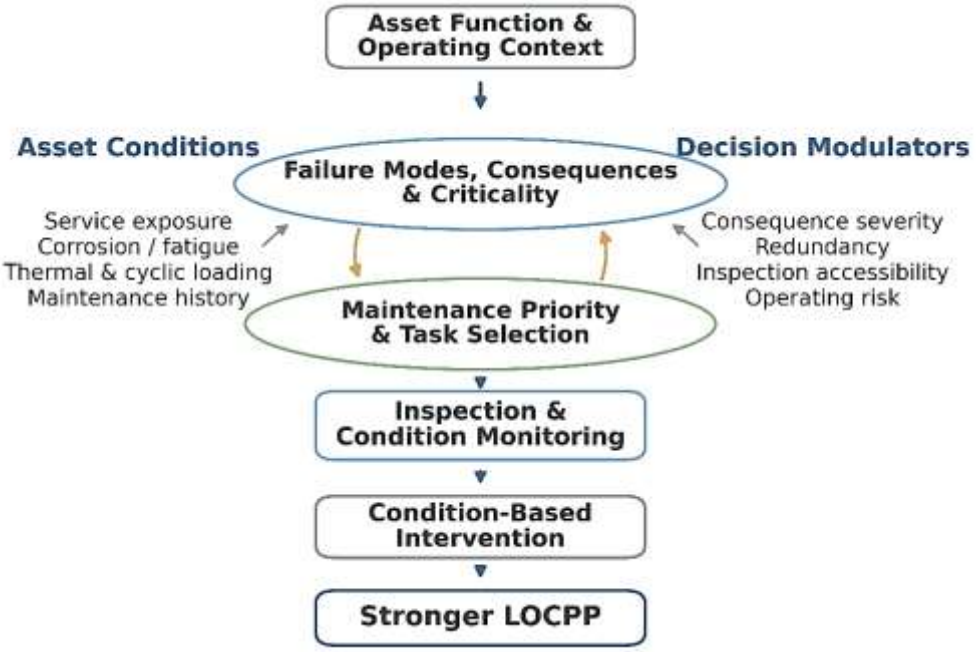
Reliability-Centered Maintenance and Mechanical Integrity Management

Reliability-Centered Maintenance (RCM) is a structured maintenance decision process that identifies the functions required from an asset, the ways those functions can fail, the consequences of each failure, and the maintenance actions capable of controlling the resulting risk (Kazi Mohammad Khalid & Sumaiya Sadmeen, 2022; Md Maksudul & Md Tazul Islam, 2022). In mechanical integrity management, this logic is especially valuable because safety-critical equipment cannot be maintained effectively through uniform time intervals or generalized preventive routines. Pressure vessels, piping, compressors, pumps, boilers, turbines, valves, and auxiliary systems experience different failure mechanisms, service conditions, loading histories, and consequence profiles, so their maintenance requirements should reflect functional importance and actual degradation exposure (Aminul Islam & Md, 2023; Mashfiqur & Md Jamil, 2023). RCM therefore begins by defining system boundaries and required functions before identifying functional failures, failure modes, causes, effects, and criticality (Sadia & Md. Mosheur, 2023). Failure Mode and Effects Analysis or Failure Mode, Effects and Criticality Analysis is commonly used to organize this information and distinguish failure mechanisms that demand preventive tasks, condition monitoring, redesign, or run-to-failure decisions. A steam-process plant case demonstrated that RCM can convert equipment failure histories and functional analysis into a structured preventive maintenance program for boilers, steam distribution equipment, pumps, dryers, and heaters, while reducing sudden failures and maintenance-related costs (Afefy, 2010). The relevance of this approach to aging oil, gas, and power-generation infrastructure lies in its ability to direct maintenance effort toward assets whose functional loss can compromise containment, safe shutdown, production continuity, or protective barriers. Mechanical integrity programs consequently gain greater analytical depth when inspection findings, maintenance history, equipment criticality, and failure consequences are incorporated into RCM decision logic. Rather than treating maintenance as repetitive servicing, RCM connects each task with a defined failure mechanism and intended reliability function, allowing integrity activities to focus on preventing degradation from reaching conditions in which leakage, rupture, forced shutdown, or loss of safety-critical functionality becomes increasingly likely. This improves consistency across integrity-related maintenance decisions overall.

RCM also strengthens mechanical integrity by linking failure analysis with root-cause understanding, criticality evaluation, and task selection. Conventional maintenance programs may repeatedly repair symptoms without addressing the physical, operational, or organizational conditions that produce recurring failures. In aging industrial facilities, this limitation is important because vibration, lubrication problems, misalignment, contamination, corrosion, thermal stress, inadequate operating practices, and material deterioration can interact over long service periods. Integrating root-cause analysis with RCM allows maintenance teams to move from restoring failed equipment toward modifying the conditions responsible for deterioration. Research in a petrochemical ethylene plant combined RCM with radical maintenance, FMECA, fault-tree analysis, and root-cause assessment to evaluate rotating-equipment failure mechanisms and establish maintenance strategies based on failure criticality and underlying causes (Li & Gao, 2010). Criticality is equally important in power-generation and transmission environments because limited personnel, budgets, outage windows, and spare resources make it impractical to apply the same maintenance intensity to every component. An RCM study of power systems showed that components can be ranked according to outage probability and cost-based consequences so that maintenance management concentrates on assets making the greatest contribution to reliability and system performance (Ghorani et al., 2015). For mechanical integrity, such prioritization provides a logical connection between equipment condition and consequence severity.

Components whose failure could cause loss of primary containment, disable protection systems, create extended outages, or expose adjacent equipment to escalation should receive stronger inspection and maintenance attention than assets with minor functional consequences. Functional analysis identifies what equipment must accomplish, failure analysis explains how performance can be lost, criticality determines the importance of those failures, and maintenance selection identifies the appropriate action. This sequence is highly relevant to aging infrastructure because accumulated defects and constrained maintenance resources require disciplined decisions about where intervention provides the greatest protection of mechanical integrity.

Figure 3: Reliability-Centered Mechanical Integrity Decision Cycle



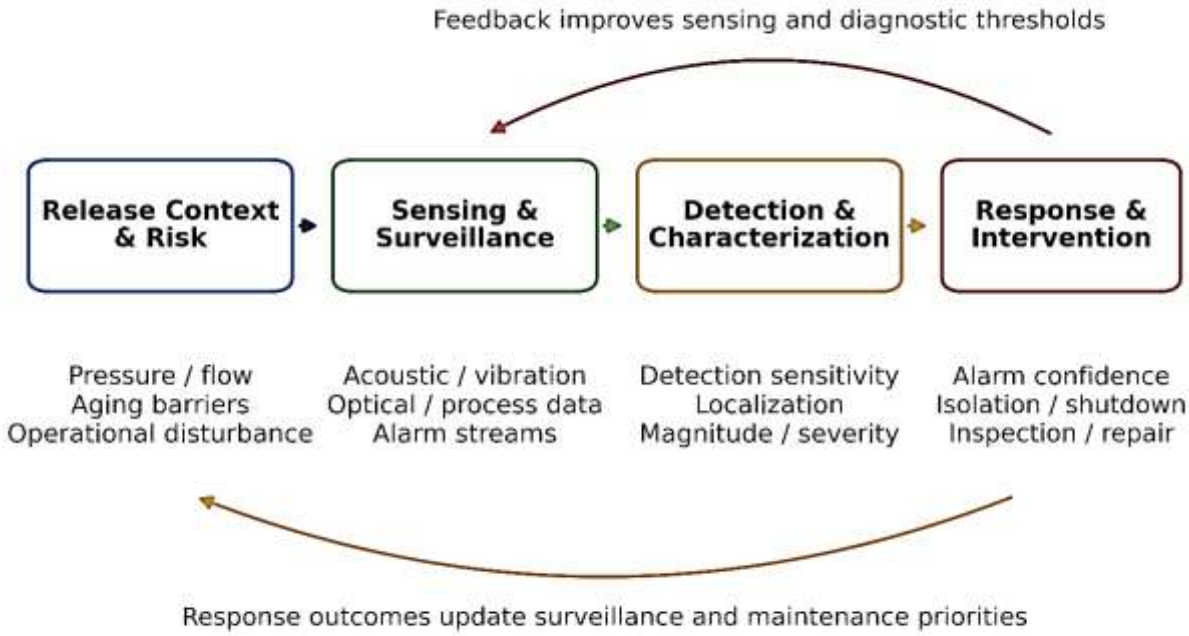
Mechanical integrity management also benefits when RCM is combined with quantitative reliability, availability, maintainability, and lifecycle cost information. Maintenance decisions for aging oil, gas, and power-generation assets involve more than identifying failure modes because engineers must determine when intervention is justified, how frequently tasks should occur, whether redundancy changes criticality, and whether repair or replacement provides better long-term control. Integration between RCM and reliability, availability, and maintainability analysis has been applied in offshore oil and gas operations to select maintenance strategies while considering equipment redundancy, uptime, downtime, safety requirements, environmental constraints, and production performance (De Sanctis et al., 2016). This integration is especially relevant to mechanical integrity because the same component can have different maintenance priorities depending on its failure frequency, repair duration, protective redundancy, accessibility, consequence of failure, and contribution to system availability. Quantitative failure histories can strengthen RCM by supplying estimates of mean time to failure, mean time between failures, mean time to repair, probability distributions, and maintenance intervals. An offshore oil and gas study incorporated probabilistic and statistical analysis into RCM to predict critical-component failure behavior and optimize maintenance or replacement intervals using historical reliability and cost information (Nithin et al., 2021). Within aging infrastructure, these measures distinguish assets requiring closer surveillance from those that can safely operate for longer intervals, while supporting decisions on spare parts, shutdowns, inspections, and replacement timing. Mechanical integrity management can therefore use RCM as an integrating mechanism that converts technical evidence into differentiated maintenance policies. Inspection data indicate physical condition, reliability records reveal recurring failure behavior, criticality analysis identifies consequence significance, and maintenance optimization determines suitable intervention strategies. When these elements are coordinated, RCM provides a basis for preserving the intended functions of safety-critical

equipment and maintaining containment barriers across service periods without relying solely on equipment age or calendar-based intervals.

Detection and Characterization of Hazardous Releases and Loss-of-Containment Events

Hazardous-release detection and characterization constitute a critical layer of loss-of-containment prevention because the consequences of a leak depend not only on whether a release occurs but also on how quickly its presence, location, magnitude, and operating context are recognized. In oil and gas infrastructure, pressurized hydrocarbons may escape through corrosion defects, cracks, flange failures, valve leakage, seal deterioration, weld defects, or accidental damage, while power-generation facilities may experience releases involving fuel gas, steam, hydrogen, lubricants, chemicals, or other hazardous process media. Detection therefore involves identifying abnormal evidence associated with material escaping from its intended boundary, whereas characterization involves determining features such as leak position, release rate, duration, pressure condition, fluid type, and severity. Different sensing principles respond to different physical effects produced by leakage, including changes in concentration, pressure, flow, temperature, sound, vibration, optical absorption, and mass balance. A major review of gas-leak detection and localization techniques classified available approaches according to sensing mechanism and localization capability, showing that no single technique provides identical performance across all release conditions, environments, and detection distances (Murvay & Silea, 2012).

Figure 4: Hazardous Release Detection and Characterization Capability Flow



Acoustic and pressure-based methods are particularly relevant to pipelines and pressurized process systems because leakage generates propagating disturbances that can be measured at locations away from the defect. When pressurized gas escapes through an opening, the resulting pressure change and turbulent flow generate acoustic energy whose characteristics depend on the leak size, internal pressure, fluid properties, pipe geometry, operating state, and distance between the leak and sensors. Effective localization requires more than identifying an abnormal signal because propagation velocity, attenuation, background noise, and process transients can introduce errors into position estimates. Experimental research on high-pressure gas pipelines developed an integrated acoustic-wave model

that combined signal de-noising, modified acoustic velocity calculations, localization logic, and least-squares support vector machine classification to distinguish operating conditions and improve the identification of leakage degree and position (Jin et al., 2014). Subsequent work on oil and natural-gas pipelines examined the propagation and attenuation of leakage-generated acoustic waves and demonstrated that wavelet-based extraction of dominant frequency bands could support a localization method based on measured propagation behavior rather than relying only on conventional velocity and time-difference assumptions (Liu et al., 2015). These findings are relevant to loss-of-containment prevention because an alarm that merely confirms the existence of leakage may still leave operators uncertain about where intervention is required. Characterization becomes operationally stronger when the system can estimate location and severity with sufficient accuracy to support isolation, shutdown, emergency response, and repair decisions. For aging facilities, the challenge is intensified by pumps, compressors, valve movements, flow changes, and rotating equipment that generate normal acoustic and pressure disturbances. Detection systems must therefore separate leak-related signatures from background variability while retaining enough sensitivity to identify developing releases. This requirement links sensor performance with signal processing, equipment condition, operating context, and response procedures within the wider mechanical-integrity system in practical operations.

