

RCM and PSM Strategies for Strengthening Asset Integrity Across U.S. Energy Facilities: A Systematic Meta-Analysis

Ashik Mahmud¹;

[1]. Sr. Engineer – Integrated Asset Management, L&T Technology Services Limited, Colorado, USA,
Email: lu20566070@gmail.com

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Abstract

This study examines how Reliability-Centered Maintenance, Process Safety Management, advanced manufacturing capability, and energy storage and grid-integration resilience contribute to Long-Term Asset Integrity Performance across U.S. energy facilities. The research addresses fragmentation among maintenance reliability, process-safety governance, digital maintenance technologies, and storage and grid-resilience practices, which can weaken failure identification, maintenance prioritization, hazard control, degradation response, and coordination across energy systems. The purpose is to determine the individual and combined effects of Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability on Long-Term Asset Integrity Performance. A quantitative, cross-sectional, multiple-case-study-based survey design was employed across U.S. energy-facility cases involving generation, transmission and distribution, renewable energy, energy storage and grid integration, process-energy, and multi-asset environments. Purposive sampling produced 298 usable responses from 330 questionnaires after screening 312 returns. Data were collected using a five-point Likert questionnaire and analyzed with descriptive statistics, Cronbach's alpha, KMO and Bartlett's tests, exploratory factor analysis, Pearson correlation, multiple regression, VIF, tolerance, Durbin-Watson analysis, and residual diagnostics. Measurement quality was strong, with alpha values of .87 to .91, overall alpha = .92, KMO = .903, and Bartlett's test $p < .001$. LTAIP recorded $M = 4.23$, $SD = 0.50$. Correlations with LTAIP were PSMIE, $r = .77$, ESGIRC, $r = .74$, RCMIE, $r = .72$, and AMMC, $r = .68$, all $p < .001$. The regression model explained 72.4% of LTAIP variance, $R^2 = .724$, adjusted $R^2 = .720$, $F(4,293) = 192.15$, $p < .001$. PSMIE was the strongest predictor, $\beta = .31$, followed by ESGIRC, $\beta = .28$, RCMIE, $\beta = .25$, and AMMC, $\beta = .19$. The findings support H1 through H5 and imply that long-term asset integrity improves when maintenance, safety, digital capability, and grid-resilience systems operate as coordinated socio-technical capabilities.

Keywords

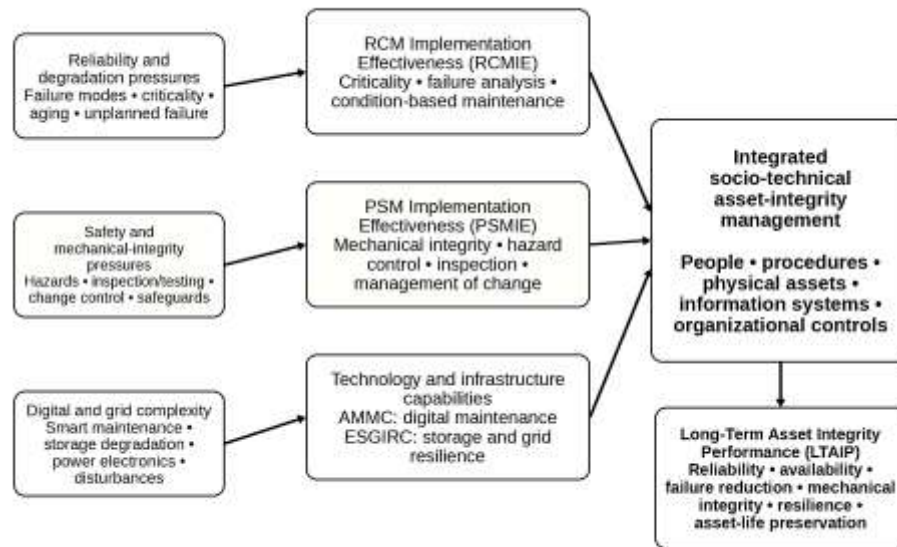
Reliability-Centered Maintenance; Process Safety Management; Asset Integrity; Advanced Maintenance Technologies; Energy Storage and Grid Resilience

ASSET-INTEGRITY CONTEXT AND RESEARCH MOTIVATION

Reliability-Centered Maintenance (RCM) can be defined as a structured maintenance decision system that identifies the functions of physical assets, determines credible failure modes and their consequences, and selects preventive, predictive, condition-based, or corrective actions according to the significance of each failure to system reliability, safety, and operating performance. Asset integrity, in a related sense, concerns the sustained ability of equipment, structures, protective systems, and associated organizational controls to perform their required functions safely and reliably throughout their operating life. Process Safety Management (PSM) complements this reliability perspective by organizing technical, procedural, maintenance, human, and managerial controls around the prevention of major process failures and the preservation of mechanical integrity. In A reliability-centered asset maintenance method (pp. 75-82), maintenance is treated as a reliability-centered asset decision problem in which component failure behavior, practical maintenance knowledge, reliability outcomes, and economic consequences are considered together rather than independently (Bertling et al., 2005). The power-generating-plant analysis in Development of a risk-based maintenance strategy (pp. 69-81) similarly establishes that equipment criticality, failure probability, failure consequences, and maintenance prioritization are interdependent dimensions of plant reliability and risk control (Krishnasamy et al., 2005). These definitions have international significance because modern energy facilities function as interconnected technical and organizational infrastructures whose reliable performance depends not only on equipment condition but also on coordination among operators, engineers, maintenance personnel, safety systems, procedures, and organizational responsibilities (Scholten, 2013). Socio-Technical Systems Theory provides an appropriate foundation for interpreting this interaction because safety and reliability emerge from relationships among human, organizational, and technological components rather than from isolated equipment performance alone (Waterson et al., 2015). Studies of offshore asset integrity have likewise identified organizational practices, technical degradation, resource allocation, inspection, maintenance, and management processes as interconnected elements of integrity performance (Kusumawardhani et al., 2016). The close relationship between plant reliability and mechanical integrity has also been demonstrated through integrated maintenance, engineering, operations, and process-safety practices (Vaughen et al., 2011). Within energy infrastructure, RCM provides a particularly relevant means of converting asset condition and failure-risk information into differentiated maintenance decisions. Rather than allocating maintenance resources uniformly, RCM identifies critical components and failure modes whose deterioration can produce disproportionate reliability, safety, outage, or economic consequences. Research on deregulated power systems has shown that critical-component identification can support maintenance prioritization while maintaining required reliability and power-quality levels (Ghorani et al., 2015). Condition-based maintenance research on wind turbines has similarly demonstrated that deterioration state, failure modes, environmental conditions, and maintenance timing can be integrated into reliability-oriented decision models (Byon & Ding, 2010). More recent distribution-system research has connected failure-mode and effects analysis directly with RCM optimization, allowing higher-risk failure modes to receive maintenance strategies that recognize practical, cost, and network constraints (Enjavimadar & Rastegar, 2022). In A three-stage reliability-centered framework, critical feeder identification, failure-mode prioritization, and maintenance-strategy assignment are integrated within a single power-distribution RCM structure (Moradi-Sarvestani et al., 2024). PSM addresses a complementary dimension by organizing systematic controls around process hazards, mechanical integrity, inspection, testing, maintenance, operational discipline, and organizational oversight. Process-safety metrics research has established that leading and lagging indicators are needed to assess management-system health and maintain attention to process-safety performance (Cummings, 2009). In Asset/mechanical integrity: A PSM element that still bedevils (pp. 512-518), asset and mechanical integrity are treated as central PSM concerns involving inspection, testing, preventive maintenance, equipment identification, and engineering practices (Hazzan & Min, 2022). Research on mature process plants further connects mechanical integrity, risk-based inspection, RCM, equipment condition, useful life, and process safety within integrated asset-management practice (Matheus et al., 2023). These streams provide the technical basis for examining RCM Implementation Effectiveness and PSM Implementation Effectiveness as distinct but connected determinants of Long-Term Asset Integrity

Performance.

Figure 1: Integrated Asset-Integrity Context Across U.S. Energy Facilities



The maintenance environment of contemporary energy facilities also includes advanced manufacturing, digital sensing, predictive analytics, digital twins, intelligent diagnostics, automated inspection, and data-supported repair capabilities, making asset integrity increasingly dependent on the quality of interactions between physical assets and digital maintenance systems. Advanced manufacturing and maintenance capability therefore extends beyond production technology and includes the ability to fabricate, restore, monitor, diagnose, and maintain critical assets using digitally enabled techniques. Additive manufacturing provides a direct example because on-demand or locally produced spare components can be incorporated into preventive-maintenance strategies where conventional spare-part availability constrains equipment support (Lastra et al., 2022). In Digital twin in energy industry (pp. 3704-3726), digital-twin architecture for power plants combines physical models, sensor information, operational data, anomaly detection, simulation, and system-level digital representation to support reliability, availability, and maintainability objectives (Sleiti et al., 2022). Data-driven asset-integrity research in the oil and gas sector also shows that artificial intelligence can connect incident data, inspection, testing, maintenance, construction, human factors, and asset reliability within a structured integrity-management environment (Sattari et al., 2022). Renewable-energy maintenance research strengthens this relationship because accurate remaining-useful-life estimation allows equipment health information to be transformed into more targeted maintenance decisions. Deep-learning analysis of wind turbines has demonstrated the use of multi-parameter operating data to forecast remaining useful life for maintenance planning (Shah et al., 2024). At the system level, the integration of AI into advanced microgrids has been examined as a sociotechnical safety problem in which autonomous technical functions interact with organizational structures and other critical system components (Gazos et al., 2025). Physics-informed predictive maintenance has also combined equipment degradation behavior, environmental operating conditions, and adaptive decision algorithms in wind-energy applications, illustrating the close relationship between advanced computational techniques and reliability-centered maintenance decisions (Zhu et al., 2025). Accordingly, Advanced Manufacturing and Maintenance Capability in the present study represents an integrated technological-maintenance construct rather than an isolated manufacturing variable. Energy storage and grid integration introduce another asset-integrity dimension because storage assets combine electrochemical cells, battery-management systems, converters, thermal-management equipment, communication systems, protection, controls, and grid interfaces whose degradation and failure behavior can influence both equipment condition and network reliability. Reliability assessment of battery energy storage systems has demonstrated that stationary operating applications expose

batteries and power-electronic converters to different duty cycles, wear mechanisms, random failures, capacity degradation, and lifetime distributions (Bakeer et al., 2022). Broader assessments of energy-storage reliability also show that storage interacts with grid-flexibility technologies, frequency regulation, voltage support, demand management, renewable integration, communication infrastructure, and network operating conditions rather than functioning as an independent asset (Ayesha et al., 2023). Degradation is especially relevant to long-term asset integrity because repeated operating cycles can create a trade-off between reliability services supplied to the network and accelerated deterioration of storage components. A reliability framework incorporating grid-scale BESS degradation has demonstrated the need to account simultaneously for reliability benefits, cycle degradation, capacity loss, and lifecycle asset-management considerations (Galeela et al., 2023). In Review on reliability assessment of energy storage systems (pp. 695-715), reliability is examined through state models, failure and repair measures, probabilistic methods, operating strategies, charging and discharging behavior, and system-level integration, establishing storage reliability as both an equipment and power-system problem (Yan et al., 2024). Current reviews of grid-connected storage likewise identify battery-management systems, state-of-charge control, conversion technologies, hybrid storage, and grid interaction as central to dependable energy-storage operation (Ahmad et al., 2025). Direct research linking BESS with electricity-distribution asset management has additionally incorporated network condition, security of supply, lifecycle costs, operational requirements, and alternative asset-development paths into storage evaluation (Haakana et al., 2025). These findings support treating Energy Storage and Grid Integration Resilience Capability as a distinct explanatory construct in the study of long-term integrity across U.S. energy facilities.

The central research problem emerges from the fragmentation of these bodies of knowledge. RCM research provides rigorous mechanisms for failure prioritization and maintenance selection, PSM research concentrates on process hazards and mechanical integrity, advanced manufacturing research emphasizes technologically enabled maintenance and component support, while energy-storage and grid-integration research concentrates on degradation, reliability, flexibility, and system interaction. Asset-integrity studies have already shown that maintenance planning cannot be separated from organizational strategy, lifecycle management, safety requirements, inspection practices, and the condition of physical assets (Kusumawardhani et al., 2017). Risk-based maintenance research in power-generating units has demonstrated that availability and asset life are connected with diagnostic intervals, degradation risk, equipment criticality, and maintenance planning (Rusin & Wojacek, 2019). Process-facility research further shows that performance measurement can connect process-safety management health with corrective organizational and operational action (Diaz & Watts, 2020). Condition-based maintenance optimization in electrical distribution systems similarly demonstrates that maintenance decisions must account for inspection states, structural dependence, failure information, and system-level cost and reliability objectives (Wang et al., 2023). From the Socio-Technical Systems Theory perspective adopted in this research, these constructs can be organized as mutually interacting subsystems: RCM represents reliability-oriented maintenance coordination, PSM represents safety and organizational control, advanced manufacturing represents technology-enabled asset support, and energy-storage and grid-integration capability represents interconnected energy-system resilience. Sociotechnical safety research establishes that performance depends on interactions across technological, human, organizational, task, and environmental levels, while energy-infrastructure research demonstrates that organizational structures are inseparable from technical reliability (Scholten, 2013; Waterson et al., 2015). The present quantitative, cross-sectional, multiple-case-study-based research therefore examines how RCM Implementation Effectiveness, PSM Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability are individually and collectively associated with Long-Term Asset Integrity Performance across selected U.S. energy facilities.

Background of the Study

Asset integrity has become a critical concern across U.S. energy facilities because the safe, reliable, and efficient performance of energy infrastructure depends on the continued functionality of complex physical, digital, organizational, and operational systems. Energy facilities increasingly operate through interconnected equipment such as turbines, generators, transformers, pipelines, pressure

vessels, pumps, power-electronic converters, battery energy storage systems, sensors, control systems, and grid-interfacing technologies. Maintaining the integrity of these assets requires more than periodic maintenance because failures can develop through mechanical degradation, thermal stress, corrosion, component fatigue, electrical faults, software-related control deficiencies, improper maintenance practices, ineffective safety procedures, and inadequate coordination among technical personnel. Reliability-Centered Maintenance provides a structured approach for determining appropriate maintenance actions according to equipment function, failure modes, failure consequences, asset criticality, and operational risk. Process Safety Management complements this approach by emphasizing hazard identification, mechanical integrity, management of change, operating procedures, inspection, testing, maintenance discipline, employee competence, and organizational control. At the same time, advanced manufacturing techniques have expanded the technological capacity of energy organizations through digital twins, automated inspection, additive manufacturing, intelligent sensors, predictive diagnostics, condition monitoring, advanced materials, and data-supported maintenance systems. Energy storage and grid integration technologies have also introduced new asset-integrity requirements because battery systems, power electronics, converters, protection devices, and grid interfaces are exposed to degradation, cycling stress, thermal risks, and complex operational interactions. The present study therefore considers asset integrity as a socio-technical performance outcome that develops through the coordinated interaction of maintenance systems, process-safety practices, technological capabilities, human expertise, organizational procedures, and energy-system infrastructure. Guided by Socio-Technical Systems Theory, the research examines how Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability jointly contribute to Long-Term Asset Integrity Performance across selected U.S. energy facilities.

Problem Statement

The central problem addressed in this study is the continued fragmentation of maintenance reliability, process safety, advanced manufacturing capability, and energy-storage and grid-integration management within asset-integrity practices across energy facilities. Many organizations apply preventive maintenance, inspection programs, process-safety procedures, digital monitoring, and reliability tools, yet these practices may operate as separate functional activities rather than as an integrated asset-integrity system. Such fragmentation can weaken the ability of facilities to identify critical failure modes, prioritize maintenance resources, control process hazards, respond to equipment degradation, and coordinate technical and organizational actions before failures affect reliability or safety. The problem becomes more significant in facilities that combine conventional energy assets with advanced manufacturing technologies, digital monitoring platforms, battery energy storage systems, renewable-energy interfaces, and modern grid-control technologies. These environments create complex dependencies between physical equipment, software, sensors, operating personnel, maintenance teams, safety professionals, and management systems. Existing approaches often emphasize individual dimensions such as equipment reliability, mechanical integrity, predictive maintenance, process safety, or storage-system performance without quantitatively assessing their combined contribution to long-term asset integrity. There is therefore a need for an empirical framework that examines whether stronger RCM implementation, stronger PSM implementation, greater advanced manufacturing and maintenance capability, and stronger energy-storage and grid-integration resilience are associated with improved asset-integrity performance. The lack of an integrated quantitative assessment also limits the ability of managers to determine which capabilities contribute most strongly to reliability, reduced unplanned failure, equipment availability, mechanical integrity, asset-life extension, and operational resilience. This study addresses this problem through a quantitative, cross-sectional, multiple-case-study-based survey of professionals working within selected U.S. energy-facility environments and statistically evaluates the relationships among the four explanatory constructs and Long-Term Asset Integrity Performance.

Purpose and Objectives of the Study

The primary objective of this study is to determine how Reliability-Centered Maintenance, Process Safety Management, advanced manufacturing and maintenance capability, and energy-storage and

grid-integration resilience contribute to Long-Term Asset Integrity Performance across selected U.S. energy facilities. More specifically, the study seeks to evaluate the extent to which Reliability-Centered Maintenance Implementation Effectiveness is associated with improved equipment reliability, reduced failure occurrence, higher availability, more effective maintenance prioritization, and sustained asset functionality. A second objective is to examine whether Process Safety Management Implementation Effectiveness contributes to long-term asset integrity through stronger mechanical-integrity practices, inspection and testing, management of change, hazard control, maintenance procedures, and organizational safety discipline. A third objective is to assess the contribution of Advanced Manufacturing and Maintenance Capability, including digital monitoring, smart maintenance systems, automated inspection, additive manufacturing, digital twins, predictive diagnostics, and other technology-enabled maintenance practices, to the performance and longevity of critical energy assets. A fourth objective is to determine whether Energy Storage and Grid Integration Resilience Capability improves asset integrity by supporting reliable battery operation, power-electronic performance, degradation management, grid-interface stability, system monitoring, and response to operational disturbances. The study also aims to identify the strength and direction of the relationships among all research variables using descriptive statistics and Pearson correlation analysis. Furthermore, it seeks to estimate the individual predictive contribution of each independent variable and the combined explanatory power of the overall model through multiple linear regression. Guided by Socio-Technical Systems Theory, the research also aims to determine whether long-term asset integrity is better understood as an outcome of coordinated technical, human, procedural, organizational, and infrastructure capabilities rather than as the result of maintenance activity alone. These objectives collectively provide the empirical basis for evaluating the proposed hypotheses and assessing the relative importance of the four principal capabilities within modern U.S. energy-facility environments.

