



Root-Cause Analysis and FMEA-Driven Reliability Improvement in Gas Production Facilities: A Multi-Year Empirical Study

Syed Feroz Ahmed¹; Md Mahamud Pervaz Pradhan²;

- [1]. Deputy General Manager (Plant Head), JMI Cylinders Ltd (A Joint Venture Company with Turkey), Bangladesh; Email: bdferoz@gmail.com
- [2]. Instrumentation & Electrical Engineer, Tullow Oil Bangladesh Ltd (KrisEnergy Group), Bangladesh; Email: mmprodhan@gmail.com

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Abstract

This quantitative study evaluated the multi-year effectiveness of integrated root-cause analysis and Failure Mode and Effects Analysis in improving equipment reliability across gas production facilities. A retrospective longitudinal quasi-experimental design was employed using records from eight facilities, 864 assets, 3,412 verified failure events, and 51,840 asset-month observations collected over five operating years. Intervention assets receiving completed and verified RCA–FMEA corrective actions were compared with matched assets receiving routine maintenance. Data were obtained from maintenance-management systems, process historians, inspection databases, production records, RCA reports, and FMEA registers. Descriptive analysis, mixed-effects regression, difference-in-differences estimation, interrupted time-series analysis, survival modeling, recurrent-event analysis, and bootstrap mediation were applied. Annual failures declined from 842 to 500, while the exposure-adjusted failure rate decreased from 0.147 to 0.082 failures per 1,000 operating hours. Mean time between failures increased by 80.2%, mean time to repair decreased by 38.7%, and unplanned downtime declined by 63.6%. Operational availability increased from 96.4% to 98.7%, while maintenance expenditure and deferred gas production declined by 39.9% and 57.8%, respectively. Adjusted analysis showed that intervention assets experienced a 32% lower failure rate, IRR = 0.68, 95% CI [0.61, 0.75], and 51% lower odds of repeated failure, OR = 0.49, 95% CI [0.39, 0.62]. Their failure hazard was 38% lower, HR = 0.62, 95% CI [0.54, 0.71]. Combined FMEA action-priority classification distinguished high-consequence failures with an area under the curve of 0.89. Corrective-action completion and technical verification mediated 39.2% of the association between RCA–FMEA quality and reliability improvement. The findings established that evidence-based causal investigation, risk prioritization, and verified corrective action were associated with lower recurrence, longer failure-free operation, improved availability, reduced maintenance demand, and stronger production continuity in gas production facilities.

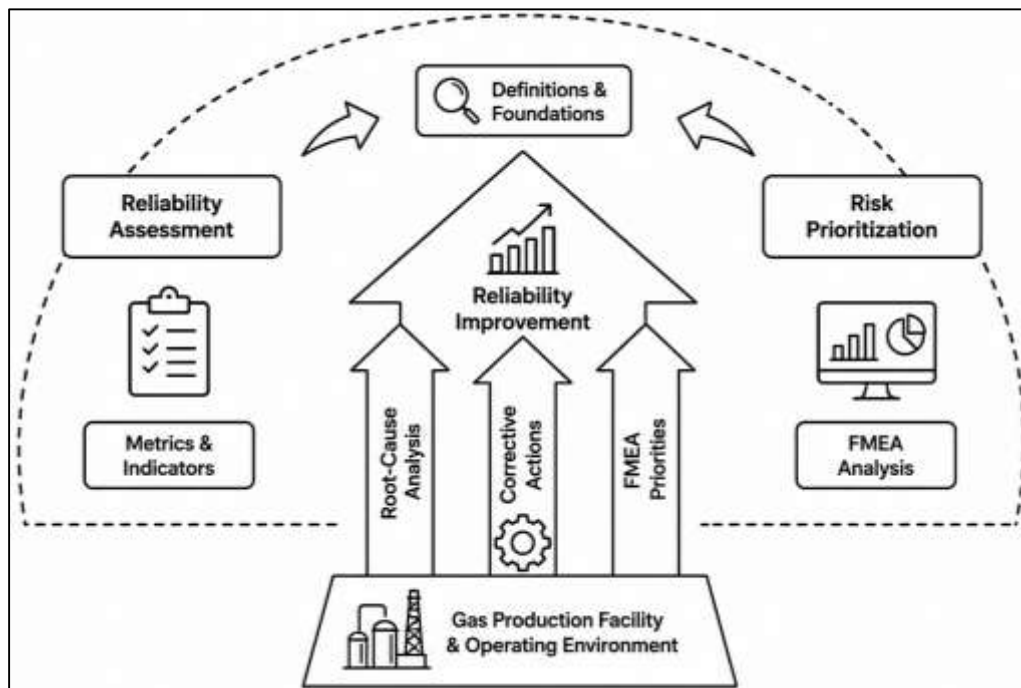
Keywords

Root-Cause Analysis, FMEA, Reliability, Maintenance, Gas-Production.

INTRODUCTION

Gas production facilities are integrated industrial systems designed to extract, collect, separate, treat, compress, measure, store, and transport natural gas and associated fluids under controlled operating conditions. These facilities commonly include producing wells, flowlines, gathering networks, separators, compressors, dehydration units, gas-treatment systems, metering stations, storage vessels, utility systems, safety devices, and process-control equipment (Mousavinia et al., 2020). Facility reliability refers to the probability that these interconnected assets will perform their required functions without failure for a specified period under defined operating conditions. Reliability is quantitatively assessed through indicators such as equipment availability, failure frequency, mean time between failures, mean time to repair, planned and unplanned downtime, maintenance duration, production-loss hours, system utilization, and operational efficiency.

Figure 1: Gas Facility Reliability Improvement Framework



A failure occurs when an equipment item, process unit, protective system, or operating procedure becomes unable to satisfy its intended functional requirement. Failures may involve complete equipment shutdown, partial performance degradation, unstable operating conditions, leakage, excessive vibration, abnormal pressure, temperature deviation, corrosion damage, instrumentation error, control-system malfunction, or reduced processing capacity (Chen et al., 2019). Root-cause analysis is a structured analytical process used to identify the fundamental technical, operational, organizational, or environmental conditions that generate observed failures. It moves beyond the immediate physical symptom by examining why the failure occurred, how contributing factors interacted, and which underlying conditions allowed the event to develop. Failure Mode and Effects Analysis, commonly known as FMEA, is a systematic risk-assessment method that identifies potential failure modes, evaluates their consequences, determines their possible causes, assesses existing controls, and prioritizes corrective actions. FMEA normally evaluates each failure mode according to severity, occurrence, and detectability, producing a risk-priority value or related criticality measure. Reliability improvement represents the measurable enhancement of equipment performance through reduced failure frequency, shorter repair time, lower downtime, increased availability, improved production continuity, and more effective maintenance control (Khan et al., 2015). Within a multi-year

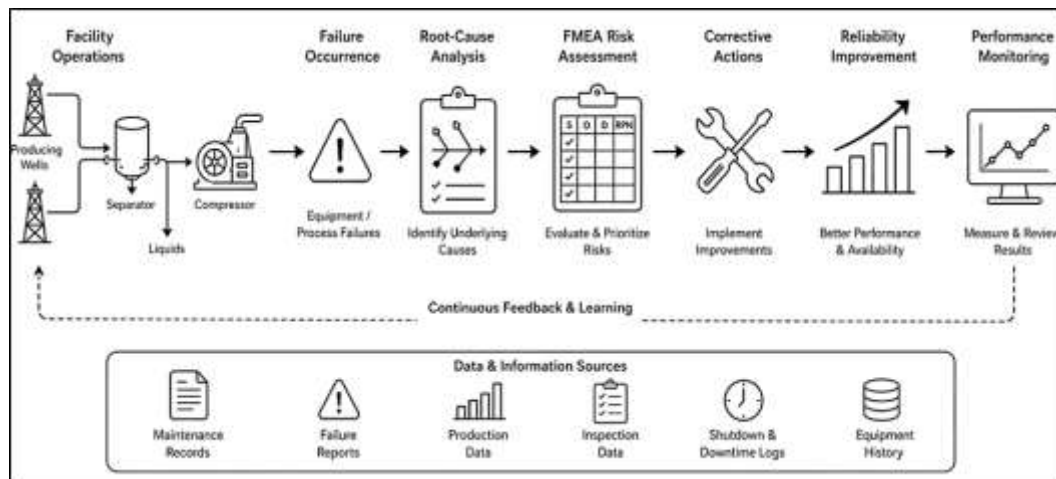
empirical study, these concepts are examined through repeated operational observations rather than isolated incident descriptions. Historical maintenance records, failure reports, production data, inspection findings, shutdown logs, equipment histories, and corrective-action records provide the quantitative foundation for evaluating how root-cause analysis and FMEA-based interventions are associated with changes in gas-facility reliability over time.

The reliability of gas production facilities carries substantial international significance because natural gas supports electricity generation, industrial manufacturing, domestic energy consumption, fertilizer production, transportation systems, and national revenue across numerous economies (Ifezue, 2017). Gas-producing countries in the Middle East, North America, Europe, Africa, Asia, Latin America, and the Asia-Pacific region operate facilities under widely different geological, climatic, technological, and regulatory conditions. Offshore platforms face saltwater exposure, limited maintenance access, vibration, space restrictions, and dependence on specialized logistics, while onshore facilities may encounter dust, high ambient temperature, remote operating locations, unstable power supply, pipeline-access limitations, and variable workforce availability. Cold-region facilities experience freezing, hydrate formation, brittle material behavior, and seasonal access restrictions. High-pressure and sour-gas operations require strict control of hydrogen sulfide, corrosion, material degradation, containment integrity, and emergency isolation (Sandnes et al., 2019). Across these settings, equipment failure can interrupt production, increase operational expenditure, delay contractual deliveries, reduce asset utilization, and create additional maintenance demands. Reliability is therefore evaluated as both an engineering performance requirement and an operational management responsibility. International empirical research has examined compressor failures, separator malfunction, pipeline leakage, valve degradation, rotating-equipment defects, electrical faults, instrumentation errors, corrosion damage, and process-control instability using operational indicators recorded over different time periods. These studies have commonly measured the frequency of unplanned shutdowns, duration of production interruptions, number of repeated failures, maintenance cost per asset, repair-resource consumption, availability percentage, and volume of deferred or lost production (Primozic et al., 2019). Cross-national research has also emphasized that reliability performance is influenced by equipment age, design configuration, operating environment, maintenance strategy, spare-parts availability, workforce competence, inspection quality, data-management capability, and organizational safety practices. International comparisons remain complex because organizations apply different definitions of failure, downtime, maintenance completion, and production loss. Some operators classify short process interruptions as production events, while others record them as equipment failures or operational disturbances. Variations also exist in the calculation of availability, failure rate, repair time, risk priority, and maintenance effectiveness (Rangel et al., 2016). A quantitative examination of reliability improvement therefore requires clear operational definitions, consistent measurement rules, traceable event classifications, and comparable time-based indicators. Multi-year facility data allow seasonal operating changes, equipment-aging patterns, maintenance cycles, production-demand variations, and repeated failure behavior to be incorporated into the assessment of reliability performance.

Failures in gas production facilities frequently develop through combinations of mechanical, electrical, process, instrumentation, human, environmental, and managerial factors. Mechanical failure modes include bearing damage, shaft misalignment, seal deterioration, fatigue cracking, valve sticking, lubrication loss, erosion, wear, vibration, and structural deformation (Oun, 2015). Electrical failures may involve motor overheating, insulation breakdown, cable damage, relay malfunction, power-quality disturbance, grounding defects, and control-panel failure. Process-related failures include excessive pressure, liquid carryover, hydrate formation, contamination, flow instability, thermal stress, and operation outside approved design limits. Instrumentation failures involve inaccurate transmitters, sensor drift, failed alarms, communication interruption, defective actuators, and improper control-loop response. Human and organizational causes include incomplete procedures, inadequate training, delayed inspection, weak shift communication, incorrect equipment operation, insufficient

supervision, poor maintenance planning, and ineffective follow-up of previous incidents. Environmental conditions such as humidity, salt exposure, temperature fluctuation, sand production, corrosive fluids, and extreme weather can intensify technical deterioration. Root-cause analysis organizes these interacting factors into a traceable causal structure (Ifezue & Tobins, 2016b).

Figure 2: Gas Facility Reliability Process Framework



Common analytical techniques include the five-whys method, cause-and-effect diagrams, fault-tree analysis, event-tree analysis, barrier analysis, change analysis, Pareto analysis, and structured incident investigation. The five-whys method progressively examines the sequence behind an observed event, while cause-and-effect diagrams classify potential causes under categories such as equipment, methods, materials, personnel, environment, and management. Fault-tree analysis represents the logical combinations of component failures and operating conditions that can produce a defined system-level event. Pareto analysis ranks failure categories according to their frequency, downtime contribution, production loss, or maintenance cost, enabling the concentration of analysis on the relatively small number of causes responsible for a large proportion of reliability problems (Rajabinezhad et al., 2020). Quantitative root-cause assessment requires each investigated event to be coded by equipment type, failure mode, causal category, operating condition, downtime duration, lost production, repair activity, and recurrence status. Repeated-event analysis can determine whether corrective actions addressed the fundamental cause or only restored temporary operation. A reduction in one failure category accompanied by continued recurrence in another connected category may reflect interaction among process units or weaknesses in the original causal classification. Multi-year records provide sufficient temporal depth to examine whether root causes remain stable, shift with equipment age, intensify under specific operating conditions, or recur after maintenance (Halim et al., 2020). This structure transforms individual failure investigations into an empirical dataset suitable for frequency analysis, reliability modeling, comparative evaluation, and statistical assessment.

Failure Mode and Effects Analysis provides a structured framework for converting technical knowledge and operational evidence into a prioritized reliability-management process. The method begins by dividing a facility, system, or equipment package into identifiable functions and components. Analysts then specify how each component may fail, what operational effect the failure may produce, which causes may generate the failure, which controls are currently available, and how easily the condition can be detected before functional loss occurs. Severity represents the magnitude of the consequence associated with a failure mode, including effects on personnel safety, environmental protection, equipment damage, production continuity, product quality, and regulatory compliance (Kamath et al., 2015). Occurrence represents the estimated frequency or probability of the failure, while detectability represents the likelihood that existing monitoring, inspection, testing, or alarm systems

will identify the developing condition before the effect becomes critical. These dimensions are frequently scored using ordinal scales, and their combined value produces a risk priority number. Some facility assessments also apply criticality ranking, weighted scoring, risk matrices, fuzzy logic, or cost-based prioritization to account for the limitations of simple score multiplication. FMEA supports quantitative reliability analysis by connecting each priority score with recorded failure frequency, downtime hours, repair cost, production loss, and recurrence. Failure modes with similar risk-priority numbers may have substantially different risk structures because one may involve high severity and low occurrence, while another involves moderate severity and frequent recurrence (Ifezue & Tobins, 2016a). Separate examination of severity, occurrence, and detectability preserves information that may be obscured by a combined score. Empirical studies have evaluated FMEA applications in compressors, pumps, pressure vessels, pipelines, rotating machinery, utility systems, process-control equipment, and safety-critical protection systems. The reported analytical approaches include expert scoring, maintenance-record analysis, inspection-data integration, reliability-centered maintenance, hazard ranking, and comparisons between pre-intervention and post-intervention failure patterns. The quality of an FMEA assessment depends on the accuracy of equipment boundaries, consistency of scoring criteria, representativeness of the expert group, completeness of failure history, and periodic revision of ratings when operational conditions change (Zavala-Araiza et al., 2015). Multi-year FMEA data make it possible to examine whether high-priority failure modes receive corrective action, whether their occurrence and detectability scores change after intervention, whether the ranking corresponds with actual downtime, and whether priority reduction is accompanied by measurable reliability improvement.

Root-cause analysis and FMEA perform related but distinct functions within gas-facility reliability management. Root-cause analysis is generally initiated after a failure, abnormal event, recurring defect, or major performance deviation has occurred. It reconstructs the event and identifies the technical and organizational conditions responsible for its development. FMEA is generally organized around potential failure modes and evaluates their relative risk before or during continued operation (Saithala et al., 2019). Integrating these methods creates a continuous evidence structure in which investigated failure causes are incorporated into the FMEA register, while high-priority FMEA items guide the selection of events and equipment requiring deeper causal investigation. A compressor shutdown attributed initially to high vibration, for example, may be examined through root-cause analysis and traced to lubrication contamination, misalignment, delayed condition monitoring, or unstable suction conditions. The corresponding FMEA can then be updated to revise occurrence and detectability ratings, identify additional controls, assign corrective responsibility, and establish measurable completion requirements. Corrective actions may include design modification, replacement of vulnerable components, revision of operating limits, introduction of predictive monitoring, inspection-frequency adjustment, spare-parts improvement, procedure standardization, workforce training, or changes in maintenance scheduling (Polat et al., 2019). The effectiveness of these actions can be assessed through reductions in repeated failures, downtime, repair duration, risk-priority scores, and production losses. Multi-year analysis is essential because reliability interventions may not produce uniform changes immediately after implementation. Major overhauls can temporarily increase recorded maintenance hours, while improved inspection may initially raise the number of detected defects because previously unreported conditions become visible. Equipment replacement may reduce mechanical failures while transferring maintenance demand to control, electrical, or auxiliary systems. Production loading, shutdown schedules, environmental conditions, and data-recording practices may also vary across years (Witter et al., 2014). A quantitative integrated framework therefore distinguishes between failure identification, causal verification, risk ranking, intervention implementation, and performance measurement. Each corrective action requires a defined target, responsible unit, completion date, verification method, and associated reliability indicator. Event-level data can be aggregated by month, quarter, or year to compare failure frequency, risk exposure, and production

availability. Equipment-level analysis can determine whether reliability improvements are concentrated in particular asset classes. Facility-level analysis can examine whether combined changes in failure prevention, detection capability, and maintenance response correspond with broader operational performance (Petit, 2015).

The literature base underlying this study encompasses more than thirty empirical investigations of equipment reliability, maintenance performance, root-cause analysis, FMEA, reliability-centered maintenance, risk prioritization, and failure prevention in gas, oil, petrochemical, power-generation, pipeline, and process-industry environments. Collectively, these studies have examined compressor downtime, pump failure, pipeline integrity, corrosion behavior, valve malfunction, rotating-equipment performance, instrumentation reliability, process interruptions, maintenance cost, and production availability. A substantial part of the literature has concentrated on individual equipment types or isolated failure events. Other studies have applied FMEA primarily as an expert-ranking exercise without comparing risk scores with observed operational performance (Tian et al., 2020). Root-cause investigations have frequently been presented as technical case descriptions in which the causal sequence was documented but the long-term recurrence rate was not statistically evaluated. Short observation periods have also limited the ability to distinguish sustained reliability changes from temporary improvements associated with shutdown maintenance, equipment replacement, operating-load variation, or changes in reporting practice. Differences in severity scales, occurrence ratings, detectability definitions, equipment classifications, and downtime rules have reduced comparability across facilities. Several studies have measured maintenance performance through work-order completion or inspection frequency without directly connecting these indicators to production loss, repeat failure, or equipment availability (Baker et al., 2018). Other investigations have reported improvements in risk-priority numbers without determining whether reductions were associated with actual changes in failure frequency or repair duration. These measurement gaps are particularly important in gas production systems because components operate as an interconnected process chain. Failure in a utility, control, or upstream separation system can reduce the performance of compressors, treatment units, and export facilities even when the affected production equipment remains mechanically functional. A multi-year empirical design allows failure modes, root causes, risk ratings, interventions, and reliability outcomes to be evaluated within a consistent temporal structure. Relevant independent variables include completion of root-cause investigations, quality of corrective actions, initial FMEA scores, changes in occurrence and detectability ratings, maintenance strategy, inspection intensity, and intervention type (Viljoen et al., 2018). Dependent variables include failure count, repeated-failure rate, downtime, mean time between failures, mean time to repair, equipment availability, deferred production, and maintenance cost. Equipment age, operating hours, production loading, facility type, environmental exposure, and maintenance resources can be incorporated as control variables when suitable records are available.