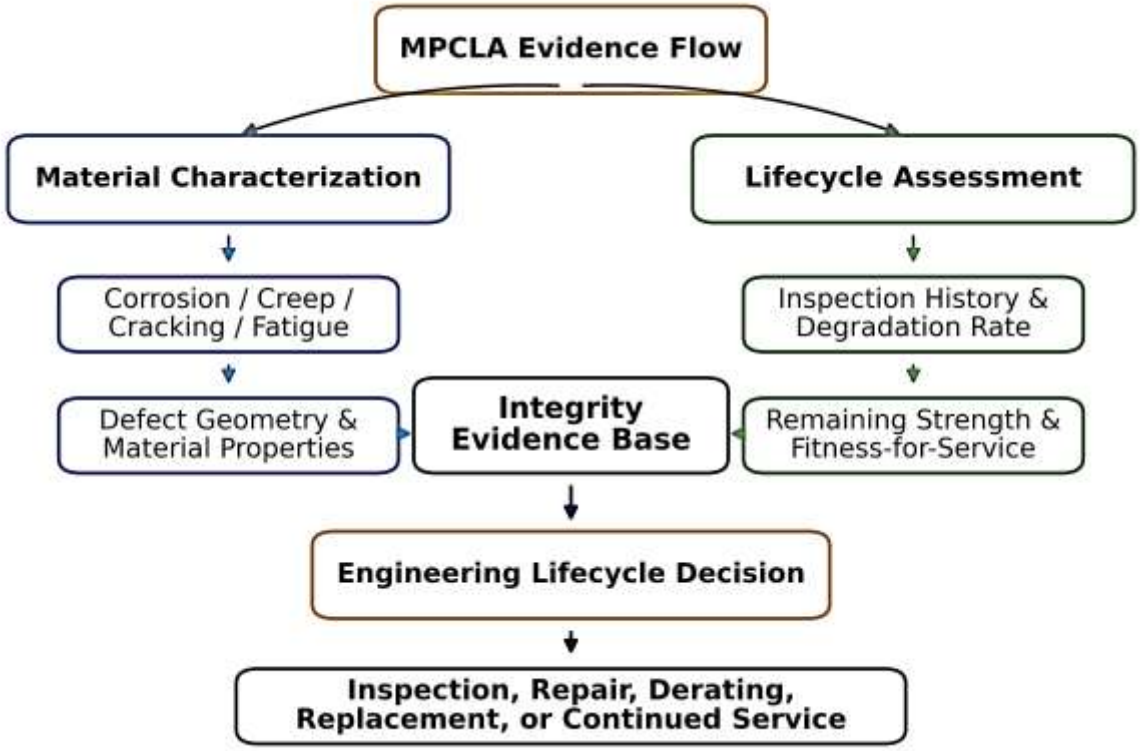
Computational leak-detection approaches extend hazardous-release monitoring by converting pressure, flow, and other process measurements into diagnostic estimates of whether a leak exists, where it is located, and how large it may be. Such approaches are valuable for long pipelines and geographically dispersed infrastructure because direct physical observation of every potential release point is impractical. Model-based methods compare expected hydraulic behavior with measured system responses, while statistical and machine-learning techniques identify patterns that separate normal operating conditions from leakage states. A long-range pipeline study combined a distributed-parameter observer with a support vector machine so that reconstructed pressure and mass-flow behavior could be used to detect leaks and estimate both leak amount and position across different simulated conditions (Xie et al., 2019). This type of approach illustrates how release characterization can move beyond binary leak alarms toward quantitative diagnostic information. Computational performance, however, depends on measurement quality, model accuracy, operating-state knowledge, sensor placement, communication reliability, and the size of the release relative to normal process variation. A comparative review of computational pipeline-leakage methods identified mass or volume balance, negative pressure wave, pressure-point analysis, statistical methods, and real-time transient modeling as major approaches, while showing that their relative performance differs in detection speed, certainty, localization capability, and sensitivity to small leaks (Sekhavati et al., 2022). For the present research, these distinctions support treating Hazardous Release Detection and Characterization Capability as an organizational and technical capability rather than as a single sensor technology. The construct should capture whether a facility can recognize abnormal releases promptly, discriminate them from routine disturbances, locate the source, assess severity, communicate reliable alarms, and provide information suitable for operational intervention. In aging oil, gas, and power-generation infrastructure, this capability complements mechanical integrity by identifying emerging containment failures and connecting real-time awareness with containment-barrier management and process-safety performance more directly.

Material Property Characterization, Degradation Mechanisms, and Lifecycle Assessment

Material property characterization and lifecycle assessment are essential to mechanical integrity because the ability of aging equipment to retain hazardous media depends on how material condition changes under actual service environments. Characterization involves determining mechanical, metallurgical, chemical, and physical properties that influence resistance to pressure, temperature, cyclic loading, corrosion, erosion, cracking, and other degradation mechanisms. In oil and gas pipelines, localized corrosion is especially important because damage can concentrate at discrete locations where metallurgical heterogeneity, fluid chemistry, deposits, coating defects, moisture, carbon dioxide, hydrogen sulfide, or electrochemical conditions accelerate metal loss. Such localized attack can reduce wall thickness and ductility, create stress concentrations, and decrease the remaining pressure-carrying capacity even when large portions of the component appear relatively intact. The study Localized Corrosion and Mitigation Approach of Steel Materials Used in Oil and Gas Pipelines

characterizes localized corrosion as a dynamic degradation problem linked with metallurgical, chemical, and physical differences across steel surfaces, while also emphasizing the need to connect corrosion understanding with mitigation strategies (Alamri, 2020). Lifecycle assessment consequently requires more than detecting that corrosion exists. Engineers must estimate defect dimensions, growth rates, spatial distribution, operating pressure, material strength, and the uncertainty associated with inspection measurements. In Probabilistic Analysis of Corroded Pipeline under Localized Corrosion Defects Based on the Intelligent Inspection Tool (pp. 1-15), the analyzed pipeline had internal and external localized defects whose dimensions and corrosion rates were incorporated into time-dependent reliability and remaining-life estimation, demonstrating how inspection data can be transformed into lifecycle information (Zelmati et al., 2020). For aging infrastructure, this combination of material characterization and probabilistic assessment supports decisions concerning inspection intervals, repair prioritization, pressure control, and continued operation before degradation reaches a containment-threatening condition. It also provides a defensible basis for distinguishing tolerable degradation from defects requiring immediate engineering evaluation, intervention, or replacement action.

Figure 5: Material Property Characterization and Lifecycle Assessment Framework



Material degradation in power-generation infrastructure requires a different but complementary characterization strategy because many components operate for long periods at elevated temperature, where creep, thermal exposure, microstructural evolution, and cyclic stresses progressively modify material behavior. Boiler headers, steam pipes, reheaters, superheaters, turbine components, and other high-temperature pressure parts may remain operational for decades, so lifecycle assessment must determine how much useful life remains rather than relying only on original design life. In Assessment of Creep Life Fraction for In-Service High-Temperature Components (pp. 578-585), grain-boundary etching was applied to aged fossil-power-plant components and correlated with the Larson-Miller parameter and creep testing, showing how metallographic degradation indicators can be linked with accumulated creep-life fraction (Kim, 2005). This type of characterization is important because high-temperature damage can develop through microstructural mechanisms that are not adequately represented by chronological age or visual examination. Hardness, surface replication, dimensional strain, microstructural cavitation, and other inspection measurements can therefore provide complementary evidence about thermal softening and creep progression. A later study on aging

CrMoV power-plant materials established empirical relationships among hardness, surface replicas, and strain using long-term inspection data, demonstrating how repeatedly collected outage information can be used to estimate residual creep life and update lifecycle forecasts as new condition data become available (Bonetti et al., 2022). Within mechanical integrity management, these approaches connect measurable material properties with decisions about continued service, enhanced inspection, repair, derating, or component replacement. They also show why lifecycle assessment should be iterative: each inspection cycle adds evidence about degradation rate, condition change, and remaining safety margin. For aging power-generation assets, material characterization therefore becomes a continuing health-assessment process in which metallurgical evidence and operating history are translated into estimates of structural capability and remaining serviceability. This reduces dependence on assumptions and supports judgments for high-temperature components approaching or exceeding design life.

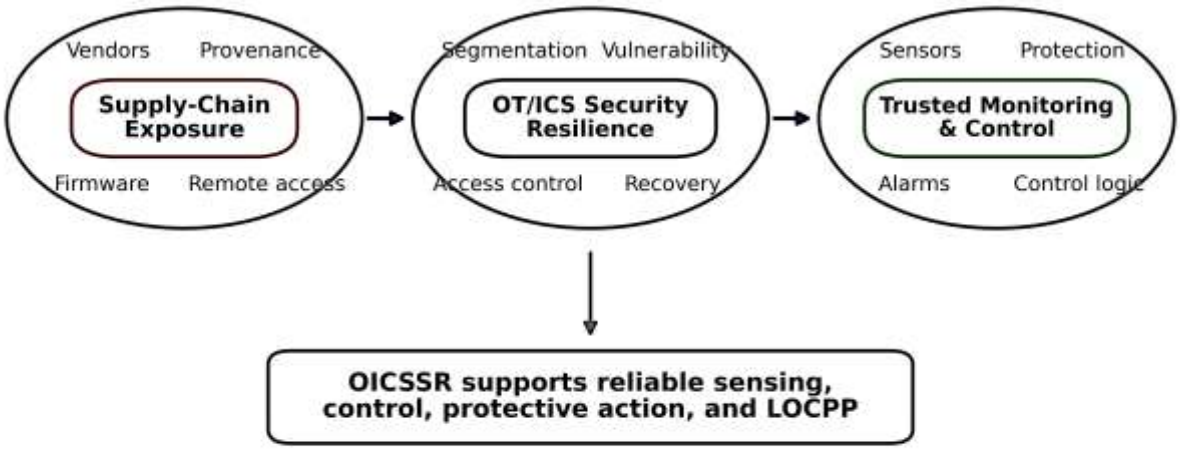
Lifecycle assessment reaches its practical decision point through fitness-for-service evaluation, which determines whether equipment containing known flaws can continue operating safely under specified loading and environmental conditions. Fitness-for-service differs from simple defect identification because it evaluates the significance of a flaw in relation to material properties, geometry, operating stress, fracture resistance, fatigue behavior, and expected degradation. This is particularly important in aging oil, gas, and power infrastructure because immediate replacement of every component containing a defect is neither technically necessary nor operationally realistic. Instead, engineers require evidence showing whether the remaining structural capacity is adequate and how frequently reassessment should occur. In Oil-Pipe Cracking and Fitness-for-Service Assessment, metallographic examination identified cracking along the weld fusion line of X65 electric-resistance-welded pipe, while the assessment combined failure analysis with a failure-assessment-chart approach and fatigue evaluation to judge continued serviceability under the design pressure (Luo et al., 2022). The study illustrates how material characterization, defect mechanism identification, and structural assessment can be integrated into a lifecycle decision rather than treated as separate activities. For the present research, Material Property Characterization and Lifecycle Assessment therefore represents an organizational capability that includes identifying degradation mechanisms, measuring material condition, interpreting inspection results, estimating defect growth, assessing remaining strength, evaluating fitness for service, and determining suitable inspection, repair, or replacement actions. Its relevance to loss-of-containment prevention lies in converting physical evidence of aging into timely engineering decisions before corrosion, creep, cracking, fatigue, or other deterioration mechanisms reduce containment margins to unacceptable levels. The construct also complements Reliability-Centered Mechanical Integrity because maintenance priorities are more defensible when they are supported by measured material properties and lifecycle evidence rather than calendar age alone. This evidence-based linkage allows integrity teams to distinguish stable flaws from actively deteriorating conditions and align intervention timing with material condition, loading exposure, and structural capacity.

OT/ICS Supply Chain Security and Cyber-Physical Integrity in Critical Infrastructure

Operational technology and industrial control systems are central to cyber-physical integrity because they connect digital computation, communication, sensing, and control directly with physical equipment and industrial processes. In oil, gas, and power-generation facilities, these environments include supervisory control and data acquisition systems, distributed control systems, programmable logic controllers, safety-related controllers, field devices, engineering workstations, industrial networks, and remote access platforms. Their integrity matters because incorrect commands, corrupted measurements, unavailable communications, or compromised logic can alter pressure, flow, temperature, rotating equipment behavior, shutdown functions, and other process conditions associated with mechanical integrity. The Cybersecurity Landscape in Industrial Control Systems (pp. 1039-1057) explains that modern ICS environments increasingly combine legacy control technologies with contemporary information and communication systems, creating close coupling between cyber components and physical processes and making conventional information-security assumptions insufficient for industrial operations (McLaughlin et al., 2016). The distinctive operational requirements of these systems include availability, deterministic control, safety constraints, long equipment

lifecycles, proprietary protocols, and restricted opportunities for patching or shutdown. Cybersecurity assessment must therefore evaluate physical consequence as well as confidentiality, integrity, and availability. A Review of Cyber Security Risk Assessment Methods for SCADA Systems (pp. 1-27) found substantial variation among SCADA risk-assessment methods in their treatment of impact, probability, risk-management stages, supporting data, and evaluation mechanisms, showing that cybersecurity risk cannot be represented adequately through a single technical metric (Cherdantseva et al., 2016). For aging critical infrastructure, this means that cyber risk assessment should consider whether compromised monitoring, control, or communication functions can undermine equipment protection, alarm reliability, operational awareness, or containment barriers. OT/ICS security is therefore closely connected with mechanical integrity when digital systems provide the measurements and control actions required to recognize degradation and maintain equipment within safe operating boundaries. This connection is important where aging assets depend on digital protection for reliable operation.