EVIDENCE BASE FOR INTEGRATED ENERGY ASSET INTEGRITY

The literature surrounding long-term asset integrity in energy facilities spans several related but often separately developed research domains, including Reliability-Centered Maintenance, Process Safety Management, mechanical integrity, advanced manufacturing, predictive maintenance, energy storage, grid integration, and organizational reliability. RCM literature generally focuses on the systematic identification of equipment functions, failure modes, failure consequences, asset criticality, and maintenance strategies, providing a structured basis for allocating maintenance resources toward assets whose failure could significantly affect reliability, safety, or operational continuity. PSM literature approaches integrity from a complementary perspective by emphasizing mechanical integrity, hazard analysis, inspection, testing, operating procedures, management of change, incident learning, and organizational control. These two areas establish the maintenance and safety foundations of the present study. A second major body of literature examines advanced manufacturing and technology-enabled maintenance, including digital twins, smart sensors, automated inspection, artificial intelligence, predictive diagnostics, advanced materials, and additive manufacturing. These capabilities increasingly influence how organizations detect degradation, manufacture or restore components, monitor asset condition, and plan maintenance interventions. Energy-storage research introduces additional integrity concerns associated with electrochemical degradation, thermal behavior, cycling stress, battery-management systems, power electronics, converters, and lifecycle reliability. Grid-integration literature further extends the discussion by examining system resilience, protection, communication, renewable-energy integration, disturbance response, and coordination between storage systems and network infrastructure. Although each of these research domains contributes valuable knowledge, their combined relationship with long-term asset integrity has received less integrated empirical attention. The present literature review therefore synthesizes these streams through the lens of Socio-Technical Systems Theory, which treats organizational procedures, human expertise, technological systems, maintenance practices, safety controls, and infrastructure interactions as mutually dependent components of overall system performance. The review is organized around RCM strategies, PSM and mechanical integrity, RCM-PSM integration, advanced manufacturing and technology-enabled maintenance, energy-storage reliability, grid-integration resilience, the Socio-Technical Systems theoretical framework, and the conceptual framework linking the four independent variables with Long-Term Asset Integrity Performance.

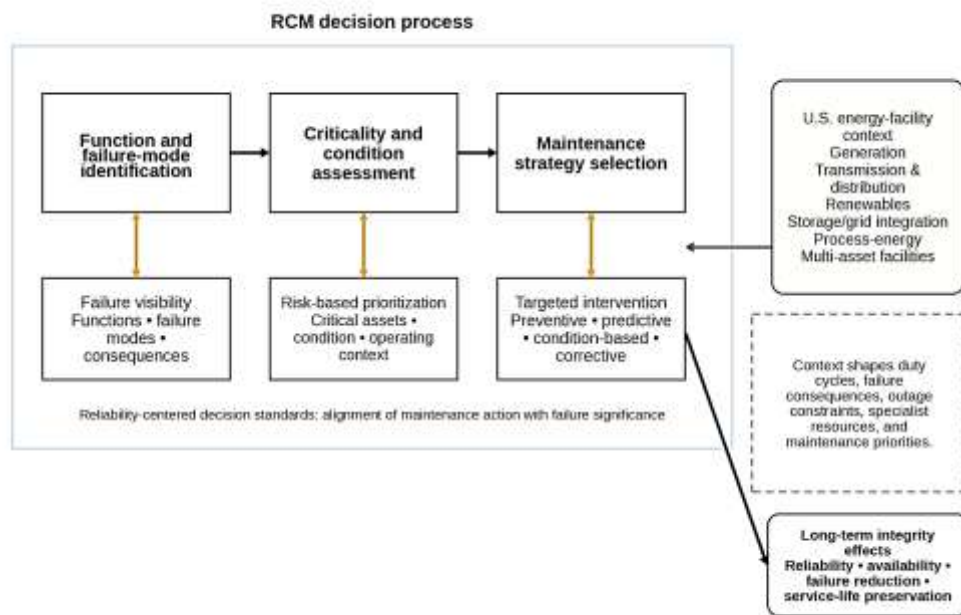
Reliability-Centered Maintenance Strategies for Energy Asset Integrity

Reliability-Centered Maintenance (RCM) has become an important strategic approach for energy asset integrity because it connects equipment functions, failure modes, criticality, maintenance tasks, and operational consequences within one structured decision process. In energy facilities, the central value of RCM lies in moving maintenance away from uniform calendar-based routines toward interventions selected according to the probability, consequence, and detectability of specific failures. In *A Systems Approach Towards Reliability-Centred Maintenance of Wind Turbines* (pp. 814-823), the analysis demonstrates that wind-turbine maintenance cannot be understood only at the component level because gearbox, generator, hydraulic, electrical, organizational, and lifecycle interactions collectively influence downtime and asset value. Its systems-oriented RCM logic is particularly relevant to energy facilities in which equipment reliability is shaped by interdependence among technical subsystems and by the manner in which operators, maintenance providers, suppliers, and engineering teams coordinate maintenance decisions. The study further demonstrates how Failure Mode, Effects and Criticality Analysis can connect failure identification with maintenance prioritization, especially where corrective interventions are expensive, technically difficult, or constrained by asset accessibility (Igba et al., 2013; Abdur & Iftekhhar, 2021). This logic corresponds closely with the present study's Socio-Technical Systems Theory foundation. RCM is therefore not treated merely as a technical algorithm; its implementation effectiveness depends on the alignment of asset information, engineering judgment, maintenance resources, operational requirements, safety expectations, and organizational routines. For U.S. energy facilities, this perspective is particularly relevant because generation, transmission, renewable-energy, storage, and process-energy assets operate under differing duty cycles, environments, and failure consequences. A mature RCM strategy therefore requires identification of functional failures, assessment of equipment criticality, selection of technically appropriate maintenance actions, and continuous coordination between personnel responsible for asset operation and technologies used for monitoring asset condition. This approach also provides a disciplined basis for distinguishing hidden, safety-related, operational, and economic failure consequences before selecting the corresponding maintenance policy for each critical asset.

The effectiveness of RCM becomes clearer when maintenance planning is examined as an optimization problem involving reliability, cost, resource allocation, equipment condition, and system-level service requirements. In *A New Approach for Reliability-Centered Maintenance Programs in Electric Power Distribution Systems Based on a Multiobjective Genetic Algorithm* (pp. 41-50), a multiobjective maintenance framework was developed to minimize preventive-maintenance costs while maximizing system reliability, with SAIDI and SAIFI constraints, equipment reliability indices, fuzzy updating, and genetic optimization used to identify efficient maintenance programs. The importance of this approach lies in recognizing that maintenance cannot simply be intensified without limits because utilities must allocate finite resources to equipment and interventions capable of producing the greatest reliability benefit (Hasan & Adnan, 2022; Piasson et al., 2016). The same principle appears at the individual-asset level in *An Approach to a Practical Optimization of Reliability Centered Maintenance: Case Study of a Power Transformer in Hydro Power Plant* (pp. 37-47), where the power transformer is treated as a critical generation asset whose failure can create prolonged plant unavailability and substantial operational loss. The study illustrates how RCM can organize preventive maintenance around equipment function, failure-mode analysis, equipment criticality, maintenance policy, and practical management requirements rather than relying primarily on generalized or fixed maintenance routines (Mahbubul et al., 2022; Martinez-Monseco, 2020). These findings clarify an important dimension of long-term asset integrity: maintenance effectiveness depends not merely on the number or frequency of maintenance activities but on whether selected interventions correspond appropriately to the risk profile, operating context, deterioration mechanisms, and functional importance of each asset. Within the present research, RCM Implementation Effectiveness therefore encompasses failure-mode identification, asset-criticality assessment, preventive and predictive maintenance selection, condition monitoring, root-cause learning, and prioritization of maintenance expenditure. This multidimensional interpretation is important for quantitative measurement because two energy facilities may report comparable maintenance intensity while differing substantially in how effectively resources are targeted toward safety-critical and reliability-critical assets. Such targeting becomes particularly

important when maintenance budgets, outage windows, specialist labor, spare parts, inspection capacity, and continuity-of-service requirements must be balanced simultaneously.

Figure 2: Reliability-Centered Maintenance Pathway for Long-Term Asset Integrity



More recent reliability-centered approaches have strengthened the analytical connection between component condition, probabilistic failure behavior, maintenance prioritization, and lifecycle asset performance. In *A Probabilistic Reliability-Centred Maintenance Approach for Electrical Distribution Networks* (pp. 1070-1080), component reliability was evaluated through a three-state Markov model that supported a systematic trade-off between corrective and preventive maintenance while determining priorities for allocating preventive-maintenance financial resources. This approach is highly relevant to asset-integrity research because it treats maintenance priority as a function of changing reliability states rather than a permanently fixed schedule, thereby linking maintenance decisions with the evolving condition and risk exposure of network components (Mashfiqur & Md, 2022; Ardabili et al., 2021). This condition-sensitive logic has been extended further in *A Reliability-Centered Maintenance Process for Equipment in Distribution Grids Based on Extended Virtual Age Model* (Article 135998), which models the individual effects of different maintenance actions on failure risks in multi-component equipment. Its closed-loop RCM process plans and prioritizes cost-effective interventions while seeking to satisfy equipment-reliability targets, and the transformer application demonstrates how differentiated maintenance actions can reduce effective equipment age and support longer service life compared with less refined maintenance approaches (Ashfaq & Mohammad, 2022; Wang et al., 2025). These developments are directly relevant to long-term asset integrity because aging energy assets do not deteriorate uniformly, while different maintenance actions vary in their capacity to restore condition, suppress specific failure modes, or delay functional failure. For the present study, RCM is consequently conceptualized as an organizational and technical capability that converts information about failure mechanisms, equipment condition, criticality, and operating context into prioritized maintenance action. Under the Socio-Technical Systems Theory perspective, the quality of this conversion depends on monitoring technologies, competent personnel, decision procedures, maintenance resources, communication, operational coordination, and managerial support. RCM Implementation Effectiveness therefore represents a measurable strategic capability associated with equipment reliability, availability, reduced unplanned failure, asset-life preservation, and stronger Long-Term Asset Integrity Performance across selected U.S. energy-facility cases.

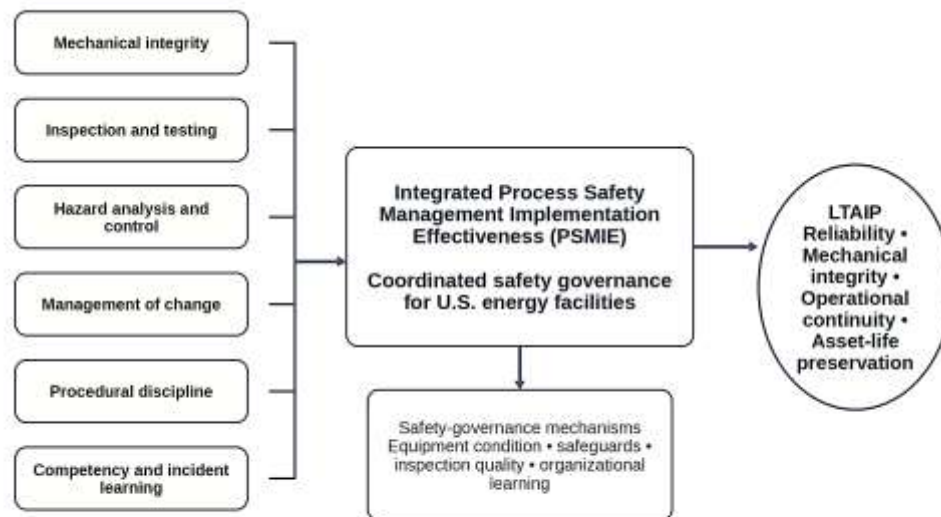
Process Safety Management and Mechanical Integrity in U.S. Energy Facilities

Process Safety Management (PSM) provides a structured organizational system for preventing major accidents by integrating hazard identification, process safety information, operating procedures, mechanical integrity, management of change, training, incident investigation, and compliance assurance into facility operations. For U.S. energy facilities that handle hazardous chemicals, fuels, high-pressure systems, thermal processes, and other safety-critical assets, the mechanical-integrity element of PSM is important because it connects equipment condition with the continued effectiveness of engineered safeguards. In Preliminary Findings on OSHA's Refinery NEP (pp. 108-112), the U.S. Occupational Safety and Health Administration's refinery inspection program documented recurring deficiencies across PSM elements and demonstrated that regulatory compliance must be evaluated through the actual quality of facility systems rather than the existence of written procedures alone. The findings are particularly relevant to asset integrity because inspection attention included mechanical integrity, process hazard analysis, operating procedures, process safety information, and management of change, all of which influence whether critical equipment remains within safe operating limits (Lay et al., 2010; Sadia & Mostari, 2022). In PSM System Upgrade in Response to an Occupational Safety and Health Administration NEP Inspection (pp. 338-342), refinery experience from the United States was used to show how PSM upgrades should focus on recurring weaknesses in mechanical integrity, hazard analysis, operating procedures, process safety information, management of change, and incident investigation rather than treating each citation as an isolated compliance problem (Shaiful et al., 2022; Walter et al., 2009). These studies establish an important foundation for the present research because PSM Implementation Effectiveness is conceptualized as a coordinated organizational capability. Under Socio-Technical Systems Theory, its effectiveness depends on the alignment of technical equipment, engineering standards, inspection knowledge, operating personnel, management systems, and decision processes. Mechanical integrity therefore represents both an equipment-management function and a sociotechnical control mechanism through which organizational practices preserve the safe and reliable performance of energy assets over time.

Mechanical integrity becomes more effective when inspection, testing, preventive maintenance, and engineering information are incorporated across the asset lifecycle. In Mechanical Integrity Inspections During Capital Projects (pp. 338-341), the importance of establishing accurate baseline thickness measurements for piping and vessels before process equipment enters service is emphasized because nominal design thickness can distort later corrosion-rate calculations and can conceal hazardous degradation or generate misleading concern. The study also demonstrates that involving inspection specialists during capital projects improves quality, supports compliance, strengthens vendor surveillance, and produces reliable information for integrity decisions (Mohammad, 2023; Schubert & Keener, 2011). This lifecycle perspective is significant for U.S. energy facilities because long-term asset integrity is influenced by decisions made during design, procurement, construction, commissioning, operation, inspection, repair, and modification. When baseline data are incomplete, maintenance programs can become reactive because deterioration rates and remaining margins are less certain. A second mechanical-integrity concern is identifying and managing equipment whose failure can defeat major-accident prevention or mitigation barriers. In Do You Feel Lucky? or Do You Want to Identify and Manage Safety Critical Equipment? (pp. 340-346), the authors describe a practical approach for identifying Safety Critical Equipment and for controlling inspection, testing, and preventive-maintenance tasks so that protective barriers remain reliable when demanded (Adnan & Iftekhhar, 2023; Broadribb & Freiburger, 2018). The study aligns with the present research because it treats process safety as an interaction among plant hardware, administrative controls, and competent people. That structure mirrors the Socio-Technical Systems Theory logic adopted here: physical assets cannot maintain integrity independently of inspection quality, workforce competence, maintenance execution, information flow, and organizational control. PSM Implementation Effectiveness is therefore expected to reflect the extent to which energy facilities identify safety-critical assets, define integrity tasks, maintain inspection intervals, control deficiencies, and coordinate technical responses before degradation escalates into loss of containment, forced outages, or process events. The quality of PSM must also be assessed through its capacity for organizational learning because formal systems can still underperform when barriers, workforce practices, risk communication, and decision processes are not

functioning as intended. In Guidance to Improve the Effectiveness of Process Safety Management Systems in Operating Facilities (Article 104257), evidence from oil, gas, and chemical environments shows that process-safety programs have become sophisticated, yet U.S. incidents continue to reveal weaknesses involving aging plants, barrier management, critical decision-making, workforce change, training, emergency response, and risk communication. The study argues for a holistic approach because contributing factors behind process-safety events are intertwined across several PSM elements rather than confined to a single technical failure or procedural deficiency (Behie et al., 2020; Sheak & Tahmedur, 2023).

Figure 3: Process Safety Management and Mechanical-Integrity Framework



This finding is relevant to long-term asset integrity because deterioration can remain undetected or insufficiently controlled when inspection information, engineering judgment, operating knowledge, and management decisions are poorly connected. For energy facilities, effective PSM requires more than compliance documentation; it requires mechanisms for identifying hazards, maintaining equipment, correcting deficiencies, managing modifications, retaining technical knowledge, and communicating changing risk conditions across organizational boundaries. The present study operationalizes PSM Implementation Effectiveness around these integrated practices and examines its relationship with Long-Term Asset Integrity Performance through quantitative analysis. Within Socio-Technical Systems Theory, PSM operates as the organizational-safety subsystem coordinating people, procedures, technical barriers, integrity information, and the physical condition of assets. This theoretical interpretation distinguishes PSM from RCM while preserving their complementarity. RCM concentrates on reliability-oriented failure management and maintenance prioritization, whereas PSM establishes the hazard-control, mechanical-integrity, and governance environment within which maintenance decisions are implemented. Measuring PSM effectiveness separately therefore allows the research to determine whether stronger process-safety and mechanical-integrity practices are associated with higher reliability, lower failure exposure, improved operational continuity, and more sustainable asset performance across selected U.S. energy facilities.