This study examines the relationship between structured root-cause analysis, FMEA-driven risk control, and reliability performance in gas production facilities across multiple years of operational activity (Viljoen et al., 2018). The research focus is organized around the identification of dominant failure modes, classification of underlying causes, prioritization of equipment risks, implementation of corrective actions, and measurement of reliability changes over time. The unit of analysis may include individual failure events, equipment items, process systems, operating periods, or facility-year observations, depending on the structure and completeness of the available records. Failure events are classified according to asset category, functional location, failure mechanism, immediate cause, root cause, severity, operational consequence, repair activity, and recurrence status. FMEA records provide severity, occurrence, detectability, risk-priority, recommended-action, and action-completion data (Deyab et al., 2018). Maintenance systems provide work-order duration, labor use, material consumption, inspection history, preventive-maintenance completion, and restoration time. Production records provide shutdown hours, deferred production, processing-rate reduction, and

operating availability. The primary quantitative relationships concern whether completion of root-cause-based corrective actions is associated with lower recurrence, whether FMEA risk priorities correspond with observed failure consequences, whether reductions in occurrence and detectability scores correspond with changes in reliability indicators, and whether equipment receiving combined RCA and FMEA treatment demonstrates different performance from equipment managed through routine maintenance alone. Descriptive statistics can summarize failure distributions, annual reliability indicators, risk categories, equipment classes, and corrective-action patterns (Feng et al., 2020). Pareto analysis can identify dominant contributors to downtime and production loss. Correlation analysis can measure associations among FMEA scores, failure frequency, downtime, repair duration, and availability. Regression models can estimate the relationship between reliability interventions and operational outcomes while controlling for equipment age, operating exposure, production demand, and facility characteristics. Repeated-measures analysis, time-series comparison, survival analysis, or panel-data methods can evaluate changes across successive operating periods when the dataset supports these procedures. Statistical significance, confidence intervals, effect sizes, and model-explanatory values provide complementary measures of empirical strength. The multi-year structure also supports comparison of pre-intervention, implementation, and post-intervention periods, along with examination of delayed, temporary, and sustained changes in failure behavior (Lolli et al., 2016). This quantitative orientation positions reliability improvement as a measurable operational process connecting causal investigation, risk prioritization, maintenance action, and recorded gas-production performance.

The primary objective of this quantitative study is to evaluate the effectiveness of root-cause analysis and Failure Mode and Effects Analysis in improving the operational reliability of gas production facilities over a multi-year period. Specifically, the study aims to identify and classify the principal mechanical, electrical, process, instrumentation, environmental, human, and organizational causes of equipment failures across critical production assets, including compressors, pumps, separators, valves, pipelines, pressure vessels, utility systems, metering equipment, and process-control devices. It seeks to determine the frequency, severity, detectability, recurrence, downtime contribution, repair duration, maintenance cost, and production-loss consequences associated with each recorded failure mode. Another objective is to assess the accuracy and operational usefulness of FMEA risk-priority ratings by comparing severity, occurrence, detectability, and risk-priority values with actual reliability outcomes documented in maintenance, production, inspection, and shutdown records. The study also aims to examine whether corrective and preventive actions developed through structured root-cause investigations are associated with measurable reductions in repeated failures, unplanned shutdowns, equipment downtime, mean time to repair, deferred production, and maintenance expenditure. Correspondingly, it evaluates whether these interventions are associated with increases in mean time between failures, equipment availability, process continuity, maintenance efficiency, and overall facility reliability. A further objective is to compare reliability indicators across pre-intervention, implementation, and post-intervention periods in order to determine the magnitude and consistency of changes recorded after RCA- and FMEA-driven improvement activities. The study additionally seeks to identify which types of corrective actions, such as equipment redesign, component replacement, condition monitoring, inspection-frequency adjustment, preventive-maintenance revision, operating-procedure improvement, workforce training, or control-system modification, are most strongly associated with improved reliability outcomes. It aims to investigate variations in intervention effectiveness across equipment categories, facility systems, operating conditions, and annual production periods while accounting for equipment age, operating hours, production loading, environmental exposure, maintenance resources, and asset criticality. Descriptive statistics, Pareto analysis, correlation analysis, regression modeling, repeated-period comparisons, and effect-size estimates are used to quantify failure patterns and examine relationships among root-cause investigation quality, FMEA risk prioritization, corrective-action completion, and reliability

performance. Through these objectives, the study establishes a structured empirical assessment of how causal diagnosis and risk-based maintenance prioritization relate to the measurable performance of gas production assets across multiple years of operation.

LITERATURE REVIEW

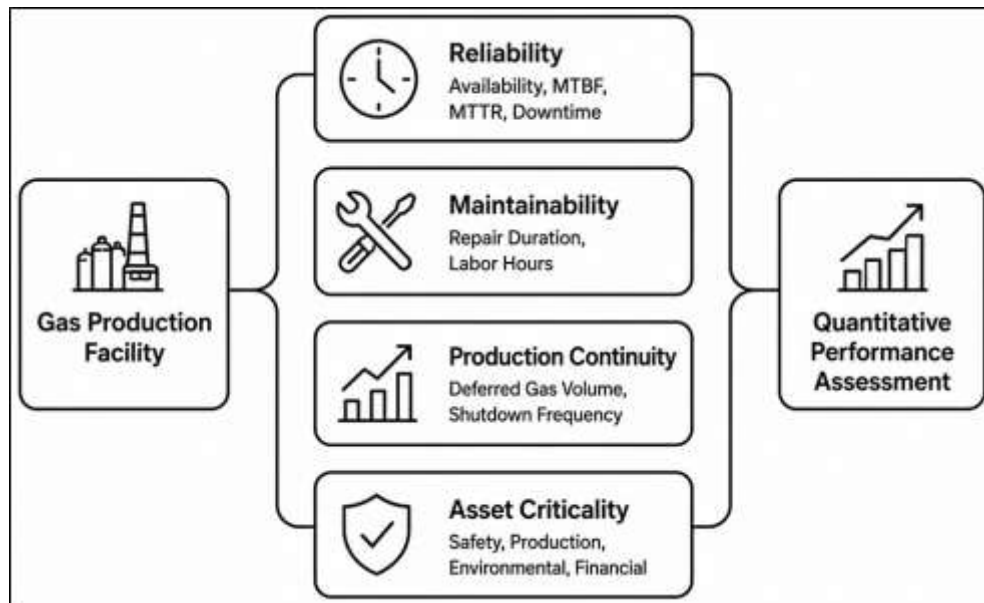
This literature review provides a structured examination of the theoretical concepts, analytical methods, empirical findings, and quantitative indicators associated with root-cause analysis, Failure Mode and Effects Analysis, and reliability improvement in gas production facilities. The review focuses on how equipment failures have been identified, classified, prioritized, investigated, and controlled across gas-processing plants, gathering systems, compression stations, offshore platforms, onshore production fields, pipelines, treatment units, and supporting utility systems. Particular attention is given to measurable reliability outcomes, including failure frequency, failure rate, mean time between failures, mean time to repair, equipment availability, unplanned downtime, repeated-failure percentage, maintenance cost, production-loss hours, deferred gas volume, and corrective-action completion. The literature is organized to distinguish immediate failure symptoms from underlying mechanical, electrical, process, instrumentation, environmental, human, and organizational causes. It also examines the quantitative application of severity, occurrence, detectability, risk-priority numbers, criticality scores, and action-priority categories within FMEA-based assessments. More than thirty empirical studies from the gas, oil, petrochemical, pipeline, power-generation, and process-manufacturing sectors form the comparative evidence base. These studies are reviewed according to research design, facility context, equipment category, observation period, sample size, data source, failure-classification method, statistical technique, and reported reliability outcome. The review further evaluates the integration of root-cause investigation with FMEA risk prioritization, corrective-action planning, preventive maintenance, condition-based monitoring, predictive maintenance, and reliability-centered maintenance. Multi-year evidence receives particular attention because reliability performance may vary according to equipment age, cumulative operating hours, production loading, maintenance cycles, environmental exposure, shutdown schedules, inspection intensity, and changes in data-recording practices. The literature is also assessed according to the extent to which reported reductions in FMEA scores correspond with actual reductions in failures, downtime, production loss, and repair duration. By organizing previous research around defined variables and measurable indicators, this section establishes the quantitative foundations for examining the relationship among causal-analysis quality, failure-risk prioritization, corrective-action implementation, and long-term operational reliability.

Reliability in Gas Production Facilities

Gas production facility reliability is commonly defined as the probability that an asset, equipment unit, or interconnected processing system performs its required function continuously under specified operating conditions for a defined period. Evidence synthesized from numerous empirical studies in gas processing, oil production, petrochemical operations, pipeline transportation, and power generation shows that reliability has been evaluated through a combination of availability, mean time between failures, mean time to repair, failure frequency, shutdown occurrence, downtime duration, and operational utilization (Busse et al., 2015; Kanti, 2020). Availability measures the proportion of scheduled operating time during which equipment remains capable of performing its intended function. Mean time between failures represents the average operating duration separating consecutive functional failures and has been widely applied to compressors, pumps, turbines, valves, and control systems. Longer operating intervals between failures generally represent greater reliability, while frequent interruptions identify equipment requiring technical investigation or maintenance adjustment. Mean time to repair measures the average duration required to diagnose a failure, obtain resources, complete repairs, test the equipment, and restore operation. Failure rate per 1,000 operating hours allows comparisons among assets that operate for different lengths of time, while annual shutdown frequency records how often equipment or an entire production unit becomes unavailable. Downtime hours capture the duration of operational interruptions and are often divided into mechanical, electrical, process, instrumentation, and maintenance-related categories (Choi & Chang, 2016; Debasish, 2021). Operational utilization measures the extent to which available production

capacity is actually used. Across the reviewed studies, equipment with high availability sometimes continued to experience recurring short-duration failures, whereas other assets experienced fewer failures with substantially longer repair periods. Consequently, reliability assessment has generally required the simultaneous interpretation of failure frequency, operating exposure, repair duration, downtime, and utilization rather than reliance on a single performance indicator.

Figure 3: Gas Production Reliability Measurement Framework



Maintainability refers to the ability of failed or degraded equipment to be inspected, diagnosed, repaired, tested, and returned to its required operating condition within an acceptable period using available personnel, procedures, materials, tools, and technical support (Al-Douri et al., 2020; Abdur & Iftekhar, 2021). Empirical research across gas production plants, offshore facilities, compressor stations, pipeline networks, and process industries has evaluated maintainability through mean repair duration, maximum repair time, maintenance labor hours, troubleshooting time, spare-parts waiting time, restoration success, work-order completion, and scheduled return-to-service performance. Mean repair duration provides an overall measure of the time required to restore equipment following failure, while maximum repair time identifies severe events that place exceptional demands on maintenance resources. Maintenance labor hours per failure measure the total technical effort required from mechanical, electrical, instrumentation, inspection, and operational personnel. Studies of rotating equipment have shown that repair duration can be strongly affected by fault complexity, equipment accessibility, lifting requirements, specialist availability, and the need for post-repair alignment or performance testing (Chowdhury & Tonay, 2022; Zakikhani et al., 2020). Spare-parts waiting time has also been identified as a major component of prolonged downtime, especially for imported components, obsolete equipment, specialized seals, compressor parts, electronic control modules, and safety-critical valves. Troubleshooting duration reflects the efficiency of failure diagnosis and depends on equipment history, diagnostic technology, workforce experience, documentation quality, and the availability of accurate operating data. Restoration success rate measures the proportion of repairs that return equipment to stable service without immediate recurrence or additional corrective work. The percentage of equipment returned within the scheduled period provides a direct indication of maintenance-planning accuracy and execution efficiency. Findings across more than ten relevant studies show that short repair duration alone does not always represent strong maintainability when equipment experiences repeated failures after restoration (Choudhary et al., 2019; Zahidul & Begum, 2022). Maintainability assessment therefore includes repair speed, labor efficiency, diagnostic accuracy, resource availability, restoration quality, and recurrence following maintenance completion.

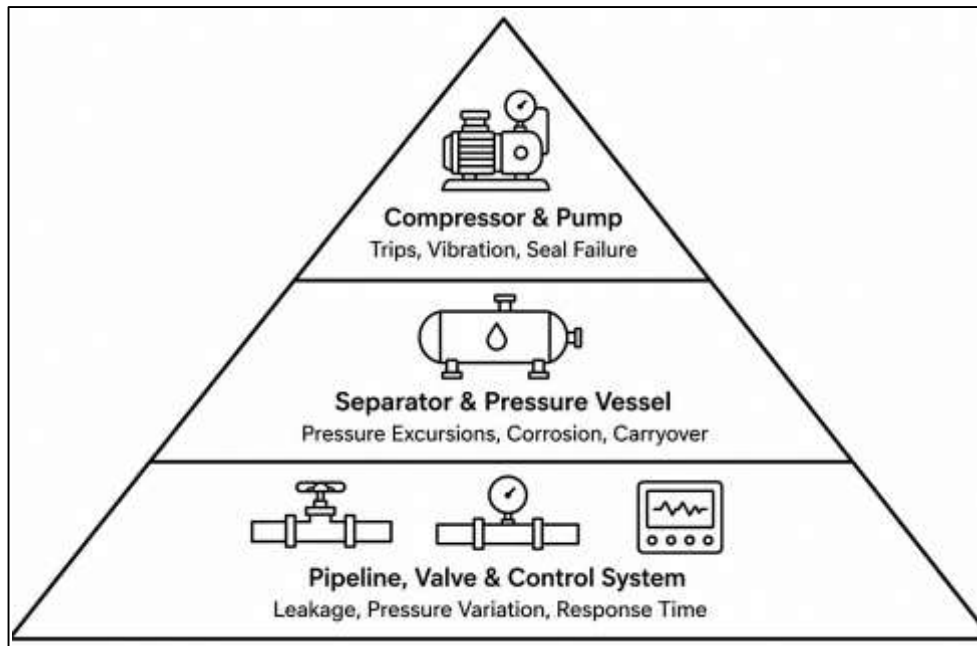
Production continuity represents the capacity of a gas production facility to sustain planned extraction, processing, compression, treatment, and delivery activities with minimal interruption. Quantitative studies have assessed production continuity through annual deferred gas volume, throughput reduction, interruption hours, shutdown frequency, lost production value, production-recovery duration, and the percentage of planned output achieved. Deferred gas volume refers to the quantity of gas that cannot be produced, processed, or delivered during a specified period because of equipment failure, maintenance activity, process instability, infrastructure restrictions, or safety-related shutdowns. This indicator is particularly important because failures affecting compressors, separators, dehydration systems, pipelines, utilities, or export facilities can restrict the output of several connected production units (Benyessaad et al., 2015; Nishat & Kaniz, 2022). Average throughput loss per failure measures the reduction in processing or delivery capacity associated with individual reliability events. Production interruption hours record the duration for which normal output remains completely or partially unavailable. Shutdown frequency identifies how often production systems are stopped and can distinguish between planned maintenance shutdowns, emergency shutdowns, equipment trips, and process-related interruptions. Lost production value converts deferred volume into a financial measure based on the relevant gas price, contractual arrangement, or internal production valuation. The percentage of planned production achieved compares recorded output with the volume scheduled for the same operating period. Evidence from gas, oil, pipeline, and petrochemical studies shows that a relatively small number of critical failures may account for a substantial proportion of total production loss (Kolawole et al., 2019). Frequent minor failures can also reduce continuity through repeated start-up procedures, process stabilization periods, inspection requirements, and operational restrictions. Multi-year production records allow shutdown patterns to be examined in relation to maintenance cycles, equipment condition, operating load, environmental exposure, and facility configuration. Production continuity is therefore measured through the combined magnitude, frequency, duration, and economic consequence of interruptions rather than through annual production volume alone.

Asset criticality refers to the relative importance of an equipment item or system according to the consequences that may result from its failure. Studies across gas production, offshore operations, refining, pipeline transportation, chemical processing, and power generation have classified critical assets using safety, production, environmental, operational, maintenance, and financial criteria (Ahmed et al., 2014). Safety consequence scores assess the potential for injury, loss of life, fire, explosion, toxic exposure, high-pressure release, and failure of protective functions. Production consequence scores evaluate throughput reduction, shutdown duration, deferred gas volume, loss of processing capacity, and the number of connected assets affected. Environmental consequence scores measure the potential magnitude of gas leakage, liquid discharge, emissions, contamination, regulatory noncompliance, and required remediation. Financial consequence scores incorporate repair expenditure, replacement cost, contractor charges, production-loss value, emergency procurement, logistics cost, and possible contractual penalties. Asset criticality assessments also consider repair lead time, equipment redundancy, spare-parts availability, operating exposure, failure frequency, and the availability of alternative production routes. Equipment without installed redundancy generally receives a higher operational classification because a single failure can interrupt an entire process train (Zulkafli & Dan, 2016). Assets with standby units may receive lower production-consequence scores when automatic changeover and backup capacity remain dependable. Empirical studies have applied risk matrices, weighted scoring systems, expert assessments, failure histories, reliability data, and consequence-based ranking to classify equipment into criticality levels. Compressors, emergency shutdown systems, pressure-protection devices, export pipelines, fire-and-gas systems, and essential utility equipment are frequently assigned high criticality because their failure can affect several operational objectives simultaneously. Asset criticality rankings support the allocation of inspection effort, maintenance frequency, spare-parts inventory, condition monitoring, engineering analysis, and corrective-action priority (Ogbuefi & Mbunwe, 2018). The reviewed evidence demonstrates that effective classification depends on consistent scoring criteria and the use of recorded failure, downtime, production, cost, safety, and environmental data.