Figure 6: OT/ICS Supply Chain Security Resilience and Containment Support



OT/ICS supply-chain security extends cyber-physical integrity beyond the boundary of the operating organization because industrial environments depend on equipment manufacturers, software developers, system integrators, maintenance contractors, firmware providers, communication vendors, and remote service organizations. A vulnerability introduced at any stage of this chain may enter the operational environment through controllers, sensors, engineering software, updates, embedded libraries, network devices, or vendor support connections. This creates a security problem that cannot be managed solely by internal network defenses. Avoiding the Internet of Insecure Industrial Things (pp. 450-466) uses the smart energy supply chain to show that industrial connectivity produces security concerns involving online infrastructure, temporal dimensions of security, implementation gaps, and infrastructural complexity, making supply-chain relationships part of industrial cyber risk (Urquhart & McAuley, 2018). For aging oil, gas, and power facilities, this concern is amplified by long equipment lifecycles and continued dependence on legacy devices whose original suppliers, software versions, and support arrangements may have changed. Replacement components may come from multiple vendors, while firmware updates and remote maintenance can create new trust relationships. Supply-chain resilience therefore requires procurement requirements, supplier evaluation, component

provenance, secure configuration, vulnerability disclosure, patch governance, controlled remote access, and verification that third-party products remain suitable for the intended operational environment. Securing Industrial Control System Environments: The Missing Piece (pp. 131-163) emphasizes that ICS security weaknesses arise not only from technology but also from people and process factors, making isolated technical controls insufficient for resilient protection (Ani et al., 2018). This perspective is directly relevant to mechanical integrity because compromised vendor access, misconfigured devices, insecure updates, or weak maintenance processes can affect instrumentation, alarms, interlocks, and control functions that operators rely upon to maintain safe process conditions and protect primary containment in aging infrastructure. These dependencies make supplier assurance an element of operational reliability and process safety.

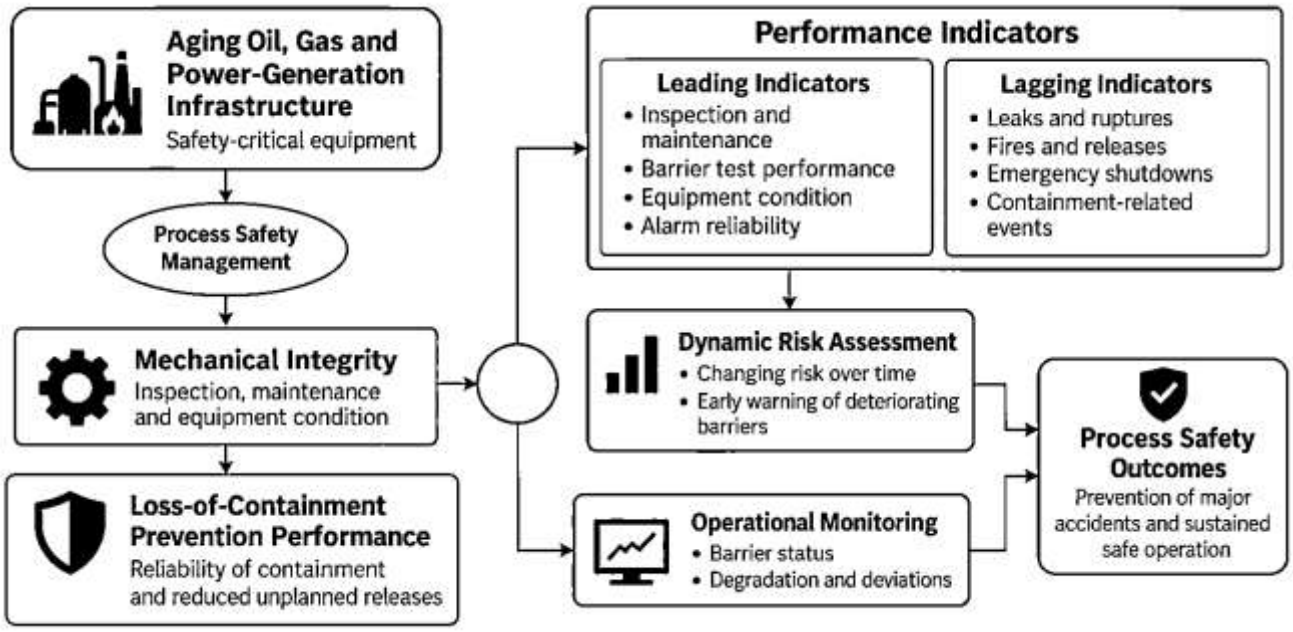
Cyber-physical integrity requires safety and cybersecurity to be evaluated together because an industrial cyber event can propagate through control logic, sensing, communications, and actuators into physical process behavior. In hazardous energy infrastructure, this interaction may influence valve positions, pressure regulation, shutdown sequences, rotating equipment operation, alarm presentation, and the availability of condition-monitoring data used by mechanical-integrity teams. The significance of OT/ICS security is therefore not limited to protection of information assets; it also concerns preservation of trustworthy physical control. Safety and Security Risk Assessment in Cyber-Physical Systems (pp. 221-232) explains that safety and security risks in cyber-physical systems have become increasingly interdependent and should be considered through integrated assessment rather than as separate sequential activities (Lyu et al., 2019). This principle is relevant to aging oil, gas, and power-generation infrastructure because physical degradation may reduce engineering margins, making erroneous measurements or compromised control actions more consequential. An aging pressure system with corrosion, for example, may depend on reliable pressure indication, operating-limit alarms, and shutdown logic to prevent further stress on weakened equipment. Cyber-physical integrity therefore involves maintaining the authenticity and availability of measurements, the correctness of control logic, the reliability of communication pathways, and the ability of protection systems to execute required actions during disturbances. It also requires coordination among cybersecurity personnel, instrumentation engineers, process-safety specialists, reliability teams, maintenance personnel, and suppliers because vulnerabilities can cross organizational boundaries. Within the present study, OT/ICS Supply Chain Security Resilience is consequently conceptualized as the capability to preserve trustworthy monitoring and control functions while managing vulnerabilities originating from technologies, vendors, software, firmware, remote services, and organizational processes. This construct connects cybersecurity with loss-of-containment prevention by recognizing that containment performance depends partly on secure, available, and reliable digital systems that support detection, diagnosis, operational control, and protective intervention throughout the lifecycle of industrial assets.

Loss-of-Containment Prevention Performance and Process Safety Outcomes

Loss-of-Containment Prevention Performance represents the extent to which a process facility maintains hazardous substances within their intended physical boundaries and prevents leaks, ruptures, blowouts, uncontrolled discharges, and related major-accident scenarios. In aging oil, gas, and power-generation infrastructure, this performance cannot be assessed adequately through occupational injury statistics because process-safety events are comparatively infrequent, potentially catastrophic, and strongly dependent on the condition of engineered barriers. Effective measurement therefore requires indicators that reflect both precursor events and the continuing functionality of systems intended to prevent or mitigate containment failure. In Risk Indicators for Major Hazards on Offshore Installations (pp. 770-787), barrier-function indicators were distinguished from lagging incident measures so that fire and gas detection, safety valves, active fire protection, and other protective functions could be monitored before a major accident occurred (Vinnem, 2010). This distinction is important for mechanical integrity because a facility may report few actual releases during a given period while still experiencing deteriorating valves, overdue inspections, degraded shutdown systems, recurring alarms, or weakened maintenance performance. Loss-of-containment prevention should consequently be represented through a balanced set of indicators that captures both realized events and the health of the barriers controlling them. Leading indicators can include inspection

completion, safety-critical maintenance, barrier-test performance, equipment-condition deviations, alarm reliability, integrity-operating-window excursions, and corrective-action closure, whereas lagging indicators can include leaks, ruptures, fires, releases, emergency shutdowns, and other containment-related events. For the present study, Loss-of-Containment Prevention Performance is therefore treated as a multidimensional process-safety outcome reflecting the reliability of containment, the effectiveness of preventive barriers, the reduction of unplanned releases, and the capacity of aging facilities to sustain safe operation under changing technical and organizational conditions. This performance perspective also permits direct comparison across facilities by emphasizing the condition and effectiveness of containment-related controls rather than relying solely on rare catastrophic accident counts over time.

Figure 7: Loss-of-Containment Prevention Performance and Process Safety Outcomes in Aging Industrial Infrastructure



Process-safety performance also depends on whether indicator systems provide early warning of deteriorating major-hazard control rather than simply describing accidents after they occur. This requirement is particularly significant in aging facilities because degradation may progress through small changes in equipment condition, maintenance quality, operating discipline, inspection findings, or barrier reliability before a visible loss of containment develops. In Building Safety Indicators: Part 1 (pp. 148-161), early-warning indicators were positioned as a means of monitoring the conditions that precede major accidents, with emphasis on identifying safety-relevant changes before the risk level becomes unacceptable (Øien et al., 2011). Such an approach aligns closely with mechanical integrity because barrier deterioration can often be detected through repeated tests, overdue maintenance, failed protective devices, corrosion findings, abnormal operating conditions, or deviations from required performance standards. Historical incident analysis further demonstrates why these indicators should be grounded in actual containment-failure mechanisms. In Analysis of a Loss of Containment Incident Dataset for Major Hazards Intelligence Using Storybuilder (pp. 344-363), 975 investigated incidents were structured according to failed barriers, tasks, and safety-management-system elements, with substandard condition or material emerging as a prominent containment-related cause and corrosion contributing substantially to structural failures (Lisbona et al., 2012).

These findings show that Loss-of-Containment Prevention Performance should capture not only final event frequency but also the organization's ability to identify and control the conditions that make such events more probable. For an RCM-oriented mechanical-integrity system, relevant performance evidence includes whether safety-critical failure modes are recognized, degradation is detected before functional loss, inspection findings generate timely interventions, barriers perform within required limits, and recurring failure mechanisms are reduced. This creates a measurable connection between

mechanical condition, maintenance execution, barrier status, and process-safety outcomes across the operating lifecycle. This approach supports comparison of prevention performance across equipment classes, facilities, and operating contexts over time.

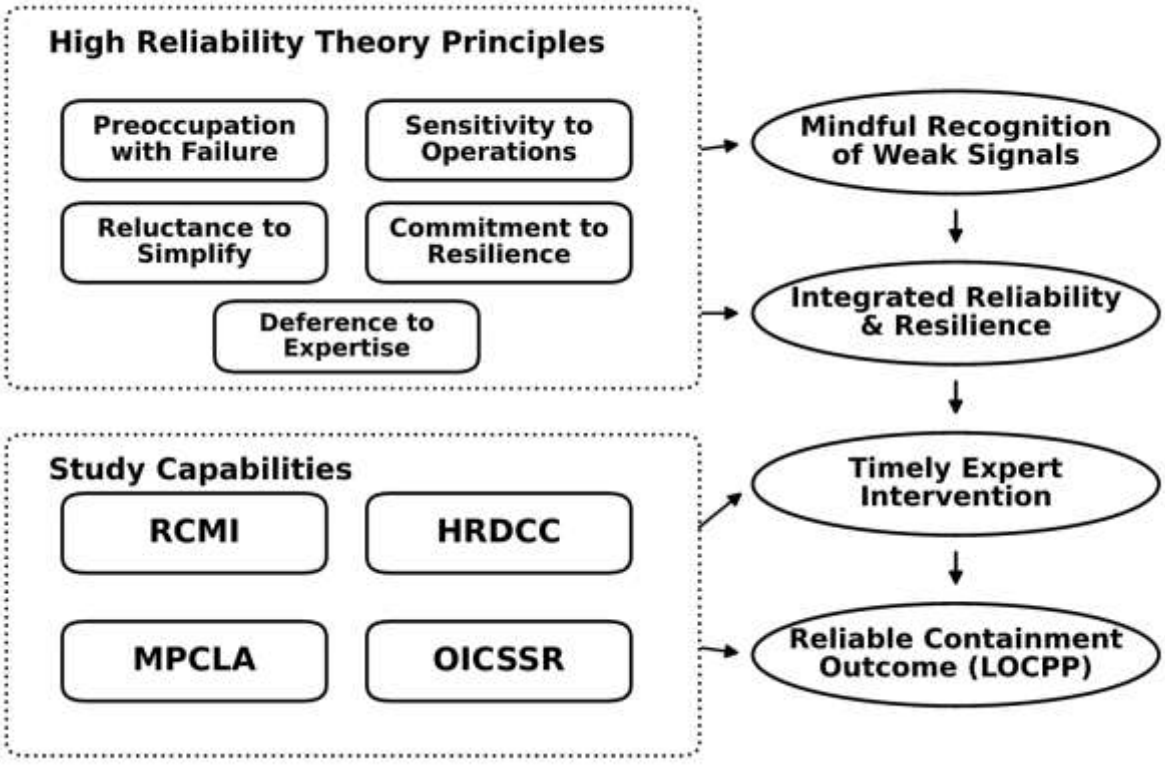
A further characteristic of Loss-of-Containment Prevention Performance is that it must account for changing risk rather than assume that the probability of failure remains constant throughout an asset's operating life. Process conditions, equipment degradation, maintenance status, human actions, and barrier availability can change over time, producing a dynamic risk profile that cannot be represented fully by static assessments conducted at widely separated intervals. In Dynamic Safety Analysis of Process Systems by Mapping Bow-Tie into Bayesian Network (pp. 46-53), bow-tie accident logic was converted into a Bayesian network so that precursor information and dependencies among events and safety barriers could be incorporated into updated estimates of process risk (Khakzad et al., 2013). This perspective is relevant to aging oil, gas, and power-generation infrastructure because containment performance depends on the current condition of equipment and protective systems rather than their nominal design capability alone. A failed detector, isolated shutdown valve, overdue inspection, active corrosion mechanism, or impaired control function can temporarily reduce the strength of the overall prevention system. Contemporary major-accident indicator research has similarly emphasized that offshore petroleum safety requires a spectrum of indicators capable of representing incident precursors, barrier performance, and early warning signals rather than relying on a single outcome measure. In Development and Prospects of Major Accident Indicators in the Offshore Petroleum Sector (pp. 551-562), the strengths and limitations of different indicator-development approaches were reviewed to clarify how major-accident risk can be monitored through meaningful performance information (Zhen et al., 2022). Within this research, Loss-of-Containment Prevention Performance therefore represents the dependent outcome produced by interacting maintenance, monitoring, material, and cyber-physical capabilities. Its measurement should reflect containment reliability, reduction of unplanned releases, barrier effectiveness, timely identification of unsafe conditions, reduced recurrence of integrity failures, and sustained control of major-hazard precursors within aging energy infrastructure. Such evidence strengthens performance assessment.