Integration of RCM Failure-Risk Reduction

The integration of Reliability-Centered Maintenance (RCM) and Process Safety Management (PSM) provides a coherent basis for managing asset reliability, mechanical integrity, and failure consequences within energy facilities because both approaches address the continued ability of critical equipment to perform required functions, although they begin from different analytical perspectives. RCM organizes maintenance around functions, functional failures, failure modes, consequences, and task selection,

whereas PSM establishes the broader hazard-control environment through mechanical integrity, process hazard analysis, management of change, operating discipline, inspection, testing, and organizational accountability. In A risk based maintenance approach for facilities complying with the US OSHA PSM regulation (pp. 680-684), maintenance attention is differentiated according to the risks created by equipment failure, and the study distinguishes mechanical-integrity failure from reliability failure while showing how preventive, predictive, and run-to-failure philosophies can be allocated according to risk significance rather than applied uniformly (Kaium, 2023; Sepeda, 2009). This approach is relevant to U.S. energy facilities because limited maintenance resources must be directed toward equipment whose failure can create safety, environmental, production, or integrity consequences. In Risk-Based Integrity and Inspection Modeling of Process Components/System (pp. 203-221), degradation modeling, failure probability, consequence assessment, inspection quality, and Bayesian updating are combined to determine inspection and replacement intervals for process equipment, demonstrating how integrity decisions can be based on evolving condition and risk exposure (Khan et al., 2006; Pervaz, 2023).

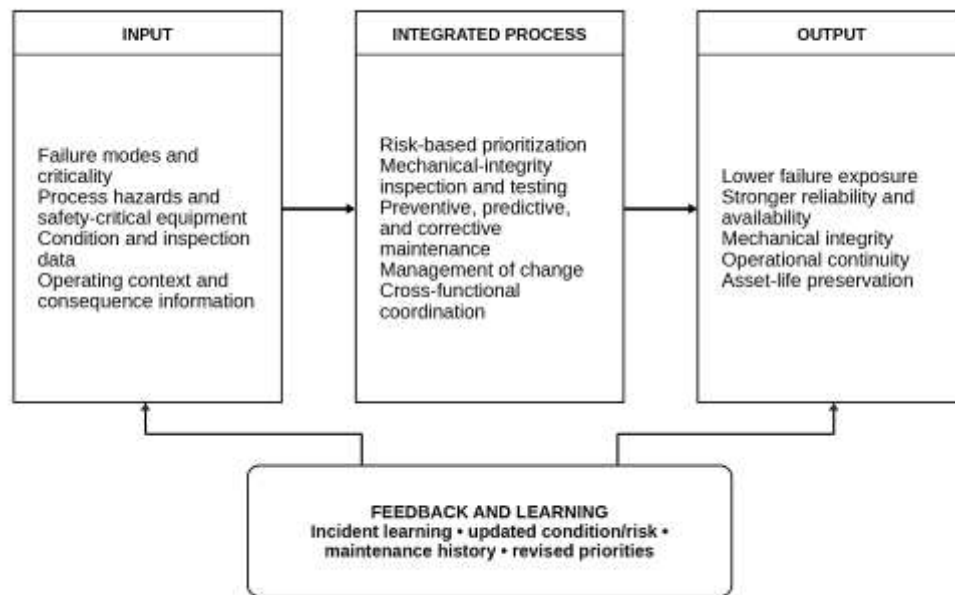
Together, these perspectives establish a bridge between RCM and PSM: reliability analysis identifies where and how equipment can fail, while process-safety and integrity controls determine how those failures should be prevented, detected, contained, or mitigated. Under the Socio-Technical Systems Theory adopted in this study, this bridge also requires coordination among inspection data, engineering judgment, operating personnel, safety specialists, maintenance teams, procedures, and management decisions because reliable equipment performance depends on interaction between technical assets and the organizational systems responsible for maintaining them.

Risk-based inspection and maintenance research demonstrates that RCM-PSM integration should be understood as a prioritization process in which maintenance and inspection are directed toward equipment according to likelihood and consequence of failure. This is important in energy facilities containing pressure equipment, rotating machinery, piping, storage systems, protective devices, electrical assets, and controls that differ in failure probability, safety significance, and production consequence. In Development of Risk-Based Inspection and Maintenance Procedures for an Oil Refinery (pp. 244-253), the RBI&M methodology combines functional analysis, risk assessment, risk evaluation, operation selection, planning, and implementation while using health and safety, environmental, economic, and reputational consequences to prioritize maintenance within limits of time, budget, and human resources (Bertolini et al., 2009; Badrul & Mominul, 2023).

The refinery application aligns with the present research because maintenance quality improves when reliability information is connected to multidimensional risk rather than evaluated only through failure frequency. In A framework for reliability and risk centered maintenance (pp. 324-331), conventional RCM is extended into Reliability and Risk Centered Maintenance by treating uncertainty and risk as explicit reference points alongside reliability and by illustrating the framework in an offshore oil and gas context (Rakib & Towhidul, 2023; Selvik & Aven, 2011). This extension matters for long-term asset integrity because an asset can appear reliable from historical failure frequency while still carrying uncertainty associated with degradation, hidden failure, changing operating conditions, or safety-critical service. An integrated RCM-PSM strategy therefore requires organizations to evaluate whether equipment is likely to fail and whether failure can defeat protective barriers, interrupt essential operations, release hazardous materials, damage interconnected assets, or compromise resilience. Such integration creates a hierarchy of maintenance attention in which safety-critical and reliability-critical equipment receive interventions proportionate to risk. This structure reinforces the socio-technical interpretation of asset integrity by linking technical risk models with organizational choices concerning inspection intervals, maintenance priorities, competence, work control, and resource allocation. RCM-PSM integration becomes more important when asset risk is dynamic because operating conditions, degradation mechanisms, inspection findings, failure history, production demands, and environmental exposure can alter the risk profile of critical equipment throughout service life. Static maintenance schedules may not capture these changes, particularly in offshore, process, generation, and other energy environments where equipment condition and consequence pathways evolve. In Dynamic risk-based maintenance for offshore processing facility (pp. 399-406), a dynamic risk-based maintenance methodology updates equipment risk and prioritizes maintenance while seeking to enhance safety and

availability, thereby connecting maintenance optimization with changing process risk rather than treating risk assessment as a one-time classification exercise (Bhandari et al., 2016; Nishat, 2023).

Figure 4: Integrated RCM-PSM Failure-Risk Governance Cycle



This perspective provides a strong conceptual link between RCM and PSM because RCM supplies structured failure-management logic, while PSM supplies the hazard, barrier, mechanical-integrity, and organizational controls required to keep high-consequence failures within tolerable limits. For the present study, RCM Implementation Effectiveness captures failure-mode analysis, asset criticality assessment, predictive and preventive maintenance, condition monitoring, root-cause learning, and maintenance prioritization, while PSM Implementation Effectiveness captures mechanical integrity, inspection and testing, hazard control, management of change, procedural discipline, safety competence, and incident learning. Examining both constructs simultaneously permits the model to test whether maintenance reliability and process-safety governance make distinct contributions to Long-Term Asset Integrity Performance and whether their combined operation supports reliability, availability, failure prevention, mechanical integrity, and operational continuity. Socio-Technical Systems Theory strengthens this interpretation because maintenance optimization cannot be separated from the people who interpret condition information, the procedures that authorize interventions, the management systems that allocate resources, and the technologies that detect deterioration. Consequently, RCM-PSM integration in U.S. energy facilities is coordinated failure-risk governance in which technical reliability analysis and process-safety control interact through maintenance decisions, organizational practices, and integrity information to preserve critical assets over extended operating periods.

Technology-Enabled Maintenance for Long-Term Asset Integrity

Advanced manufacturing and technology-enabled maintenance have transformed asset-integrity management by allowing organizations to move from predominantly time-based intervention toward continuous condition assessment, fault diagnosis, prognostics, and data-supported maintenance decision-making. Within energy facilities, this transition is particularly important because turbines, rotating machinery, transformers, pumps, compressors, generators, robotic inspection systems, and other critical assets operate under variable loads and environmental conditions that cannot always be represented adequately through fixed maintenance intervals. In *A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance* (pp. 1483-1510), condition-based maintenance is structured around three connected activities: data acquisition, data processing, and maintenance decision-making, with diagnostics identifying the nature and location of faults while

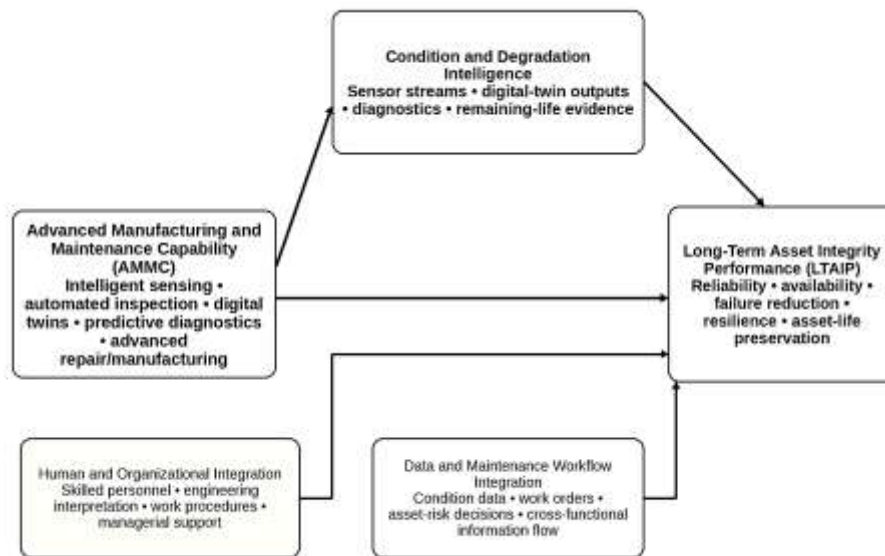
prognostics estimate future equipment condition and remaining operating capability. The study also emphasizes multisensor data fusion as an important technological foundation for complex equipment because individual sensors may capture only partial representations of developing faults (Jardine et al., 2006; Feroz, 2023). This principle is directly relevant to modern energy facilities where vibration, temperature, acoustic, electrical, lubrication, pressure, and operational data can be combined to identify deterioration before functional failure occurs. In *Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges* (pp. 2595-2630), monitoring technologies based on vibration analysis, oil analysis, electrical signals, acoustic emission, temperature, strain, and supervisory control data are examined as mechanisms for detecting faults in gearboxes, bearings, generators, blades, and other turbine subsystems (Tahmedur & Rifat, 2023; Tchakoua et al., 2014). These developments show that advanced maintenance capability does not depend solely on acquiring sophisticated equipment. Its effectiveness also requires the ability to collect reliable condition information, interpret diagnostic indicators, identify deterioration patterns, and convert technical evidence into appropriate maintenance actions. Under Socio-Technical Systems Theory, sensing technologies, analytical platforms, engineers, maintenance personnel, work procedures, and organizational decision structures operate as interdependent elements of a maintenance subsystem. Advanced Manufacturing and Maintenance Capability in the present study therefore represents the combined ability to deploy modern diagnostic technologies and integrate their outputs into coordinated asset-integrity decisions.

Technology-enabled maintenance also supports long-term asset integrity by improving condition assessment, remaining useful life estimation, and lifecycle decisions for aging energy infrastructure. Energy assets are commonly exposed to corrosion, erosion, fatigue, wear, thermal stress, creep, cyclic loading, and other degradation mechanisms that accumulate over years of operation. When facilities seek to continue operating equipment near or beyond its original design life, maintenance decisions become increasingly dependent on accurate information concerning present condition, deterioration rate, remaining safety margin, and expected future performance. In *Condition Assessment, Remaining Useful Life Prediction and Life Extension Decision Making for Offshore Oil and Gas Assets* (pp. 17-28), an integrated framework combines condition assessment, remaining useful life prediction, and life-extension decision-making to support aging offshore assets exposed to multiple deterioration mechanisms. Its application to an offshore separator illustrates how integrity decisions can incorporate inspection information and degradation knowledge to reduce unplanned shutdowns, production losses, and environmental consequences associated with unexpected equipment failure (Animah & Shafiee, 2018; Asheke, 2024).

Such lifecycle-oriented analysis is closely aligned with the dependent variable of Long-Term Asset Integrity Performance because asset longevity cannot be evaluated independently from deterioration evidence and maintenance intervention quality. Digital-twin technology strengthens this capability by linking physical equipment with synchronized virtual models. In *The Use of Digital Twin for Predictive Maintenance in Manufacturing* (pp. 1067-1080), physics-based simulation, controller information, external sensor data, prognostics and health-management techniques are combined to estimate machinery condition and remaining useful life, with an industrial robot used to demonstrate the predictive-maintenance methodology (Aivaliotis et al., 2019; Ashrafuzzaman, 2024). Although developed in a manufacturing context, this approach is directly relevant to energy-facility assets because the same principles can support simulation-based condition evaluation of rotating equipment, automated systems, and other complex machinery. Advanced manufacturing capability therefore contributes to integrity not merely through production efficiency but through digitally supported inspection, diagnosis, life assessment, repair planning, and maintenance timing. Digitalization further strengthens maintenance by creating continuous connections between physical assets, virtual representations, operational data, maintenance records, and organizational decision processes. Digital twins are especially significant because they can combine real-time asset information with simulation, historical behavior, degradation models, and maintenance knowledge, allowing asset condition to be evaluated without relying solely on periodic physical inspection. In *Digital Twin for Maintenance: A Literature Review* (Article 103316), maintenance is identified as one of the most developed industrial applications of digital-twin technology, particularly in energy and manufacturing environments where

maintenance interventions can create major production interruptions, inspection costs, or safety exposure. The reviewed studies show that digital twins can support condition monitoring, fault detection, predictive maintenance, maintenance planning, simulation, and decision support by maintaining digital representations that interact with physical equipment and relevant operational information (Errandonea et al., 2020; Kaium, 2024).

Figure 5: Advanced Manufacturing and Technology-Enabled Maintenance Pathway



This capability is important for U.S. energy facilities because asset-integrity decisions increasingly involve large quantities of heterogeneous data generated by sensors, inspection platforms, computerized maintenance systems, control networks, and engineering models. The value of these technologies depends on whether organizations can integrate information into maintenance workflows rather than simply accumulate data. Accordingly, Advanced Manufacturing and Maintenance Capability in this research incorporates digital twins, automated inspection, intelligent sensing, predictive diagnostics, condition monitoring, advanced modeling, and technology-supported maintenance coordination. From a Socio-Technical Systems Theory perspective, technological sophistication alone does not determine maintenance performance. Effective asset-integrity outcomes require alignment among digital technologies, physical equipment, personnel competence, maintenance procedures, engineering interpretation, communication, and managerial support. This theoretical position also explains why the present quantitative model treats advanced manufacturing and maintenance capability as an organizational-technical construct rather than as a collection of isolated technologies. Its association with Long-Term Asset Integrity Performance can therefore be assessed through improvements in early fault recognition, maintenance precision, asset availability, degradation control, remaining-life management, and reduction of unplanned equipment failures.

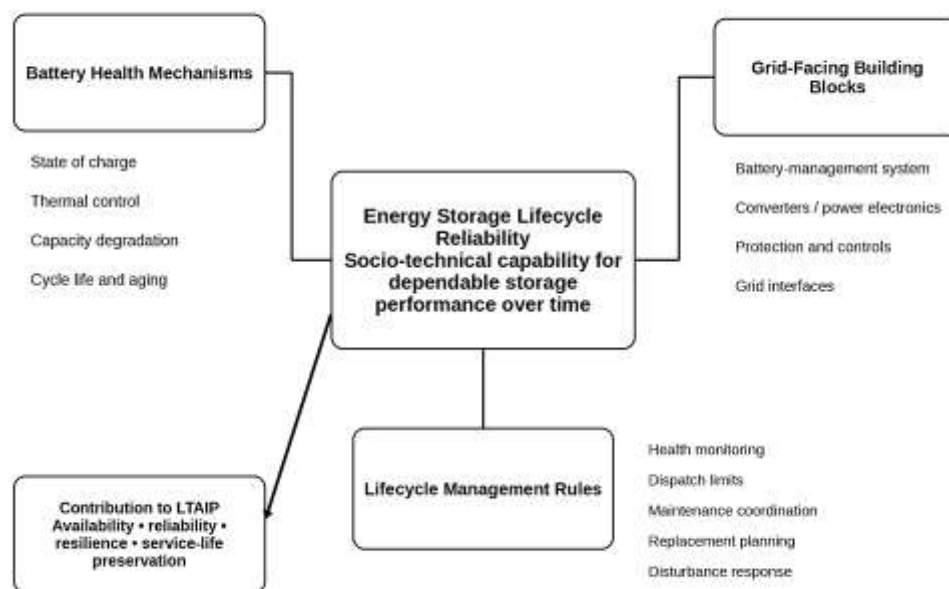
Energy Storage Technologies and Lifecycle Asset Reliability

Energy-storage technologies have become central to the integrity of energy facilities because they provide rapid balancing, reserve support, renewable-energy smoothing, peak management, and operational flexibility while introducing degradation mechanisms that must be managed throughout the asset lifecycle. Battery energy storage systems are not static infrastructure; their performance changes with state of charge, temperature, current, depth of discharge, control strategy, and time in service. In Battery Energy Storage System Battery Durability and Reliability Under Electric Utility Grid Operations: Analysis of 3 Years of Real Usage (pp. 65-73), three years of field operation from a lithium-titanate BESS installed on an island power system demonstrated that real grid service can expose storage assets to intensive cycling and operating conditions that differ from simplified laboratory assumptions. The system remained operational for most of the observed period and transferred energy,

showing why field data are essential for understanding deterioration and long-term reliability in grid-connected storage assets (Dubarry et al., 2017; Kanti, 2024). Storage health must therefore be considered alongside the network services that batteries deliver. In Optimal Operation of a Battery Energy Storage System: Trade-Off Between Grid Economics and Storage Health (pp. 342-349), a mixed-integer optimization framework connected charge-discharge scheduling, variable efficiency, cycle-life degradation, and the economic value of energy arbitrage. The study showed that operating decisions maximizing short-term grid value can impose degradation costs, making battery health an operational constraint rather than a separate issue (Sarker et al., 2017; Feroz, 2024). For the present research, this relationship is fundamental because Energy Storage and Grid Integration Resilience Capability captures not only whether storage is deployed, but whether organizations operate, monitor, and maintain storage in ways that preserve dependable performance. From a Socio-Technical Systems Theory perspective, lifecycle reliability depends on alignment among battery chemistry, power electronics, monitoring systems, dispatch algorithms, maintenance personnel, operating rules, and management decisions across complex energy systems.