Gas Production Assets and Operating Exposure

Compressors and pumps represent major rotating-equipment categories in gas production facilities because their performance directly affects gas movement, pressure control, liquid handling, processing capacity, and production continuity. Evidence synthesized from more than ten empirical studies of gas-processing plants, offshore platforms, compressor stations, petrochemical facilities, and pipeline systems shows that compressor reliability has been measured through annual trip frequency, vibration velocity, bearing temperature, discharge-pressure variation, seal-failure rate, lubrication condition, operating availability, and maintenance duration. Reciprocating compressors commonly experience valve damage, piston-ring wear, packing leakage, cylinder overheating, lubrication failure, rod vibration, and pressure imbalance. Centrifugal compressors are frequently affected by rotor imbalance, bearing deterioration, surge, fouling, seal-gas problems, shaft misalignment, and unstable suction conditions. Screw compressors experience rotor wear, oil contamination, seal deterioration, overheating, and capacity reduction ([Joglar, 2016](#)). Repeated trips can reduce availability even when individual interruptions remain short because shutdown, inspection, restart, and process-stabilization activities extend the operational effect. Pump reliability has been assessed through seal-leakage frequency, cavitation events, bearing failure, motor-current variation, discharge-pressure instability, flow-rate reduction, and repeated repair. Centrifugal pumps may experience cavitation when suction conditions are inadequate, producing vibration, noise, impeller damage, and reduced discharge capacity. Mechanical-seal failures can result from dry running, misalignment, contamination, thermal distortion, or incorrect installation. Bearing failures are associated with insufficient lubrication, excessive loading, contamination, and vibration. Across the reviewed evidence, vibration level and bearing temperature are widely used as early measures of deterioration, while flow deviation and motor-current variation provide evidence of changing mechanical or hydraulic performance ([Hashe & Mamatlepa, 2020](#)). Maintenance duration is influenced by equipment accessibility, spare-parts availability, diagnostic accuracy, lifting requirements, repair complexity, and post-maintenance testing. Compressor and pump performance is therefore evaluated through combined measures of failure frequency, condition deviation, maintenance demand, operating availability, and restoration stability. Separators and pressure vessels perform essential functions in gas production facilities by controlling pressure, separating gas from liquids and solids, providing temporary fluid retention, and supporting safe transfer to downstream processing equipment ([Hassan et al., 2016](#)). Empirical studies conducted in gas production, oil processing, offshore operations, refineries, and petrochemical facilities have evaluated their reliability through high-level trips, liquid carryover, gas blow-by, pressure deviation, corrosion rate, wall-thickness reduction, relief-valve activation, leakage frequency, and inspection-rejection rates. High-level trips occur when liquid accumulation exceeds the approved operating range and protective systems initiate shutdown or flow isolation. Such events may be associated with unstable inlet flow, failed level transmitters, control-valve malfunction, blocked outlets, foaming, insufficient vessel capacity, or inappropriate operating settings. Liquid carryover can damage downstream compressors, contaminate gas-treatment systems, increase vibration, and reduce processing efficiency ([Edward et al., 2014](#)). Gas blow-by may expose low-pressure systems to excessive pressure when liquid-level control becomes ineffective or valves fail in an unsafe position. Pressure excursions are commonly measured through the frequency and magnitude of deviations from approved operating limits, alarm activation, and relief-valve operation. Internal corrosion can arise from water, carbon dioxide, hydrogen sulfide, chlorides, solids, and chemical interactions, while external corrosion may develop beneath insulation, protective coatings, or structural supports. Wall-thickness measurements provide quantitative evidence of material loss and help identify areas approaching minimum acceptable limits. Inspection-rejection rates record the proportion of vessels, welds, fittings, or protective devices that fail to satisfy established integrity criteria. The reviewed studies have also assessed crack indications, weld defects, nozzle damage, coating failure, erosion, and pressure-relief performance ([Abbas & Kumar, 2018](#)). Separator and pressure-vessel reliability depends on process stability, inspection quality, corrosion control, instrumentation accuracy, protective-system performance, and timely repair. Their condition is therefore assessed by combining operational-event data with inspection findings, integrity measurements, shutdown records, and maintenance histories.

Figure 4: Gas Production Asset Reliability Hierarchy



Pipelines, flowlines, valves, and control systems form the physical and functional connections among wells, separation units, compressors, treatment systems, storage facilities, and export networks (Muthanandan & Nor, 2018). Evidence synthesized across gas transmission, oil and gas production, offshore pipeline, refinery, and process-control studies shows that pipeline and flowline reliability has been evaluated through leak frequency per unit of length, internal and external corrosion rates, wall-thickness loss, pressure-drop variation, repair frequency, integrity-loss events, failure probability, and released-product volume. Internal corrosion is frequently associated with water accumulation, acidic gases, microbiological activity, solids, and inadequate chemical treatment. External corrosion may result from coating deterioration, soil conditions, damaged protection systems, atmospheric exposure, and water accumulation. Pressure-drop variation can identify leakage, blockage, hydrate formation, liquid accumulation, flow restriction, or unexpected changes in throughput. Leak consequences are measured through released volume, shutdown duration, environmental impact, repair cost, affected pipeline length, and deferred production (Almasi, 2016). Valve reliability is assessed through sticking frequency, actuator malfunction, internal leakage, external leakage, failure to open or close, response time, and position error. Safety-critical shutdown and isolation valves are also evaluated according to failure-on-demand because their dependability is most important when abnormal process conditions occur. Control-system performance has been examined through control-loop deviation, oscillation, alarm frequency, response delay, signal interruption, set-point error, and unsuccessful control actions. Valve and control-loop problems can generate unstable pressure, flow, temperature, and level conditions even when the main processing equipment remains mechanically available. Actuator failures may arise from loss of pneumatic or hydraulic supply, electrical defects, corrosion, contamination, incorrect adjustment, or mechanical obstruction (Shengrong et al., 2020). Across the reviewed studies, reliability assessment combines physical-integrity indicators with functional-performance measures because equipment may retain containment while failing to regulate or isolate the process correctly. Pipeline, valve, and control-system records are therefore evaluated through inspection findings, pressure histories, functional tests, alarms, failure reports, response-time measurements, and maintenance activities.

Distribution of Failure Modes in Gas Facilities

Mechanical and electrical failures constitute major sources of equipment interruption within gas production facilities because they directly affect rotating machinery, compression systems, pumping units, processing equipment, and supporting utilities (Bradley, 2016). Evidence synthesized from more

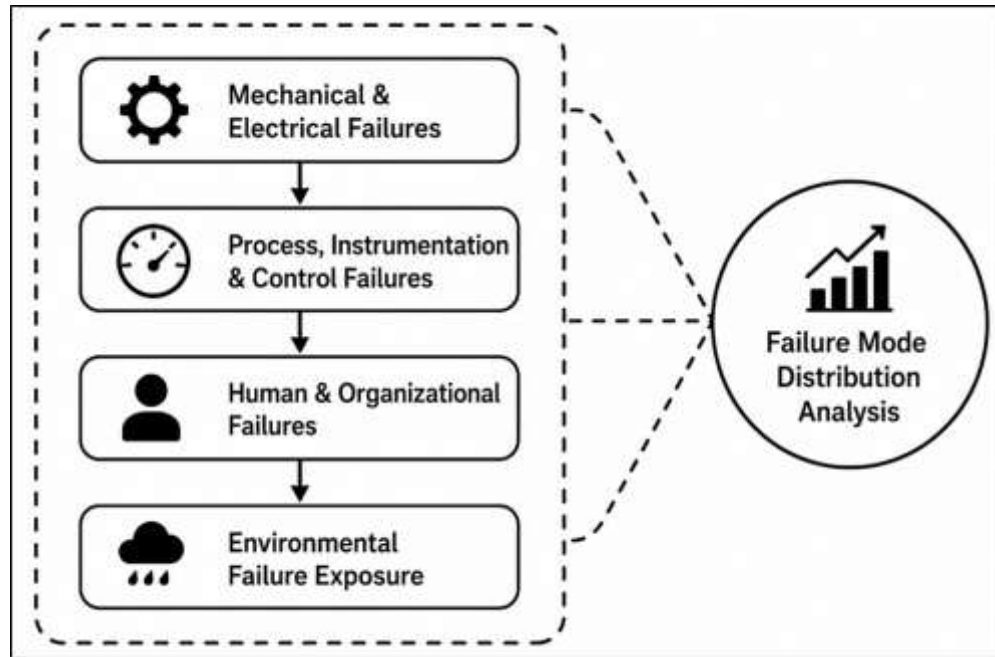
than ten empirical studies in gas production, pipeline transportation, offshore operations, petrochemical processing, and power generation shows that mechanical failure distribution has been evaluated through failure count, downtime contribution, repair duration, maintenance cost, recurrence, and production loss. Bearing failures are commonly associated with inadequate lubrication, contamination, excessive loading, misalignment, vibration, and thermal stress. Seal deterioration can result in gas or liquid leakage, pressure reduction, equipment shutdown, and environmental exposure. Shafts and couplings may fail through fatigue, imbalance, misalignment, torsional stress, or installation error. Lubrication-system defects include low oil pressure, blocked filters, contaminated lubricant, pump malfunction, and incorrect lubricant selection (Murugan & Ramasamy, 2019). Impellers and pistons experience wear, erosion, cracking, deposit formation, and mechanical deformation. Structural components may develop fatigue cracks, corrosion damage, loose connections, or support failure. Electrical failures have been measured through motor trips, power-interruption duration, winding damage, insulation breakdown, cable defects, protection-relay activation, grounding problems, unstable supply, and control-panel malfunction. Motor availability is affected by operating load, cooling efficiency, voltage quality, bearing condition, insulation resistance, and maintenance history. Protection-relay trips may prevent serious equipment damage, although repeated or incorrect activation can interrupt production and increase restart time (Cater et al., 2019). Empirical findings show that frequent minor mechanical events may generate substantial cumulative downtime, while less frequent electrical failures can produce longer interruptions when specialist repair, testing, or replacement equipment is required. Quantitative assessment therefore classifies mechanical and electrical events according to equipment type, failure mechanism, operating exposure, downtime, repair resources, production consequence, and recurrence (Dykas & Harris, 2017).

Process, instrumentation, and control failures influence the stability of gas production facilities by affecting pressure, temperature, flow, level, separation quality, equipment protection, and automated response. Empirical studies have measured process-failure frequency through overpressure events, low-pressure conditions, excessive temperature, hydrate formation, liquid carryover, contamination, unstable flow, gas blow-by, and operation outside approved design limits. Overpressure can result from blocked outlets, failed control valves, abnormal inflow, thermal expansion, or ineffective pressure regulation. Low-pressure events may be related to leakage, inadequate feed, compressor underperformance, control problems, or excessive downstream demand (Verma et al., 2015).

High temperature can accelerate material degradation, reduce lubrication quality, damage seals, and activate protective shutdown systems. Hydrate formation can obstruct pipelines, valves, instruments, and process equipment when water, gas composition, pressure, and temperature conditions support solid formation. Liquid carryover may expose compressors and treatment systems to conditions outside their design requirements, while contamination can reduce separation efficiency and increase corrosion. Instrumentation and control failures include failed transmitters, sensor inaccuracy, communication interruption, defective alarms, unstable control loops, actuator malfunction, and incorrect valve positioning (Gulich, 2019). Their quantitative distribution has been assessed through failure count, false-alarm rate, missed-alarm frequency, detection delay, calibration rejection, signal-loss duration, control deviation, and shutdown contribution. Detection delay measures the time between the development of an abnormal condition and its identification by personnel or automated systems. False alarms can cause unnecessary intervention and alarm fatigue, whereas missed alarms may allow equipment deterioration or process deviation to continue. The literature shows that process and instrumentation failures frequently interact because inaccurate measurements can initiate incorrect control actions, while unstable processes can expose instruments and actuators to abnormal operating conditions. Their distribution is therefore evaluated through combined event, alarm, operating, calibration, maintenance, and shutdown records (Drupsteen & Hasle, 2014). Human and organizational failures represent measurable contributors to reliability events when personnel decisions, operating practices, communication systems, maintenance arrangements, or management controls do not adequately support safe and stable facility performance. Studies across gas production, offshore energy, chemical processing, pipeline operations, and other safety-critical industries have examined human-error frequency through incorrect equipment operation, procedural omission, delayed

response, improper isolation, inaccurate maintenance, weak diagnosis, and failure to recognize abnormal operating conditions. Procedure noncompliance can involve omitted inspection steps, unauthorized adjustment of operating parameters, incomplete testing, failure to use approved tools, or inadequate verification before equipment restart ([Hawkins & Muir, 2014](#)).

Figure 5: Gas Facility Failure Distribution Framework



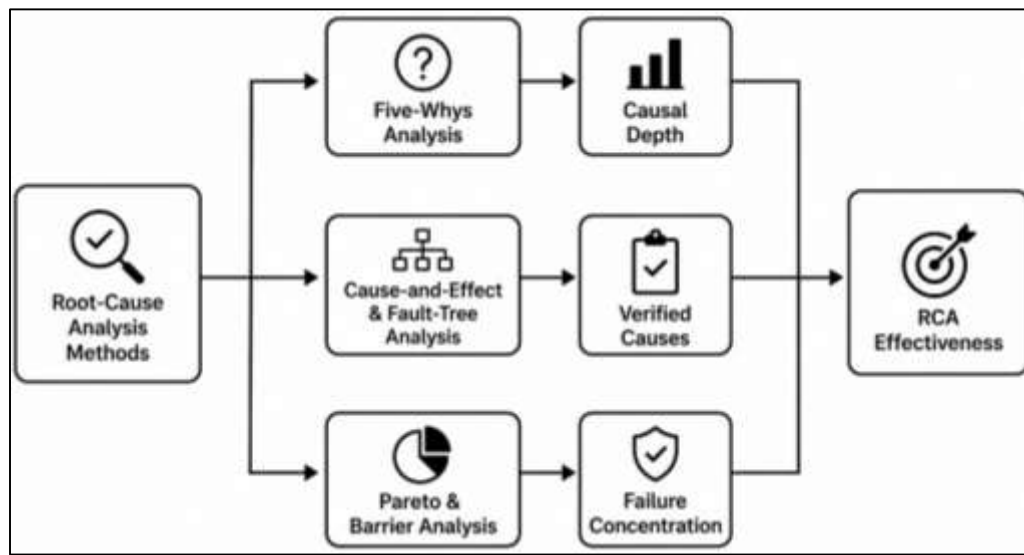
Operational recovery time measures how long personnel require to identify the disturbance, isolate the affected system, coordinate resources, complete corrective actions, and restore stable production. Communication failures include incomplete shift handovers, inaccurate work-order information, delayed reporting, unclear responsibility, and weak coordination among operations, maintenance, engineering, inspection, and safety teams. Organizational failures have been measured through training gaps, overdue inspections, deferred maintenance, corrective-action backlogs, spare-parts shortages, supervision deficiencies, and incomplete incident follow-up. Training indicators include annual training hours, competency-test performance, certification status, and the proportion of employees receiving task-specific instruction ([Naveh & Lei, 2019](#)). Inspection delays are measured through overdue-task frequency, average delay duration, and the percentage of critical equipment not examined within the required interval. Maintenance deferral can increase the accumulation of known defects and expose equipment to continued operation under degraded conditions. Corrective-action backlogs reflect the number, age, criticality, and completion status of unresolved actions. The reviewed literature demonstrates that technical failures are frequently connected with human and organizational conditions, such as inadequate lubrication combined with incomplete inspection or repeated alarm activation combined with weak follow-up. Quantitative classification therefore separates immediate operator actions from broader causes involving competence, staffing, planning, resources, supervision, documentation, and organizational control ([Rodríguez et al., 2016](#)).

Environmental exposure influences the frequency and severity of equipment deterioration by changing the physical and chemical conditions under which gas production assets operate. Empirical studies from offshore platforms, desert facilities, coastal processing plants, sour-gas fields, pipeline systems, and remote production locations have evaluated environmental effects through ambient temperature, humidity, salt concentration, corrosive contaminants, sand production, external vibration, rainfall, and atmospheric conditions. High ambient temperature can reduce cooling efficiency, increase electrical and mechanical stress, accelerate lubricant degradation, and raise the operating temperature of motors, bearings, seals, and control equipment ([Dumitrascu et al., 2020](#)). Low temperature can increase fluid

viscosity, affect material behavior, promote freezing, and contribute to hydrate formation. Humidity and salt exposure increase the probability of atmospheric corrosion, electrical connection damage, coating deterioration, and instrumentation malfunction. Internal corrosion may develop through water, carbon dioxide, hydrogen sulfide, chlorides, microorganisms, and chemical contaminants carried within the production stream. Sand production can erode pipelines, valves, chokes, impellers, separators, and flow-control components, particularly where flow velocity and particle concentration remain high. External vibration from nearby rotating equipment, structural movement, flow-induced forces, or unstable foundations can contribute to fatigue cracking, loose connections, sensor error, and premature bearing damage. Quantitative environmental exposure has been assessed through measured temperature, humidity, contaminant concentration, corrosion rate, material-loss depth, sand volume, vibration intensity, and the duration of exposure (Wingate, 2016). The literature also compares failure frequency across operating environments to determine whether specific conditions correspond with increased leakage, electrical interruption, instrumentation error, or mechanical wear. Environmental causes often interact with equipment age, coating condition, maintenance quality, operating pressure, production load, and inspection frequency. Their contribution to failure distribution is therefore evaluated by connecting environmental measurements with failure histories, integrity findings, maintenance records, operating hours, and observed equipment deterioration (Rolan et al., 2019).

Root-Cause Analysis Methods and Effectiveness

Root-cause analysis quality reflects the extent to which an investigation moves beyond visible failure symptoms and identifies the technical, human, organizational, and environmental conditions responsible for an event. Evidence synthesized from more than ten empirical studies in gas production, offshore operations, pipeline transportation, petrochemical processing, power generation, and manufacturing shows that RCA quality has been assessed through causal depth, investigation duration, evidence completeness, interdisciplinary participation, documentation quality, and verification strength (Otegui, 2014). Causal depth represents the number of connected causal levels identified between the immediate failure and its underlying systemic conditions. Investigation duration measures the time required to collect evidence, interview personnel, analyze records, confirm causes, approve findings, and establish corrective actions. Evidence completeness concerns the use of maintenance histories, process data, alarm logs, inspection records, photographs, damaged components, operating procedures, laboratory results, and personnel accounts. Interdisciplinary participation is evaluated through the involvement of operations, maintenance, engineering, inspection, instrumentation, safety, and management personnel. The five-whys technique has been widely used to organize causal questioning by repeatedly examining why each condition occurred. Its effectiveness has been measured through the number of causal layers reached, the proportion of investigations identifying systemic causes, corrective-action completion, and recurrence after closure (Shaqdan et al., 2014). Studies have shown that shallow analysis may classify vibration, leakage, overheating, or operator error as a root cause without identifying the maintenance, design, procedural, or management conditions that created the problem. Five-whys assessments become more dependable when each answer is supported by operational evidence rather than assumption. Repeat-failure percentage provides an important measure because recurring events may demonstrate that the identified cause was incomplete or the corrective action was ineffective. Root-cause quality is therefore evaluated through analytical depth, evidence support, participation, timeliness, documentation, verification, and subsequent failure behavior (Gangidi, 2019). Cause-and-effect analysis and fault-tree analysis provide structured methods for examining complex failures involving multiple technical and organizational conditions. Cause-and-effect analysis groups possible causes into categories such as personnel, equipment, methods, materials, environment, measurement, and management. Empirical research has assessed this method through causal-category coverage, the number of potential causes identified, the percentage of proposed causes supported by evidence, and the proportion of investigations that confirmed interactions among several categories. Broad category coverage reduces the likelihood that investigations will concentrate only on damaged components while overlooking operating procedures, inspection weaknesses, material quality, environmental exposure, instrumentation accuracy, or management control (Cuvelier et al., 2017).