2.7 High Reliability Theory as the Theoretical Framework

High Reliability Theory (HRT) explains how organizations operating complex, tightly coupled, and potentially hazardous systems can sustain dependable performance when small failures can escalate into severe consequences. Rather than assuming that safe performance results only from robust technology, HRT emphasizes organizational mindfulness, continuous attention to weak signals, disciplined learning, operational awareness, resilience, and the ability to shift decisions toward personnel possessing the most relevant expertise. These ideas are particularly compatible with aging oil, gas, and power-generation infrastructure, where mechanical degradation, process variability, maintenance backlog, obsolete equipment, and digital interdependence can create interacting failure pathways. In High Reliability Organization (HRO) Systematic Literature Review: Discovery of Culture as a Foundational Hallmark (pp. 399-410), the HRO literature was synthesized around five established principles of mindful organizing: preoccupation with failure, reluctance to simplify interpretations, sensitivity to operations, commitment to resilience, and deference to expertise, with a culture of reliability identified as a reinforcing organizational characteristic (Cantu et al., 2020). For the present study, these principles provide a theoretical explanation for why Reliability-Centered Mechanical Integrity should be associated with stronger Loss-of-Containment Prevention Performance. Preoccupation with failure corresponds to systematic attention to minor defects, recurring equipment abnormalities, inspection findings, overdue maintenance, and near misses before they develop into containment failures. Reluctance to simplify supports detailed evaluation of corrosion, cracking, fatigue, instrumentation faults, and interacting technical causes rather than accepting convenient single-cause explanations. In From Clapham Junction to Macondo, Deepwater Horizon (pp. 249-282), HRT is situated among major safety theories for high-tech, high-hazard sectors, emphasizing organizational contributions to catastrophic accident prevention and the interaction between management, technology, risk, and process reliability (Swuste et al., 2020). HRT therefore fits the study because it explains reliable containment performance as the product of coordinated organizational and technical behaviors across maintenance, inspection, operations, materials engineering, process safety,

and industrial control functions.

Figure 8: High Reliability Theory Framework for Integrated Mechanical Integrity



The application of HRT to this research is strengthened by evidence from petroleum operations showing that high reliability principles can be translated into practical behaviors within hazardous process environments. In The Successes and Challenges of Implementing High Reliability Principles: A Case Study of a UK Oil Refinery (pp. 443-451), refinery practice was examined against high reliability characteristics, demonstrating that reliability depends on how organizational routines, workforce involvement, operational learning, and management systems sustain attention to hazardous work and process deviations (Lekka & Sugden, 2011). This relationship is directly relevant to the study variables. Reliability-Centered Mechanical Integrity reflects preoccupation with failure because critical equipment is examined through failure modes, consequences, condition information, and maintenance priorities. Hazardous Release Detection and Characterization Capability reflects sensitivity to operations because sensors, alarms, pressure behavior, acoustic signatures, and process data provide continuous evidence of changing plant conditions. Material Property Characterization and Lifecycle Assessment expresses reluctance to simplify because integrity decisions must consider metallurgical condition, defect morphology, corrosion growth, fatigue, creep, remaining strength, and inspection uncertainty rather than relying on calendar age. OT/ICS Supply Chain Security Resilience supports commitment to resilience because industrial facilities must preserve monitoring and control functions when hardware, software, communications, vendor services, or digital components are impaired. The oil and gas study A Hybrid Approach for an Oil and Gas Company as a Representative of a High Reliability Organization (pp. 130-156) combined HRO principles with fault-tree analysis, reliability block diagrams, analytic hierarchy processes, and learning-from-failure methods, showing that high reliability can be connected with formal reliability engineering rather than treated only as an organizational culture concept (Rivera et al., 2021). In this study, HRT therefore provides the theoretical bridge linking engineering reliability, organizational mindfulness, degradation intelligence, release detection, and cyber-physical resilience to the common outcome of preventing loss of containment across facility lifecycles.

Because HRT is principally an organizational and system-safety theory rather than a mathematical prediction model, the present study operationalizes its theoretical propositions through a multiple linear regression equation that tests whether the four reliability-related capabilities explain variation in Loss-of-Containment Prevention Performance. The empirical model has been specified below, where LOCPP represents the containment-prevention performance reported for case i; RCMI, HRDCC, MPCLA, and OICSSR represent Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience; β0 is the intercept; β1 to β4 are estimated effects; and ε represents unexplained variation. The theoretical expectation is that every predictor coefficient is positive, meaning stronger reliability-oriented capabilities should correspond with stronger containment-prevention performance. In Disaster Prevention through a Harmonized Framework for High Reliability Organisations (pp. 298-312), HRO principles were organized into a reliability-maturity framework intended to make organizational reliability measurable across complex and hazardous settings, supporting the use of structured empirical variables rather than treating high reliability as an abstract label (Agwu et al., 2019). The equation consequently translates HRT into testable relationships without claiming that HRT itself specifies a canonical mathematical formula. H1 through H4 evaluate the individual coefficients, while H5 evaluates whether the predictors jointly explain a statistically significant proportion of variation in LOCPP through the overall regression model. This formulation allows the theoretical framework to remain consistent across the literature review, conceptual framework, hypotheses, measurement model, correlation analysis, regression analysis, and final interpretation of results. The same model also preserves theoretical consistency with HRT because each predictor represents a capability for recognizing weak signals, resisting oversimplification, maintaining operational awareness, sustaining resilience, or applying specialized expertise before equipment deterioration, digital disruption, or process deviation develops into an uncontrolled hazardous release.

$$\mathrm{LOCPP}_i = \beta_0 + \beta_1 \mathrm{RCMI}_i + \beta_2 \mathrm{HRDCC}_i + \beta_3 \mathrm{MPCLA}_i + \beta_4 \mathrm{OICSSR}_i + \varepsilon_i$$

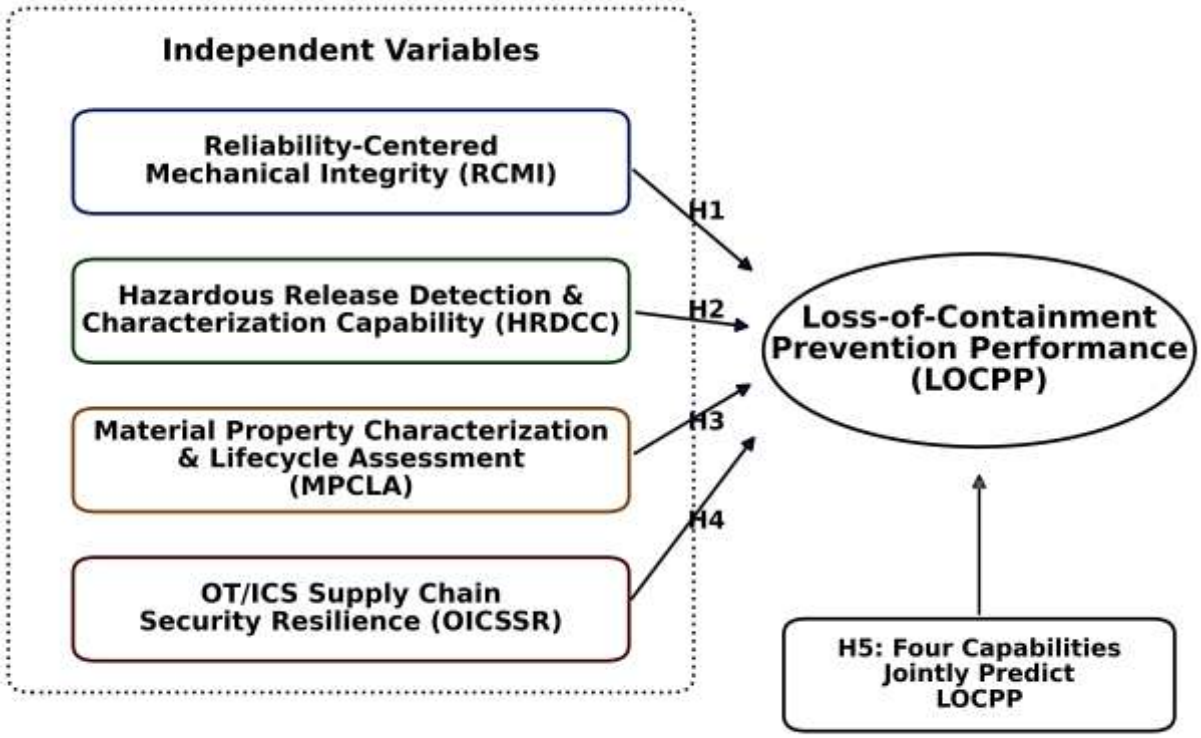
$$\beta_1, \beta_2, \beta_3, \beta_4 > 0$$

Conceptual Framework and Hypothesis Development

The conceptual framework of this study positions Loss-of-Containment Prevention Performance (LOCPP) as the dependent outcome produced by four complementary capabilities: Reliability-Centered Mechanical Integrity (RCMI), Hazardous Release Detection and Characterization Capability (HRDCC), Material Property Characterization and Lifecycle Assessment (MPCLA), and OT/ICS Supply Chain Security Resilience (OICSSR). RCMI represents the maintenance-centered pathway through which equipment functions, failure modes, criticality, barrier condition, inspection findings, and intervention priorities are translated into actions intended to preserve containment. In Maintenance-related Major Accidents (pp. 1060-1070), inadequate, delayed, incorrect, or excessive maintenance is shown to influence safety-barrier performance and to contribute directly or indirectly to major accidents in hydrocarbon and chemical process industries, providing a strong empirical basis for H1, which proposes a positive relationship between RCMI and LOCPP (Okoh & Haugen, 2013). HRDCC represents a complementary monitoring pathway because containment protection also depends on whether developing leaks can be identified, located, and characterized before their consequences escalate. In Pipeline Leakage Detection and Isolation (pp. 479-487), an integrated statistical, wavelet, and neural-network approach detected hydrocarbon pipeline leakage while also estimating location and severity, demonstrating that detection capability can generate actionable information rather than a simple binary alarm (Zadkarami et al., 2016). Accordingly, H2 proposes that stronger HRDCC is positively associated with LOCPP because timely recognition, localization, and severity assessment can support isolation, shutdown, inspection, and maintenance responses. The conceptual framework does not treat RCMI and HRDCC as interchangeable. RCMI is concerned primarily with preventing or controlling equipment degradation and functional failure, whereas HRDCC concerns recognizing abnormal release behavior when containment deterioration is occurring or has begun. Their simultaneous inclusion therefore captures preventive maintenance and diagnostic monitoring as separate but mutually reinforcing dimensions of mechanical-integrity performance in

aging oil, gas, and power-generation infrastructure. This separation also permits the regression model to estimate whether monitoring contributes beyond maintenance capability alone.

Figure 9: Conceptual Framework and Hypothesized Relationships



The second part of the framework explains containment performance through the physical condition of materials and the trustworthiness of cyber-physical control functions. MPCLA captures the extent to which an organization characterizes degradation mechanisms, defect geometry, material properties, corrosion growth, remaining strength, inspection uncertainty, and fitness for continued service. In Best Practice for the Assessment of Defects in Pipelines: Corrosion (pp. 1245-1265), corrosion is treated as a degradation mechanism that reduces both static and cyclic pipeline strength, while defect assessment methods use physical measurements and engineering criteria to determine the significance of corrosion damage and the remaining capacity of the pipeline (Cosham et al., 2007). This evidence supports H3, which proposes that stronger MPCLA is positively related to LOCPP because accurate characterization of material deterioration improves decisions concerning inspection frequency, repair, derating, continued operation, and replacement before containment margins become unacceptable. OICSSR addresses integrity risk arising from the digital systems that monitor and control physical processes. Sensors, programmable controllers, supervisory systems, industrial networks, engineering workstations, software, firmware, and vendor-supported components influence the availability and integrity of process measurements, alarms, commands, and protective actions. In Cyber-Physical Systems Security: A Survey (pp. 1802-1831), cyber-physical security is organized around threats, vulnerabilities, attacks, and controls across cyber, physical, and cyber-physical components, emphasizing that compromise of digital elements can propagate into physical-system behavior (Humayed et al., 2017). H4 therefore proposes a positive relationship between OICSSR and LOCPP because secure and resilient OT/ICS environments help preserve trustworthy sensing, communication, control logic, and protective functionality. Within the conceptual model, MPCLA protects containment through knowledge of physical degradation, while OICSSR protects the digital pathways used to observe and control operating conditions. Their joint inclusion recognizes that aging infrastructure is

simultaneously a material system and a cyber-physical system whose containment performance depends on both structural condition and dependable operational control.