Battery lifecycle integrity is influenced by how storage assets are used because identical battery technologies can experience different degradation trajectories under different grid duties, climates, and cycling patterns. In Battery Durability and Reliability Under Electric Utility Grid Operations: Representative Usage Aging and Calendar Aging (pp. 185-195), controlled experiments were designed around usage patterns representative of grid-connected BESS applications and compared with more aggressive and milder operating profiles. The analysis demonstrated that temperature and current affect capacity loss and that calendar aging and cycling behavior must both be considered when assessing durability when storage provides repeated grid services over extended periods (Dubarry & Devie, 2018; Uddin & Risha, 2024).

Figure 6: Energy Storage Lifecycle Reliability Architecture



This evidence reinforces the asset-integrity principle that remaining useful life cannot be inferred from chronological age alone. A storage system may be relatively young yet experience accelerated deterioration if it is repeatedly exposed to demanding current, temperature, or state-of-charge conditions. The same lifecycle logic appears in Analysis of Degradation in Residential Battery Energy Storage Systems for Rate-Based Use-Cases (Article 114632), which compared lithium-ion chemistries, climates, and operating strategies including self-consumption, time-of-use management, demand-charge reduction, and backup-oriented use. By combining operational control with battery-life models, the study found variation in predicted service life because usage patterns and environmental

conditions change internal battery stresses (Jahanara, 2025; Mishra et al., 2020). Although the application was residential, the degradation mechanisms are relevant to larger energy-facility storage assets because asset health still depends on interactions among duty cycle, thermal environment, state of charge, and chemistry. Long-term asset reliability therefore requires health-aware operating policies, thermal management, accurate state estimation, suitable charging and discharging limits, and maintenance decisions based on condition information. In this study, these practices form part of the technological and organizational capability through which storage assets contribute to resilient energy-facility performance rather than becoming sources of reliability risk under varied operating conditions. Lifecycle asset reliability requires storage planning to incorporate capacity fade, usable service life, and replacement timing into facility decisions. Battery systems lose usable capacity and efficiency, meaning that an installation that initially satisfies power requirements may provide less effective service as it ages unless degradation is incorporated into sizing, operating, and replacement strategies.

In *Optimal Sizing of Battery Energy Storage in a Microgrid Considering Capacity Degradation and Replacement Year* (Article 107170), battery sizing was modeled together with service life, cycle life, float life, depth of discharge, capacity degradation, technology selection, and replacement year. The optimization showed that long-term microgrid planning becomes more realistic when degradation and replacement are treated as explicit decision variables instead of assuming constant battery capability throughout the project life (Amini et al., 2021; Jannatul, 2025). This perspective is applicable to U.S. energy facilities integrating storage with generation, renewable resources, distribution assets, and critical loads. Storage resilience depends on whether operators can maintain availability and grid-support capability while cells, modules, converters, thermal systems, and control equipment age. The present research therefore conceptualizes Energy Storage and Grid Integration Resilience Capability as a lifecycle-oriented capability involving battery health monitoring, degradation management, thermal control, state-of-charge management, power-electronic reliability, maintenance coordination, replacement planning, and reliable grid interaction. Socio-Technical Systems Theory strengthens this interpretation because storage reliability is produced through interactions among batteries, digital controls, engineering models, personnel, maintenance teams, procedures, and resource decisions. Weakness in any one element can reduce the effectiveness of the storage subsystem. Accordingly, long-term asset integrity should be evaluated by more than installed capacity; it requires the facility's ability to preserve dependable storage performance over time while coordinating grid services, maintenance requirements, degradation constraints, and organizational controls. This perspective supports testing whether stronger Energy Storage and Grid Integration Resilience Capability is associated with higher Long-Term Asset Integrity Performance in selected U.S. facilities.

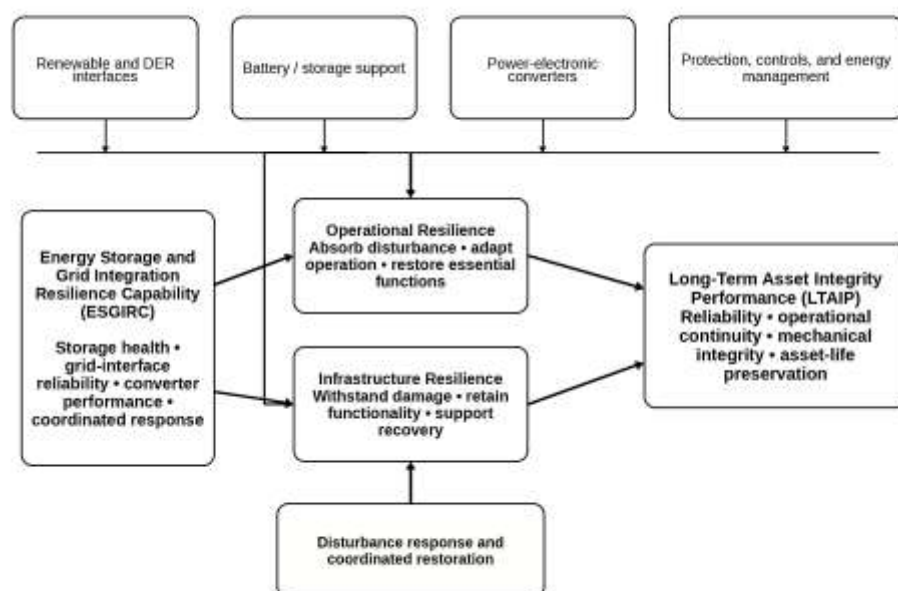
Grid Integration Technologies and Infrastructure Integrity

Grid integration technologies are fundamental to the operational resilience and infrastructure integrity of modern energy facilities because the increasing interconnection of renewable generation, energy storage, distributed resources, power-electronic converters, automated protection, and digital controls changes how disturbances propagate across electrical networks. Operational resilience refers to the capability of a power system to absorb disturbances, maintain essential functions, adapt its operating condition, and restore service following disruptive events, whereas infrastructure resilience concerns the physical capacity of network assets to withstand damage and retain sufficient functionality. In *Metrics and Quantification of Operational and Infrastructure Resilience in Power Systems* (pp. 4732-4742), a time-dependent resilience framework distinguishes operational resilience from infrastructure resilience and evaluates the degradation and recovery phases experienced by power systems during severe disturbances. The proposed resilience trapezoid demonstrates that asset performance must be evaluated across disturbance absorption, degradation, restoration, and recovery rather than through conventional reliability indices alone (Mostari, 2025; Panteli et al., 2017). This distinction is highly relevant to the present research because long-term asset integrity requires both physically dependable infrastructure and operational capabilities that enable facilities to respond effectively when components or interconnected systems experience abnormal conditions. In *System-Level Assessment of Reliability and Resilience Provision from Microgrids* (pp. 374-392), microgrids containing distributed energy resources and storage were shown to provide different forms of reserve support under both routine reliability contingencies and longer-duration resilience events. The study further found that

aggregation of microgrids can create system-level reliability and resilience benefits exceeding the simple sum of individual resources, emphasizing the importance of coordinated operation across interconnected assets (Mashiat, 2025; Zhou et al., 2018). From a Socio-Technical Systems Theory perspective, these findings indicate that infrastructure resilience emerges from coordinated interactions among physical assets, distributed resources, control systems, operating personnel, protection arrangements, and organizational decision procedures rather than from individual equipment reliability alone.

Grid integration also changes the technical conditions under which generation and network assets maintain stable operation. The displacement of conventional synchronous generators by inverter-connected renewable resources can alter frequency response, rotational inertia, voltage behavior, protection requirements, and system balancing, making integration capability an important dimension of asset reliability. In *Evaluating Rotational Inertia as a Component of Grid Reliability with High Penetrations of Variable Renewable Energy* (pp. 258-271), the Electric Reliability Council of Texas system was modeled under different renewable penetration and generation-retirement scenarios to evaluate changes in system inertia and frequency-related reliability. The results showed that substantial renewable penetration could be accommodated under the modeled conditions, while reductions in synchronous generation could produce periods of insufficient inertia unless dispatch decisions explicitly maintained minimum system-stability requirements (Johnson et al., 2019; Arif Uz et al., 2025). The relevance to U.S. energy-facility integrity is direct because renewable and storage integration cannot be treated solely as capacity expansion; grid-connected assets must operate within frequency, voltage, protection, converter, and network constraints that affect the dependable performance of physical infrastructure. In *Integrating Reliability and Resilience to Support the Transition from Passive Distribution Grids to Islanding Microgrids* (Article 115254), a mathematical optimization framework integrates techno-economic, reliability, and resilience objectives while considering distributed generation, storage, network reconfiguration, internal faults, and uncertain islanding events. Using U.S. Department of Energy-based network data, the study reported substantial potential reliability and resilience improvements through appropriately designed microgrid configurations and distributed-resource placement (Kaïum, 2025; Wu & Sansavini, 2020).

Figure 7: Grid-Integration Resilience Pathway to Long-Term Asset Integrity



These studies demonstrate that Grid Integration Resilience Capability involves more than connecting new resources to existing networks. It requires coordinated planning of resource placement, storage capacity, network topology, frequency support, protection, islanding capability, restoration

procedures, and operational controls. Such coordination influences whether facilities can sustain critical loads, isolate disturbances, protect equipment, and restore service without exposing interconnected assets to excessive operational stress.

The integrity of increasingly decentralized energy infrastructure also depends on control architecture, power quality, energy-management systems, and reliable coordination among distributed energy resources. Solar photovoltaic generation, wind generation, battery systems, electric vehicles, controllable loads, and conventional generation introduce different dynamic characteristics that must be coordinated through primary, secondary, and tertiary control layers if microgrids and integrated facilities are to maintain frequency, voltage, power sharing, and reliable operation. In *Distributed Energy Resources Based Microgrid: Review of Architecture, Control, and Reliability* (pp. 2223-2235), microgrid architectures, hierarchical controls, energy-management strategies, power-quality challenges, energy storage, electric vehicles, and distributed generation are analyzed collectively to determine how resource composition and operating strategies influence resilient and reliable microgrid performance (Pervaz, 2025; Muhtadi et al., 2021). The study is especially relevant to the present research because grid-integration reliability depends simultaneously on physical resources and on the controls governing their interaction. This relationship supports the Socio-Technical Systems Theory foundation of the study: sensors, inverters, storage devices, protection systems, control algorithms, operators, engineers, maintenance teams, and organizational procedures constitute an interconnected system in which failure or misalignment within one element can influence broader infrastructure performance. Accordingly, Energy Storage and Grid Integration Resilience Capability is conceptualized here as the facility-level ability to maintain dependable storage operation, stable grid interfaces, appropriate power-electronic performance, effective disturbance response, coordinated distributed-resource control, and continuity of critical energy services. This construct connects directly with Long-Term Asset Integrity Performance because poorly coordinated grid integration can increase thermal, electrical, mechanical, and operational stresses on interconnected assets, while effective integration provides flexibility, redundancy, islanding capability, and system restoration capacity. Evaluating this capability alongside RCM, PSM, and Advanced Manufacturing and Maintenance Capability therefore allows the study to examine asset integrity as the outcome of coordinated maintenance, safety, technological, and network-resilience functions across selected U.S. energy facilities.

SOCIO-TECHNICAL ASSET-INTEGRITY ARCHITECTURE AND HYPOTHESES

Socio-Technical Systems Theory provides the principal theoretical foundation for this study because long-term asset integrity in energy facilities is produced through coordinated interactions among physical equipment, maintenance technologies, organizational structures, human expertise, operating procedures, safety controls, and institutional arrangements. The theory rejects the assumption that technical performance can be understood independently from the social system responsible for designing, operating, maintaining, and governing technology. In *Socio-technical systems: From design methods to systems engineering* (pp. 4-17), the theory is developed as a practical systems-engineering perspective that connects technological development with organizational change, work design, stakeholder participation, and the relationships among technical and human elements. The study emphasizes that system effectiveness depends on constructive engagement between technological and organizational domains rather than optimization of one domain in isolation (Baxter & Sommerville, 2011; Chandra, 2025). This principle is directly applicable to U.S. energy facilities because RCM, PSM, advanced manufacturing, storage systems, and grid-integration technologies are implemented through work systems containing engineers, maintenance personnel, operators, digital platforms, procedures, standards, and management decisions. In *Infrastructure transformation as a socio-technical process* (pp. 538-550), energy distribution networks are interpreted as infrastructures whose technical configurations and governance arrangements evolve together across the infrastructure lifecycle, demonstrating that energy-system performance cannot be separated from institutional coordination and organizational responsibility (Ahmed, 2026; Bolton & Foxon, 2015). For the present research, STS Theory therefore provides a coherent explanation for why RCM Implementation Effectiveness and PSM Implementation Effectiveness should not be treated as isolated maintenance and safety practices. Their effectiveness depends on how technical information, maintenance resources, safety procedures, workforce competence, communication, and managerial controls interact. The same theoretical logic

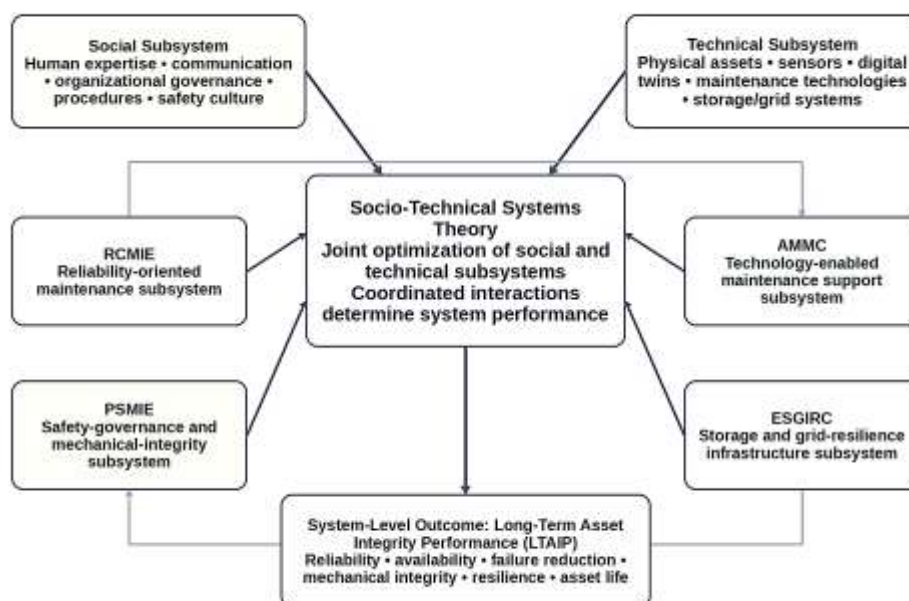
applies to advanced manufacturing and grid-integrated storage, where asset condition monitoring, digital tools, control systems, and human decision-making jointly shape operational reliability and integrity. This alignment supports consistent measurement across energy facilities with different technical configurations and organizational arrangements.

The suitability of Socio-Technical Systems Theory becomes stronger when energy infrastructure is considered as a layered system in which physical networks and institutional arrangements jointly determine technical operation. In *Towards the Comprehensive Design of Energy Infrastructures*, energy infrastructures are conceptualized as complex adaptive socio-technical systems in which engineering design must be coordinated with economic and institutional arrangements, including infrastructure access, responsibility allocation, and coordination among actors (Scholten & Künneke, 2016). This perspective aligns closely with the structure of the present conceptual model. RCM Implementation Effectiveness represents the reliability-oriented maintenance subsystem through failure-mode analysis, asset criticality, condition monitoring, preventive maintenance, and maintenance prioritization. PSM Implementation Effectiveness represents the safety-governance subsystem through mechanical integrity, hazard control, inspection, management of change, procedural discipline, and safety competence. Advanced Manufacturing and Maintenance Capability represents the technological support subsystem through digital twins, intelligent sensing, automated inspection, advanced diagnostics, additive manufacturing, and digitally assisted maintenance. Energy Storage and Grid Integration Resilience Capability represents the interconnected infrastructure subsystem through battery-health management, power-electronic reliability, thermal management, control coordination, disturbance response, and dependable grid interfaces. Long-Term Asset Integrity Performance represents the system-level outcome expressed through asset reliability, availability, reduced unplanned failure, equipment longevity, mechanical integrity, and operational resilience. The central STS relationship has therefore been translated into a regression-ready form that enables the theoretical architecture to be tested empirically while preserving the joint-optimization logic of social and technical subsystems.

$$LTAIP_i = \beta_0 + \beta_1 RCMIE_i + \beta_2 PSMIE_i + \beta_3 AMMC_i + \beta_4 ESGIRC_i + \varepsilon_i$$

In the equation, LTAIP_i represents Long-Term Asset Integrity Performance for respondent *i*; β_0 represents the intercept; β_1 through β_4 estimate the unique contributions of Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability; and ε_i represents unexplained variation.

Figure 8: Socio-Technical Systems Theoretical Framework for Integrated Asset Integrity



The same specification has been retained in the methodology and results so that the theoretical model, hypotheses, measurements, and statistical tests remain directly aligned.