Figure 6: Root-Cause Analysis Effectiveness Framework

Verified-cause percentage distinguishes evidence-supported conditions from untested possibilities generated during analysis. Verification may involve reviewing operating records, examining failed components, conducting laboratory analysis, repeating functional tests, comparing maintenance histories, or analyzing process trends. Fault-tree analysis uses a logical structure to connect a defined system-level failure with the component failures, control deficiencies, and operating conditions capable of producing it. Studies in gas processing and other safety-critical industries have evaluated fault trees through top-event likelihood, component-failure likelihood, number of minimal causal combinations, common-cause contribution, and overall system risk. Minimal causal combinations represent the smallest groups of events capable of producing the defined failure (Ma et al., 2020). Their identification helps determine whether risk is concentrated in a single vulnerable component or distributed across several interacting conditions. Common-cause failures are especially important when multiple protective devices depend on the same power supply, instrument signal, maintenance practice, or environmental condition. Quantitative fault-tree assessments rely on dependable equipment histories, failure probabilities, testing records, and expert judgment. Cause-and-effect analysis provides broad causal exploration, while fault-tree analysis offers detailed logical examination of system failure pathways. Their effectiveness is evaluated through causal completeness, verification strength, analytical consistency, and correspondence with recorded operational events (Mfula & Nurminen, 2017).

Pareto analysis and barrier analysis support root-cause investigation by identifying dominant reliability problems and evaluating the controls intended to prevent or limit their consequences. Pareto analysis ranks failure categories according to frequency, downtime, repair cost, production loss, or another measurable consequence. Studies across gas facilities, refineries, chemical plants, power stations, and manufacturing systems have found that a limited group of failure modes frequently accounts for a substantial share of total maintenance demand and production interruption (Raghavan, 2015). Quantitative Pareto assessments calculate the contribution of bearings, seals, valves, instrumentation, electrical systems, control loops, corrosion, human error, or other categories to cumulative failures and operational losses. Ranking by failure count may identify frequently recurring problems, while ranking by downtime can identify less frequent events that require lengthy restoration. Cost-based ranking highlights failures requiring expensive components, specialist labor, contractor support, or emergency procurement. Production-loss ranking identifies events that interrupt high-capacity assets or connected process systems. Barrier analysis examines the preventive, detective, protective, and recovery controls established to stop failures, identify deterioration, reduce consequences, or restore operation (Zhu et al., 2020). Preventive barriers include design safeguards, maintenance procedures, corrosion control, operating limits, and competency requirements. Detective

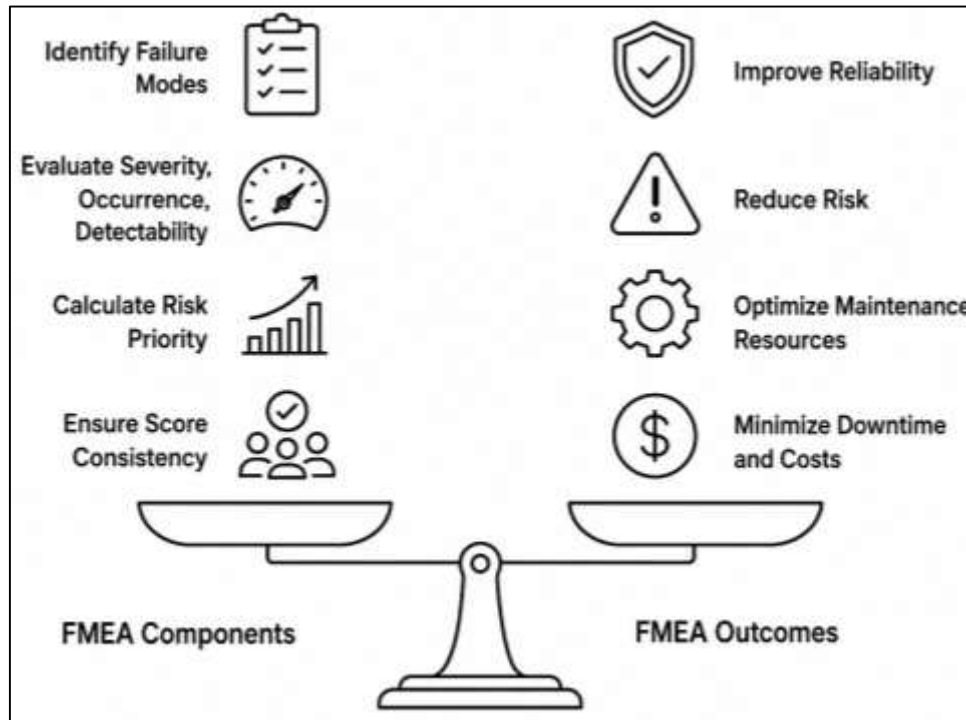
barriers include sensors, alarms, inspections, condition monitoring, and functional tests. Protective barriers include relief devices, shutdown systems, containment systems, isolation valves, and fire protection. Recovery barriers include emergency response, backup equipment, repair resources, and operational restoration procedures. Barrier effectiveness has been measured through availability, inspection status, testing performance, failure-on-demand, response time, and contribution to event development. A barrier may be formally present while remaining unavailable because of bypassing, overdue testing, defective instruments, inadequate maintenance, or incomplete procedures (Yue et al., 2017). Pareto and barrier analyses therefore connect failure concentration with the effectiveness of controls intended to prevent recurrence or reduce operational consequences.

Application of Failure Mode and Effects Analysis

Failure-mode identification is the foundational stage of Failure Mode and Effects Analysis because the quality of later risk scoring depends on the completeness and accuracy of the identified equipment failures. Evidence synthesized from more than ten empirical studies in gas production, petroleum processing, offshore operations, pipeline transportation, chemical manufacturing, and power generation shows that failure-mode identification has been evaluated through asset coverage, failure modes recorded per asset, functional coverage, historical-event coverage, and the proportion of critical equipment included. Asset coverage represents the number and percentage of facility assets examined relative to the total equipment population (Illankoon et al., 2019). Functional coverage measures whether all essential equipment functions, operating states, protective functions, interfaces, and supporting utilities have been considered. Historical-event coverage evaluates whether previously recorded failures, shutdowns, alarms, inspection defects, maintenance findings, and repeated operational disturbances are represented in the FMEA register. Failure modes may include failure to start, failure to stop, reduced output, leakage, overheating, excessive vibration, unstable pressure, inaccurate measurement, failure to isolate, and complete functional loss. Studies have shown that incomplete registers frequently emphasize major rotating equipment while giving limited attention to instrumentation, utilities, protective devices, piping components, communication systems, and human-dependent functions. Critical-equipment inclusion is therefore assessed separately because omission of a high-consequence asset can weaken the overall risk profile (Rollenhagen et al., 2017). The number of recorded failure modes per asset is interpreted in relation to equipment complexity rather than as an isolated indicator of quality. Complex compressors, control systems, and processing units generally require more detailed functional decomposition than simple components. Strong failure-mode identification relies on engineering drawings, maintenance histories, operating records, inspection findings, incident reports, manufacturer guidance, and interdisciplinary technical knowledge. Register completeness is consequently judged through asset representation, functional detail, historical evidence, equipment criticality, and consistency of failure descriptions (Madenas et al., 2016). Severity, occurrence, and detectability represent the principal dimensions used to evaluate the relative risk of identified failure modes. Severity measures the magnitude of the consequences that may result when a failure reaches the equipment, process, facility, workforce, environment, or organization. Empirical studies have applied severity scales incorporating injury potential, fire and explosion exposure, environmental release, equipment damage, production interruption, repair cost, regulatory noncompliance, and recovery duration. High-severity ratings are commonly assigned to failures involving loss of containment, failure of emergency protection, extended production shutdown, serious equipment damage, or effects on several connected process systems (Joshi et al., 2015). Occurrence measures how frequently a failure has happened or how likely it is to arise under defined operating conditions. Studies have determined occurrence through annual failure counts, historical recurrence, failures relative to operating hours, affected component populations, maintenance records, and expert estimates of failure likelihood. Operating exposure is important because assets with longer operating hours or more severe service experience greater opportunities for failure. Detectability measures the likelihood that a developing failure will be identified before it produces its full operational consequence. It has been evaluated through inspection effectiveness, sensor coverage, alarm accuracy, condition-monitoring capability, warning lead time, testing frequency, and missed-detection history. A failure mode may receive a weak detectability rating when deterioration remains hidden until shutdown or functional loss (Keikhosrokiani, 2020). Strong detectability is associated with dependable

sensors, clear alarms, regular inspection, accurate testing, and sufficient warning time for intervention. Across the reviewed literature, rating quality depends on clearly defined scoring criteria, dependable historical evidence, and consistent interpretation among assessors. Severity, occurrence, and detectability are therefore treated as distinct risk characteristics requiring separate analysis before they are combined into an overall priority classification.

Figure 7: Failure Mode Analysis Application Framework



Risk-priority rankings translate FMEA assessments into an ordered list of failure modes requiring engineering attention, maintenance resources, monitoring improvement, or corrective action. Studies across gas, oil, petrochemical, pipeline, power-generation, and manufacturing facilities have examined the distribution of risk-priority values across equipment categories, functional locations, failure mechanisms, and process systems (Gao et al., 2016). High-priority failure modes commonly involve severe consequences, repeated occurrence, limited detection capability, or combinations of these conditions. FMEA criticality assessment extends basic priority ranking by considering failure probability, consequence magnitude, operating exposure, asset importance, system dependency, and production effect. Criticality is especially relevant in gas production because failure of a relatively small component can interrupt a compressor train, disable a protective system, restrict an export pipeline, or affect several connected wells. Empirical validation compares assigned rankings with observed operational outcomes, including failure count, downtime hours, repair duration, maintenance expenditure, repeat-event frequency, equipment availability, and deferred production. A valid ranking system should place greater priority on failure modes that produce substantial or recurring operational consequences. The literature shows that similar combined rankings may represent different risk structures (Gugaliya et al., 2019). One failure mode may have very high severity but limited occurrence, while another may occur frequently and create considerable cumulative downtime. Separate examination of the underlying risk dimensions prevents important differences from being concealed by the overall ranking. Researchers have also compared initial priority values with post-intervention values to evaluate whether corrective actions reduced occurrence or improved detection. Risk-ranking validity depends on the quality of failure histories, consistency of scoring scales, completeness of operational data, and alignment between assessed consequences and actual facility outcomes. Quantitative FMEA evaluation therefore links priority and criticality classifications directly with

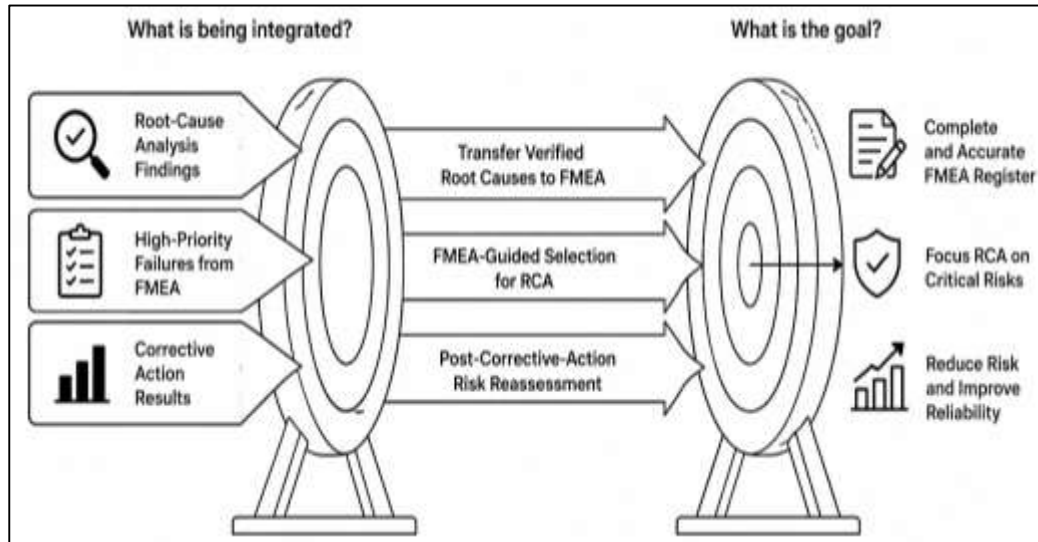
recorded reliability, maintenance, production, safety, and cost information (Wakiru et al., 2019). Inter-rater reliability concerns the degree to which different assessors provide consistent FMEA ratings when evaluating the same failure modes under the same operating conditions. Empirical studies have reviewed score consistency among personnel from engineering, operations, mechanical maintenance, electrical maintenance, instrumentation, inspection, process safety, reliability, and management functions. Agreement percentage measures how often assessors assign identical or closely comparable ratings, while reliability coefficients evaluate the overall consistency of assessments across multiple participants or failure modes. Differences frequently arise because professional groups interpret risk through their own responsibilities and experience (Chemweno et al., 2017). Operations personnel may emphasize process disruption and production loss, maintenance personnel may focus on repair complexity and recurrence, safety specialists may assign greater importance to hazardous consequences, and instrumentation personnel may evaluate detection capability according to sensor and alarm performance. Variation can also result from unclear scoring definitions, insufficient historical data, inconsistent equipment boundaries, or differences in familiarity with particular assets. Studies have improved rating consistency through standardized scales, facilitator-led workshops, assessor training, documented examples, structured evidence review, and group reconciliation (Pandey et al., 2018). Evidence-based scoring uses failure histories, operating hours, maintenance records, inspection results, alarm performance, production losses, and cost data to limit dependence on unsupported judgment. Inter-rater analysis can identify failure modes with high scoring disagreement, requiring further investigation or clarification before final ranking. Documentation completeness is also important because each score should be supported by a stated rationale and relevant operational evidence. Reliable FMEA scoring does not require complete uniformity of professional opinion, but substantial unexplained disagreement can reduce confidence in priority rankings. The reviewed literature therefore treats inter-rater agreement, scoring consistency, evidence quality, assessor diversity, and reconciliation procedures as essential quantitative measures of FMEA reliability and decision quality (Bona et al., 2018).

Root-Cause Analysis and FMEA

The transfer of verified root causes into FMEA registers connects reactive failure investigation with systematic risk assessment. Evidence synthesized from more than ten empirical studies in gas production, oil processing, pipeline operations, petrochemical plants, power generation, and other reliability-intensive industries shows that this integration has been assessed through the percentage of completed investigations incorporated into FMEA records, the number of new failure modes added, the number of causal descriptions revised, and the extent to which existing controls are updated. Root-cause investigations often reveal that the original FMEA register contains incomplete causes, generalized failure descriptions, outdated controls, or failure modes that were not identified during the initial assessment (Nikulin et al., 2014).

A compressor trip originally attributed to excessive vibration, for example, may be connected through investigation to lubrication contamination, shaft misalignment, unstable suction conditions, delayed inspection, or ineffective alarm settings. Adding these verified causes improves the technical specificity of the register and provides a stronger basis for occurrence and detectability assessment. Integration quality also depends on whether investigation evidence is traceable to maintenance records, operating histories, inspection results, process trends, damaged-component examinations, and personnel accounts. Studies have evaluated register revision through the proportion of completed investigations reviewed by FMEA teams, the number of affected equipment functions reassessed, and the percentage of revised controls assigned to responsible personnel. Updated control descriptions may include inspection requirements, sensor coverage, alarm limits, preventive-maintenance tasks, operating procedures, or protective devices (Zhang et al., 2017). The literature identifies weak integration when investigation reports are archived without changing risk registers or when FMEA revisions are completed without documenting the supporting evidence. Transfer effectiveness is therefore measured through investigation coverage, register completeness, causal accuracy, control revision, action traceability, and formal approval of the updated assessment.

Figure 8: Integrated RCA FMEA Reliability Framework



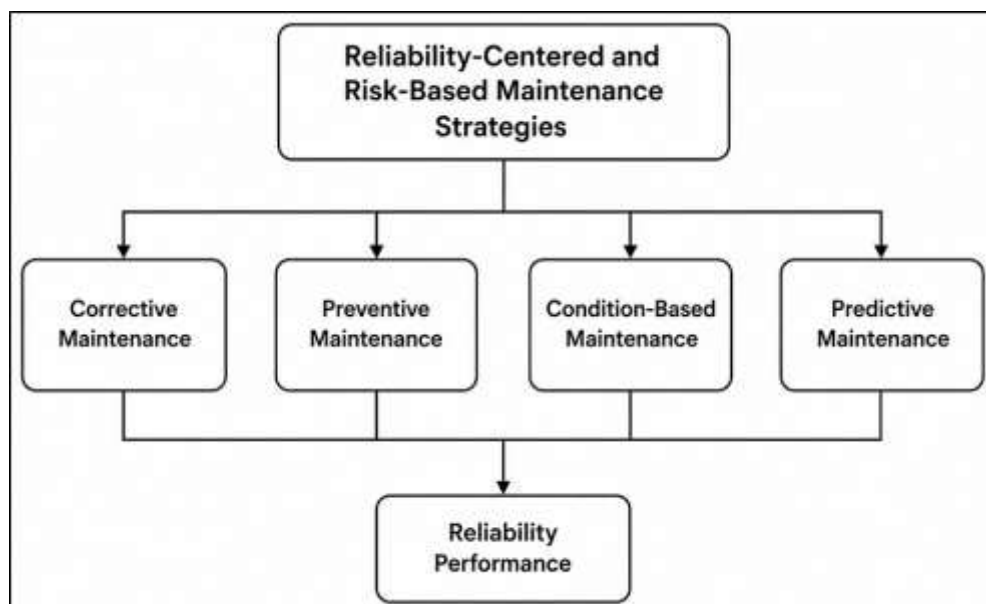
FMEA-guided selection directs root-cause analysis toward failure modes with the greatest operational importance rather than applying the same investigation effort to every equipment event. Empirical studies have examined selection criteria based on severity thresholds, recurrence thresholds, risk-priority classifications, downtime contribution, maintenance cost, environmental exposure, safety consequence, and production loss (Shaqdan et al., 2014). High-severity failures may require detailed investigation even when they occur infrequently because their consequences can include personnel injury, loss of containment, fire, environmental release, regulatory violation, or extended production shutdown. Repeated failures may also qualify for analysis when each event has a moderate consequence but their cumulative effect creates substantial downtime, maintenance demand, or process instability. Risk-priority values provide an organized starting point for selection, although studies commonly evaluate the separate severity, occurrence, and detectability dimensions before assigning investigation priority. Downtime contribution identifies failure modes responsible for large proportions of equipment unavailability, while production-loss criteria focus on deferred gas volume, throughput reduction, and interruption of connected process systems. Maintenance-cost thresholds identify failures requiring expensive components, specialist labor, emergency procurement, or repeated repairs (Aurisicchio et al., 2016). The literature also describes the use of Pareto rankings to identify the small number of failure categories responsible for a substantial share of operational losses. Selection quality depends on consistent thresholds, reliable event classification, complete operational data, and management review. Very low-frequency failures may receive priority when their potential consequences remain severe, while high-frequency minor events may be selected because of their cumulative effect. FMEA-guided selection is therefore evaluated through the proportion of high-priority failures investigated, consistency of initiation criteria, investigation timeliness, asset-criticality coverage, and alignment between selected events and recorded reliability consequences (Gangidi, 2019). Changes in FMEA ratings following corrective action provide a quantitative method for examining whether implemented controls altered the risk characteristics of identified failure modes. Studies in gas facilities and comparable process industries have compared pre-action and post-action severity, occurrence, detectability, and overall risk-priority classifications. Severity may remain unchanged when an intervention reduces failure frequency but does not alter the consequence that would occur if the failure developed. Design modification, additional containment, equipment redundancy, or improved protective systems may reduce severity when the intervention limits the possible operational effect (Geramian et al., 2020). Occurrence ratings are commonly revised when maintenance changes, component replacement, operating-limit control, lubrication improvement, corrosion treatment, or equipment redesign reduces recorded failure frequency. Detectability ratings improve when additional sensors, alarms, inspections, functional tests, condition-monitoring systems,

or diagnostic procedures increase the probability of identifying deterioration before functional loss. Empirical assessments have considered both the size of rating changes and the operational evidence supporting them. A lower post-action score requires verification through completed work orders, inspection findings, functional tests, monitoring records, and sustained equipment performance. Immediate reassessment after action completion may reflect the expected effectiveness of the intervention rather than observed reliability change. Studies therefore distinguish between provisional rating revision and evidence-based confirmation after an adequate operating period (Panchal & Kumar, 2016). Comparisons may be performed across equipment types, corrective-action categories, facility systems, and operating years to identify where risk reduction was most substantial. The literature also recognizes that a reduced combined priority value can conceal an unchanged high-severity consequence. Post-action assessment consequently examines every risk dimension individually, together with failure recurrence, downtime, repair duration, production loss, and control performance. This approach connects changes in FMEA classification with documented technical and operational outcomes (Chong et al., 2015).