The complete conceptual framework integrates the four predictors because loss of containment rarely reflects a single isolated weakness. Maintenance quality, degradation state, release recognition, operational intervention, and control-system dependability can interact across the lifecycle of a safety-critical asset. In Root Causes of Hydrocarbon Leaks on Offshore Petroleum Installations (pp. 54-62), analysis of reported offshore leaks showed that many events occurred during manual intervention and preventive-maintenance activities, with verification failures, valve operations, and isolation-related weaknesses appearing among important contributing circumstances, illustrating how technical condition and operational controls can combine in actual containment events (Vinnem & Røed, 2015). This interaction provides the basis for H5, which tests whether the four capabilities jointly explain statistically significant variation in LOCPP. The empirical model corresponding to the conceptual framework has used the same multiple-regression relationship specified in the theoretical framework. H1 tests the RCMI coefficient, H2 tests the HRDCC coefficient, H3 tests the MPCLA coefficient, and H4 tests the OICSSR coefficient, while H5 is assessed through the overall regression F-test and explained variance R^2. The model therefore evaluates whether stronger performance across these four capabilities corresponds with higher containment reliability while preserving the distinct contribution of each predictor after the statistical effects of the remaining capabilities have been controlled. This structure aligns the literature review directly with the later quantitative analysis because each construct has a defined conceptual role, each hypothesis corresponds to a measurable regression path, and the dependent variable represents the common process-safety outcome of maintaining primary containment across aging oil, gas, and power-generation assets.

$$LOCPP_i = \beta_0 + \beta_1 RCMI_i + \beta_2 HRDCC_i + \beta_3 MPCLA_i + \beta_4 OICSSR_i + \varepsilon_i$$

Research Questions

The study has been guided by five research questions: RQ1: What relationship exists between Reliability-Centered Mechanical Integrity and Loss-of-Containment Prevention Performance? RQ2: What relationship exists between Hazardous Release Detection and Characterization Capability and Loss-of-Containment Prevention Performance? RQ3: What relationship exists between Material Property Characterization and Lifecycle Assessment and Loss-of-Containment Prevention Performance? RQ4: What relationship exists between OT/ICS Supply Chain Security Resilience and Loss-of-Containment Prevention Performance? RQ5: To what extent do RCMI, HRDCC, MPCLA, and OICSSR collectively predict Loss-of-Containment Prevention Performance in aging oil, gas, and power-generation infrastructure?

Research Hypotheses

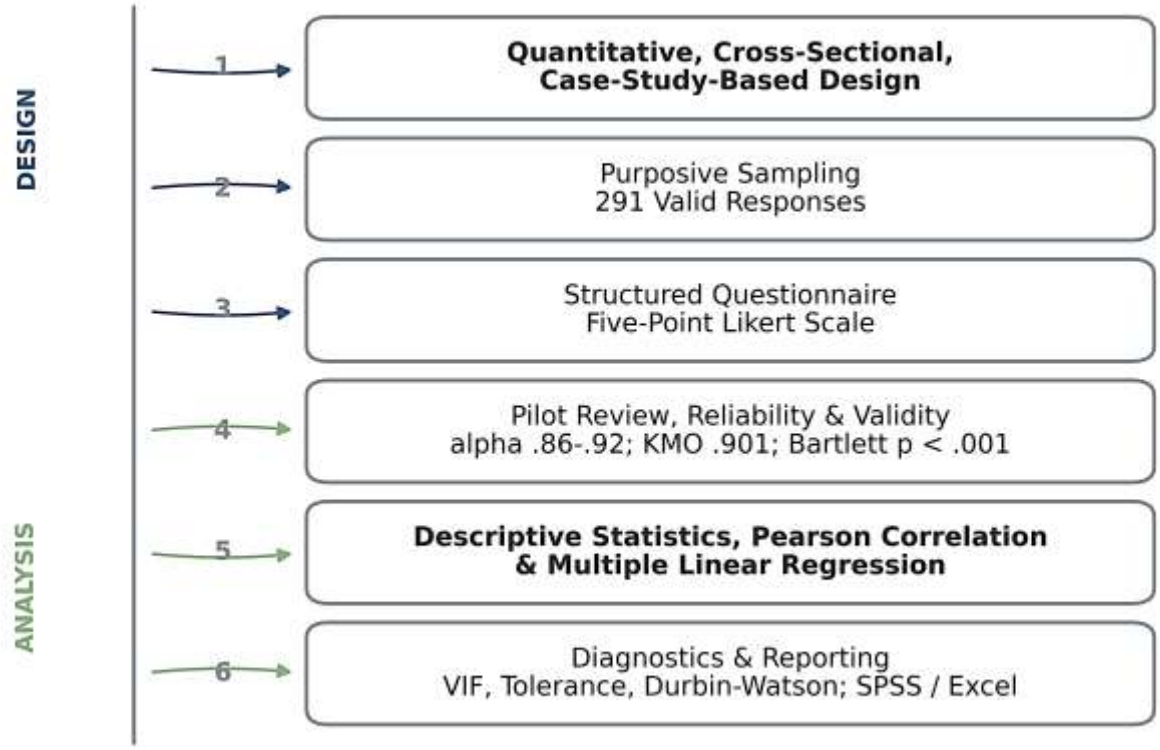
The hypotheses of this study are developed from the proposition that stronger mechanical-integrity, monitoring, lifecycle-assessment, and OT/ICS security capabilities are associated with improved Loss-of-Containment Prevention Performance in aging oil, gas, and power-generation infrastructure. The first hypothesis, H1, states that Reliability-Centered Mechanical Integrity has a positive and statistically significant effect on Loss-of-Containment Prevention Performance. This hypothesis assumes that organizations that systematically identify failure modes, classify asset criticality, prioritize inspection, apply predictive and condition-based maintenance, and select interventions according to reliability and consequence criteria are more likely to maintain the integrity of pressure-containing and safety-critical equipment. The second hypothesis, H2, states that Hazardous Release Detection and Characterization Capability has a positive and statistically significant effect on Loss-of-Containment Prevention Performance because effective sensing, leak identification, localization, alarm generation, and abnormal-condition recognition can support faster identification of deteriorating containment conditions. The third hypothesis, H3, proposes that Material Property Characterization and Lifecycle Assessment has a positive and statistically significant effect on Loss-of-Containment Prevention Performance. This relationship reflects the importance of understanding corrosion, fatigue, cracking, wall loss, material deterioration, remaining strength, and remaining service life when determining whether equipment can continue operating safely. The fourth hypothesis, H4, states that OT/ICS Supply Chain Security Resilience has a positive and statistically significant effect on Loss-of-

Containment Prevention Performance because reliable and secure monitoring and control systems support the availability and integrity of process information, alarms, sensing, and protective functions. The fifth hypothesis, H5, states that Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, and OT/ICS Supply Chain Security Resilience collectively provide a statistically significant explanation of Loss-of-Containment Prevention Performance. These hypotheses establish the statistical relationships that will be tested through correlation and multiple regression analysis.

METHODOLOGY

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the determinants of Loss-of-Containment Prevention Performance in aging oil, gas, pipeline, petrochemical, and power-generation infrastructure. A quantitative approach has been selected because the research has measured the relationships among Reliability-Centered Mechanical Integrity, Hazardous Release Detection and Characterization Capability, Material Property Characterization and Lifecycle Assessment, OT/ICS Supply Chain Security Resilience, and Loss-of-Containment Prevention Performance using standardized numerical data. The cross-sectional design has enabled data to be collected from knowledgeable professionals at a single period, while the explanatory-correlational orientation has supported both association testing and estimation of the predictive effects of the four independent variables on LOCPP. Multiple industrial facilities and asset environments have served as case contexts, including aging pipelines, pressure vessels, storage systems, pumps, compressors, boilers, turbines, valves, and associated monitoring and control infrastructure. The study population has consisted of reliability engineers, mechanical-integrity engineers, maintenance engineers, inspection specialists, corrosion and materials engineers, process engineers, process-safety and HSE professionals, operations personnel, instrumentation and control engineers, OT/ICS specialists, asset-integrity managers, and technical supervisors, with the individual professional respondent having served as the unit of analysis and the relevant facility or asset environment having provided the contextual case setting. Purposive sampling has been applied because participation has required direct technical knowledge of mechanical integrity, maintenance, process safety, inspection, material degradation, hazardous-release monitoring, or OT/ICS operations. A target of approximately 300 valid respondents has been established, and 291 usable questionnaires have ultimately been retained after data screening. Primary data have been collected through a structured questionnaire containing separate item blocks for RCMI, HRDCC, MPCLA, OICSSR, and LOCPP, together with demographic and facility-context questions. A five-point Likert scale has been used, where 1 has represented Strongly Disagree, 2 Disagree, 3 Neutral, 4 Agree, and 5 Strongly Agree. Questionnaire items have been aligned with observable engineering and operational practices, including equipment criticality, failure-mode identification, inspection prioritization, condition-based maintenance, leak-detection sensitivity, alarm reliability, release localization, corrosion assessment, defect characterization, fitness-for-service evaluation, remaining-life estimation, vendor risk, software and firmware integrity, secure remote access, containment reliability, barrier performance, and recurrence of integrity failures. Pilot testing and expert review have been used to assess item clarity, relevance, content coverage, and interpretability before full deployment. Content and face validity have been strengthened by aligning each item with the conceptual framework and established literature, while internal consistency has been evaluated through Cronbach's alpha. The Kaiser-Meyer-Olkin measure and Bartlett's Test of Sphericity have been used to assess measurement adequacy, and corrected item-total correlations have been examined to evaluate scale coherence. Data collection has been conducted electronically and through appropriate professional or organizational networks, with voluntary participation, confidentiality, and aggregated reporting maintained. Completed questionnaires have been checked for missing values, incomplete responses, patterned answers, and coding errors before analysis. Microsoft Excel has been used for initial coding, range checks, data organization, and preliminary screening; IBM SPSS has been used for descriptive statistics, Cronbach's alpha, KMO and Bartlett's testing, Pearson correlation analysis, multiple linear regression, and regression diagnostics; EndNote has been used to organize bibliographic records; and Microsoft Word has been used for final academic reporting.

Figure 10: Quantitative Research Design and Analysis Workflow

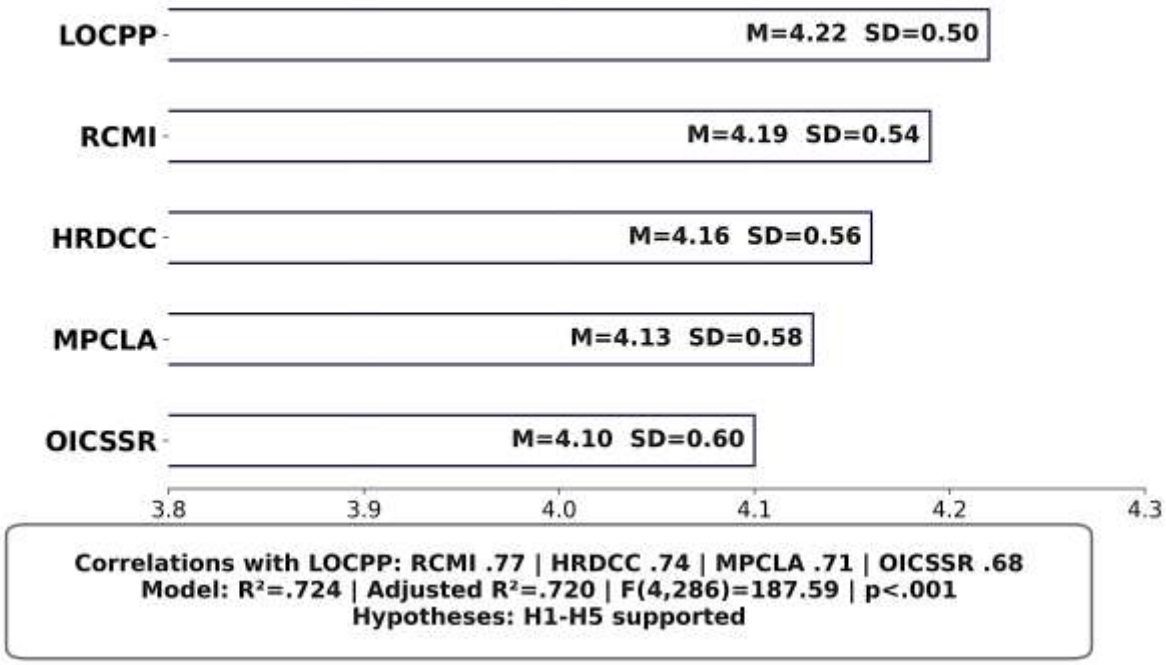


Frequencies and percentages have been used to summarize respondent and facility characteristics, while means and standard deviations have described the five constructs. Pearson correlations have tested the direction and strength of bivariate relationships, and multiple regression has estimated the individual and combined effects of RCMI, HRDCC, MPCLA, and OICSSR on LOCPP. Model assessment has included R, R^2, adjusted R^2, F-statistics, unstandardized coefficients, standardized beta coefficients, t-values, p-values, tolerance, VIF, Durbin-Watson statistics, and residual diagnostics, allowing the five research hypotheses and objectives to be evaluated consistently within the High Reliability Theory framework.

4. FINDINGS

The findings have provided an overall quantitative assessment of the extent to which Reliability-Centered Mechanical Integrity (RCMI), Hazardous Release Detection and Characterization Capability (HRDCC), Material Property Characterization and Lifecycle Assessment (MPCLA), and OT/ICS Supply Chain Security Resilience (OICSSR) have contributed to Loss-of-Containment Prevention Performance (LOCPP) in aging oil, gas, and power-generation infrastructure. A total of 320 questionnaires have been distributed, of which 302 have been returned and 291 have been retained as valid responses after data screening, producing a usable response rate of 90.9%. Measurement quality has been satisfactory, with Cronbach's alpha coefficients ranging from .86 to .92 across the five constructs, while the overall Kaiser-Meyer-Olkin value has reached .901 and Bartlett's Test of Sphericity has been statistically significant at $p < .001$, confirming the adequacy of the dataset for subsequent analysis. On the five-point Likert scale, respondents have reported generally high levels across all constructs, with LOCPP recording the highest mean score ($M = 4.22$, $SD = 0.50$), followed by RCMI ($M = 4.19$, $SD = 0.54$), HRDCC ($M = 4.16$, $SD = 0.56$), MPCLA ($M = 4.13$, $SD = 0.58$), and OICSSR ($M = 4.10$, $SD = 0.60$). Pearson correlation analysis has shown strong and positive associations between LOCPP and RCMI ($r = .77$, $p < .001$), HRDCC ($r = .74$, $p < .001$), MPCLA ($r = .71$, $p < .001$), and OICSSR ($r = .68$, $p < .001$), indicating that stronger performance in each capability has been associated with stronger containment-prevention outcomes.