Socio-Technical Systems Theory is especially appropriate for the safety and maintenance dimensions of the research because contemporary process and energy facilities are characterized by nonlinear interactions among equipment condition, human performance, organizational decisions, procedures, controls, and changing operating environments. In A novel methodology to measure safety level of a process plant using a system theory based method (pp. 296-309), process-plant safety is modeled through a systems perspective in which accidents can arise from inadequate constraints and dysfunctional interactions among components rather than only from independent hardware failure. The theory connects safety with feedback, control structures, organizational levels, operating activities, and maintenance of safety requirements (Yousefi & Hernández, 2020). This logic supports the use of STS Theory in a study integrating RCM and PSM because mechanical integrity and maintenance reliability depend on both technical condition and the organizational controls governing inspection, testing, modification, and corrective action. In An advanced approach to the system safety in sociotechnical systems (Article 105961), maintenance operations in chemical process plants are evaluated through a holistic taxonomy of performance-shaping factors covering human, organizational, and technological elements. The model demonstrates that safety performance varies through interactions across these elements and that maintenance-related safety measures should consider the wider sociotechnical system rather than human performance alone (Jahanara, 2026; Zarei et al., 2023). Accordingly, the four independent variables are interpreted as connected organizational-technical capabilities rather than isolated programs. The framework supports testing H1 through H4 as direct relationships with asset integrity and H5 as the combined contribution of the four capabilities. Strong RCM cannot fully protect asset integrity when process-safety governance is weak, while advanced technologies lose value when personnel, procedures, data, or maintenance resources are poorly coordinated. The theoretical emphasis is coordinated system performance, with regression quantifying associations between the four capabilities and Long-Term Asset Integrity Performance across selected U.S. energy facilities.

Conceptual Framework

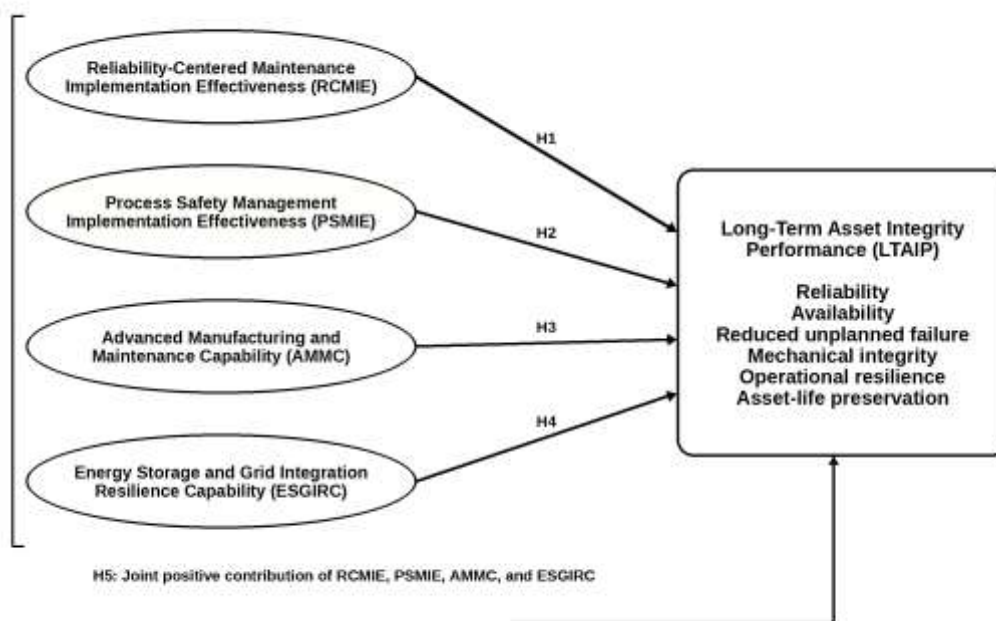
The conceptual framework of this study translates Socio-Technical Systems Theory into an empirical structure in which four organizational and technological capabilities are expected to explain differences in Long-Term Asset Integrity Performance across selected U.S. energy facilities. The dependent variable, Long-Term Asset Integrity Performance (LTAIP), captures sustained reliability, availability, mechanical integrity, reduced unplanned failure, asset-life preservation, and operational resilience. The first independent variable, Reliability-Centered Maintenance Implementation Effectiveness (RCMIE), represents the extent to which facilities identify functional failures, assess equipment criticality, use condition information, prioritize preventive and predictive interventions, and align maintenance resources with reliability consequences. In A Holistic Framework for Supporting Maintenance and Asset Management Life Cycle Decisions for Power Systems, maintenance and asset-management decisions for power transformers are integrated through health indices, lifecycle cost, engineering failure analysis, human reliability, and structured decision support, demonstrating that long-term power-system performance depends on coordinated technical and managerial maintenance choices (Ayu & Yunusa-Kaltungo, 2020). The second independent variable, Process Safety Management Implementation Effectiveness (PSMIE), captures mechanical integrity, hazard control, inspection and testing, management of change, procedural discipline, safety competence, and incident learning. In Development of Risk-Based Process Safety Indicators (pp. 133-143), leading and lagging process-safety indicators are combined through a risk-based hierarchy in an LNG facility, with deterioration linked to operation, maintenance, management, organization, and safety-culture factors (Jannatul, 2026; Khan et al., 2010). Together, RCMIE and PSMIE represent complementary socio-technical control capabilities: RCMIE directs maintenance attention toward failure consequences and reliability needs, while PSMIE maintains the safety-governance and integrity controls within which those maintenance activities are performed. Their inclusion as separate predictors allows the study to test whether maintenance reliability and process-safety governance contribute independently to LTAIP while remaining interdependent in day-to-day facility operations.

The third independent variable, Advanced Manufacturing and Maintenance Capability (AMMC), extends the framework beyond conventional maintenance by representing the facility's ability to use digital twins, intelligent sensing, automated inspection, predictive diagnostics, advanced modeling, data analytics, and technology-supported repair or replacement processes. In Review of Computational Mechanics, Optimization, and Machine Learning Tools for Digital Twins Applied to Infrastructures (Article 11997), digital twins are described as continuously updated cyber-physical representations that combine sensors, operational data, computational models, optimization, and machine learning to support degradation prediction, remaining-life assessment, and predictive maintenance for infrastructure exposed to fatigue and extreme loading (Khalid, 2026; Stavroulakis et al., 2022). This evidence supports the proposed AMMC-to-LTAIP path because advanced maintenance technologies are valuable when they convert asset-condition information into timely integrity decisions. The fourth independent variable, Energy Storage and Grid Integration Resilience Capability (ESGIRC), represents battery-health management, grid-interface reliability, converter performance, disturbance response, storage dispatch, protection coordination, and continuity of critical energy services. In Optimal Allocation of Battery Energy Storage Systems for Peak Shaving and Reliability Enhancement in Distribution Systems (Article 112305), an optimization model using realistic utility load and outage data showed that strategically sized and located BESS capacity could support peak reduction and substantially improve distribution-system reliability during normal and outage conditions (Inaolaji et al., 2024; Kaium, 2026). The conceptual framework therefore treats RCMIE, PSMIE, AMMC, and ESGIRC as four distinguishable but interacting socio-technical capabilities. Their statistical relationship with LTAIP has been specified through the same multiple-regression equation used throughout the study.

$$LTAIP_i = \beta_0 + \beta_1 RCMIE_i + \beta_2 PSMIE_i + \beta_3 AMMC_i + \beta_4 ESGIRC_i + \varepsilon_i$$

Consistent with H1 through H4, the expected coefficient signs are $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$, and $\beta_4 > 0$, while H5 concerns the statistically significant joint explanatory contribution of all four predictors to LTAIP. This structure has allowed the conceptual model to retain the theoretical proposition that a facility's long-term integrity depends on coordinated reliability, safety, technological, and infrastructure capabilities while also enabling each capability to be evaluated separately through its partial regression coefficient.

Figure 9: Conceptual Framework Linking RCMIE, PSMIE, AMMC, ESGIRC, and LTAIP



The framework is intentionally structured around a single system-level outcome because asset integrity is not a separate consequence of each maintenance or technology practice; it is the cumulative performance condition created when reliability management, safety governance, digital maintenance capability, and grid-resilience capability operate coherently. From the STS perspective, the four predictors encompass both technical and social elements. RCMIE requires failure data, monitoring technology, maintenance engineering, skilled personnel, and prioritization rules; PSMIE requires safety-critical equipment, procedures, inspection systems, competent personnel, communication, and management oversight; AMMC requires cyber-physical technologies, reliable data, engineering interpretation, work-process integration, and organizational readiness; and ESGIRC requires storage hardware, controls, power electronics, network interfaces, operators, maintenance processes, and disturbance-response procedures. In *Digital Asset Performance Management: Taking Utility Asset Management to the Next Level* (pp. 9-14), utility asset management is described as increasingly digital and device-intensive, with asset-performance management connecting maintenance, reliability, safety, operational efficiency, and asset-life objectives in modernized power networks (Belmont et al., 2020; Pervaz, 2026). This utility-centered evidence reinforces the decision to measure LTAIP as a multidimensional outcome rather than as a single failure-frequency indicator. Empirically, descriptive statistics have established the perceived level of each construct, Pearson correlation has identified the direction and strength of bivariate relationships, and multiple regression has estimated the unique predictive contribution of each independent variable while holding the others constant. The framework has not treated cross-sectional regression coefficients as proof of temporal causality; instead, they have quantified theoretically specified associations and predictive contributions within the sampled U.S. energy-facility cases. Accordingly, support for H1-H4 has required positive and statistically significant beta coefficients for the respective predictors, while support for H5 has required a statistically significant overall regression model interpreted through F , R^2 , adjusted R^2 , and the joint pattern of coefficients.

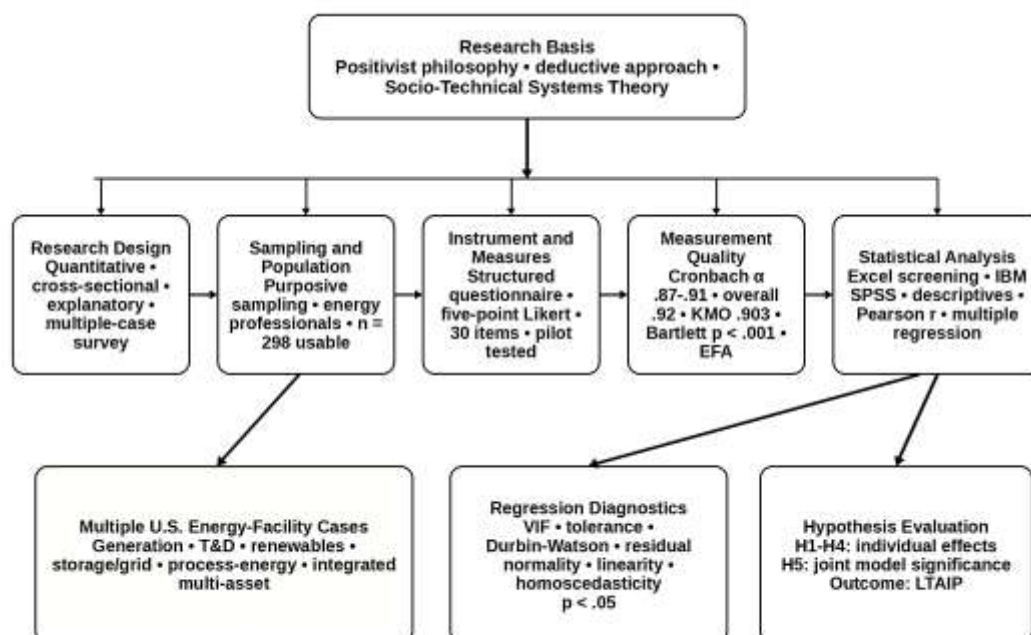
Research Hypotheses

The hypotheses of this study have been developed to test the proposed relationships between the four independent variables and Long-Term Asset Integrity Performance. The first hypothesis, H1, proposes that Reliability-Centered Maintenance Implementation Effectiveness has a significant positive effect on Long-Term Asset Integrity Performance because systematic failure-mode analysis, asset-criticality assessment, predictive maintenance, condition monitoring, and maintenance prioritization are expected to strengthen equipment reliability and reduce integrity-related failures. The second hypothesis, H2, proposes that Process Safety Management Implementation Effectiveness has a significant positive effect on Long-Term Asset Integrity Performance because effective mechanical-integrity programs, inspection, testing, management of change, operating procedures, and safety controls should strengthen the condition and operational reliability of critical assets. The third hypothesis, H3, proposes that Advanced Manufacturing and Maintenance Capability has a significant positive effect on Long-Term Asset Integrity Performance because digital diagnostics, automated inspection, intelligent monitoring, advanced repair technologies, digital twins, and data-supported maintenance can improve detection, maintenance quality, and asset-life management. The fourth hypothesis, H4, proposes that Energy Storage and Grid Integration Resilience Capability has a significant positive effect on Long-Term Asset Integrity Performance because effective storage monitoring, degradation management, converter reliability, thermal control, grid-interface management, and disturbance response can support reliable operation of increasingly interconnected energy assets. The fifth hypothesis, H5, proposes that Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability jointly have a significant positive effect on Long-Term Asset Integrity Performance. Under the Socio-Technical Systems Theory adopted in this study, H5 is especially important because it reflects the expectation that asset integrity emerges from the coordinated functioning of technical equipment, maintenance systems, organizational controls, human expertise, safety practices, and interconnected energy technologies rather than from any single capability operating independently.

EMPIRICAL RESEARCH DESIGN AND EVALUATION PROTOCOL

The methodology for this study has been developed within a positivist research philosophy and a deductive research approach because the relationships among Reliability-Centered Maintenance Implementation Effectiveness (RCMIE), Process Safety Management Implementation Effectiveness (PSMIE), Advanced Manufacturing and Maintenance Capability (AMMC), Energy Storage and Grid Integration Resilience Capability (ESGIRC), and Long-Term Asset Integrity Performance (LTAIP) have been examined through measurable quantitative indicators and hypotheses derived from the literature, conceptual framework, and Socio-Technical Systems Theory. A quantitative, cross-sectional, explanatory, multiple-case-study-based survey design has been adopted to provide a structured assessment of current maintenance, safety, technological, and infrastructure capabilities across selected U.S. energy-facility environments, including electric-power generation, transmission and distribution, renewable-energy, energy-storage and grid-integration, process-energy, and integrated multi-asset settings. The population has comprised reliability engineers, maintenance engineers, asset-integrity specialists, process-safety and HSE professionals, electrical and mechanical engineers, energy-storage and grid-integration specialists, operations and facility managers, condition-monitoring personnel, and related technical professionals, while the individual professional has served as the primary unit of analysis. A purposive sampling strategy has been applied because respondents have needed direct operational knowledge of at least one major study domain. A target sample of approximately 300 valid cases has been established, and the completed dataset has comprised 298 usable questionnaires from 330 distributed instruments after 312 returns have been screened for completeness and response quality. Primary data have been collected through a structured questionnaire using Likert's five-point scale from 1 = Strongly Disagree to 5 = Strongly Agree. The instrument has operationalized RCMIE through asset criticality, failure-mode analysis, condition monitoring, preventive and predictive maintenance, root-cause learning, and maintenance prioritization; PSMIE through mechanical integrity, hazard analysis, inspection and testing, management of change, procedural discipline, competency, and incident learning; AMMC through digital twins, intelligent sensing, automated inspection, predictive diagnostics, advanced repair/manufacturing technologies, and digital maintenance integration; ESGIRC through battery-health monitoring, degradation management, thermal control, power-electronic reliability, grid-interface stability, and disturbance response; and LTAIP through equipment reliability, availability, failure reduction, mechanical integrity, operational resilience, and asset-life preservation.

Figure 10: Empirical Research Design and Evaluation Protocol



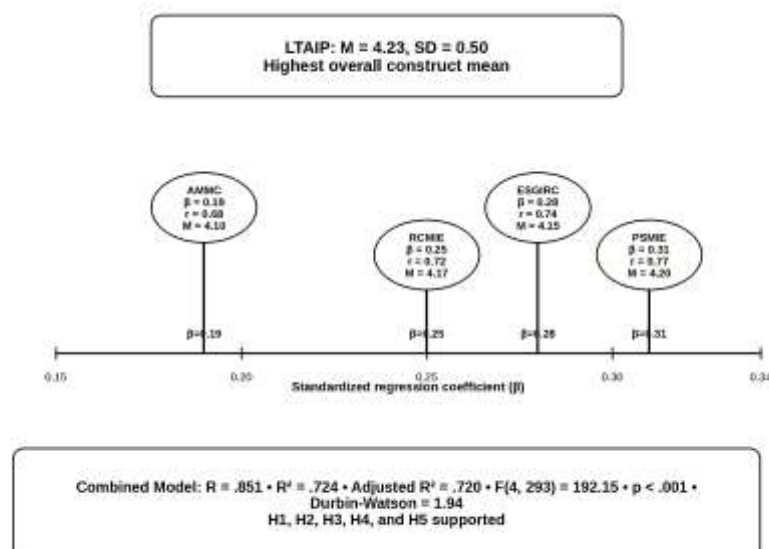
A pilot test has been conducted with respondents comparable to the target population to assess item clarity, relevance, sequencing, completion time, and preliminary response variability, and wording has been refined where necessary. Content and face validity have been supported through alignment with the theoretical and conceptual framework, while construct validity has been assessed through the Kaiser-Meyer-Olkin measure, Bartlett's Test of Sphericity, and exploratory factor analysis. Internal consistency has been evaluated using Cronbach's alpha, with $\alpha \geq .70$ used as the minimum acceptable criterion. The dataset has been coded and initially screened in Microsoft Excel and has been analyzed in IBM SPSS Statistics using frequencies, percentages, means, standard deviations, reliability analysis, validity tests, Pearson correlations, and multiple linear regression. Regression diagnostics have included VIF, tolerance, the Durbin-Watson statistic, residual normality, linearity, and homoscedasticity, with $p < .05$ used as the inferential significance criterion. EndNote has been used to organize bibliographic records and Microsoft Word has been used to prepare the manuscript, while citations in the present document have remained normal Word text. Throughout the methodology, Socio-Technical Systems Theory has guided the interpretation of the four independent variables as interconnected maintenance, safety, technological, and infrastructure subsystems whose coordinated operation has been tested statistically against the system-level outcome of Long-Term Asset Integrity Performance.

$$LTAIP_i = \beta_0 + \beta_1 RCMIE_i + \beta_2 PSMIE_i + \beta_3 AMMC_i + \beta_4 ESGIRC_i + \varepsilon_i$$

EMPIRICAL VALIDATION OF THE SOCIO-TECHNICAL ASSET-INTEGRITY MODEL

The findings have provided an overall quantitative assessment of how Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability have been associated with Long-Term Asset Integrity Performance across the selected U.S. energy-facility cases. A total of 330 questionnaires have been distributed, 312 have been returned, and 298 usable responses have been retained after data screening, producing a valid response rate of 90.3%.