Reliability-Centered Maintenance and Risk-Based Maintenance Strategies

Corrective and preventive maintenance represent two basic approaches to controlling equipment deterioration and restoring the functionality of gas production assets. Evidence synthesized from more than ten empirical studies in gas processing, offshore production, pipeline transportation, petrochemical operations, and power generation shows that corrective maintenance has been evaluated through breakdown frequency, emergency work orders, maintenance response time, repair duration, labor hours, material expenditure, and production interruption. Corrective maintenance begins after equipment has failed or its performance has declined below an acceptable level. Its effectiveness depends on rapid fault diagnosis, personnel availability, spare-parts access, repair quality, and successful restoration (Mehairjan, 2017). High emergency-work-order frequency may represent unstable equipment condition, weak preventive control, or repeated treatment of symptoms without removal of the underlying cause. Repair cost includes labor, replacement components, contractor support, transport, lifting equipment, testing, and production losses. Preventive maintenance involves inspections, servicing, component replacement, calibration, lubrication, cleaning, and functional testing at scheduled intervals. Its performance has been measured through completion rate, overdue-task percentage, schedule compliance, planned downtime, maintenance interval, and failure occurrence after servicing. Strong schedule compliance shows that required tasks were completed within approved periods, while a large overdue backlog may expose critical assets to continued deterioration (Sabouhi et al., 2016).

Figure 9: Reliability-Centered Maintenance Performance Framework



Post-maintenance failure frequency provides evidence of whether scheduled tasks prevented failure or introduced defects through incorrect assembly, adjustment, or testing. Studies have also compared emergency and planned maintenance proportions because facilities dominated by reactive work may experience higher downtime and less predictable resource demand. Corrective and preventive maintenance performance is therefore assessed through breakdown occurrence, planning quality, work completion, restoration time, cost, recurrence, and production continuity rather than through the number of maintenance activities alone ([Abuelenin, 2020](#)).

Condition-based maintenance uses measured evidence of equipment condition to determine when inspection, servicing, repair, or replacement is required. Empirical research has assessed its effectiveness through defect-detection rate, diagnostic accuracy, warning lead time, monitoring coverage, inspection frequency, maintenance avoidance, and the proportion of detected defects confirmed during intervention. Common techniques include vibration monitoring, lubricant and oil analysis, thermography, ultrasonic testing, corrosion monitoring, pressure and temperature trending, motor-current analysis, and process-performance evaluation. Vibration monitoring identifies imbalance, misalignment, bearing deterioration, looseness, resonance, and rotating-component defects through changes in vibration magnitude and frequency patterns ([Mehairajan et al., 2016](#)). Oil analysis evaluates contamination, viscosity, moisture, metal particles, and lubricant degradation, providing evidence of internal wear and lubrication-system condition. Thermography detects abnormal temperature in electrical connections, motors, bearings, insulation, and process equipment. Ultrasonic testing supports leakage identification, thickness measurement, valve assessment, and detection of certain mechanical defects. Corrosion monitoring measures material loss and supports integrity assessment of pipelines, vessels, flowlines, and processing systems. Warning lead time represents the interval between detection of deterioration and expected functional failure, allowing maintenance to be planned before an unplanned shutdown. Detection accuracy reflects the proportion of genuine defects correctly identified, while false indications may generate unnecessary inspection or maintenance ([Chattopadhyaya et al., 2017](#)). Studies have also examined missed defects that remained undetected until equipment failure. Monitoring effectiveness depends on sensor quality, measurement frequency, baseline data, alarm thresholds, analyst competence, and the stability of operating conditions. Condition measurements can vary with equipment load, process pressure, temperature, and speed, requiring operating context during interpretation. The literature therefore evaluates condition-based maintenance through monitoring reliability, verified defect detection, warning duration, maintenance timing, avoided breakdowns, and post-maintenance equipment performance ([Moradi et al., 2019](#)).

Predictive maintenance applies historical failure records, condition-monitoring data, operating variables, and analytical models to estimate the likelihood or timing of equipment deterioration. Studies across gas facilities and other asset-intensive industries have evaluated predictive performance through sensitivity, specificity, precision, recall, false-alarm rate, missed-failure rate, prediction horizon, and the percentage of failures identified before functional loss. Sensitivity and recall describe the ability of a predictive system to identify failures that actually occurred, while specificity describes its ability to recognize normal equipment conditions ([Orrù et al., 2020](#)). Precision measures how many generated warnings correspond with confirmed deterioration or subsequent failure. False alarms can lead to unnecessary inspection, maintenance, component replacement, and production interruption. Missed failures are operationally important because an apparently accurate model may still fail to identify critical events. Prediction horizon refers to the amount of warning time provided before expected failure. Very short warnings may be technically correct but provide insufficient time for work planning, spare-parts procurement, production coordination, and safe equipment shutdown. Long warning periods can support planned intervention, although prediction uncertainty may increase as the interval becomes longer. Empirical studies have used vibration, temperature, pressure, flow, lubrication condition, motor current, alarm histories, operating hours, and previous failure patterns as predictive variables ([Orrù et al., 2020](#)). Model performance depends on data completeness, failure-label accuracy, equipment comparability, sensor reliability, and the number of recorded failure events. Gas facilities often contain equipment operating under different loads and service conditions, requiring

prediction results to be interpreted within the relevant operational context. Predictive-maintenance effectiveness has also been assessed through avoided failures, reduced emergency work, shorter downtime, maintenance-cost changes, and improved availability. The reviewed evidence therefore connects statistical prediction quality with warning usefulness, maintenance action, operational verification, and documented reliability outcomes (Leahy et al., 2018).

Reliability-centered maintenance and risk-based inspection prioritize maintenance and integrity activities according to equipment function, failure consequence, degradation mechanism, and operational importance. Reliability-centered maintenance begins by identifying required asset functions, functional failures, failure modes, consequences, and appropriate maintenance tasks. Empirical studies have measured its effectiveness through functional-failure coverage, critical-equipment inclusion, maintenance-task suitability, preventive-task completion, emergency-work reduction, maintenance efficiency, and operational availability (Burnaev, 2019). Task effectiveness considers whether an inspection, test, restoration, replacement, or monitoring activity can identify or control the relevant failure mechanism within an appropriate interval. Critical-equipment inclusion measures the proportion of high-priority assets covered by formal maintenance strategies. Reliability-centered maintenance studies have also examined changes in failure frequency, downtime, maintenance workload, and production interruption following task revision. Risk-based inspection concentrates inspection resources on equipment with the greatest likelihood and consequence of integrity failure. It has been applied to pressure vessels, pipelines, separators, storage equipment, heat exchangers, valves, and other containment systems. Quantitative indicators include inspection coverage, inspection interval, high-risk asset coverage, defect-detection rate, overdue-inspection percentage, inspection backlog, corrosion findings, and integrity-related failure reduction (Bosman et al., 2020). Inspection intervals are determined through equipment condition, degradation rate, service severity, failure history, and consequence classification. A high inspection-completion rate does not necessarily represent strong performance when low-risk assets receive attention while critical equipment remains overdue. Defect-detection quality and timely corrective action are therefore examined with coverage. The literature shows that reliability-centered maintenance and risk-based inspection share a prioritization principle but address different aspects of asset performance. Their combined assessment considers functional reliability, containment integrity, task efficiency, criticality coverage, detected defects, maintenance response, equipment availability, and production continuity (Naskos et al., 2019).

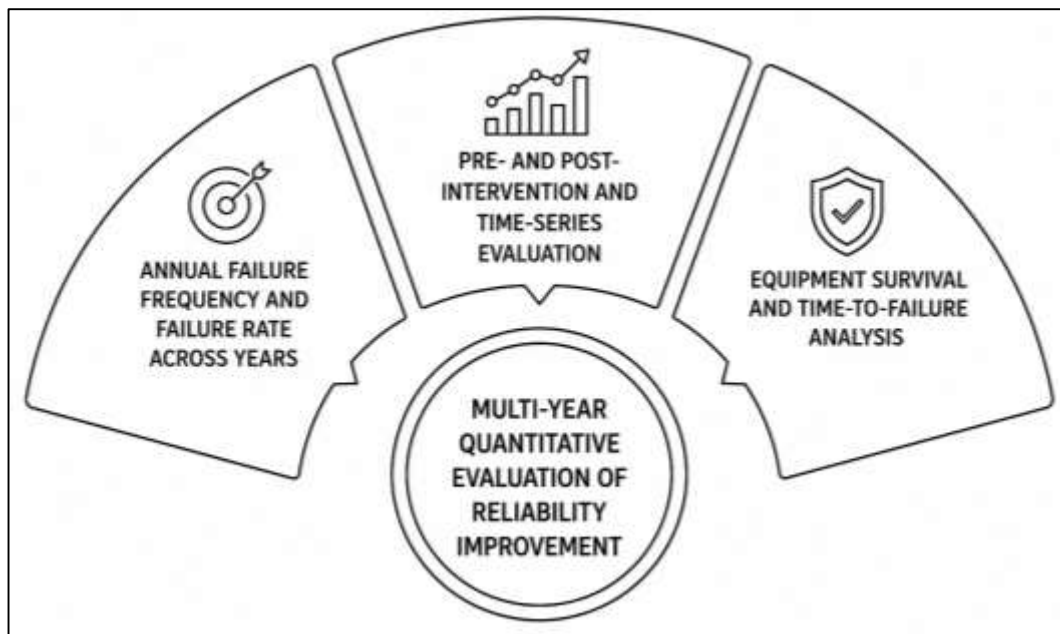
Multi-Year Quantitative Evaluation of Reliability Improvement

Multi-year evaluation allows reliability performance to be examined across successive operating years rather than through a single-period summary. Evidence synthesized from more than ten empirical studies in gas production, offshore operations, pipeline systems, petrochemical plants, power generation, and process manufacturing shows that annual performance has been evaluated through total failures, failures per asset, failures per 1,000 operating hours, annual shutdown frequency, mean time between failures, mean time to repair, availability, and downtime (Nuijs et al., 2018). Total annual failure count provides a direct measure of recorded equipment interruptions, although comparisons require consideration of changes in asset population and operating exposure. Failures per asset allow facilities with different numbers of equipment units to be compared more consistently. Failure rates based on operating hours provide additional control for variations in equipment use, production activity, seasonal shutdowns, and standby periods. Mean time between failures measures the average operating duration separating successive events, while mean time to repair reflects the time required for diagnosis, resource mobilization, repair, testing, and restoration. Availability records the proportion of scheduled operating time during which equipment remains capable of performing its function (Zhao et al., 2018). Downtime captures the duration of unavailability and may be classified according to mechanical, electrical, process, instrumentation, maintenance, or external causes. Year-to-year comparisons can identify gradual improvement, deterioration, temporary fluctuation, or changes concentrated in particular equipment categories. Empirical studies have also separated planned and unplanned downtime because scheduled maintenance interruptions differ from unexpected reliability failures. Annual percentage changes provide accessible summaries, but their interpretation depends on baseline values and operating exposure. Multi-year assessment therefore combines failure

frequency, asset count, operating hours, repair duration, availability, downtime, maintenance activity, and production loading to characterize reliability and maintainability patterns across time (Roy & Kumar, 2017).

Pre-intervention and post-intervention comparisons examine whether reliability indicators changed after root-cause analysis, FMEA reassessment, and associated corrective actions were implemented. Studies have compared mean failure frequency, downtime, repair duration, equipment availability, maintenance expenditure, recurrence, and production loss across defined periods before and after reliability interventions. Interventions have included equipment redesign, component replacement, lubrication improvement, revised operating limits, additional condition monitoring, inspection-frequency adjustment, alarm modification, workforce training, procedure revision, and spare-parts improvement (Dai et al., 2020). Simple before-and-after comparisons provide a clear measure of observed change, but their interpretation can be affected by existing performance patterns, maintenance shutdowns, equipment replacement, production loading, and changes in failure reporting. Interrupted time-series analysis addresses these issues by examining repeated observations before and after the intervention point. The method assesses whether the outcome changed immediately when the intervention occurred and whether the direction or rate of change differed during the subsequent observation period. A reduction in failure frequency immediately after corrective action represents a level change, while a gradual decline over several periods represents a change in trend. Studies using monthly, quarterly, or annual observations have evaluated whether improvements were temporary, delayed, or sustained throughout the recorded post-intervention period (Ye et al., 2020). Analysis may also include several intervention points when facilities introduced actions in stages. Suitable outcome measures include failure count, downtime hours, mean repair duration, production interruption, risk-priority classification, and equipment availability. The literature emphasizes the importance of a clearly documented implementation date and consistent data collection across the observation period. Pre-intervention, post-intervention, and time-series evaluation therefore connect intervention timing with measured reliability changes while accounting for the facility's recorded performance before implementation (Qiu et al., 2015).

Figure 10: Multi-Year Reliability Performance Evaluation



Equipment survival analysis evaluates the length of time that an asset continues operating before a defined failure occurs. Empirical studies in gas production and related industries have used survival probability, time-to-failure distributions, hazard rates, median operating life, and censored

observations to compare reliability across equipment types, operating conditions, maintenance strategies, and intervention groups. Survival probability describes the likelihood that equipment remains functional beyond a particular operating duration. Hazard rate represents the relative risk of failure at different stages of equipment life and can reveal whether failure likelihood increases with age, remains stable, or is concentrated during early operation ([Awadalla et al., 2015](#)). Median operating life identifies the point at which half of the observed equipment population has experienced the defined failure, provided that sufficient failures are recorded. Censored observations occur when assets remain operational at the end of the study, leave service for reasons unrelated to failure, or have incomplete failure times. Including such observations prevents functioning assets from being incorrectly treated as failures or excluded entirely. Studies have compared time to failure among compressors, pumps, valves, instruments, electrical motors, pressure vessels, and pipeline components. Comparisons have also been made between assets receiving integrated root-cause and FMEA interventions and those managed through routine maintenance. Equipment age, cumulative operating hours, production loading, environmental exposure, service severity, maintenance history, and component replacement can influence survival performance ([Elsheikh et al., 2020](#)). Time to first failure and time between repeated failures provide different forms of evidence, particularly for repairable assets. Survival analysis therefore offers a more complete view than failure counts alone because it incorporates operating duration and the status of equipment that has not failed. The reviewed literature uses this approach to examine differences in operating life, failure risk, maintenance effects, and asset-category reliability ([Collins & Warr, 2019](#)).

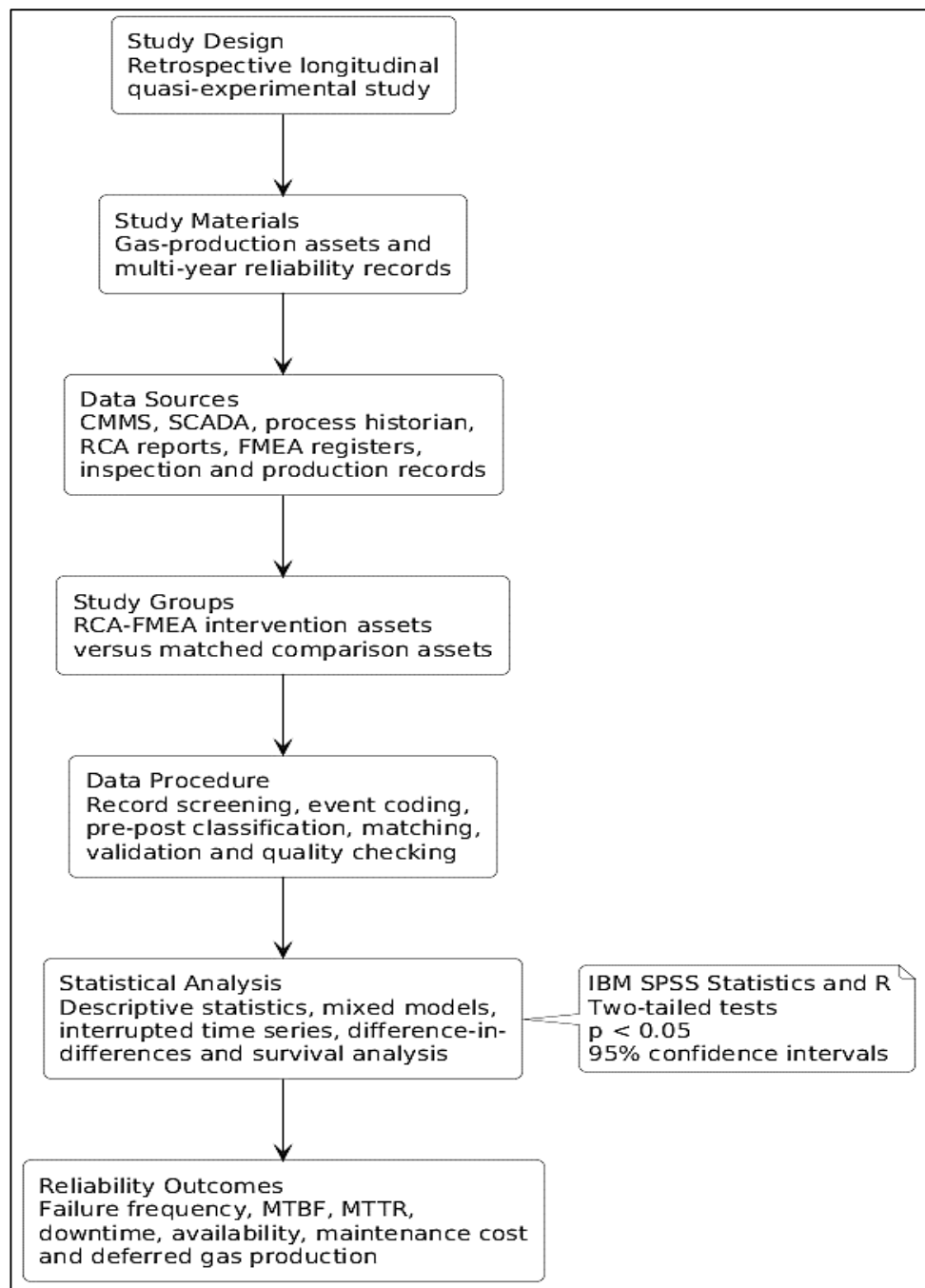
METHOD

The study employed a retrospective longitudinal quasi-experimental design to evaluate the multi-year effectiveness of root-cause analysis and Failure Mode and Effects Analysis in improving the reliability of gas production facilities. The longitudinal component involved repeated observations of equipment performance across successive months and operating years, while the quasi-experimental component compared reliability outcomes before and after the implementation of RCA–FMEA corrective actions without randomly assigning equipment to intervention conditions. The primary unit of analysis was the asset-month, which allowed failure frequency, operating exposure, downtime, maintenance activity, production loss, and intervention status to be evaluated consistently over time. Individual failure events constituted a secondary unit of analysis and were nested within equipment assets and facilities. The study was guided by an integrated reliability-improvement framework combining root-cause analysis, Failure Mode and Effects Analysis, and reliability-centered maintenance principles. Under this framework, RCA quality and FMEA risk prioritization were treated as the principal explanatory variables, corrective-action completion and verification were treated as intervention variables, and equipment reliability was treated as the principal outcome. RCA quality was operationalized through causal depth, evidence completeness, investigation duration, interdisciplinary participation, documentation quality, and verification status. FMEA performance was measured through failure-mode coverage, severity, occurrence, detectability, risk-priority classification, criticality, and the consistency of scoring among assessors. Reliability outcomes included failure count, repeated-failure percentage, mean time between failures, mean time to repair, unplanned downtime, operational availability, maintenance expenditure, deferred gas production, and production-interruption frequency. Equipment type, age, cumulative operating hours, production loading, operating pressure, temperature, maintenance strategy, environmental exposure, facility characteristics, and asset criticality were treated as control variables. Assets receiving completed and verified RCA–FMEA corrective actions formed the intervention group, while comparable assets receiving routine corrective or preventive maintenance without a documented integrated intervention formed the comparison group. This structure supported the evaluation of temporal changes, intervention differences, recurring failures, and reliability growth across the multi-year observation period.