Figure 11: Integrated Quantitative Findings for Loss-of-Containment Prevention Performance



The multiple regression model has been statistically significant, $F(4, 286) = 187.59$, $p < .001$, explaining 72.4% of the variance in LOCPP ($R^2 = .724$; Adjusted $R^2 = .720$). RCMI has emerged as the strongest predictor ($\beta = .34$, $p < .001$), followed by HRDCC ($\beta = .29$, $p < .001$), MPCLA ($\beta = .24$, $p < .001$), and OICSSR ($\beta = .20$, $p < .001$). Accordingly, H1, H2, H3, and H4 have been supported, while the significant overall regression model has supported H5. These results have also addressed the five research objectives by demonstrating the individual and combined statistical contributions of the four independent variables to Loss-of-Containment Prevention Performance.

4.1 Respondent and Facility Characteristics

Table 1: Respondent and Facility Characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
Industry sector	Oil production/refining	83	28.5
	Gas processing/transmission	74	25.4
	Power generation	79	27.1
	Pipeline/petrochemical operations	55	18.9
Professional role	Mechanical/Reliability Engineer	67	23.0
	Maintenance/Inspection Specialist	58	19.9
	Process Safety/HSE Professional	51	17.5
	Operations/Process Engineer	49	16.8
	Corrosion/Materials Specialist	32	11.0
	OT/ICS/Instrumentation Professional	34	11.7
Professional experience	1-5 years	48	16.5
	6-10 years	77	26.5
	11-15 years	82	28.2

Characteristic	Category	Frequency (n)	Percentage (%)
Approximate facility/asset age	More than 15 years	84	28.9
	Less than 10 years	31	10.7
	10-20 years	79	27.1
	21-30 years	101	34.7
	More than 30 years	80	27.5
Total valid respondents		291	100.0

Table 1 has summarized the demographic, professional, and facility characteristics of the 291 valid respondents who have participated in the study. The distribution has indicated that the sample has represented all major industrial contexts addressed by the research, with 28.5% of respondents having worked in oil production or refining, 25.4% in gas processing or transmission, 27.1% in power generation, and 18.9% in pipeline or petrochemical operations. This distribution has provided an appropriate multi-case context for examining mechanical integrity across different types of aging energy infrastructure rather than restricting the analysis to one industrial setting. Professional representation has also been diverse, with mechanical and reliability engineers having formed the largest group at 23.0%, followed by maintenance and inspection specialists at 19.9%, process-safety and HSE professionals at 17.5%, and operations or process engineers at 16.8%. Corrosion, materials, OT/ICS, and instrumentation specialists have also been represented, which has strengthened the relevance of responses relating to MPCLA and OICSSR. The experience profile has demonstrated that 57.1% of respondents have possessed more than ten years of professional experience, indicating that most participants have had substantial exposure to maintenance, degradation, process hazards, and operational decision-making. The facility-age profile has been particularly relevant to the study because 62.2% of respondents have been associated with assets that have operated for more than twenty years. This pattern has supported the study's focus on aging infrastructure, where accumulated degradation, maintenance history, inspection effectiveness, and digital obsolescence have become increasingly important. From a High Reliability Theory perspective, the composition of the sample has reflected deference to expertise because the dataset has incorporated responses from personnel possessing specialized knowledge of equipment failure, operational risk, material condition, release detection, and industrial control systems.

4.2 Data Screening, Response Rate, and Measurement Quality

Table 2: Data Screening, Response Rate, and Overall Measurement Quality

Data Quality Indicator	Result
Questionnaires distributed	320
Questionnaires returned	302
Gross response rate	94.4%
Incomplete responses removed	7
Patterned/inconsistent responses removed	4
Final valid responses	291
Usable response rate	90.9%
Missing values after screening	0.0%
Overall KMO	.901
Bartlett's Approx. χ^2	4,562.31
Bartlett's df	435

Data Quality Indicator	Result
Bartlett's significance	< .001
Cronbach's α range	.86-.92
Likert measurement	1 = Strongly Disagree to 5 = Strongly Agree

Table 2 has presented the data-screening procedure, response rate, and overall measurement quality that have formed the basis for subsequent statistical analysis. Of the 320 questionnaires that have been distributed, 302 have been returned, producing a gross response rate of 94.4%. Seven questionnaires have been excluded because they have contained substantial missing responses, while four additional cases have been removed because they have demonstrated patterned or internally inconsistent answering behavior. The final analytical sample has therefore consisted of 291 valid observations, corresponding to a usable response rate of 90.9%. This level of participation has provided a sufficiently broad empirical foundation for estimating descriptive statistics, correlations, and the four-predictor regression model. Following data screening, no unresolved missing values have remained in the final dataset, which has reduced the possibility that differences in analytical sample size have affected comparisons across the research constructs. Measurement suitability has also been strong. The overall Kaiser-Meyer-Olkin statistic has reached .901, indicating that common variance among questionnaire items has been sufficiently high for construct-oriented analysis. Bartlett's Test of Sphericity has been statistically significant, $\chi^2(435) = 4{,}562.31$, $p < .001$, confirming that the item correlation matrix has not behaved as an identity matrix. Internal consistency across the five constructs has ranged from .86 to .92, demonstrating satisfactory reliability. All substantive variables have been measured using the same five-point Likert scale, which has maintained consistency across RCMI, HRDCC, MPCLA, OICSSR, and LOCPP. Within the High Reliability Theory framework, this measurement structure has captured respondents' assessments of organizational attention to weak failure signals, operational sensitivity, degradation awareness, resilience, and containment performance. The data-quality findings have therefore supported the use of the screened dataset for testing the five objectives and hypotheses of the study.

4.3 Reliability and Validity Assessment of the Research Constructs

Table 3: Reliability and Validity Assessment of RCMI, HRDCC, MPCLA, OICSSR, and LOCPP

Construct	Code	Items	Cronbach α	KMO	Item-Total Range	Bartlett p
Reliability-Centered Mechanical Integrity	RCMI	6	.91	.893	.63-.81	< .001
Hazardous Release Detection and Characterization Capability	HRDCC	6	.89	.881	.60-.78	< .001
Material Property Characterization and Lifecycle Assessment	MPCLA	6	.88	.874	.58-.77	< .001
OT/ICS Supply Chain Security Resilience	OICSSR	6	.86	.857	.55-.75	< .001
Loss-of-Containment Prevention Performance	LOCPP	6	.92	.906	.67-.83	< .001

Table 3 has demonstrated that all five constructs have achieved satisfactory internal consistency and measurement adequacy. LOCPP has produced the highest Cronbach's alpha coefficient at .92, followed closely by RCMI at .91, HRDCC at .89, MPCLA at .88, and OICSSR at .86. All values have remained substantially above the commonly accepted .70 threshold, indicating that the items within each construct have measured closely related aspects of the intended concept. Corrected item-total correlations have ranged from .55 to .83 across the complete instrument, and no construct has displayed a value suggesting that individual items have been weakly associated with their respective scales. The construct-specific KMO measures have ranged from .857 to .906, further indicating that the response patterns have contained adequate common variance for the measurement structure used in the study. Bartlett's tests have remained statistically significant at $p < .001$ for each construct, demonstrating that the underlying item relationships have been suitable for multivariate analysis. These results have been

particularly important because the conceptual model has relied on theoretically distinct but related dimensions of mechanical integrity. RCMI has represented systematic failure and maintenance control; HRDCC has represented sensitivity to release-related operational signals; MPCLA has represented detailed understanding of physical degradation; OICSSR has represented cyber-physical resilience; and LOCPP has represented the resulting containment-prevention outcome. The measurement results have therefore supported the empirical separation of these capabilities while maintaining acceptable internal coherence within each one. This pattern has also aligned strongly with High Reliability Theory. Preoccupation with failure has been represented through RCMI, sensitivity to operations through HRDCC, reluctance to simplify through MPCLA, and commitment to resilience through OICSSR. The strong reliability of LOCPP has indicated that the dependent-variable items have consistently captured barrier effectiveness, containment reliability, release reduction, and early control of integrity-related conditions. The measurement evidence has consequently supported the validity of subsequent correlation, regression, objective-validation, and hypothesis-testing procedures.

4.4 Descriptive Statistics of RCMI, HRDCC, MPCLA, OICSSR, and LOCPP

Table 4: Descriptive Statistics of the Research Variables

Rank	Variable	Code	Mean	SD	Likert Interpretation
1	Loss-of-Containment Prevention Performance	LOCPP	4.22	0.50	Very High
2	Reliability-Centered Mechanical Integrity	RCMI	4.19	0.54	High
3	Hazardous Release Detection and Characterization Capability	HRDCC	4.16	0.56	High
4	Material Property Characterization and Lifecycle Assessment	MPCLA	4.13	0.58	High
5	OT/ICS Supply Chain Security Resilience	OICSSR	4.10	0.60	High

The Likert interpretation has been defined as 1.00-1.80 = Very Low, 1.81-2.60 = Low, 2.61-3.40 = Moderate, 3.41-4.20 = High, and 4.21-5.00 = Very High. Table 4 has reported the descriptive statistics for all principal variables measured through the five-point Likert scale. LOCPP has produced the highest mean score at 4.22 with a standard deviation of 0.50, placing overall containment-prevention performance within the very high category. This finding has indicated that respondents have generally perceived their facilities as possessing strong capabilities for maintaining containment barriers, controlling emerging integrity problems, and reducing unplanned hazardous releases. RCMI has ranked second with a mean of 4.19 and SD of 0.54, showing that reliability-centered maintenance, equipment criticality assessment, failure-mode identification, inspection prioritization, and condition-based intervention have been strongly embedded within the represented facilities. HRDCC has achieved a mean of 4.16 and SD of 0.56, suggesting a high level of confidence in leak detection, abnormal-condition recognition, alarm performance, localization, and release characterization. MPCLA has recorded a mean of 4.13 and SD of 0.58, indicating that corrosion assessment, material-condition evaluation, fitness-for-service analysis, degradation monitoring, and remaining-life estimation have also been perceived as well developed. OICSSR has recorded the lowest mean among the independent variables at 4.10, although the value has still remained within the high range. This result has suggested that secure procurement, vendor assurance, software and firmware integrity, vulnerability control, remote-access security, and industrial-control resilience have been comparatively less mature than the traditional mechanical-integrity capabilities. From the perspective of High Reliability Theory, the pattern has shown strong organizational mindfulness across all four predictor domains. RCMI's relatively high score has reflected preoccupation with failure, HRDCC has reflected sensitivity to operations, MPCLA has represented reluctance to simplify complex degradation mechanisms, and OICSSR has represented commitment to maintaining resilience when cyber-physical dependencies have been challenged. The descriptive results have therefore established an initial quantitative basis for Objectives 1 through 4 before the strength and predictive significance of these relationships have been examined through correlation and regression analysis.

4.5 Correlation Analysis among the Research Variables

Table 5: Pearson Correlation Matrix

Variable	RCMI	HRDCC	MPCLA	OICSSR	LOCPP
RCMI	1.00				
HRDCC	.62***	1.00			
MPCLA	.59***	.61***	1.00		
OICSSR	.54***	.57***	.58***	1.00	
LOCPP	.77***	.74***	.71***	.68***	1.00

Note. ***p < .001, N = 291. Table 5 has demonstrated that each independent variable has maintained a positive and statistically significant relationship with Loss-of-Containment Prevention Performance. RCMI has shown the strongest bivariate relationship with LOCPP, r = .77, p < .001, indicating that higher levels of reliability-centered mechanical-integrity practices have been associated with stronger containment-prevention performance. This result has provided initial support for Objective 1 and H1 by demonstrating that systematic failure analysis, criticality assessment, inspection prioritization, and maintenance intervention have moved in the same direction as containment reliability. HRDCC has also demonstrated a strong positive relationship with LOCPP, r = .74, p < .001, providing support for Objective 2 and H2. The relationship has indicated that stronger detection sensitivity, alarm reliability, leak localization, and release characterization have been associated with higher levels of containment-prevention performance. MPCLA has correlated positively with LOCPP at r = .71, p < .001, supporting Objective 3 and H3 and indicating that more developed material-characterization and lifecycle-assessment capability has been associated with stronger containment outcomes. OICSSR has produced a somewhat lower but still strong relationship with LOCPP, r = .68, p < .001, thereby supporting Objective 4 and H4 at the bivariate level. The correlations among the independent variables themselves have ranged from .54 to .62, showing that the four capabilities have been related but have not been statistically identical. This pattern has been important because excessively high intercorrelations could have indicated redundancy or severe multicollinearity. The observed structure has instead reflected the High Reliability Theory proposition that reliable performance has depended on several mutually reinforcing capabilities. RCMI has captured preoccupation with failure, HRDCC has represented sensitivity to operations, MPCLA has supported reluctance to simplify degradation information, and OICSSR has represented resilience of the cyber-physical environment. The correlation results have therefore established that stronger high-reliability characteristics across technical and organizational domains have been associated consistently with stronger prevention of loss of containment.