Figure 11: Quantitative Findings Profile of the Socio-Technical Asset-Integrity Model



Measurement reliability has been satisfactory, with Cronbach's alpha coefficients ranging from .87 to .91 across the five principal constructs and an overall instrument coefficient of .92, while the Kaiser-Meyer-Olkin value has reached .903 and Bartlett's Test of Sphericity has been statistically significant at

$p < .001$, supporting the suitability of the dataset for multivariate analysis. Using the five-point Likert scale, where 1 has represented Strongly Disagree and 5 has represented Strongly Agree, all constructs have recorded relatively high mean scores. Long-Term Asset Integrity Performance has produced the highest overall mean ($M = 4.23$, $SD = 0.50$), followed by Process Safety Management Implementation Effectiveness ($M = 4.20$, $SD = 0.53$), Reliability-Centered Maintenance Implementation Effectiveness ($M = 4.17$, $SD = 0.55$), Energy Storage and Grid Integration Resilience Capability ($M = 4.15$, $SD = 0.56$), and Advanced Manufacturing and Maintenance Capability ($M = 4.10$, $SD = 0.59$). These results have satisfied the descriptive objectives by demonstrating strong perceived implementation of the four explanatory capabilities and correspondingly strong asset-integrity performance. Pearson correlation analysis has shown statistically significant positive relationships between LTAIP and PSMIE ($r = .77$, $p < .001$), ESGIRC ($r = .74$, $p < .001$), RCMIE ($r = .72$, $p < .001$), and AMMC ($r = .68$, $p < .001$). Multiple regression analysis has further shown that the four predictors jointly have explained 72.4% of the variance in Long-Term Asset Integrity Performance ($R^2 = .724$, adjusted $R^2 = .720$), with the overall model reaching statistical significance, $F(4, 293) = 192.15$, $p < .001$. PSMIE has demonstrated the strongest standardized contribution ($\beta = .31$, $p < .001$), followed by ESGIRC ($\beta = .28$, $p < .001$), RCMIE ($\beta = .25$, $p < .001$), and AMMC ($\beta = .19$, $p < .001$). Accordingly, H1 through H4 have been supported through significant positive individual coefficients, while H5 has been supported through the significant overall regression model. Collectively, the findings have also supported the Socio-Technical Systems Theory perspective by indicating that stronger asset-integrity performance has been associated with the coordinated functioning of maintenance reliability, process-safety governance, technological capability, and grid-connected energy-system resilience.

Study System and Sample Characterization

Response Rate and Data Screening

Table 1: Response Rate and Data Screening Results

Response Category	Frequency	Percentage
Questionnaires Distributed	330	100.0%
Questionnaires Returned	312	94.5%
Incomplete/Invalid Responses	14	4.2%
Cases with Major Missing Data	8	2.4%
Cases Removed for Response-Pattern Problems	6	1.8%
Valid Responses Retained / Final Analytical Sample	298	90.3%

The response-rate and data-screening analysis has established a strong empirical basis for the subsequent statistical procedures. A total of 330 questionnaires have been distributed among professionals associated with selected U.S. energy-facility environments, of which 312 questionnaires have been returned, representing a gross response rate of 94.5%. Following systematic screening, 14 questionnaires have been excluded because they have contained substantial missing information or response patterns that have reduced their analytical reliability. Eight responses have contained levels of missing data considered unsuitable for construct scoring, while six responses have shown patterned answering or insufficient response variation. Consequently, 298 questionnaires have been retained as valid observations, producing a final usable response rate of 90.3%. This response level has provided adequate representation for descriptive statistics, reliability testing, factor-based validity assessment, Pearson correlation, and multiple regression involving the four principal independent variables. The screening process has also strengthened the quality of the dataset because only responses meeting the established completeness and consistency criteria have been included. From the perspective of Socio-Technical Systems Theory, maintaining data quality has been particularly important because the study has attempted to capture perceptions of interconnected technological, organizational, maintenance, and safety practices rather than isolated technical conditions. The retained sample has therefore represented respondents who have provided sufficiently complete information across RCMIE, PSMIE, AMMC, ESGIRC, and LTAIP. The final analytical sample of 298 respondents has consequently provided a stable foundation for testing the research objectives and hypotheses and for evaluating the combined socio-technical determinants of asset integrity across the selected energy-facility cases. It has

also preserved adequate degrees of freedom for the four-predictor regression model and has allowed the study to compare response patterns across technical roles and facility categories without altering the numerical structure established in the introductory findings.

Respondent Demographic and Professional Profile

Table 2: Respondent Demographic and Professional Profile

Characteristic	Category	Frequency	Percentage
Professional Role	Reliability/Maintenance Engineering	74	24.8%
	Process Safety/HSE	52	17.4%
	Operations/Facility Management	61	20.5%
	Electrical/Grid Engineering	48	16.1%
	Energy Storage/Renewable Systems	35	11.7%
	Other Technical Roles	28	9.4%
Professional Experience	2-5 Years	51	17.1%
	6-10 Years	83	27.9%
	11-15 Years	74	24.8%
	More Than 15 Years	90	30.2%

The respondent profile has indicated that the study has captured a technically diverse group of professionals with direct exposure to the maintenance, safety, operational, electrical, storage, and asset-management functions relevant to the research model. Reliability and maintenance engineers have represented the largest single professional group at 24.8%, while operations and facility managers have accounted for 20.5%. Process-safety and HSE professionals have represented 17.4%, electrical and grid engineers have represented 16.1%, and energy-storage and renewable-system professionals have represented 11.7%. The remaining 9.4% have included other technical roles associated with condition monitoring, asset management, engineering support, and facility performance. The experience profile has also shown that the sample has been dominated by professionals with substantial exposure to energy operations. Approximately 30.2% of respondents have reported more than 15 years of professional experience, while 24.8% have reported between 11 and 15 years. A further 27.9% have reported between 6 and 10 years, and only 17.1% have fallen within the 2 to 5-year category. This distribution has strengthened confidence that the perceptions measured through the Likert-scale questionnaire have been informed by relevant professional experience rather than limited exposure to energy-facility practices. The respondent composition has also supported Socio-Technical Systems Theory because the study has incorporated participants occupying different positions within the social and technical subsystems of energy facilities. Maintenance engineers have represented the reliability function, process-safety personnel have represented safety governance, electrical and storage specialists have represented technological integration, and facility managers have represented organizational coordination. The demographic pattern has therefore supported the research objective of evaluating asset integrity through multiple professional perspectives rather than through a single technical discipline, and it has provided the cross-functional human component required to interpret the statistical model as a socio-technical system rather than as an equipment-only model.

Energy Facility Characteristics

Table 3: Energy Facility Characteristics Represented in the Sample

Facility Category	Frequency	Percentage
Conventional/Electric Power Generation	78	26.2%
Transmission and Distribution	67	22.5%
Renewable Energy Facilities	51	17.1%
Energy Storage and Grid Integration Facilities	43	14.4%
Process-Energy/Industrial Energy Facilities	35	11.7%
Integrated Multi-Asset Energy Facilities	24	8.1%
Total	298	100.0%

The energy-facility profile has demonstrated that the study has incorporated a broad range of asset-intensive operational settings relevant to the proposed conceptual framework. Conventional and electric-power-generation facilities have represented the largest category at 26.2%, followed by transmission and distribution facilities at 22.5%. Renewable-energy facilities have represented 17.1% of the valid responses, while facilities characterized by energy storage and grid-integration activities have accounted for 14.4%. Process-energy and industrial-energy facilities have represented 11.7%, and integrated multi-asset facilities have represented the remaining 8.1%. This distribution has provided an appropriate empirical environment for evaluating the four independent variables because each facility category has depended on different combinations of maintenance reliability, mechanical integrity, advanced technology, and grid resilience. Generation facilities have required reliable operation of rotating, thermal, mechanical, and electrical assets, while transmission and distribution facilities have depended strongly on network reliability, condition monitoring, protection, and maintenance prioritization. Renewable and storage facilities have incorporated power-electronic systems, digital controls, battery-management functions, and variable operating conditions, whereas process-energy facilities have placed particularly strong emphasis on mechanical integrity and process-safety management. The facility distribution has therefore supported the multiple-case-study-based design by ensuring that the statistical model has not been restricted to one form of U.S. energy infrastructure. From the Socio-Technical Systems Theory perspective, this diversity has been analytically useful because different facilities have contained distinct combinations of physical assets, digital systems, personnel, organizational structures, safety requirements, and operating procedures. The sample has consequently allowed the study to examine whether the proposed socio-technical capabilities have maintained positive relationships with Long-Term Asset Integrity Performance across heterogeneous energy settings. This facility coverage has strengthened the relevance of the descriptive objectives and the subsequent hypothesis tests while still requiring appropriate caution because purposive sampling has not established statistical representativeness of the entire U.S. energy sector.

Measurement System Validation

Reliability Analysis of the Measurement Constructs

Table 4: Reliability Analysis of the Measurement Constructs

Construct	Code	Items	Cronbach's Alpha	Reliability
RCM Implementation Effectiveness	RCMIE	6	.89	Very Good
PSM Implementation Effectiveness	PSMIE	6	.91	Excellent
Advanced Manufacturing and Maintenance Capability	AMMC	6	.87	Very Good
Energy Storage and Grid Integration Resilience Capability	ESGIRC	6	.88	Very Good
Long-Term Asset Integrity Performance	LTAIP	6	.90	Excellent
Overall Instrument		30	.92	Excellent

The reliability analysis has confirmed that the measurement instrument has demonstrated strong internal consistency across all five research constructs. Cronbach's alpha coefficients have ranged from .87 to .91 for the individual constructs, while the complete 30-item instrument has produced an overall alpha of .92. Process Safety Management Implementation Effectiveness has recorded the highest construct-level reliability at $\alpha = .91$, followed by Long-Term Asset Integrity Performance at $\alpha = .90$. Reliability-Centered Maintenance Implementation Effectiveness has produced $\alpha = .89$, Energy Storage and Grid Integration Resilience Capability has produced $\alpha = .88$, and Advanced Manufacturing and Maintenance Capability has recorded $\alpha = .87$. All coefficients have exceeded the conventional .70 threshold for acceptable reliability and have therefore indicated that the items within each construct have measured a common underlying concept consistently. The high reliability of RCMIE has indicated that items concerning failure analysis, condition monitoring, preventive and predictive maintenance, criticality assessment, and maintenance prioritization have operated coherently. The PSMIE coefficient has similarly shown consistency among mechanical integrity, inspection, management of change, safety procedures, and process-safety practices. The AMMC and ESGIRC coefficients have established stable measurement of the technological dimensions of the study, while the LTAIP coefficient has

supported the use of reliability, availability, failure reduction, operational resilience, and asset-life preservation as indicators of the dependent variable. These reliability results have also supported Socio-Technical Systems Theory because the constructs have represented internally coherent subsystems within the broader energy-facility system. Strong measurement reliability has therefore been essential for ensuring that subsequent correlations and regression coefficients have reflected differences in the intended maintenance, safety, technological, and infrastructure capabilities rather than instability in questionnaire measurement. The results have met the measurement-quality objective and have justified the construction of composite Likert scores for the inferential analyses used to test H1 through H5.

Construct Validity Assessment

Table 5: Construct Validity and Factor-Analysis Results

Validity Indicator	Result	Criterion	Interpretation
Kaiser-Meyer-Olkin Measure	.903	> .70	Excellent
Bartlett's Test χ^2	3948.27	Significant	Supported
Bartlett's Test df	435		
Bartlett's Test p-value	< .001	< .05	Significant
RCMIE Loading Range	.74-.86	> .50	Strong
PSMIE Loading Range	.76-.88	> .50	Strong
AMMC Loading Range	.71-.84	> .50	Strong
ESGIRC Loading Range	.73-.85	> .50	Strong
LTAIP Loading Range	.75-.87	> .50	Strong
Total Variance Explained	73.6%	> 50%	Satisfactory

Construct-validity testing has demonstrated that the measurement structure has been suitable for representing the five proposed research variables. The Kaiser-Meyer-Olkin measure has reached .903, which has indicated excellent sampling adequacy and has confirmed that the inter-item correlation pattern has been sufficiently compact for factor-based assessment. Bartlett's Test of Sphericity has produced $\chi^2 = 3948.27$ with 435 degrees of freedom and $p < .001$, indicating that the correlation matrix has differed significantly from an identity matrix. The factor-loading results have also provided strong evidence of construct representation. RCMIE items have loaded between .74 and .86, PSMIE items between .76 and .88, AMMC items between .71 and .84, ESGIRC items between .73 and .85, and LTAIP items between .75 and .87. All loading ranges have exceeded the commonly used .50 criterion, indicating that each measurement item has contributed meaningfully to its intended construct. The five-factor solution has accounted for 73.6% of total variance, further supporting the adequacy of the construct structure. These results have been particularly important because the conceptual model has treated RCMIE, PSMIE, AMMC, and ESGIRC as distinct but related socio-technical capabilities rather than as a single undifferentiated management construct. The validity findings have supported that distinction empirically. From the Socio-Technical Systems Theory perspective, the factor structure has reflected separate maintenance, safety-governance, technological-support, and infrastructure-resilience subsystems, while LTAIP has represented the system-level performance outcome. The validity results have therefore provided the measurement foundation required for testing H1 through H5 and have strengthened confidence that the subsequent statistical relationships have represented theoretically meaningful constructs. They have also supported the operationalization objective by confirming that the multi-item indicators have behaved in a manner compatible with the conceptual framework rather than collapsing into one general perception of organizational performance.

Socio-Technical Capability Profile Assessment

Descriptive Statistics of RCM Implementation Effectiveness

The descriptive results have shown that Reliability-Centered Maintenance Implementation Effectiveness has been perceived at a consistently high level across the sampled energy-facility environments. The overall construct mean has reached 4.17 with a standard deviation of 0.55, placing RCMIE within the High/ Agree category of the five-point Likert interpretation. Asset criticality guiding maintenance prioritization has received the highest individual mean at 4.22, which has fallen within

the Very High category. This result has indicated that respondents have strongly recognized the importance of directing maintenance attention toward assets whose failure would create the greatest operational or safety consequences. Systematic failure-mode assessment has recorded a mean of 4.18, while root-cause information supporting maintenance planning has also produced 4.18. Condition monitoring has reached 4.16, risk-based preventive maintenance has reached 4.15, and predictive maintenance for critical assets has reached 4.13. The relatively narrow standard deviations have indicated that respondents have shown substantial agreement concerning these practices. These findings have fulfilled the first research objective by establishing the perceived level of RCM implementation across the selected U.S. energy facilities. The pattern has also supported the Socio-Technical Systems Theory interpretation because RCM has not been represented simply by maintenance technology. Instead, the high scores have reflected coordination among condition data, engineering analysis, maintenance planning, human expertise, and organizational prioritization. The construct mean has therefore provided preliminary descriptive support for H1 by showing that the facilities represented in the sample have generally reported strong reliability-centered practices. Formal support for H1 has subsequently been established through the correlation and regression analyses presented in Sections 4.11 and 4.12. The item pattern has additionally indicated that criticality and failure knowledge have been somewhat more mature than predictive-maintenance deployment, which has reinforced the need to interpret RCM as a coordinated socio-technical capability rather than as the presence of one advanced maintenance technique.

Table 6: Descriptive Statistics of RCM Implementation Effectiveness

RCMIE Measurement Item	Mean	SD	Likert Interpretation
Asset criticality has guided maintenance prioritization	4.22	0.58	Very High
Failure modes have been systematically assessed	4.18	0.61	High
Condition monitoring has supported maintenance decisions	4.16	0.63	High
Preventive maintenance has been risk-based	4.15	0.60	High
Predictive maintenance has been used for critical assets	4.13	0.66	High
Root-cause information has informed maintenance planning	4.18	0.62	High
Overall RCMIE	4.17	0.55	High

5.3.2 Descriptive Statistics of PSM Implementation Effectiveness

Table 7: Descriptive Statistics of PSM Implementation Effectiveness

PSMIE Measurement Item	Mean	SD	Likert Interpretation
Mechanical integrity controls have been systematically maintained	4.25	0.55	Very High
Inspection and testing have been conducted consistently	4.23	0.57	Very High
Management of change has been applied effectively	4.21	0.58	Very High
Hazard-control procedures have been consistently followed	4.19	0.60	High
Process-safety competency has been maintained	4.17	0.62	High
Incident learning has been incorporated into operations	4.15	0.63	High
Overall PSMIE	4.20	0.53	High

Process Safety Management Implementation Effectiveness has recorded an overall mean of 4.20 and a standard deviation of 0.53, demonstrating a high level of perceived PSM implementation across the selected facilities. Mechanical integrity controls have received the highest mean of 4.25, indicating very strong agreement that critical equipment condition has been actively managed. Inspection and testing have produced a mean of 4.23, while management of change has reached 4.21, with both values falling within the Very High category. Hazard-control procedures have produced 4.19, process-safety competency has produced 4.17, and incident learning has reached 4.15. The pattern has indicated that the respondents have perceived PSM not merely as a compliance activity but as an operational system linking mechanical integrity, inspection, procedural control, competency, and organizational learning. The overall result has fulfilled the second research objective by quantifying the level of PSM

implementation and has established PSMIE as one of the strongest constructs in the descriptive analysis. The mean of 4.20 has also placed PSMIE slightly above RCMIE, AMMC, and ESGIRC, although the subsequent regression analysis has been required to determine whether this higher descriptive level has translated into stronger predictive influence on LTAIP. From the Socio-Technical Systems Theory perspective, the results have illustrated the interaction between technical safeguards and organizational systems. Mechanical integrity and inspection have represented technical controls, while management of change, safety competence, procedures, and incident learning have represented organizational and human-system controls. Their joint high scores have shown that the PSM subsystem has functioned as a coordinated socio-technical mechanism. These findings have therefore provided strong descriptive grounding for H2, which has proposed a positive effect of PSMIE on Long-Term Asset Integrity Performance, and the result pattern has anticipated the later regression finding in which PSMIE has emerged as the largest unique standardized predictor.