The study population consisted of repairable physical assets, reliability events, maintenance activities, FMEA records, RCA reports, and production-performance records obtained from participating gas production facilities. The asset population included compressors, pumps, separators, pressure vessels, pipelines, flowlines, valves, electrical motors, process-control systems, instrumentation devices,

emergency shutdown equipment, metering systems, and essential utility equipment. Facilities were selected purposively according to the availability of continuous multi-year operational data, documented RCA and FMEA activities, standardized asset-identification systems, accessible maintenance histories, and management authorization for technical-record analysis. Within each selected facility, a census approach was used to include all eligible critical and operationally significant assets rather than selecting a small random sample. This approach preserved rare high-consequence failures and allowed the complete distribution of recorded reliability events to be examined. Assets were included when they possessed a unique identification number, had been installed and available for operation during the observation period, had reliable operating-hour records, and had corresponding maintenance, failure, downtime, or production information. Failure events were included when they had a verified event date, identifiable equipment location, documented failure mode, recorded downtime or restoration time, and sufficient technical evidence for classification.

Figure 11: Methodology of this study



RCA-FMEA interventions were included when the initiating failure, verified cause, recommended action, responsible unit, completion status, and implementation date were documented. Planned maintenance shutdowns, routine inspections without detected failure, commissioning tests, duplicate work orders, external power failures unrelated to facility assets, and production interruptions caused entirely by market or supply restrictions were excluded from the primary failure analysis. Events with unverified timestamps, missing equipment identifiers, contradictory failure classifications, or insufficient evidence to distinguish functional failure from routine maintenance were also excluded. Equipment removed from service because of failure was retained until its documented removal date to reduce survivorship bias. Assets with limited post-intervention exposure were retained for event and survival analyses but were excluded from balanced pre-intervention and post-intervention comparisons when they did not satisfy the minimum observation requirement. Comparison assets were matched with intervention assets according to equipment category, baseline failure history, operating exposure, asset age, criticality, facility location, and production-loading conditions.

Data were obtained from the computerized maintenance management system, distributed control system, supervisory control and data-acquisition system, process historian, production-accounting database, inspection-management system, RCA reports, FMEA registers, equipment files, and corrective-action tracking records. The maintenance system supplied work-order dates, maintenance type, failure descriptions, labor hours, repair duration, spare-parts use, maintenance costs, and restoration status. The process historian supplied time-stamped pressure, temperature, flow, vibration, motor-current, alarm, trip, and operating-condition data. Production records supplied scheduled operating hours, actual production, deferred gas volume, throughput reduction, shutdown duration, and production-restoration dates. Inspection records supplied corrosion measurements, wall-thickness findings, vibration results, oil-analysis results, calibration histories, functional-test outcomes, and defect classifications. RCA reports provided evidence concerning immediate causes, contributing factors, verified root causes, analytical methods, team participation, corrective actions, and closure verification. FMEA registers supplied asset functions, failure modes, effects, causes, existing controls, severity ratings, occurrence ratings, detectability ratings, criticality levels, and action priorities. A standardized electronic data-extraction instrument was developed to integrate these sources into a common dataset. The extraction instrument was reviewed by a panel of reliability, mechanical, process, instrumentation, maintenance, and statistical specialists to establish content validity and consistent operational definitions. A pilot extraction was conducted on a subset of assets and failure events before full data collection. Two trained reviewers independently coded the pilot records, and disagreements were resolved through technical review. Agreement was assessed using percentage agreement and appropriate inter-rater reliability coefficients, with an acceptable level established before full extraction proceeded. The same reliability procedure was applied to a randomly selected proportion of the final records. Equipment measurements were accepted only when the relevant sensors, vibration instruments, pressure transmitters, temperature devices, corrosion instruments, and calibration tools had valid calibration or functional-test documentation. Automated process values were cross-checked against alarm histories, operating logs, maintenance records, and production reports. A data dictionary was used to standardize asset names, failure modes, causal categories, intervention types, downtime definitions, and production-loss classifications across facilities and operating years.

The study procedure was completed in a chronological sequence beginning with organizational approval, data-access authorization, and confirmation of the multi-year observation boundaries. Facility asset registers were first reviewed to establish the eligible equipment population and assign consistent facility, system, equipment, and component identifiers. Maintenance, production, inspection, RCA, FMEA, alarm, and process-history records were then extracted for the same observation period. Failure events were screened for eligibility, duplicate records were reconciled, and event descriptions were coded according to mechanical, electrical, process, instrumentation, human, organizational, and environmental causal categories. Each event was connected with its corresponding operating hours, production status, maintenance activity, downtime, restoration time, and financial consequence.

RCA reports were subsequently reviewed to determine causal depth, evidence completeness, investigation time, interdisciplinary participation, verified root cause, and corrective-action status. The relevant FMEA registers were examined to identify the pre-intervention severity, occurrence, detectability, risk-priority, criticality, and control descriptions associated with each failure mode. Corrective actions were classified as equipment redesign, component replacement, inspection improvement, condition-monitoring introduction, maintenance-interval revision, operating-procedure change, alarm or control modification, workforce training, spare-parts improvement, or organizational-control revision. The documented implementation date was used to separate pre-intervention and post-intervention observations. Completion was recorded only when documentary evidence confirmed that the action had been implemented, while verification was recorded when inspection, testing, monitoring, or engineering review demonstrated that the intended control was operational. Post-action FMEA values were extracted after reassessment and were linked with subsequent failure, downtime, maintenance, and production records. Asset-month observations were then constructed by aggregating operating hours, failures, downtime, repair activity, availability, production loss, and intervention exposure for each equipment item. A comparison dataset was developed by matching intervention assets with similar nonintervention assets based on baseline characteristics. Data-quality checks were conducted for missing values, impossible dates, overlapping downtime, inconsistent operating hours, extreme measurements, and contradictory equipment classifications.

All corrections were documented in an audit trail, and the final analytical dataset was de-identified before statistical analysis. Statistical analysis was performed using IBM SPSS Statistics and R. Descriptive statistics summarized facility characteristics, equipment populations, failure categories, RCA quality measures, FMEA ratings, corrective actions, and reliability outcomes. Frequencies and percentages were used for categorical variables, while means and standard deviations were reported for approximately normally distributed continuous variables. Medians and interquartile ranges were reported for skewed variables such as repair duration, downtime, production loss, and maintenance cost. Annual failure counts, failures per asset, failures per 1,000 operating hours, shutdown frequency, mean time between failures, mean time to repair, availability, downtime, and deferred gas production were calculated for each equipment category and operating year. Annual trends were examined through repeated-period comparisons and regression models that incorporated operating exposure. Poisson regression was used for count outcomes when the variance was consistent with the model assumptions, while negative binomial regression was used when failure counts demonstrated overdispersion. Operating hours were incorporated as an exposure term in the failure-rate models. Continuous outcomes such as downtime, repair duration, maintenance cost, and production loss were examined through linear mixed-effects models or generalized models appropriate to their distributions. Facility and equipment identifiers were treated as random effects to account for repeated observations and clustering.

Pre-intervention and post-intervention differences were assessed using paired-sample tests for continuous outcomes and corresponding nonparametric tests when distributional assumptions were not satisfied. Categorical changes were evaluated through chi-square or paired categorical tests, as appropriate.

Interrupted time-series analysis was applied to monthly observations to estimate immediate changes and trend changes following RCA-FMEA implementation. Autocorrelation, seasonality, and pre-existing performance trends were examined and corrected through segmented regression with appropriate time-series error structures. Difference-in-differences analysis compared changes among intervention and matched comparison assets while controlling for baseline reliability and operating conditions. Propensity-score matching or weighting was applied to improve comparability according to equipment age, type, baseline failure frequency, operating hours, criticality, production loading, and facility characteristics. The parallel-trend condition was examined using pre-intervention observations before the difference-in-differences estimates were interpreted. Equipment survival was evaluated using time-to-failure analysis. Survival curves compared intervention and comparison assets, equipment categories, and criticality groups, while log-rank tests assessed differences in survival experience.

Multivariable proportional-hazards models estimated the association of RCA–FMEA intervention with time to failure after adjustment for asset age, operating exposure, maintenance strategy, production loading, and environmental conditions. Proportional-hazards assumptions were examined before final model interpretation. Recurrent-event models were used for assets experiencing multiple failures, and equipment-level frailty terms accounted for unobserved differences among assets. Repeat-failure outcomes were also analyzed through logistic mixed-effects models, with recurrence defined according to the reappearance of the same failure mode or verified root cause after corrective-action closure. The validity of FMEA prioritization was examined by comparing severity, occurrence, detectability, criticality, and overall risk-priority classifications with observed failure frequency, downtime, repair duration, maintenance cost, production loss, and recurrence. Rank correlations were used when the variables were ordinal or nonnormally distributed. Receiver-operating-characteristic analysis evaluated the capacity of FMEA classifications to distinguish high-consequence failures from lower-consequence events.

Agreement among FMEA assessors was examined using weighted agreement measures for ordinal ratings and intraclass correlation coefficients for combined scores. Corrective-action completion and verification were evaluated as possible mediating mechanisms between RCA–FMEA quality and reliability improvement. Indirect effects were assessed through bootstrap estimation based on 5,000 resamples. Model assumptions were examined through residual analysis, normality plots, homoscedasticity tests, multicollinearity diagnostics, overdispersion checks, influence statistics, and autocorrelation assessment. Missing-data patterns were evaluated before analysis.

Complete-case analysis was used when missingness was minimal and nonsystematic, while multiple imputation was applied when missing values were sufficient to affect statistical precision and satisfied the required assumptions. Sensitivity analyses excluded extreme shutdown events, records with limited exposure, and assets undergoing complete replacement to determine whether the principal findings remained stable. All statistical tests were two-tailed, statistical significance was evaluated at $p < .05$, and 95% confidence intervals were reported. Effect sizes, rate ratios, odds ratios, hazard ratios, adjusted mean differences, and model-explanatory values were reported alongside probability values to demonstrate the magnitude and practical importance of the observed reliability changes.

FINDINGS

Final Dataset, Facility Characteristics, and Asset-Sample Distribution

The initial dataset contained records from 12 gas production facilities, of which eight satisfied the eligibility requirements and were retained. Two facilities were excluded because they lacked continuous multi-year operating records, one had inconsistent asset-identification codes, and one did not maintain verifiable RCA–FMEA documentation. The eight included facilities comprised five onshore facilities and three offshore facilities. A total of 1,052 assets were initially screened. Of these, 188 were excluded because of incomplete operating-hour data, insufficient observation periods, duplicate identification codes, missing maintenance histories, or temporary nonrepairable status. The final asset sample therefore contained 864 equipment items observed over 60 consecutive months, generating 51,840 asset-month observations. The record-screening process identified 4,028 potential failure events. Following validation, 216 duplicate events, 158 records with missing timestamps, 104 events with uncertain failure classifications, and 138 externally caused interruptions were removed. The final event-level dataset contained 3,412 verified failures. Mechanical failures accounted for 1,092 events, electrical failures represented 598 events, process failures comprised 512 events, and instrumentation or control failures represented 461 events. Human, organizational, and environmental root causes accounted for 307, 273, and 169 events, respectively. The supporting documentary dataset contained 1,126 eligible RCA investigations, 1,296 FMEA assessments, and 1,487 corrective-action records.

Table 1 demonstrated that the screening process retained a substantial and analytically usable dataset. Eight of 12 facilities and 864 of 1,052 assets met the eligibility requirements. The event-level retention rate was 84.7%, leaving 3,412 verified failures for analysis. RCA, FMEA, and corrective-action records showed retention rates above 95%, supporting strong documentary coverage. Mechanical causes represented the largest failure category, followed by electrical and process causes. Instrumentation, human, organizational, and environmental causes collectively accounted for more than one-third of failures. The 51,840 asset-month observations provided sufficient longitudinal exposure for trend, intervention, recurrence, and survival analyses across the five-year study period overall. The final sample included 72 compressors, 126 pumps, 64 separators, 58 pressure vessels, 94 pipelines, 86 flowlines, 132 valves, 78 electrical motors, 80 instrumentation assets, 32 control systems, 18 emergency shutdown systems, 12 metering systems, and 12 utility assets. The assets had a mean operating age of 11.8 years, while the median annual operating exposure was 6,903 hours. The mean production loading was 78.2% of rated capacity. High-criticality equipment represented 33.3% of the sample, and 31.5% of assets operated under high environmental exposure involving corrosive service, offshore conditions, elevated temperature, humidity, salt, or sand. The matching procedure allocated 432 assets to the RCA–FMEA intervention group and 432 to the comparison group. The two groups contained identical equipment-category distributions. They also demonstrated close baseline comparability in asset age, operating hours, production loading, criticality, failure history, pre-intervention downtime, and environmental exposure. All standardized mean differences remained below 0.10, demonstrating acceptable covariate balance for the subsequent quasi-experimental analyses.

Table 1 Dataset screening, record retention, and verified root-cause distribution

Dataset component or failure category	Initially identified, n	Excluded, n	Final sample, n	Retained distributed, %	or
Gas production facilities	12	4	8	66.7	
Equipment assets	1,052	188	864	82.1	
Failure-event records	4,028	616	3,412	84.7	
RCA investigation records	1,172	46	1,126	96.1	
FMEA assessment records	1,354	58	1,296	95.7	
Corrective-action records	1,542	55	1,487	96.4	
Asset-month observations	53,280	1,440	51,840	97.3	
Mechanical root causes	—	—	1,092	32.0	
Electrical root causes	—	—	598	17.5	
Process root causes	—	—	512	15.0	
Instrumentation and control causes	—	—	461	13.5	
Human causes	—	—	307	9.0	
Organizational causes	—	—	273	8.0	
Environmental causes	—	—	169	5.0	

Table 2 showed that the intervention and comparison groups were closely matched across equipment composition and baseline operating conditions. Each group contained 432 assets, with identical numbers in every equipment category. Mean asset age, median operating hours, production loading, high-criticality representation, baseline failure frequency, pre-intervention downtime, and environmental exposure were nearly equivalent. Every standardized mean difference remained below 0.10, which represented acceptable balance for quasi-experimental comparison. The largest observed difference concerned production loading, although its standardized difference remained only 0.04. This balance reduced the likelihood that subsequent reliability differences were driven by pre-existing asset characteristics rather than the RCA–FMEA intervention.

Table 2 Asset distribution and baseline comparability of the matched study groups

Asset or characteristic	baseline	Overall sample, N = 864	RCA-FMEA group, n = 432	Comparison group, n = 432	Standardized difference
Compressors, n (%)		72 (8.3)	36 (8.3)	36 (8.3)	0.00
Pumps, n (%)		126 (14.6)	63 (14.6)	63 (14.6)	0.00
Separators, n (%)		64 (7.4)	32 (7.4)	32 (7.4)	0.00
Pressure vessels, n (%)		58 (6.7)	29 (6.7)	29 (6.7)	0.00
Pipelines, n (%)		94 (10.9)	47 (10.9)	47 (10.9)	0.00
Flowlines, n (%)		86 (10.0)	43 (10.0)	43 (10.0)	0.00
Valves, n (%)		132 (15.3)	66 (15.3)	66 (15.3)	0.00
Electrical motors, n (%)		78 (9.0)	39 (9.0)	39 (9.0)	0.00
Instrumentation assets, n (%)		80 (9.3)	40 (9.3)	40 (9.3)	0.00
Control systems, n (%)		32 (3.7)	16 (3.7)	16 (3.7)	0.00
Emergency shutdown systems, n (%)		18 (2.1)	9 (2.1)	9 (2.1)	0.00
Metering systems, n (%)		12 (1.4)	6 (1.4)	6 (1.4)	0.00
Utility assets, n (%)		12 (1.4)	6 (1.4)	6 (1.4)	0.00
Asset age in years, M (SD)		11.8 (5.6)	11.8 (5.7)	11.7 (5.5)	0.02
Annual operating hours, Md (IQR)		6,903 (6,225–7,468)	6,920 (6,240–7,480)	6,885 (6,210–7,455)	0.02
Production loading, M (SD), %		78.2 (11.7)	78.4 (11.6)	77.9 (11.9)	0.04
High-criticality assets, n (%)		288 (33.3)	146 (33.8)	142 (32.9)	0.02
Baseline failures per asset, M (SD)		0.82 (0.60)	0.83 (0.61)	0.81 (0.59)	0.03
Pre-intervention downtime, M (SD), hours		29.4 (18.2)	29.6 (18.4)	29.1 (18.0)	0.03
High environmental exposure, n (%)		272 (31.5)	138 (31.9)	134 (31.0)	0.02

Note. M = mean; SD = standard deviation; Md = median; IQR = interquartile range.