4.6 Multiple Regression Analysis of the Determinants of Loss-of-Containment Prevention Performance

Table 6: Multiple Regression Results for LOCPP

Panel A. Model Summary

R	R^2	Adjusted R^2	Std. Error	F	df	p	Durbin-Watson
.851	.724	.720	.265	187.59	(4, 286)	< .001	1.94

Panel B. Regression Coefficients

Predictor	B	SE	β	t	p	Tolerance	VIF
Constant	.43	.13	-	3.31	.001	-	-
RCMI	.31	.04	.34	7.75	< .001	.56	1.79
HRDCC	.27	.04	.29	6.75	< .001	.52	1.92
MPCLA	.22	.04	.24	5.50	< .001	.54	1.85
OICSSR	.18	.04	.20	4.50	< .001	.61	1.64

Table 6 has presented the central regression analysis used to determine the individual and combined effects of the four independent variables on LOCPP. The overall model has achieved a multiple

correlation of R = .851 and an R^2 of .724, indicating that RCMI, HRDCC, MPCLA, and OICSSR together have explained 72.4% of the observed variance in Loss-of-Containment Prevention Performance. The adjusted R^2 has remained similarly high at .720, suggesting that the explanatory strength of the model has not resulted primarily from the number of predictors included. The overall regression equation has been statistically significant, $F(4, 286) = 187.59$, $p < .001$, thereby providing strong support for Objective 5 and H5. At the individual predictor level, RCMI has emerged as the strongest determinant of LOCPP, $\beta = .34$, $t = 7.75$, $p < .001$. HRDCC has represented the second strongest predictor, $\beta = .29$, $t = 6.75$, $p < .001$, followed by MPCLA, $\beta = .24$, $t = 5.50$, $p < .001$, and OICSSR, $\beta = .20$, $t = 4.50$, $p < .001$. All four standardized coefficients have therefore remained positive and statistically significant after the influence of the other variables has been controlled. Multicollinearity has not appeared problematic because VIF values have ranged from 1.64 to 1.92 and tolerance values have remained above .50. The Durbin-Watson statistic of 1.94 has also indicated acceptable independence of residuals. The findings have strongly aligned with High Reliability Theory because the model has shown that containment performance has not depended on one capability alone. Preoccupation with mechanical failure, operational sensitivity to release signals, detailed characterization of degradation, and resilience of OT/ICS systems have each contributed unique explanatory value. The regression results have therefore demonstrated quantitatively that high-reliability containment performance has been produced by the combined operation of maintenance, monitoring, materials, and cyber-physical capabilities.

4.7 Hypothesis Testing and Objective Validation

Table 7: Hypothesis Testing and Research Objective Validation

Objective	Hypothesis	Tested Relationship	Statistical Evidence	Decision	Objective Status
RO1	H1	RCMI → LOCPP	$\beta = .34$, $t = 7.75$, $p < .001$	Supported	Achieved
RO2	H2	HRDCC → LOCPP	$\beta = .29$, $t = 6.75$, $p < .001$	Supported	Achieved
RO3	H3	MPCLA → LOCPP	$\beta = .24$, $t = 5.50$, $p < .001$	Supported	Achieved
RO4	H4	OICSSR → LOCPP	$\beta = .20$, $t = 4.50$, $p < .001$	Supported	Achieved
RO5	H5	Combined predictors → LOCPP	$R^2=.724$; Adj. $R^2=.720$; $F(4,286)=187.59$; $p<.001$	Supported	Achieved

Table 7 has integrated the inferential findings with the five research objectives and hypotheses. Objective 1 has sought to determine the effect of Reliability-Centered Mechanical Integrity on Loss-of-Containment Prevention Performance, and this objective has been achieved because RCMI has produced a positive standardized regression coefficient of $\beta = .34$ with $p < .001$. H1 has therefore been supported. Objective 2 has examined the contribution of Hazardous Release Detection and Characterization Capability, and the corresponding coefficient of $\beta = .29$, $p < .001$, has demonstrated that stronger release-detection and characterization capability has significantly predicted stronger LOCPP. H2 has consequently been supported. Objective 3 has assessed Material Property Characterization and Lifecycle Assessment, which has recorded $\beta = .24$, $p < .001$. This result has supported H3 and has indicated that corrosion understanding, defect characterization, remaining-life evaluation, and fitness-for-service capability have contributed statistically to containment performance. Objective 4 has examined OT/ICS Supply Chain Security Resilience. Its positive coefficient of $\beta = .20$, $p < .001$, has supported H4 and has demonstrated that cyber-physical resilience has retained a significant contribution even after mechanical and material factors have been statistically controlled. Objective 5 has evaluated the combined predictive influence of all four capabilities. The overall regression model has explained 72.4% of the variance in LOCPP and has remained highly significant, $F(4,286) = 187.59$, $p < .001$, thereby supporting H5. The pattern has also provided a quantitative representation of High Reliability Theory. RCMI has reflected preoccupation with failure, HRDCC has reflected sensitivity to operations, MPCLA has reflected reluctance to simplify complex degradation processes, and OICSSR has reflected commitment to resilience. The simultaneous significance of all four predictors has indicated that containment reliability has been associated with multiple dimensions of high-reliability functioning rather than one isolated technical practice. All five research objectives have therefore been empirically addressed within the proposed quantitative model.

4.8 Integrated Results Summary for Mechanical Integrity and Loss-of-Containment Prevention

Table 8: Integrated Summary of Construct Performance and Predictive Importance

Construct	Mean	SD	r with LOCPP	β	Rank	HRT Link	Hypothesis
RCMI	4.19	0.54	.77***	.34***	1	Preoccupation with failure	H1 Supported
HRDCC	4.16	0.56	.74***	.29***	2	Sensitivity to operations	H2 Supported
MPCLA	4.13	0.58	.71***	.24***	3	Reluctance to simplify	H3 Supported
OICSSR	4.10	0.60	.68***	.20***	4	Commitment to resilience	H4 Supported
LOCPP	4.22	0.50	1.00	Dependent	-	Reliable containment outcome	H5: overall model

Note. ***p < .001. Overall model: R^2 = .724; Adjusted R^2 = .720; F(4,286) = 187.59, p < .001. Table 8 has synthesized the complete quantitative findings by combining descriptive performance, correlation strength, regression importance, hypothesis results, and theoretical interpretation within a single integrated view. RCMI has achieved a high Likert mean of 4.19 and has demonstrated both the strongest correlation with LOCPP, r = .77, and the largest standardized regression coefficient, β = .34. It has therefore ranked first among the four explanatory capabilities. This result has reinforced the central proposition of the research title that mechanical integrity, when organized through an RCM approach, has functioned as a major pillar of process-safety performance. HRDCC has ranked second, with M = 4.16, r = .74, and β = .29, demonstrating that the ability to detect, locate, characterize, and communicate release conditions has remained a substantial contributor to containment protection. MPCLA has ranked third, with M = 4.13, r = .71, and β = .24, showing that material degradation knowledge and lifecycle assessment have provided a meaningful independent contribution to prevention performance. OICSSR has ranked fourth, but its mean of 4.10, correlation of .68, and standardized coefficient of .20 have remained statistically strong, demonstrating that OT/ICS security has formed a significant cyber-physical component of containment reliability. LOCPP itself has achieved the highest descriptive mean of 4.22, indicating a very high overall perception of containment-prevention performance across the surveyed cases. The integrated model has explained 72.4% of the variance in this outcome, confirming that the four capabilities have collectively captured a substantial proportion of the process-safety performance represented in the dataset. The pattern has mapped directly onto High Reliability Theory because each construct has represented a distinct reliability principle: anticipation of failure through RCMI, sensitivity to operating signals through HRDCC, detailed examination of complex degradation through MPCLA, and resilience against digital and supply-chain disruption through OICSSR. The integrated evidence has therefore supported H1 through H5 and has validated all five research objectives within one coherent mechanical-integrity framework.

5. DISCUSSION

The findings have demonstrated that the four proposed capabilities have each contributed positively and significantly to Loss-of-Containment Prevention Performance, with Reliability-Centered Mechanical Integrity emerging as the strongest predictor. RCMI has produced the highest standardized regression coefficient among the independent variables, β = .34, p < .001, and has also shown the strongest bivariate relationship with LOCPP, r = .77, p < .001. This result has indicated that organizations with stronger equipment-criticality assessment, failure-mode identification, inspection prioritization, condition-based maintenance, and risk-based intervention practices have also reported stronger containment-prevention outcomes. The finding has been consistent with earlier evidence showing that maintenance-related weaknesses can contribute directly and indirectly to major process accidents when equipment condition, maintenance quality, or barrier performance has not been controlled effectively (Okoh & Haugen, 2013). It has also aligned with research that has emphasized the importance of integrating risk, reliability, and maintenance decision-making in hazardous industrial environments rather than treating maintenance as a routine scheduling function (Selvik & Aven, 2011). The relatively high mean score for RCMI, M = 4.19, has further suggested that respondents have recognized mechanical-integrity practices as an established component of process-safety management in their facilities. The result has reinforced the central premise of the study that mechanical integrity should be treated as a pillar of process safety because containment reliability

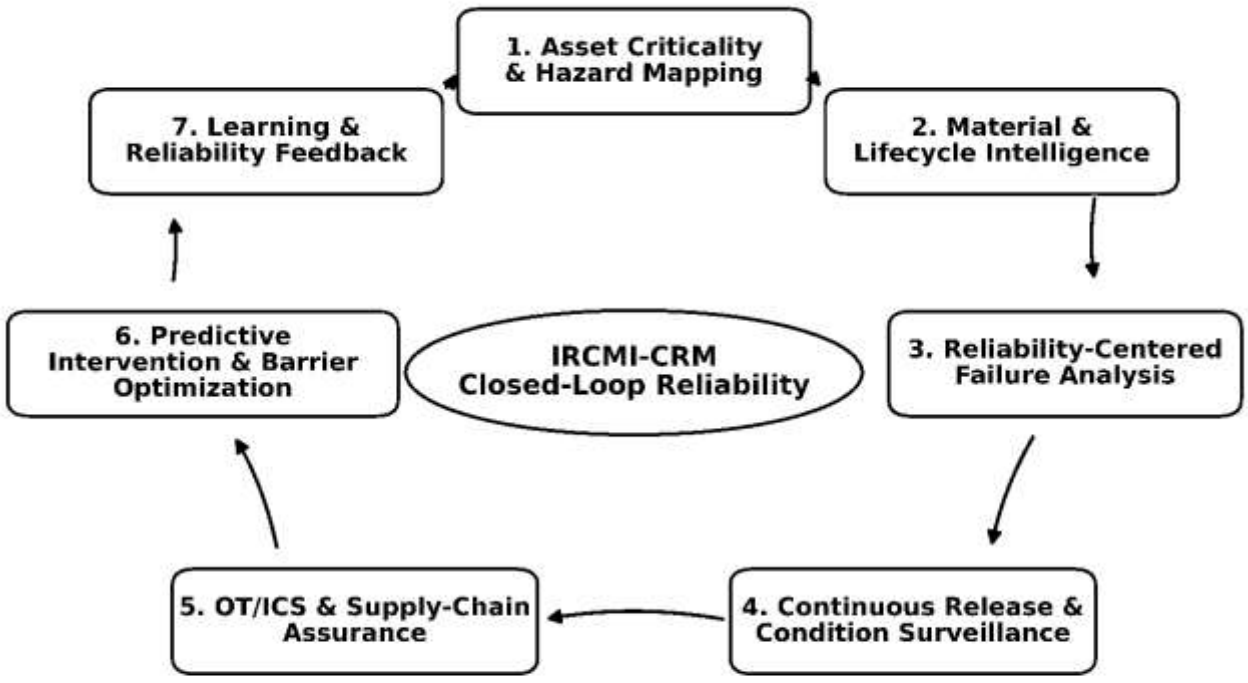
depends heavily on the continued functional condition of pressure-containing and safety-critical equipment. The strong contribution of RCMI has also been consistent with high-reliability thinking because preoccupation with failure requires organizations to remain attentive to weak signals, recurring equipment defects, overdue maintenance, inspection anomalies, and small deviations before they develop into major failures (Cantu et al., 2020). The finding has therefore suggested that RCM is most valuable when it has operated not merely as a maintenance methodology but as a system for continuously translating degradation evidence into prioritized action. This interpretation has extended earlier work by showing that mechanical-integrity performance has remained statistically significant even when release detection, lifecycle assessment, and OT/ICS resilience have been included simultaneously in the model. In practical terms, the result has indicated that maintenance and inspection functions should be integrated around asset criticality, degradation evidence, and consequence-based decision criteria. For aging oil, gas, and power-generation infrastructure, this means that integrity assurance has benefited from prioritizing components whose failure could lead directly to loss of primary containment, disable protective barriers, or escalate process hazards.