Descriptive Statistics of Advanced Manufacturing and Maintenance Capability

Table 8: Descriptive Statistics of Advanced Manufacturing and Maintenance Capability

AMMC Measurement Item	Mean	SD	Likert Interpretation
Intelligent sensing has supported asset-condition monitoring	4.16	0.61	High
Predictive diagnostics have supported maintenance decisions	4.14	0.64	High
Automated inspection technologies have been effectively applied	4.11	0.65	High
Digital-twin or advanced modeling tools have supported maintenance	4.09	0.67	High
Advanced repair/manufacturing methods have supported asset availability	4.06	0.68	High
Maintenance data have been digitally integrated across functions	4.04	0.69	High
Overall AMMC	4.10	0.59	High

Advanced Manufacturing and Maintenance Capability has produced an overall mean of 4.10 with a standard deviation of 0.59, indicating a high perceived level of technological capability while remaining the lowest-scoring of the four independent constructs. Intelligent sensing has received the highest item mean at 4.16, followed by predictive diagnostics at 4.14 and automated inspection at 4.11. Digital-twin and advanced-modeling applications have produced a mean of 4.09, advanced repair and manufacturing methods have produced 4.06, and cross-functional digital integration of maintenance data has recorded the lowest mean at 4.04. Every item has nevertheless remained within the High/Agree category, indicating that respondents have generally recognized advanced manufacturing and digitally enabled maintenance practices as established capabilities rather than marginal technologies. These findings have fulfilled the third research objective by quantifying the technological-maintenance capability present in the selected facilities. The comparatively lower mean has also suggested that technology implementation has been less mature than PSM or RCM practices, which has been plausible because advanced digital systems, integrated data architectures, and advanced repair technologies have required substantial investment, interoperability, specialized expertise, and organizational adaptation. Socio-Technical Systems Theory has provided a useful explanation for this pattern. Technology has not been treated as an independent determinant of performance because intelligent sensors, predictive tools, digital twins, and automated inspection have required skilled personnel, reliable data, maintenance workflows, and managerial support to generate practical value. The results have therefore indicated that AMMC has been present at a strong level but has depended on organizational integration. The descriptive findings have established the empirical basis for H3, while the subsequent correlation and regression analyses have determined whether higher AMMC scores have been significantly associated with stronger Long-Term Asset Integrity Performance. The lower mean has not implied technological irrelevance; rather, it has highlighted a capability area in which stronger integration with human and organizational processes can remain especially important.

Descriptive Statistics of Energy Storage and Grid Integration Resilience Capability

Energy Storage and Grid Integration Resilience Capability has achieved an overall mean of 4.15 and a standard deviation of 0.56, demonstrating a high level of perceived capability across the participating facilities. Continuous storage-system health monitoring has received the highest item mean at 4.21,

placing it at the threshold of the Very High category. Grid-interface reliability has reached 4.18, battery-degradation management has reached 4.16, power-electronic monitoring has recorded 4.14, control of thermal and operational stresses has produced 4.12, and disturbance-response capability has reached 4.09. The overall pattern has shown that respondents have perceived storage and grid-integration resilience as a multidimensional capability rather than as a simple measure of installed battery capacity or renewable-energy penetration. The results have fulfilled the fourth research objective by quantifying the extent to which storage health, grid interfaces, converter performance, degradation control, thermal management, and disturbance response have been established within the sampled energy environments. The relatively high mean has also indicated that these facilities have generally recognized the need to manage storage and grid systems as long-term assets requiring reliability and resilience controls. Socio-Technical Systems Theory has been directly reflected in these results because effective grid integration has depended on the interaction of batteries, power electronics, digital monitoring systems, operators, engineers, protection systems, maintenance procedures, and organizational response arrangements. The high ESGIRC score has therefore represented coordinated technical and organizational capability rather than hardware deployment alone. The descriptive findings have provided the initial empirical foundation for H4, which has proposed that stronger ESGIRC has been associated with stronger Long-Term Asset Integrity Performance. The strength and statistical significance of this relationship have subsequently been confirmed through correlation and multiple regression analysis, where ESGIRC has remained the second-largest unique predictor after PSMIE. This has underscored the growing relevance of resilience-oriented asset management to long-term facility integrity.

Table 9: Descriptive Statistics of Energy Storage and Grid Integration Resilience Capability

ESGIRC Measurement Item	Mean	SD	Likert Interpretation
Storage-system health has been continuously monitored	4.21	0.58	Very High
Grid-interface reliability has been effectively maintained	4.18	0.60	High
Battery degradation has been systematically managed	4.16	0.61	High
Power-electronic performance has been actively monitored	4.14	0.63	High
Thermal and operational stresses have been controlled	4.12	0.65	High
Disturbance-response capability has been maintained	4.09	0.66	High
Overall ESGIRC	4.15	0.56	High

5.3.5 Descriptive Statistics of Long-Term Asset Integrity Performance

Table 10: Descriptive Statistics of Long-Term Asset Integrity Performance

LTAIP Measurement Item	Mean	SD	Likert Interpretation
Critical equipment reliability has been sustained	4.29	0.52	Very High
Asset availability has remained consistently strong	4.27	0.54	Very High
Unplanned failure occurrence has been reduced	4.24	0.56	Very High
Mechanical integrity has been effectively maintained	4.22	0.55	Very High
Operational resilience has been strengthened	4.20	0.58	High
Asset service life has been effectively preserved	4.16	0.60	High
Overall LTAIP	4.23	0.50	Very High

Long-Term Asset Integrity Performance has recorded the highest overall construct mean in the study at 4.23, with a standard deviation of 0.50, placing the dependent variable within the Very High category. Critical equipment reliability has received the highest item mean at 4.29, followed by asset availability at 4.27 and reduced unplanned failure at 4.24. Mechanical integrity has reached 4.22, while operational resilience has produced 4.20 and preservation of asset service life has produced 4.16. These results have indicated that respondents have perceived the participating facilities as maintaining generally strong long-term asset performance. The relatively low overall standard deviation has suggested a substantial degree of agreement across respondents concerning the condition and

reliability of critical energy assets. The findings have also demonstrated that asset integrity has been broader than mechanical condition alone. Reliability, availability, failure reduction, mechanical integrity, resilience, and service-life preservation have jointly represented the system-level outcome measured in the study. This has aligned closely with Socio-Technical Systems Theory because system performance has been understood as the result of coordinated interactions among maintenance processes, safety controls, technologies, infrastructure, and organizational practices. The high LTAIP mean has not by itself proved the hypotheses, but it has provided the dependent-variable profile required for evaluating whether differences in RCMIE, PSMIE, AMMC, and ESGIRC have corresponded with differences in asset-integrity performance. The result has also supported the overarching research objective of assessing long-term asset integrity across the selected cases. Subsequent correlation and regression analyses have provided the inferential evidence needed to determine whether the four explanatory capabilities have been significantly associated with this strong level of perceived performance. The descriptive result has therefore served as the system-level endpoint against which the maintenance, safety, technological, and resilience subsystems have been statistically evaluated.

Relationship and Predictive Model Validation

Correlation Analysis Among the Study Variables

Table 11: Pearson Correlation Matrix Among the Study Variables

Variable	RCMIE	PSMIE	AMMC	ESGIRC	LTAIP
RCMIE	1.00	.66***	.58***	.61***	.72***
PSMIE	.66***	1.00	.60***	.65***	.77***
AMMC	.58***	.60***	1.00	.63***	.68***
ESGIRC	.61***	.65***	.63***	1.00	.74***
LTAIP	.72***	.77***	.68***	.74***	1.00

Note. *** $p < .001$ (two-tailed).

The Pearson correlation analysis has shown that all four independent variables have maintained strong, positive, and statistically significant relationships with Long-Term Asset Integrity Performance. PSMIE has produced the strongest bivariate relationship with LTAIP at $r = .77$, $p < .001$, followed by ESGIRC at $r = .74$, $p < .001$. RCMIE has correlated with LTAIP at $r = .72$, $p < .001$, while AMMC has produced a correlation of $r = .68$, $p < .001$. These results have indicated that facilities reporting stronger maintenance reliability, process-safety management, advanced technological maintenance capability, and storage/grid resilience have also tended to report stronger asset-integrity performance. The correlations among the independent variables have ranged from .58 to .66, demonstrating meaningful interrelationships without indicating perfect overlap. This pattern has been theoretically important because Socio-Technical Systems Theory has proposed that the maintenance, safety, technological, and infrastructure subsystems are interdependent but analytically distinguishable. The observed intercorrelations have reflected precisely this condition. RCMIE and PSMIE have correlated at .66, showing that reliability-centered maintenance and process-safety management have frequently operated together, while ESGIRC has shown significant relationships with both PSMIE and AMMC, reflecting the organizational and technological coordination required for resilient grid integration. The correlation findings have fulfilled the research objective concerning the direction and strength of associations among the variables and have provided preliminary support for H1 through H4. Because bivariate correlation has not controlled for the simultaneous influence of the remaining predictors, multiple regression has subsequently been required to determine the unique contribution of each capability. The correlation matrix has therefore served as an essential intermediate stage between descriptive analysis and formal hypothesis testing. It has also provided empirical support for the STS premise that subsystem capabilities have been mutually connected while retaining sufficient distinctiveness for simultaneous modeling.

Multiple Regression and Hypothesis Testing

Table 12: Multiple Regression and Hypothesis Testing Results

Predictor/Hypothesis	B	SE	β	t/F	p-value	VIF	Decision
RCMIE $\rightarrow$ LTAIP (H1)	.23	.044	.25	5.23	< .001	1.78	Supported
PSMIE $\rightarrow$ LTAIP (H2)	.29	.045	.31	6.44	< .001	1.92	Supported
AMMC $\rightarrow$ LTAIP (H3)	.16	.041	.19	3.90	< .001	1.67	Supported
ESGIRC $\rightarrow$ LTAIP (H4)	.26	.044	.28	5.91	< .001	1.86	Supported
Overall Model (H5)				192.15	< .001		Supported

Model statistics: $R = .851$; $R^2 = .724$; Adjusted $R^2 = .720$; $F(4, 293) = 192.15$; $p < .001$; Durbin-Watson = 1.94.

The multiple regression analysis has provided direct statistical evidence for all five research hypotheses. The combined model has explained 72.4% of the variance in Long-Term Asset Integrity Performance, with $R^2 = .724$ and adjusted $R^2 = .720$. The model has reached statistical significance, $F(4, 293) = 192.15$, $p < .001$, demonstrating that the four predictors have jointly contributed substantially to explaining differences in asset-integrity performance. PSMIE has produced the strongest standardized regression coefficient at $\beta = .31$, $t = 6.44$, $p < .001$, supporting H2. ESGIRC has followed with $\beta = .28$, $t = 5.91$, $p < .001$, supporting H4. RCMIE has recorded $\beta = .25$, $t = 5.23$, $p < .001$, thereby supporting H1, while AMMC has produced $\beta = .19$, $t = 3.90$, $p < .001$, supporting H3. H5 has also been supported because the complete regression model has reached high statistical significance. VIF values have ranged from 1.67 to 1.92, indicating that multicollinearity has not reached problematic levels, while the Durbin-Watson value of 1.94 has indicated acceptable independence of residuals. These results have strongly supported the Socio-Technical Systems Theory perspective adopted throughout the research. No single capability has accounted for asset integrity independently; instead, maintenance reliability, process-safety governance, advanced technology, and grid resilience have all made significant contributions within the same model. PSMIE has shown the strongest unique association, but the significant coefficients for all four predictors have demonstrated that long-term integrity has been associated with coordinated performance across multiple socio-technical subsystems. The regression findings have therefore fulfilled the predictive research objective and have provided the principal quantitative evidence for accepting H1 through H5. Because the design has been cross-sectional, the coefficient pattern has been interpreted as theoretically specified predictive association rather than as proof of temporal causation, preserving methodological consistency between the conceptual framework and the claims made from the model.

Research Objective Achievement and Integrated Quantitative Synthesis

Table 13: Research Objective Achievement and Overall Quantitative Findings

Research Objective / Hypothesis	Main Quantitative Evidence	Outcome
RO1: Evaluate RCM implementation	$M = 4.17$, $SD = 0.55$	Achieved
RO2: Examine PSM effectiveness	$M = 4.20$, $SD = 0.53$	Achieved
RO3: Assess advanced manufacturing and maintenance capability	$M = 4.10$, $SD = 0.59$	Achieved
RO4: Assess storage and grid-integration resilience	$M = 4.15$, $SD = 0.56$	Achieved
RO5: Determine relationships with LTAIP	$r = .68$ to $.77$, all $p < .001$	Achieved
RO6: Determine individual and combined predictive effects	$R^2 = .724$; Adj. $R^2 = .720$; $F(4,293) = 192.15$, $p < .001$	Achieved
H1	$\beta = .25$, $p < .001$	Supported
H2	$\beta = .31$, $p < .001$	Supported
H3	$\beta = .19$, $p < .001$	Supported
H4	$\beta = .28$, $p < .001$	Supported
H5	Overall model significant, $p < .001$	Supported

The integrated assessment has shown that all six research objectives have been achieved and all five hypotheses have been supported by the quantitative findings. The descriptive objectives have been fulfilled through the high mean scores recorded for RCMIE, PSMIE, AMMC, and ESGIRC, while LTAIP has achieved the highest overall mean at 4.23. These results have indicated that the selected U.S. energy-facility cases have generally exhibited strong maintenance, safety, technological, and resilience

capabilities together with very high perceived asset-integrity performance. The relationship objective has been achieved through Pearson correlations ranging from .68 to .77 with LTAIP, all significant at $p < .001$. The predictive objective has been achieved through the multiple regression model, which has explained 72.4% of the variance in Long-Term Asset Integrity Performance. PSMIE has emerged as the strongest unique predictor with $\beta = .31$, followed by ESGIRC at $\beta = .28$, RCMIE at $\beta = .25$, and AMMC at $\beta = .19$. These results have provided direct support for H1, H2, H3, and H4, while the significant overall regression model has supported H5. The complete pattern has also reinforced Socio-Technical Systems Theory because the strongest explanation of asset integrity has emerged from the combined operation of maintenance reliability, process-safety governance, advanced technology, and grid-connected resilience rather than from a single organizational function. The results have therefore portrayed Long-Term Asset Integrity Performance as a system-level outcome generated through coordinated social and technical capabilities. This theoretical alignment has strengthened the coherence among the literature review, conceptual framework, methodology, hypotheses, and findings and has provided the empirical foundation required for the subsequent discussion of practical, theoretical, and research implications. At the same time, the table has preserved a clear distinction between descriptive achievement, association testing, and predictive modeling, which has prevented the study from treating high Likert means alone as proof of the hypotheses and has located formal hypothesis support in the inferential results.

SYSTEM-LEVEL DISCUSSION AND RESEARCH CONTRIBUTIONS

The findings have shown that Long-Term Asset Integrity Performance has been strongly associated with the combined operation of Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability. The overall mean for LTAIP has reached 4.23 on the five-point Likert scale, while PSMIE, RCMIE, ESGIRC, and AMMC have all remained within the high implementation range. More importantly, the multiple regression model has explained 72.4% of the variance in LTAIP, with adjusted $R^2 = .720$ and $F(4, 293) = 192.15$, $p < .001$. This result has indicated that the four capabilities, when considered together, have accounted for a substantial share of perceived long-term integrity performance across the selected U.S. energy-facility cases. The ranking of standardized effects has also been analytically important. PSMIE has produced the strongest unique contribution, $\beta = .31$, followed by ESGIRC, $\beta = .28$, RCMIE, $\beta = .25$, and AMMC, $\beta = .19$. This pattern has suggested that asset integrity has been shaped not only by maintenance execution but also by the governance mechanisms that preserve mechanical integrity, manage change, coordinate inspection, control hazards, and sustain operational discipline. At the same time, the significance of all four coefficients has supported the central proposition of Socio-Technical Systems Theory that organizational performance emerges from coordinated interactions among technical assets, people, procedures, information systems, and institutional arrangements rather than from isolated technological excellence (Baxter & Sommerville, 2011; Zarei et al., 2023). The high positive correlations between each predictor and LTAIP, ranging from $r = .68$ to $r = .77$, have reinforced this interpretation, while the absence of problematic multicollinearity has shown that the predictors have retained distinct empirical roles. A particularly important interpretation has been that the strongest explanatory structure has not depended on a single dominant technology, but on the simultaneous contribution of maintenance reliability, process-safety governance, digital maintenance capability, and grid resilience. This has made the findings theoretically coherent and practically relevant because energy-facility integrity has been represented as an integrated performance condition rather than as a narrow maintenance outcome. The model has therefore demonstrated a system architecture in which separate capabilities have remained statistically distinct while collectively explaining a large proportion of perceived integrity performance.