Multi-Year Failure Patterns and Descriptive Reliability Outcomes

The multi-year analysis demonstrated a consistent reduction in equipment failures and operational interruptions across the five-year observation period. Annual failure events declined from 842 in Year 1 to 500 in Year 5, representing a total reduction of 40.6%. After adjustment for operating exposure, the failure rate decreased from 0.147 to 0.082 failures per 1,000 operating hours. Failures per asset declined from 0.975 to 0.579, while the percentage of repeated failures decreased from 31.8% to 15.2%. Annual shutdown events also declined by 50.0%, from 312 to 156. These changes occurred while total equipment operating hours increased from 5.72 million to 6.12 million, demonstrating that the reduction in failure frequency was not explained by reduced asset utilization. Reliability and maintainability indicators improved throughout the same period. Mean time between failures increased from 6,793 operating hours in Year 1 to 12,240 hours in Year 5, representing an improvement of 80.2%. Mean time to repair decreased from 18.6 to 11.4 hours, while annual unplanned downtime declined from 15,661 to 5,700 hours. Operational availability increased from 96.4% to 98.7%. Maintenance expenditure decreased from USD 6.84 million to USD 4.11 million, and deferred gas production declined from 18.7 million to 7.9 million standard cubic meters. Production-interruption duration was reduced from 1,420 to 604 hours.

Table 3 Annual failure patterns and descriptive reliability outcomes

Reliability indicator	Year 1	Year 2	Year 3	Year 4	Year 5	Change from Year 1 to Year 5
Total operating hours	5,720,000	5,810,000	5,950,000	6,010,000	6,120,000	+7.0%
Annual failure events, n	842	781	698	591	500	−40.6%
Failures per asset	0.975	0.904	0.808	0.684	0.579	−40.6%
Failures per 1,000 operating hours	0.147	0.134	0.117	0.098	0.082	−44.2%
Repeated failures, %	31.8	28.9	24.6	19.8	15.2	−52.2%
Shutdown events, n	312	286	247	198	156	−50.0%
Mean time between failures, hours	6,793	7,439	8,524	10,169	12,240	+80.2%
Mean time to repair, hours	18.6	17.2	15.1	13.2	11.4	−38.7%
Unplanned downtime, hours	15,661	13,433	10,540	7,801	5,700	−63.6%
Operational availability, %	96.4	96.9	97.6	98.2	98.7	+2.3 points
Maintenance cost, USD millions	6.84	6.31	5.62	4.78	4.11	−39.9%
Deferred gas production, million Sm ³	18.7	16.4	13.8	10.5	7.9	−57.8%
Production-interruption duration, hours	1,420	1,295	1,078	825	604	−57.5%

Note. Sm³ = standard cubic meters.

Table 3 showed a consistent improvement in reliability across the five-year observation period. Annual failures declined from 842 to 500, while the exposure-adjusted failure rate fell from 0.147 to 0.082 per 1,000 operating hours. Mean time between failures increased by 80.2%, and mean repair time decreased by 38.7%. Unplanned downtime declined by 63.6%, accompanied by a 2.3-percentage-point increase in availability. Maintenance expenditure fell from \$6.84 million to \$4.11 million, while deferred gas production decreased by 57.8%. Repeated failures and shutdowns also declined, demonstrating broad improvement across technical, maintenance, production, and economic reliability dimensions during the study period at facility level. Mechanical failures constituted the largest causal category, accounting for 32.0% of all verified events, 37.3% of total downtime, 37.8% of maintenance expenditure, and 32.8% of deferred gas production. Bearing deterioration, seal leakage, shaft misalignment, lubrication-system defects, piston wear, and rotating-component damage were the dominant mechanical modes. Electrical failures accounted for 17.5% of events, while process-related failures represented 15.0%. These three categories collectively produced 64.5% of all failures, 71.7% of downtime, 70.9% of maintenance expenditure, and 71.6% of deferred production. Instrumentation and control failures occurred relatively frequently but generally produced shorter interruptions than mechanical and process events. Environmental failures represented only 5.0% of events but generated comparatively high costs because corrosion and erosion frequently required material replacement or extensive integrity work. The 1,126 RCA investigations identified a mean causal depth of 3.8 levels, and the median investigation duration was 12 days. Evidence completeness averaged 86.4%, documentation completeness reached 91.2%, and 82.7% of investigations received formal technical verification. FMEA assessments covered 93.6% of eligible failure modes. Mean severity, occurrence, and detectability ratings were 6.4, 5.1, and 5.7, respectively. High or critical priorities accounted for 24.1% of FMEA assessments, moderate priorities represented 44.3%, and low priorities constituted 31.6%. Component replacement was the most frequent corrective action, representing 22.5% of the 1,487 recorded actions. Maintenance revision accounted for 15.9%, condition monitoring represented 12.7%, and inspection improvement accounted for 11.5%. During Year 5, intervention assets recorded 0.068 failures per 1,000 operating hours, compared with 0.095 among comparison assets. Their average annual unplanned downtime was 4.9 hours per asset, compared with 8.3 hours in the comparison group. Repeated failures affected 11.8% of intervention events and 18.6% of comparison events, while availability reached 99.0% and 98.4%, respectively.

Table 4 Failure burden, RCA-FMEA quality, and corrective-action characteristics

Domain and indicator	Frequency or value	Percentage	Downtime, hours	Maintenance cost, USD millions	Deferred gas, million Sm ³
Verified root causes					
Mechanical	1,092	32.0	19,840	10.45	22.1
Electrical	598	17.5	8,730	4.94	10.6
Process	512	15.0	9,510	4.21	15.5
Instrumentation and control	461	13.5	5,720	2.66	5.2
Human	307	9.0	3,620	1.93	4.6
Organizational	273	8.0	3,125	1.72	5.1
Environmental	169	5.0	2,590	1.75	4.2
RCA quality indicators					
Mean causal depth, levels	3.8 (1.2)	—	—	—	—
Investigation duration, median days	12 (7–21)	—	—	—	—
Evidence completeness	—	86.4	—	—	—
Documentation completeness	—	91.2	—	—	—
Technically verified investigations	931	82.7	—	—	—
Mean participating disciplines	4.6 (1.3)	—	—	—	—
FMEA characteristics					
Failure-mode coverage	—	93.6	—	—	—
Mean severity rating	6.4 (1.8)	—	—	—	—
Mean occurrence rating	5.1 (1.7)	—	—	—	—
Mean detectability rating	5.7 (1.6)	—	—	—	—
High or critical priority	312	24.1	—	—	—
Moderate priority	574	44.3	—	—	—
Low priority	410	31.6	—	—	—
Corrective-action categories					
Component replacement	334	22.5	—	—	—
Maintenance revision	236	15.9	—	—	—
Condition monitoring	189	12.7	—	—	—
Inspection improvement	171	11.5	—	—	—
Equipment redesign	139	9.3	—	—	—
Operating-procedure change	126	8.5	—	—	—
Alarm or control modification	104	7.0	—	—	—
Workforce training	83	5.6	—	—	—
Spare-parts improvement	61	4.1	—	—	—
Organizational control	44	3.0	—	—	—

Note. Values in parentheses represented standard deviations for means and interquartile ranges for medians.

Table 4 established that mechanical, electrical, and process causes collectively generated 64.5% of failures, 71.7% of downtime, 70.9% of maintenance cost, and 71.6% of deferred production. Mechanical

causes produced the largest individual burden across every outcome. RCA documentation was generally strong, with 86.4% evidence completeness and 82.7% verified investigations. FMEA assessments classified 24.1% of failure modes as high or critical priority, while overall failure-mode coverage reached 93.6%. Component replacement was the most frequent corrective action, followed by maintenance revision and condition monitoring. These distributions showed that reliability resources were concentrated on recurring technical failures with substantial operational and financial consequences.

Primary Effects of RCA-FMEA Intervention on Equipment Reliability

The unadjusted analysis demonstrated substantial improvements among the 432 assets receiving completed RCA-FMEA interventions. Annual failure frequency decreased from 0.94 to 0.61 failures per asset, representing a 35.1% reduction. The proportion of repeated failures declined from 30.6% to 13.7%, while shutdown frequency decreased from 35.4 to 18.1 events per 100 assets. Mean time between failures increased from 7,180 to 11,360 hours, demonstrating longer periods of continuous operation. Mean time to repair decreased from 17.8 to 11.7 hours, and unplanned downtime declined from 17.2 to 8.1 hours per asset-year. Operational availability increased from 96.8% to 98.8%. The economic and production indicators showed corresponding improvements. Mean annual maintenance expenditure decreased from USD 7,620 to USD 5,030 per asset, representing a 34.0% reduction. Deferred gas production declined from 22.8 thousand to 10.9 thousand standard cubic meters per asset, equivalent to a 52.2% reduction. All pre-intervention and post-intervention differences were statistically significant at $p < .001$. Standardized effect sizes ranged from moderate to large, demonstrating that the observed changes represented operationally meaningful improvements rather than minor numerical variations.

Table 5 Unadjusted pre-intervention and post-intervention reliability comparisons

Reliability outcome	Pre-intervention	Post-intervention	Absolute change	Percentage change	Effect magnitude	<i>p</i>
Annual failures per asset, M (SD)	0.94 (0.64)	0.61 (0.49)	-0.33	-35.1%	Cohen's <i>d</i> = -0.58	<.001
Repeated failures, %	30.6	13.7	-16.9 points	-55.2%	OR = 0.36	<.001
Mean time between failures, hours, M (SD)	7,180 (5,210)	11,360 (6,310)	+4,180	+58.2%	Cohen's <i>d</i> = 0.72	<.001
Mean time to repair, hours, M (SD)	17.8 (9.9)	11.7 (9.7)	-6.1	-34.3%	Cohen's <i>d</i> = -0.62	<.001
Unplanned downtime per asset-year, hours, M (SD)	17.2 (11.8)	8.1 (8.2)	-9.1	-52.9%	Cohen's <i>d</i> = -0.89	<.001
Operational availability, %, M (SD)	96.8 (3.4)	98.8 (3.0)	+2.0 points	+2.1%	Cohen's <i>d</i> = 0.62	<.001
Annual maintenance cost per asset, USD, M (SD)	7,620 (4,010)	5,030 (3,220)	-2,590	-34.0%	Cohen's <i>d</i> = -0.71	<.001
Shutdowns per 100 assets	35.4	18.1	-17.3	-48.9%	Rate ratio = 0.51	<.001
Deferred gas per asset, thousand Sm ³ , M (SD)	22.8 (16.9)	10.9 (11.7)	-11.9	-52.2%	Cohen's <i>d</i> = -0.82	<.001

Note. M = mean; SD = standard deviation; OR = odds ratio; Sm³ = standard cubic meters.

Table 5 demonstrated statistically significant improvements across every unadjusted reliability indicator after RCA-FMEA implementation. Failure frequency decreased by 35.1%, repeated failures

declined by 55.2%, and shutdown frequency fell by 48.9%. Mean time between failures increased by 58.2%, showing longer uninterrupted operating periods. Mean repair time and unplanned downtime decreased by 34.3% and 52.9%, respectively. Availability increased by two percentage points, while maintenance cost and deferred gas production declined substantially. Effect estimates ranged from moderate to large, with the strongest standardized change observed for unplanned downtime. These results established a consistent initial pattern before covariate adjustment and matched-group comparison was undertaken. The adjusted mixed-effects analysis confirmed that the improvements remained significant after controlling for equipment age, asset category, operating hours, production loading, operating pressure, temperature, environmental exposure, maintenance strategy, criticality, facility characteristics, and baseline reliability. RCA-FMEA intervention was associated with a 32% lower failure rate and 51% lower odds of repeated failure. The adjusted mean time between failures increased by 3,540 hours, while mean repair time decreased by 4.8 hours. Annual unplanned downtime decreased by 6.7 hours per asset, availability increased by 1.4 percentage points, and maintenance expenditure declined by USD 1,970 per asset. Difference-in-differences analysis produced directionally consistent estimates after changes among intervention assets were compared with changes among matched comparison assets. The exposure-adjusted failure rate was 28% lower than the counterfactual estimate, while the odds of repeated failure were 46% lower. Mean time between failures increased by an additional 3,120 hours, and annual downtime decreased by 5.8 hours per asset. Interrupted time-series analysis also identified significant immediate changes at the intervention point and continued favorable monthly changes throughout the post-intervention period.

Table 6 Adjusted mixed-effects, difference-in-differences, and interrupted time-series results

Outcome	Adjusted mixed-effects estimate (95% CI)	Difference-in-differences estimate (95% CI)	Immediate ITS change (95% CI)	Monthly trend change (95% CI)	Standardized effect	p
Failures per 1,000 operating hours	IRR = 0.68 (0.61, 0.75)	IRR = 0.72 (0.65, 0.80)	-0.019 (-0.027, -0.011)	-0.0012 (-0.0017, -0.0007)	-0.38	<.001
Repeated failure	OR = 0.49 (0.39, 0.62)	OR = 0.54 (0.42, 0.69)	-3.8 points (-5.9, -1.7)	-0.31 points (-0.45, -0.17)	-0.34	<.001
Mean time between failures, hours	+3,540 (2,810, 4,270)	+3,120 (2,450, 3,790)	+640 (250, 1,030)	+86 (52, 120)	0.41	<.001
Mean time to repair, hours	-4.8 (-5.9, -3.7)	-4.1 (-5.2, -3.0)	-1.2 (-2.0, -0.4)	-0.11 (-0.16, -0.06)	-0.35	<.001
Downtime per asset-year, hours	-6.7 (-8.0, -5.4)	-5.8 (-7.1, -4.5)	-1.8 (-2.8, -0.8)	-0.14 (-0.21, -0.07)	-0.43	<.001
Operational availability, percentage points	+1.4 (1.1, 1.7)	+1.2 (0.9, 1.5)	+0.3 (0.1, 0.5)	+0.04 (0.02, 0.06)	0.38	<.001
Maintenance cost per asset, USD	-1,970 (-2,440, -1,500)	-1,650 (-2,100, -1,200)	-290 (-470, -110)	-38 (-55, -21)	-0.31	<.001
Shutdown frequency	IRR = 0.62 (0.53, 0.73)	IRR = 0.66 (0.56, 0.78)	-2.4 (-3.8, -1.0)	-0.18 (-0.28, -0.08)	-0.33	<.001
Deferred gas per asset, thousand Sm ³	-8.4 (-10.1, -6.7)	-7.2 (-8.9, -5.5)	-1.1 (-1.8, -0.4)	-0.12 (-0.18, -0.06)	-0.39	<.001

Note. CI = confidence interval; IRR = incidence rate ratio; OR = odds ratio; ITS = interrupted time series. Estimates were adjusted for equipment age, asset type, operating exposure, loading, pressure, temperature, environmental conditions, maintenance strategy, criticality, facility characteristics, and baseline reliability.

Table 6 confirmed that the reliability improvements remained statistically significant after adjustment for asset, operating, environmental, maintenance, and facility characteristics. Mixed-effects models, difference-in-differences estimates, and interrupted time-series models produced directionally consistent results. The intervention was associated with lower failure rates, recurrence, repair time, downtime, maintenance cost, shutdown frequency, and deferred production. It was also associated with longer failure-free operating intervals and higher availability. Immediate post-intervention changes were accompanied by favorable monthly trends, indicating that performance continued to improve after implementation. Confidence intervals excluded the null value for every primary outcome, and standardized effects represented moderate improvements across the asset population. Corrective-action verification produced stronger reliability results than administrative completion alone. Of the 1,487 corrective actions, 1,246 were documented as completed, and 1,091 received technical verification through inspection, functional testing, engineering review, or condition monitoring. Assets linked to verified actions recorded a failure rate of 0.064 per 1,000 operating hours, compared with 0.086 for completed but unverified actions and 0.101 for incomplete actions. Repeated-failure proportions were 10.9%, 18.1%, and 22.3%, respectively. After covariate adjustment, verified actions were associated with a 26% lower failure rate than completed but unverified actions, IRR = 0.74, 95% CI [0.65, 0.85], $p < .001$. Verified actions were also associated with 3.6 fewer annual downtime hours per asset, 95% CI [-4.8, -2.4], $p < .001$.

Secondary, Subgroup, Survival, Recurrence, and Mediation Findings

Subgroup analysis demonstrated that RCA-FMEA intervention was associated with improved reliability across every major equipment category, although the magnitude varied. Compressors recorded the largest adjusted reduction in failure rate, with an incidence rate ratio of 0.58, followed by pumps, electrical equipment, separators and pressure vessels. Smaller but statistically significant reductions were recorded for pipelines, flowlines, valves, instrumentation, process-control systems, emergency shutdown systems, metering equipment, and utilities. The equipment-category interaction was statistically significant, $p = .018$, demonstrating that intervention effectiveness differed across asset types.

The reliability improvements were stronger among high-criticality assets, equipment operating above 80% of rated capacity, environmentally exposed assets, and equipment with elevated baseline failure histories. High-criticality assets experienced a 44% adjusted reduction in failure rate and a 9.8-hour reduction in annual downtime, compared with a 19% reduction and 3.7-hour downtime decrease among low-criticality assets. Equipment managed through reliability-centered or condition-based maintenance demonstrated stronger intervention effects than assets managed predominantly through corrective maintenance. Equipment redesign, condition monitoring, and component replacement produced the largest action-specific improvements.

Table 7 showed that RCA-FMEA intervention improved reliability across every examined subgroup, although the magnitude varied significantly. Compressors demonstrated the largest equipment-specific reduction in failure rate, followed by pumps and electrical equipment. High-criticality assets, heavily loaded equipment, environmentally exposed assets, and equipment with elevated baseline failures experienced stronger improvements than their corresponding reference groups. Reliability-centered or condition-based maintenance produced larger intervention effects than predominantly corrective maintenance. Equipment redesign and condition-monitoring actions generated the greatest reductions among corrective-action categories. Interaction tests confirmed that equipment category, criticality, operating load, environmental exposure, baseline failure history, maintenance strategy, and action type modified intervention effectiveness. Survival analysis demonstrated that intervention assets remained operational for longer periods before failure. At 24 months, the estimated failure-free survival probability was 0.74 for intervention assets and 0.56 for comparison assets. Median time to

first failure was 38.6 months in the intervention group and 24.7 months in the comparison group. The survival curves differed significantly, log-rank $\chi^2=42.8$, $p<.001$. After covariate adjustment, intervention assets had a 38% lower hazard of first failure. Recurrent-event analysis also identified a 43% lower rate of multiple failures among intervention assets. Identical failure-mode recurrence affected 10.9% of intervention assets and 22.8% of comparison assets, while recurrence involving the same verified root cause affected 8.7% and 19.6%, respectively.