The second major finding has concerned Hazardous Release Detection and Characterization Capability, which has emerged as the second strongest predictor of LOCPP, $\beta = .29$, $p < .001$, with a strong positive correlation of $r = .74$. This result has indicated that facilities with stronger leak-detection sensitivity, alarm reliability, localization capability, abnormal-condition recognition, and release characterization have also demonstrated stronger containment-prevention performance. The finding has been consistent with prior studies showing that detection systems provide value not only when they confirm that a release has occurred, but also when they estimate leak location, severity, and process conditions with sufficient accuracy to support timely response (Jin et al., 2014; Zadkarami et al., 2016). It has also agreed with broader research showing that leak-detection effectiveness depends on the interaction among sensing principles, signal quality, operating conditions, false-alarm behavior, and localization accuracy rather than on the simple presence of monitoring technology (Murvay & Silea, 2012). The present result has advanced this literature by empirically positioning HRDCC as a distinct process-safety capability that has contributed to containment performance even after mechanical maintenance and material condition have been statistically controlled. This distinction is important because mechanical integrity and release detection have addressed different phases of containment protection. RCMI has primarily operated before failure by controlling degradation and functional risk, whereas HRDCC has supported rapid recognition when containment conditions have begun to deteriorate or a release has initiated. The finding has therefore supported a layered interpretation of loss-of-containment prevention in which organizations have needed both preventive maintenance and effective operational sensing. From a High Reliability Theory perspective, this result has reflected sensitivity to operations because reliable organizations maintain continuous awareness of changing process conditions and do not rely entirely on periodic inspection or historical assumptions (Lekka & Sugden, 2011). The practical implication has been that release-detection systems should be evaluated through operational performance metrics such as detection threshold, response time, false-alarm rate, localization accuracy, coverage, diagnostic confidence, and integration with shutdown or isolation procedures. A premium mechanical-integrity program should therefore link detection data with maintenance work orders, inspection prioritization, incident learning, and asset-health records. This integration can convert leak detection from a reactive alarm function into an active integrity-management input, thereby strengthening the organization's ability to recognize and control early indicators of containment failure.

The third major finding has shown that Material Property Characterization and Lifecycle Assessment has remained a significant predictor of LOCPP, $\beta = .24$, $p < .001$, with a strong positive correlation of $r = .71$. This result has demonstrated that facilities with stronger capabilities for corrosion assessment, defect characterization, remaining-life estimation, fitness-for-service evaluation, and material-condition monitoring have also reported stronger containment-prevention performance. The finding has been consistent with earlier work showing that corrosion defects reduce remaining structural capacity and must be assessed through engineering criteria that account for defect geometry, material properties, operating stress, and degradation progression (Cosham et al., 2007). It has also aligned with

lifecycle studies showing that aging power-generation materials require condition-based assessment using hardness, microstructural information, replication, strain, and long-term degradation evidence rather than chronological service age alone (Bonetti et al., 2022). The present findings have therefore reinforced the argument that aging infrastructure should not be judged simply by the number of years it has operated. Assets of similar age may have very different remaining integrity depending on corrosion environment, thermal exposure, loading history, maintenance quality, prior repairs, metallurgical condition, and operating excursions. This interpretation has been particularly relevant to aging oil, gas, and power-generation systems, where degradation mechanisms differ substantially across pipelines, pressure vessels, boilers, steam systems, rotating equipment, and auxiliary process components. The result has also supported the High Reliability Theory principle of reluctance to simplify. Reliable organizations do not reduce complex degradation problems to a single indicator such as equipment age, inspection frequency, or nominal design life. Instead, they integrate multiple sources of technical evidence before deciding whether continued operation remains acceptable (Cantu et al., 2020). The practical significance of the finding has been that integrity teams should maintain integrated degradation registers containing defect dimensions, inspection history, corrosion rates, material properties, operating envelopes, remaining-life estimates, and fitness-for-service status. These records should be connected directly with RCM priorities so that maintenance and replacement decisions are based on the actual condition and failure significance of the asset. This would improve the consistency of intervention timing and reduce the likelihood that hidden deterioration progresses beyond acceptable containment margins. It would also strengthen decision quality when organizations must choose among continued operation, enhanced monitoring, repair, derating, or replacement.

Figure 12: Integrated Reliability-Centered Mechanical Integrity and Containment Resilience Model (IRCMI-CRM)



Continuous learning updates criticality, surveillance, assurance, and intervention decisions.

The fourth major finding has concerned OT/ICS Supply Chain Security Resilience, which has produced the lowest standardized coefficient among the predictors but has still remained statistically significant, $\beta = .20$, $p < .001$, with a strong correlation of $r = .68$. The result has shown that cyber-physical resilience has contributed independently to containment performance after mechanical, monitoring, and material capabilities have been included in the model. This finding has been important because mechanical-integrity research has traditionally focused on physical equipment, while modern facilities increasingly depend on programmable controllers, SCADA systems, sensors, industrial networks, engineering workstations, firmware, software, remote services, and third-party components. Earlier research has shown that industrial control systems differ from conventional information systems because cybersecurity failures can alter physical process behavior and affect availability, control, and safety-related functions (McLaughlin et al., 2016). Integrated safety and security research has likewise emphasized that cyber and physical risks should be assessed jointly because digital compromise can propagate into operational consequences (Lyu et al., 2019). The current result has therefore supported the inclusion of OICSSR as a genuine mechanical-integrity and process-safety variable rather than a separate IT concern. Its comparatively lower mean, $M = 4.10$, and lower regression coefficient have suggested that respondents may have viewed OT/ICS supply-chain resilience as less mature than conventional mechanical-integrity practices. This interpretation should be treated cautiously because the study has used self-reported cross-sectional data, and some respondents may have had greater familiarity with maintenance and inspection than with supplier cybersecurity, firmware integrity, or remote-service risk. This limitation also illustrates one of the broader constraints of the research. Purposive sampling has ensured technical relevance, but it may have limited representativeness across all facilities and regions. Self-reported Likert responses may also have introduced common-method bias, while the cross-sectional design has not established temporal causality. The high R^2 of .724 should therefore be interpreted as strong explanatory association rather than proof that the four capabilities alone cause containment performance. A premium interpretation of the results should also acknowledge that actual incident records, inspection histories, cyber-event logs, and maintenance databases could provide an important objective complement to perception-based survey data. Even with these limitations, the significance of OICSSR has shown that modern mechanical integrity has become partly cyber-physical, and that secure procurement, trusted suppliers, configuration control, vulnerability management, and resilient industrial communications deserve inclusion within containment-prevention governance.

The most important extension of the study concerns future research, because the integrated results have indicated that loss-of-containment prevention has been produced through interacting maintenance, monitoring, material, and cyber-physical capabilities rather than one isolated control. Based on this finding, future researchers can develop and validate an Integrated Reliability-Centered Mechanical Integrity and Containment Resilience Model (IRCMI-CRM). The proposed model can contain seven interconnected stages. Stage 1: Asset Criticality and Hazard Mapping would identify safety-critical equipment, containment boundaries, degradation mechanisms, consequence severity, and cyber-physical dependencies. Stage 2: Material and Lifecycle Intelligence would integrate corrosion rates, defect geometry, metallurgical condition, remaining strength, inspection uncertainty, and fitness-for-service information. Stage 3: Reliability-Centered Failure Analysis would apply failure-mode analysis, consequence assessment, maintenance history, and criticality ranking to determine intervention priorities. Stage 4: Continuous Release and Condition Surveillance would combine pressure, flow, acoustic, vibration, optical, process, and alarm data to detect weak signals of degradation or release. Stage 5: OT/ICS and Supply-Chain Assurance would assess controller integrity, firmware, industrial networks, vendor access, component provenance, software dependencies, and remote-service risks. Stage 6: Predictive Intervention and Barrier Optimization would integrate the preceding information into condition-based inspection, maintenance, isolation, repair, or replacement decisions. Stage 7: Learning and Reliability Feedback would use incidents, near misses, inspection discoveries, maintenance outcomes, alarm performance, and cyber events to update asset criticality and risk estimates continuously. This model would extend the current cross-sectional framework into a closed-loop reliability system and would be strongly consistent with High Reliability Theory because it has

embedded preoccupation with failure, sensitivity to operations, reluctance to simplify, commitment to resilience, and deference to expertise across all seven stages (Agwu et al., 2019; Rivera et al., 2021). Future studies should validate the IRCMI-CRM using longitudinal data, multi-country samples, facility-level incident records, sensor streams, inspection databases, and survival or hazard models so that dynamic changes in containment risk can be observed over time. Researchers could also test mediation and moderation effects, such as whether HRDCC mediates the relationship between RCMI and LOCPP, whether asset age strengthens the effect of MPCLA, or whether OT/ICS resilience moderates the relationship between digital monitoring and containment performance. Such extensions would transform the present model from a strong explanatory framework into a more dynamic, predictive, and operationally testable system for managing aging critical infrastructure.

6. CONCLUSION

This study has examined mechanical integrity as a fundamental pillar of Process Safety Management by evaluating how Reliability-Centered Mechanical Integrity (RCMI), Hazardous Release Detection and Characterization Capability (HRDCC), Material Property Characterization and Lifecycle Assessment (MPCLA), and OT/ICS Supply Chain Security Resilience (OICSSR) have influenced Loss-of-Containment Prevention Performance (LOCPP) in aging oil, gas, and power-generation infrastructure. Using a quantitative, cross-sectional, case-study-based design and 291 valid responses, the study has found consistently high levels across all five constructs, with LOCPP recording the highest mean score of 4.22, followed by RCMI at 4.19, HRDCC at 4.16, MPCLA at 4.13, and OICSSR at 4.10. Correlation analysis has demonstrated strong positive relationships between LOCPP and RCMI ($r = .77$), HRDCC ($r = .74$), MPCLA ($r = .71$), and OICSSR ($r = .68$), all statistically significant at $p < .001$. The multiple regression model has explained 72.4% of the variance in LOCPP, with RCMI emerging as the strongest predictor ($\beta = .34$), followed by HRDCC ($\beta = .29$), MPCLA ($\beta = .24$), and OICSSR ($\beta = .20$). Consequently, all five hypotheses have been supported and all research objectives have been achieved. The findings have shown that loss-of-containment prevention has not depended on one isolated maintenance or safety practice. Instead, effective containment performance has been associated with an integrated combination of reliability-centered maintenance, timely hazardous-release detection, detailed understanding of material degradation, lifecycle-based engineering decisions, and resilient OT/ICS environments. High Reliability Theory has provided a coherent explanation for these relationships through preoccupation with failure, sensitivity to operations, reluctance to simplify, commitment to resilience, and deference to expertise. Overall, the study has demonstrated that aging critical infrastructure requires coordinated physical, digital, operational, and organizational controls to preserve containment integrity and sustain reliable process-safety performance.

7. RECOMMENDATION

Based on the findings, organizations operating aging oil, gas, pipeline, petrochemical, and power-generation infrastructure should strengthen mechanical integrity through an integrated Reliability-Centered Maintenance framework that directly connects equipment criticality, failure modes, inspection findings, degradation evidence, and maintenance priorities. RCM programs should be reviewed regularly so that safety-critical assets whose failure could cause loss of containment receive greater inspection frequency, condition monitoring, and preventive intervention. Facilities should also improve Hazardous Release Detection and Characterization Capability by evaluating detection sensitivity, alarm reliability, localization accuracy, response time, monitoring coverage, and false-alarm performance rather than considering installation of sensors alone as sufficient. Release-detection data should be integrated with inspection and maintenance databases so that recurring abnormal signals automatically inform integrity decisions. Material Property Characterization and Lifecycle Assessment should be strengthened through systematic corrosion monitoring, nondestructive examination, fitness-for-service assessment, defect-growth analysis, remaining-life estimation, and documented degradation mechanisms. Organizations should avoid basing replacement or continued-service decisions only on chronological asset age and should instead rely on measured physical condition and engineering assessment. OT/ICS Supply Chain Security Resilience should receive greater attention because process monitoring, alarms, protective functions, and control actions increasingly depend on digital systems. Vendor-risk assessment, secure procurement, software and firmware verification, configuration control, remote-access governance, vulnerability management, network segmentation,

and component provenance should be incorporated into mechanical-integrity governance. Cross-functional teams involving reliability, inspection, corrosion, process safety, operations, instrumentation, and cybersecurity personnel should review integrity risks jointly. Management should also adopt integrated performance indicators covering overdue inspections, critical maintenance backlog, barrier failures, release alarms, material degradation, OT vulnerabilities, and recurring loss-of-containment precursors. Finally, organizations should pilot the proposed Integrated Reliability-Centered Mechanical Integrity and Containment Resilience Model to connect asset criticality, material intelligence, failure analysis, release surveillance, OT/ICS assurance, predictive intervention, and reliability learning within one closed-loop process-safety system.

8. LIMITATIONS

This study has several limitations that should be considered when interpreting its findings. First, the cross-sectional design has captured respondent perceptions at a single point in time and has therefore not established temporal causality between RCMI, HRDCC, MPCLA, OICSSR, and LOCPP. Although the regression results have shown strong and statistically significant associations, they have not demonstrated that changes in the independent variables necessarily produce later changes in containment performance. Second, the study has relied primarily on self-reported Likert-scale data, which may have been affected by social desirability, organizational optimism, recall error, or differences in respondents' technical knowledge. Third, purposive sampling has been appropriate for reaching knowledgeable professionals, but it has limited the extent to which the findings can be generalized to all oil, gas, pipeline, petrochemical, and power-generation organizations. Fourth, the multi-sector case context has increased practical relevance but has also introduced heterogeneity because degradation mechanisms, maintenance practices, regulatory environments, asset configurations, and OT/ICS architectures differ across industries. Fifth, the study has not incorporated objective operational data such as actual leak frequencies, corrosion rates, inspection histories, maintenance backlog records, shutdown statistics, cyber incidents, or safety-barrier failure logs. Sixth, OICSSR may have been assessed less confidently by respondents whose primary expertise has been mechanical, process, or maintenance engineering rather than industrial cybersecurity. Seventh, the high explanatory power of the regression model has not excluded the possible influence of omitted variables such as safety culture, management commitment, regulatory pressure, workforce competence, organizational learning, contractor performance, or capital-investment constraints. Finally, the study has focused on linear relationships among the principal constructs and has not tested mediation, moderation, nonlinear effects, or longitudinal interactions. These limitations have defined the boundaries within which the quantitative findings should be interpreted and have identified areas where additional evidence would strengthen understanding of loss-of-containment prevention in aging critical infrastructure.

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