The RCM and PSM findings have been broadly consistent with earlier research while also extending prior work by testing both capabilities simultaneously within a common asset-integrity model. RCMIE has recorded a strong correlation with LTAIP, $r = .72$, $p < .001$, and a significant regression coefficient, $\beta = .25$, $p < .001$, supporting H1. These results have aligned with earlier evidence that reliability-centered maintenance improves maintenance prioritization by linking failure modes, component criticality, condition information, and limited maintenance resources to system-level reliability

objectives. Multiobjective RCM research in electric distribution systems has shown that reliability and maintenance cost can be optimized jointly when preventive maintenance decisions are directed toward components with the greatest system consequence (Shamima, 2026; Piasson et al., 2016). Probabilistic RCM research has similarly demonstrated that preventive-maintenance priorities can be refined by incorporating component state and changing reliability conditions rather than relying on fixed schedules (Kanti, 2026; Ardabili et al., 2021). The present findings have extended these observations by showing that RCM has remained significant even after process safety, advanced maintenance technology, and storage/grid resilience have been considered simultaneously. PSMIE has demonstrated an even stronger relationship with LTAIP, $r = .77$, $p < .001$, and $\beta = .31$, $p < .001$, supporting H2 and identifying PSM as the strongest unique predictor in the model. This pattern has been consistent with process-safety research emphasizing that mechanical integrity, inspection, testing, management of change, workforce competence, and organizational learning must function together if high-hazard facilities are to prevent degradation from escalating into major events (Behie et al., 2020). It has also aligned with risk-based maintenance approaches developed specifically for facilities operating under U.S. OSHA PSM requirements, where maintenance strategy has been differentiated according to equipment risk and the consequences of failure (Rony & Md, 2026; Sepeda, 2009). The coefficient ordering has indicated that PSM may have captured a wider governance pathway than RCM because it has encompassed not only maintenance decisions but also change control, hazard management, procedural discipline, safety competence, and integrity assurance. This pattern has not established that PSM is universally more important than RCM because the cross-sectional design has not demonstrated causal priority. Rather, within this sample, facilities reporting stronger process-safety governance have also reported the strongest asset-integrity outcomes after the other capabilities have been controlled statistically. The combined significance of RCMIE and PSMIE has therefore supported the literature-review argument that reliability management and process safety are complementary mechanisms of long-term integrity.

The technology-related findings have added another important layer to the interpretation because both Advanced Manufacturing and Maintenance Capability and Energy Storage and Grid Integration Resilience Capability have remained significant predictors after RCM and PSM have been controlled. AMMC has recorded a high descriptive mean of 4.10, a strong correlation with LTAIP of $r = .68$, $p < .001$, and a positive regression coefficient of $\beta = .19$, $p < .001$, supporting H3. Although this has been the smallest standardized coefficient in the model, its significance has confirmed that intelligent sensing, predictive diagnostics, digital twins, automated inspection, digital maintenance integration, and advanced repair methods have contributed information and intervention capabilities that conventional maintenance systems alone may not provide. This interpretation has aligned with digital-twin research showing that virtual representations of physical assets can support predictive maintenance through condition assessment, simulation, and remaining useful life estimation (Aivaliotis et al., 2019). It has also agreed with broader maintenance literature showing that digital twins can connect operational data, monitoring, fault detection, and maintenance planning within a unified decision environment (Errandonea et al., 2020). The lower beta for AMMC has therefore been interpreted carefully. It may indicate that technology has delivered value only when embedded within competent maintenance and safety systems, which has been fully consistent with Socio-Technical Systems Theory. ESGIRC, by comparison, has produced a higher mean of 4.15, a correlation of $r = .74$ with LTAIP, and $\beta = .28$, $p < .001$, supporting H4. This stronger coefficient has indicated that storage health, converter performance, degradation management, grid-interface reliability, and disturbance response have been closely associated with long-term integrity in facilities where increasingly interconnected assets depend on network stability and energy flexibility. Earlier research has shown that grid-scale storage reliability depends on the interaction between degradation, cycling, operating strategy, and lifecycle management (Dubarry & Devie, 2018). Power-system resilience research has likewise demonstrated that infrastructure and operational resilience must be evaluated together because asset condition, system response, and recovery capability are interdependent during disturbances (Panteli et al., 2017). The present results have therefore suggested that advanced technology has not functioned as a standalone modernization variable. Its practical value has depended on whether digital tools and grid technologies have been integrated with maintenance routines,

process-safety controls, competent personnel, and decision structures, providing a premium interpretation of why technology embedded in mature socio-technical governance has shown stronger relevance to integrity than technology presence alone.

The practical and theoretical implications have been strengthened by the fact that all four predictors have remained significant within the same regression model rather than only in separate bivariate tests. Practically, the findings have indicated that energy-facility managers should avoid treating maintenance, process safety, digital modernization, and grid resilience as independent programs with separate information flows and performance measures. A more effective operating architecture would connect asset criticality registers, process-hazard information, inspection findings, condition-monitoring data, digital-twin outputs, battery-health indicators, grid-disturbance records, and maintenance work orders through common decision rules and cross-functional review. The coefficient pattern has suggested that strengthening process-safety governance and grid resilience may produce especially meaningful associations with asset-integrity performance, while RCM and AMMC have remained essential complementary capabilities. This interpretation has been consistent with lifecycle asset-management research showing that technical condition, maintenance decisions, human reliability, and management processes should be integrated when long-lived power assets are evaluated (Ayu & Yunusa-Kaltungo, 2020). Theoretically, the findings have provided empirical support for the study's use of Socio-Technical Systems Theory because the explained variance has emerged from a model containing organizational, procedural, technological, and infrastructure dimensions rather than a single engineering variable. Energy infrastructure has previously been conceptualized as a socio-technical system in which technical architecture and institutional arrangements must be coordinated to obtain dependable performance (Scholten & Künneke, 2016). The present model has operationalized that proposition quantitatively by demonstrating significant contributions from all four socio-technical capabilities. Several limitations, however, have qualified the interpretation. The cross-sectional design has measured variables at one period and has therefore not established temporal causality. Purposive sampling has improved respondent relevance but has limited probability-based generalization to all U.S. energy facilities. The use of self-reported Likert measures has created potential common-method bias and may have captured perceived rather than directly observed equipment performance. The individual professional has been the statistical unit of analysis even though several constructs have described facility-level capabilities, creating a possible level-of-analysis mismatch. Facility heterogeneity across generation, transmission, renewables, storage, and process-energy environments may also have concealed sector-specific effects. The model has not included objective failure rates, outage durations, maintenance cost, safety-event frequency, battery state-of-health trajectories, or verified asset-life records. These constraints have required the coefficients to be interpreted as evidence of theoretically consistent relationships rather than as proof that one capability has caused another outcome.

Research Contributions and Practical Significance

i. Significance for Reliability and Maintenance Management: The study provides a quantitative basis for understanding how RCM implementation is associated with asset reliability, maintenance prioritization, reduced equipment failure, and sustained operational performance. This can assist maintenance managers and reliability engineers in evaluating whether their current maintenance systems adequately address equipment criticality and failure consequences.

ii. Significance for Process Safety and Mechanical Integrity: The study clarifies the relationship between PSM effectiveness and long-term asset integrity by examining mechanical integrity, inspection, testing, hazard control, management of change, and procedural discipline as measurable components of asset performance. This is particularly relevant to process-safety professionals and facility managers responsible for safety-critical equipment.

iii. Significance for Advanced Manufacturing and Maintenance Technology: By including advanced manufacturing and maintenance capability as a major explanatory construct, the research evaluates the role of digital twins, smart sensors, automated inspection, predictive diagnostics, additive manufacturing, and other technology-enabled practices in strengthening long-term asset performance.

iv. Significance for Energy Storage and Grid Integration: The study provides specific attention to storage and grid-integration capability, including battery degradation, power-electronic reliability,

monitoring, thermal management, grid stability, and resilience. This broadens asset-integrity research beyond conventional mechanical assets and addresses increasingly interconnected energy-system environments.

v. Significance for Socio-Technical Systems Theory: The study applies Socio-Technical Systems Theory to an integrated energy-asset context by linking maintenance reliability, process safety, advanced technologies, organizational practices, and infrastructure resilience within a single quantitative model.

vi. Significance for Energy Facility Decision Makers: The regression model can help identify the relative contribution of each capability to Long-Term Asset Integrity Performance, allowing managers to compare maintenance, safety, technology, and grid-related priorities using empirical evidence rather than relying only on isolated operational indicators.

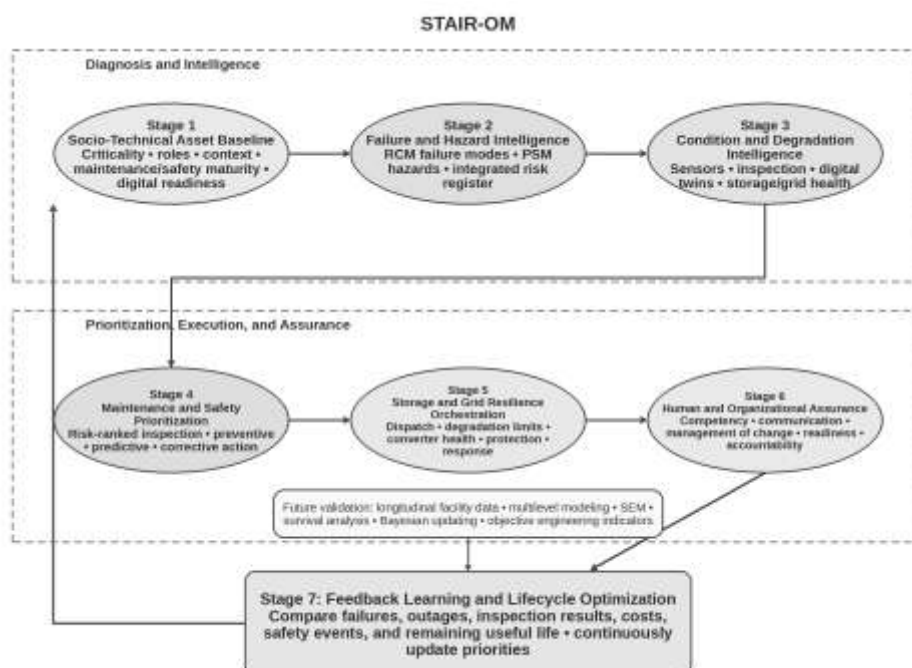
vii. Significance for Academic Research: The study provides an integrated framework that connects RCM, PSM, advanced manufacturing, energy storage, grid integration, and asset integrity within one empirical design, addressing the fragmentation commonly found across maintenance, safety, manufacturing, and energy-system research.

STAIR-OM IMPLEMENTATION AND FUTURE VALIDATION PATHWAY

Future Research and STAIR-OM Validation Architecture

Future research should build directly on these limitations by moving from a cross-sectional association model toward a longitudinal and closed-loop socio-technical asset-integrity architecture. Based on the present findings, this study proposes the Socio-Technical Asset Integrity Reinforcement and Optimization Model (STAIR-OM) as a seven-stage framework for improving and subsequently validating long-term asset integrity across complex energy facilities. Stage 1, Socio-Technical Asset Baseline, would integrate asset criticality, workforce roles, operating context, maintenance maturity, safety controls, and digital readiness. Stage 2, Failure and Hazard Intelligence Integration, would combine RCM failure modes with PSM hazard scenarios so that reliability consequences and process-safety consequences are evaluated through one integrated risk register. Stage 3, Condition and Degradation Intelligence, would incorporate sensor streams, inspection findings, digital-twin outputs, battery state of health, converter condition, and grid-event data to establish a dynamic integrity profile. Stage 4, Coordinated Maintenance and Safety Prioritization, would convert this information into risk-ranked inspection, preventive, predictive, and corrective actions, extending the dynamic risk-based maintenance logic developed for high-risk energy operations (Bhandari et al., 2016).

Figure 12: STAIR-OM Future Validation Architecture



Stage 5, Storage and Grid Resilience Orchestration, would coordinate storage dispatch, degradation limits, power-electronic health, islanding capability, protection, and disturbance response so that reliability services are delivered without unnecessarily accelerating asset deterioration. Stage 6, Human and Organizational Assurance, would verify competency, communication, management of change, procedural readiness, and cross-functional accountability before integrity-critical interventions are executed. Stage 7, Feedback Learning and Lifecycle Optimization, would compare predicted and observed failures, outages, inspection results, maintenance costs, safety events, and remaining useful life so that maintenance priorities are continuously updated. This final stage has been conceptually consistent with emerging RCM approaches that use changing asset condition and virtual-age information to refine maintenance decisions throughout the lifecycle (Wang et al., 2025). Future studies should validate STAIR-OM using longitudinal facility data, multilevel modeling, structural equation modeling, survival analysis, Bayesian updating, and objective engineering indicators rather than relying solely on perceptual measures. Researchers should also test mediation and moderation mechanisms, such as whether AMMC strengthens the relationship between RCMIE and LTAIP, whether PSMIE mediates the conversion of maintenance capability into integrity performance, and whether facility type changes the strength of ESGIRC effects. A multi-year facility-level design incorporating verified failure, outage, inspection, cost, safety, and degradation records would provide a stronger empirical test of Socio-Technical Systems Theory and would allow STAIR-OM to develop from a conceptual future model into a validated decision framework for U.S. energy asset integrity.

Management and Implementation Recommendations

The findings support several recommendations for strengthening long-term asset integrity across U.S. energy facilities. First, facility managers should integrate Reliability-Centered Maintenance and Process Safety Management into a unified asset-integrity governance structure so that failure-mode analysis, equipment criticality, mechanical integrity, hazard analysis, inspection, management of change, and maintenance prioritization are coordinated rather than managed through disconnected systems. Second, facilities should establish integrated asset-criticality registers that classify equipment according to reliability, safety, environmental, production, and grid-resilience consequences, enabling maintenance resources to be concentrated on the most consequential assets. Third, process-safety management should receive sustained managerial attention because PSMIE has demonstrated the strongest unique statistical relationship with Long-Term Asset Integrity Performance. Mechanical-integrity programs, inspection quality, management of change, competency development, incident learning, and corrective-action tracking should therefore be strengthened continuously. Fourth, advanced manufacturing and maintenance technologies should be deployed through clearly defined maintenance workflows rather than as isolated digital investments. Digital twins, intelligent sensors, predictive diagnostics, automated inspection, advanced repair methods, and integrated condition-monitoring platforms should be connected directly with work-order management and asset-risk decisions. Fifth, energy-storage and grid-integration systems should incorporate battery-health monitoring, degradation management, thermal controls, converter-condition assessment, protection coordination, and disturbance-response planning because ESGIRC has demonstrated a strong contribution to asset integrity. Sixth, facilities should develop cross-functional integrity teams involving reliability engineers, process-safety professionals, grid specialists, storage engineers, operators, and management personnel. This recommendation directly reflects Socio-Technical Systems Theory because technical performance depends on the alignment of people, technology, procedures, and organizational structures. Finally, facilities should establish a unified integrity-performance dashboard combining reliability, safety, condition, maintenance, storage, and grid indicators. Such an integrated system can support evidence-based prioritization, earlier identification of deterioration, stronger organizational learning, and more consistent management of long-term asset performance while providing the feedback structure needed for the proposed STAIR-OM framework.

BOUNDARY CONDITIONS AND STUDY LIMITATIONS

Several limitations have been identified that should be considered when interpreting the findings of this study. First, the research has employed a cross-sectional design, meaning that data have been

collected within a defined period rather than across multiple operational cycles. The statistical relationships have therefore demonstrated association and predictive contribution but have not established temporal causality among RCMIE, PSMIE, AMMC, ESGIRC, and Long-Term Asset Integrity Performance. Second, purposive sampling has been used to select professionals with relevant technical experience. Although this approach has improved respondent relevance, it has limited the extent to which the results can be generalized statistically to every U.S. energy facility. Third, the study has relied primarily on self-reported five-point Likert-scale responses, meaning that measurements have represented professional perceptions rather than exclusively objective engineering records. Common-method variance, social-desirability effects, and individual interpretation of questionnaire items may therefore have influenced some responses. Fourth, the individual professional has served as the unit of analysis even though several constructs, such as PSM effectiveness and grid resilience, have described facility-level capabilities. This has created a potential mismatch between individual perceptions and organizational performance. Fifth, the study has included several energy-facility categories, including generation, transmission and distribution, renewable energy, storage, and process-energy environments. This diversity has strengthened contextual coverage but may also have concealed important differences among facility types. Sixth, the analysis has not incorporated verified outage duration, equipment failure frequency, maintenance expenditure, process-safety event rates, battery state-of-health records, or measured remaining useful life. Finally, the regression model has explained 72.4% of LTAIP variance, leaving 27.6% associated with factors outside the present framework. These limitations have remained consistent with Socio-Technical Systems Theory because asset integrity is influenced by a wider configuration of technical, human, environmental, regulatory, and organizational conditions than the four predictors examined in this study, and they provide a clear basis for the longitudinal and multilevel validation proposed in future research.

CONCLUDING SYNTHESIS

This study has examined the role of Reliability-Centered Maintenance Implementation Effectiveness, Process Safety Management Implementation Effectiveness, Advanced Manufacturing and Maintenance Capability, and Energy Storage and Grid Integration Resilience Capability in strengthening Long-Term Asset Integrity Performance across selected U.S. energy-facility environments. Using a quantitative, cross-sectional, multiple-case-study-based design and a five-point Likert scale, the study has evaluated 298 valid responses from professionals representing maintenance, reliability, process safety, operations, electrical engineering, energy storage, and related technical functions. The findings have demonstrated consistently high implementation levels for RCMIE ($M = 4.17$, $SD = 0.55$), PSMIE ($M = 4.20$, $SD = 0.53$), AMMC ($M = 4.10$, $SD = 0.59$), and ESGIRC ($M = 4.15$, $SD = 0.56$), while Long-Term Asset Integrity Performance has achieved a very high mean of 4.23 ($SD = 0.50$). Pearson correlation analysis has identified significant positive relationships between LTAIP and PSMIE ($r = .77$), ESGIRC ($r = .74$), RCMIE ($r = .72$), and AMMC ($r = .68$), with all relationships significant at $p < .001$. The multiple regression model has explained 72.4% of the variance in asset-integrity performance, $R^2 = .724$, adjusted $R^2 = .720$, $F(4, 293) = 192.15$, $p < .001$. PSMIE has produced the strongest standardized effect ($\beta = .31$), followed by ESGIRC ($\beta = .28$), RCMIE ($\beta = .25$), and AMMC ($\beta = .19$), resulting in support for H1 through H5. These results have reinforced the Socio-Technical Systems Theory foundation of the research by demonstrating that long-term asset integrity has been associated with the coordinated functioning of maintenance systems, safety governance, technological capabilities, human expertise, organizational processes, and grid-connected infrastructure. The study has therefore established asset integrity as an integrated socio-technical performance outcome rather than a narrowly defined maintenance result, while preserving the methodological distinction that the cross-sectional findings have demonstrated significant associations and predictive contributions rather than temporal causal effects.

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