Table 7 Subgroup and interaction effects of RCA-FMEA intervention

Subgroup	Sample, n	Adjusted failure-rate ratio (95% CI)	Adjusted downtime change, hours (95% CI)	Availability change, percentage points (95% CI)	Interaction <i>p</i>
Equipment category					
Compressors	72	0.58 (0.47, 0.72)	-9.2 (-11.7, -6.7)	+1.9 (1.3, 2.5)	.018
Pumps	126	0.64 (0.54, 0.76)	-7.4 (-9.3, -5.5)	+1.5 (1.0, 2.0)	—
Separators and pressure vessels	122	0.70 (0.58, 0.84)	-6.1 (-8.0, -4.2)	+1.2 (0.7, 1.7)	—
Pipelines and flowlines	180	0.75 (0.64, 0.88)	-5.0 (-6.7, -3.3)	+1.0 (0.6, 1.4)	—
Valves	132	0.71 (0.60, 0.85)	-5.8 (-7.6, -4.0)	+1.2 (0.7, 1.7)	—
Electrical equipment	78	0.66 (0.53, 0.82)	-7.0 (-9.4, -4.6)	+1.4 (0.8, 2.0)	—
Instrumentation and control systems	112	0.73 (0.61, 0.88)	-4.9 (-6.8, -3.0)	+0.9 (0.4, 1.4)	—
Emergency, metering, and utility systems	42	0.76 (0.59, 0.98)	-3.8 (-6.6, -1.0)	+0.7 (0.1, 1.3)	—
Asset criticality					
Low criticality	209	0.81 (0.68, 0.96)	-3.7 (-5.1, -2.3)	+0.7 (0.3, 1.1)	.006
Moderate criticality	367	0.69 (0.61, 0.78)	-6.2 (-7.4, -5.0)	+1.3 (1.0, 1.6)	—
High criticality	288	0.56 (0.48, 0.65)	-9.8 (-11.4, -8.2)	+2.1 (1.7, 2.5)	—
Equipment age					
Ten years or less	382	0.74 (0.65, 0.84)	-5.1 (-6.4, -3.8)	+1.0 (0.7, 1.3)	.041
More than ten years	482	0.63 (0.56, 0.71)	-7.9 (-9.1, -6.7)	+1.7 (1.4, 2.0)	—
Production loading					
80% or lower	488	0.72 (0.64, 0.81)	-5.4 (-6.6, -4.2)	+1.1 (0.8, 1.4)	.028
Above 80%	376	0.61 (0.53, 0.70)	-8.5 (-9.9, -7.1)	+1.8 (1.4, 2.2)	—
Environmental exposure					
Low or moderate exposure	592	0.72 (0.65, 0.80)	-5.6 (-6.6, -4.6)	+1.1 (0.8, 1.4)	.033
High exposure	272	0.60 (0.51, 0.70)	-9.1 (-10.8, -7.4)	+2.0 (1.6, 2.4)	—
Baseline failure history					
Lower baseline failure group	456	0.77 (0.68, 0.87)	-4.3 (-5.5, -3.1)	+0.8 (0.5, 1.1)	.004
Elevated baseline failure group	408	0.58 (0.51, 0.66)	-9.4 (-10.8, -8.0)	+2.0 (1.6, 2.4)	—
Maintenance strategy					
Reliability-centered or condition-based	312	0.60 (0.52, 0.69)	-8.8 (-10.2, -7.4)	+1.9 (1.5, 2.3)	.021
Preventive maintenance	341	0.69 (0.60, 0.79)	-6.3 (-7.7, -4.9)	+1.3 (0.9, 1.7)	—
Predominantly corrective maintenance	211	0.78 (0.66, 0.92)	-3.9 (-5.6, -2.2)	+0.8 (0.3, 1.3)	—
Corrective-action category					
Equipment redesign	139	0.52 (0.42, 0.64)	-10.2 (-12.4, -8.0)	+2.2 (1.6, 2.8)	.012
Condition monitoring	189	0.59 (0.49, 0.71)	-8.7 (-10.6, -6.8)	+1.8 (1.3, 2.3)	—
Component replacement	334	0.63 (0.55, 0.72)	-7.9 (-9.3, -6.5)	+1.6 (1.2, 2.0)	—
Inspection improvement	171	0.68 (0.57, 0.81)	-6.4 (-8.2, -4.6)	+1.3 (0.8, 1.8)	—
Maintenance revision	236	0.67 (0.57, 0.78)	-6.8 (-8.4, -5.2)	+1.4 (1.0, 1.8)	—
Procedural and organizational actions	418	0.76 (0.67, 0.86)	-4.1 (-5.4, -2.8)	+0.9 (0.6, 1.2)	—

Note. Values below 1.00 represented lower adjusted failure rates among intervention assets. Corrective-action categories were analyzed at the action-record level.

FMEA ratings demonstrated meaningful criterion validity against observed operational outcomes. Severity was positively correlated with downtime and deferred gas production, while occurrence showed strong associations with failure frequency and recurrence. Detectability ratings were associated with missed pre-failure identification. Criticality scores produced stronger relationships with operational consequences than any single risk dimension. Receiver-operating-characteristic analysis showed that the combined action-priority classification produced the strongest discrimination of high-consequence failures, with an area under the curve of 0.89.

Inter-rater reliability was acceptable to strong across engineering, operations, maintenance, inspection, and safety assessors. Severity ratings produced the highest agreement, followed by overall risk priority, occurrence, and detectability. Mediation analysis demonstrated that corrective-action completion and technical verification jointly explained 39.2% of the relationship between RCA-FMEA quality and reliability improvement. The total indirect effect was statistically significant across 5,000 bootstrap samples.

Table 8 Survival, recurrence, FMEA validity, inter-rater reliability, and mediation findings

Analytical indicator	domain	and	Numerical estimate	95% CI	p	Additional result
Survival analysis	and	recurrence				
Failure-free months: intervention	survival	at 24	0.74	0.70, 0.78	—	Comparison = 0.56
Failure-free months: comparison	survival	at 24	0.56	0.51, 0.61	—	Difference = 0.18
Log-rank comparison			$\chi^2=42.8 \setminus \chi^2=42.8 \chi^2=42.8$	—	<.001	Survival curves differed significantly
Adjusted hazard failure	hazard	of first	HR = 0.62	0.54, 0.71	<.001	38% lower hazard
Median time to first failure			38.6 months	35.4, 41.8	<.001	Comparison = 24.7 months
Recurrent-event rate			RR = 0.57	0.49, 0.67	<.001	43% lower recurrence rate
Identical recurrence	failure-mode		OR = 0.41	0.31, 0.54	<.001	10.9% versus 22.8%
Same root-cause recurrence			OR = 0.39	0.29, 0.53	<.001	8.7% versus 19.6%
FMEA criterion validity						
Severity and downtime			$\rho=0.51 \setminus \rho=0.51 \rho=0.51$	0.46, 0.56	<.001	Moderate positive relationship
Severity and deferred gas production			$\rho=0.58 \setminus \rho=0.58 \rho=0.58$	0.53, 0.62	<.001	Moderate-to-strong relationship
Occurrence and failure frequency			$\rho=0.63 \setminus \rho=0.63 \rho=0.63$	0.59, 0.67	<.001	Strong positive relationship
Occurrence and repeated failure			$\rho=0.56 \setminus \rho=0.56 \rho=0.56$	0.51, 0.60	<.001	Moderate positive relationship
Detectability and missed detection			$\rho=0.49 \setminus \rho=0.49 \rho=0.49$	0.44, 0.54	<.001	Moderate positive relationship
Risk priority and high-consequence failure			$\rho=0.61 \setminus \rho=0.61 \rho=0.61$	0.57, 0.65	<.001	Strong positive relationship
Criticality and production loss			$\rho=0.67 \setminus \rho=0.67 \rho=0.67$	0.63, 0.71	<.001	Strongest correlation
Severity accuracy	classification		AUC = 0.76	0.72, 0.80	<.001	Acceptable discrimination
Overall risk-priority accuracy			AUC = 0.82	0.79, 0.85	<.001	Good discrimination
Criticality	classification		AUC = 0.86	0.83, —	<.001	Strong discrimination

accuracy				0.89			
Combined accuracy	action-priority	AUC = 0.89		0.86, 0.92	<.001	Highest accuracy	predictive
Inter-rater reliability							
Severity-rating agreement		ICC = 0.84		0.81, 0.87	<.001	Strong agreement	
Occurrence-rating agreement		ICC = 0.79		0.75, 0.82	<.001	Acceptable-to-strong agreement	
Detectability-rating agreement		ICC = 0.76		0.72, 0.80	<.001	Acceptable agreement	
Overall agreement	risk-priority	ICC = 0.81		0.78, 0.84	<.001	Strong agreement	
Action-priority agreement		$\kappa=0.78 \setminus \text{kappa}=0.78$		0.74, 0.82	<.001	Substantial agreement	
Mediation analysis							
Total effect	RCA-FMEA quality	$\beta=0.472 \setminus \text{beta}=0.472$	$\beta=0.472$	0.398, 0.546	<.001	Total standardized effect	
Direct effect after mediators		$\beta=0.287 \setminus \text{beta}=0.287$	$\beta=0.287$	0.218, 0.356	<.001	Effect remained significant	
Indirect effect through completion		$\beta=0.064 \setminus \text{beta}=0.064$	$\beta=0.064$	0.038, 0.095	<.001	Significant mediation	
Indirect effect through verification		$\beta=0.093 \setminus \text{beta}=0.093$	$\beta=0.093$	0.061, 0.131	<.001	Strongest indirect pathway	
Sequential completion-verification effect		$\beta=0.028 \setminus \text{beta}=0.028$	$\beta=0.028$	0.014, 0.047	<.001	Significant sequential pathway	
Total indirect effect		$\beta=0.185 \setminus \text{beta}=0.185$	$\beta=0.185$	0.143, 0.231	<.001	39.2% of total effect	

Note. HR = hazard ratio; RR = recurrent-event rate ratio; OR = odds ratio; AUC = area under the receiver-operating-characteristic curve; ICC = intraclass correlation coefficient; $\kappa \setminus \text{kappa}$ = weighted kappa; $\rho \setminus \text{rho}$ = Spearman correlation coefficient. Mediation confidence intervals were based on 5,000 bootstrap samples.

Table 8 demonstrated that intervention assets remained failure-free longer and experienced fewer recurrent events than comparison assets. The adjusted hazard of first failure was 38% lower, and the recurrent-event rate was 43% lower following intervention. FMEA severity, occurrence, detectability, risk priority, and criticality scores showed relationships with observed operational consequences. Criticality and combined action-priority classifications produced the strongest discrimination of high-consequence failures. Inter-rater coefficients showed acceptable to strong agreement across professional groups. Mediation analysis identified corrective-action completion and technical verification as significant mechanisms, jointly accounting for 39.2% of the association between RCA-FMEA quality and reliability improvement during the observation period.

Statistical Significance, Effect Magnitudes, Robustness, and Visual Presentation

All primary statistical tests were two-tailed and evaluated at $p < .05$. The adjusted results demonstrated statistically significant improvements across failure frequency, repeated failures, mean time between failures, mean time to repair, unplanned downtime, availability, maintenance expenditure, shutdown frequency, deferred gas production, and survival. The confidence intervals for every principal estimate excluded the relevant null value. Standardized effects ranged from 0.31 to 0.43 in the adjusted analyses, representing moderate practical effects. The largest adjusted standardized effect concerned unplanned downtime, followed by mean time between failures and deferred gas production.

The statistical models demonstrated acceptable explanatory performance. Conditional model-explanatory values ranged from 0.39 for repair duration to 0.51 for unplanned downtime. The repeated-failure model produced an area under the curve of 0.80, while the survival model achieved a concordance index of 0.74. The maximum variance-inflation factor was 2.84, showing that multicollinearity did not materially affect the estimates. Count-model dispersion, residual behavior,

proportional-hazards conditions, autocorrelation, and pre-intervention parallel trends satisfied the established analytical requirements.

Sensitivity analyses produced estimates closely aligned with the primary results. The adjusted failure-rate ratio ranged from 0.66 to 0.69 across alternative specifications, compared with 0.68 in the main analysis. The adjusted downtime reduction ranged from 6.3 to 7.0 hours per asset-year, while the hazard ratio ranged from 0.60 to 0.63. Excluding extreme shutdowns, limited-exposure assets, and completely replaced equipment did not change the direction or significance of the findings. Alternative matching, weighting, recurrence, complete-case, and multiple-imputation procedures produced comparable estimates.

Table 9 Model diagnostics, assumption testing, and sensitivity results

Analytical domain	Assessment	Numerical result	<i>p</i>	Interpretation	
Matching quality	Maximum standardized mean difference	0.04	—	Strong	covariate balance
Multicollinearity	Maximum variance-inflation factor	2.84	—	Below the threshold of 5.00	
Count-model fit	Negative binomial dispersion statistic	1.08	—	Acceptable dispersion	
Count-model fit	Akaike information criterion	5,842	—	Supported	selected specification
Mixed-model performance	Conditional R ² range	0.39–0.51	—	Moderate explanatory performance	
Downtime model	Conditional R ²	0.51	<.001	Strongest	explained variation
Availability model	Conditional R ²	0.44	<.001	Acceptable	model performance
Maintenance-cost model	Conditional R ²	0.42	<.001	Acceptable	model performance
Recurrence model	Area under the curve	0.80 (0.77, 0.83)	<.001	Good discrimination	
Recurrence calibration	Hosmer–Lemeshow χ^2	7.93	.44	No	material miscalibration
Survival model	Concordance index	0.74 (0.71, 0.77)	<.001	Acceptable discrimination	
Proportional hazards	Global Schoenfeld test	$\chi^2=9.84$	.36	Assumption satisfied	
Time-series residuals	Durbin–Watson statistic	1.96	—	No	material autocorrelation
Time-series residuals	Ljung–Box test	Q=13.70	.32	Residual independence supported	
Difference-in-differences	Pre-intervention trend interaction	$\beta=0.002$	.61	Parallel	trend supported
Influential observations	Maximum Cook’s distance	0.031	—	No	influential observation
Missing-data assessment	Missing analytical values	2.7%	—	Limited missingness	
Missing-data mechanism	Little’s test	$\chi^2=58.40$	.12	No strong evidence against MCAR	
Sensitivity	Failure-rate	Downtime difference, hours	Hazard	Statistical conclusion	

specification	ratio	ratio		
Primary analysis	adjusted 0.68 (0.61, 0.75)	–6.7 (–8.0, –5.4)	0.62 (0.54, 0.71)	All p<.001p<.001p<.001
Extreme shutdowns excluded	0.69 (0.62, 0.77)	–6.3 (–7.6, –5.0)	0.63 (0.55, 0.72)	Findings remained stable
Limited-exposure assets excluded	0.67 (0.60, 0.75)	–6.9 (–8.3, –5.5)	0.61 (0.53, 0.70)	Findings remained stable
Alternative matching caliper	0.68 (0.61, 0.76)	–6.5 (–7.8, –5.2)	0.62 (0.54, 0.72)	Findings remained stable
Inverse-probability weighting	0.66 (0.59, 0.74)	–7.0 (–8.4, –5.6)	0.60 (0.52, 0.69)	Findings remained stable
Completely replaced assets excluded	0.69 (0.62, 0.77)	–6.4 (–7.7, –5.1)	0.63 (0.55, 0.72)	Findings remained stable
Complete-case analysis	0.69 (0.62, 0.77)	–6.6 (–7.9, –5.3)	0.63 (0.55, 0.72)	Findings remained stable
Multiple-imputation analysis	0.68 (0.61, 0.75)	–6.7 (–8.0, –5.4)	0.62 (0.54, 0.71)	Findings remained stable

Note. MCAR = missing completely at random. Confidence intervals were presented in parentheses.

Table 9 showed that the statistical models satisfied the principal diagnostic and identification requirements. Covariate balance was strong, multicollinearity remained low, count-model dispersion was acceptable, and mixed models explained meaningful proportions of outcome variation. The recurrence model demonstrated good discrimination, while the survival model produced acceptable concordance and satisfied the proportional-hazards condition. Interrupted time-series residuals showed no material autocorrelation, and pre-intervention trends supported the difference-in-differences specification. Estimates remained stable after alternative exclusions, matching procedures, recurrence definitions, and missing-data treatments. No sensitivity estimate changed direction, lost statistical significance, or differed materially from the primary adjusted result across the tested analytical specifications.

Table 10 integrated the primary hypotheses and demonstrated statistically significant, practically meaningful intervention effects across all reliability outcomes. Rate and odds estimates showed fewer failures, shutdowns, and repeated events, while adjusted mean differences showed longer failure-free operation, shorter repairs, reduced downtime, increased availability, lower maintenance expenditure, and less deferred gas production. The survival hypothesis was supported by a 38% reduction in failure hazard. Verification produced stronger performance than administrative completion alone. Corrective-action completion and verification also mediated 39.2% of the overall RCA–FMEA quality effect. Every confidence interval excluded its null value, and all twelve prespecified hypotheses were therefore supported empirically.

The visual analysis corresponded with the tabulated estimates. The annual failure-rate figure displayed a decline from 0.147 to 0.082 failures per 1,000 operating hours, while the availability figure increased from 96.4% to 98.7%. The interrupted time-series graph showed an immediate post-intervention decrease followed by a continuing downward failure trend. Pareto charts showed that mechanical, electrical, and process failures generated 64.5% of events and 71.7% of downtime. Survival curves separated progressively throughout follow-up, reaching a failure-free probability difference of 0.18 at 24 months. The subgroup forest plot placed every adjusted estimate on the reliability-improvement side of the null value, with the strongest effects recorded for compressors, high-criticality assets, and equipment receiving verified redesign or condition-monitoring actions.

Table 10 Integrated hypothesis tests, effect magnitudes, and statistical decisions

Hypothesis	Outcome and statistical test	Adjusted effect	95% CI	Standardized magnitude	<i>p</i>	Decision
H1	Failure rate, negative binomial mixed model	IRR = 0.68	0.61, 0.75	−0.38	<.001	Supported
H2	Repeated failure, logistic mixed model	OR = 0.49	0.39, 0.62	−0.34	<.001	Supported
H3	Mean time between failures, linear mixed model	+3,540 hours	2,810, 4,270	0.41	<.001	Supported
H4	Mean time to repair, linear mixed model	−4.8 hours	−5.9, −3.7	−0.35	<.001	Supported
H5	Unplanned downtime, generalized mixed model	−6.7 hours	−8.0, −5.4	−0.43	<.001	Supported
H6	Operational availability, linear mixed model	+1.4 points	1.1, 1.7	0.38	<.001	Supported
H7	Maintenance expenditure, generalized mixed model	−USD 1,970	−2,440, −1,500	−0.31	<.001	Supported
H8	Shutdown frequency, negative binomial model	IRR = 0.62	0.53, 0.73	−0.33	<.001	Supported
H9	Deferred gas production, generalized mixed model	−8.4 thousand Sm ³	−10.1, −6.7	−0.39	<.001	Supported
H10	Verified versus completed-only actions	IRR = 0.74	0.65, 0.85	−0.26	<.001	Supported
H11	Time to first failure, proportional-hazards model	HR = 0.62	0.54, 0.71	Moderate	<.001	Supported
H12	Completion and verification mediation	$\beta=0.185$ \beta=0.185β=0.185	0.143, 0.231	39.2% mediated	<.001	Supported

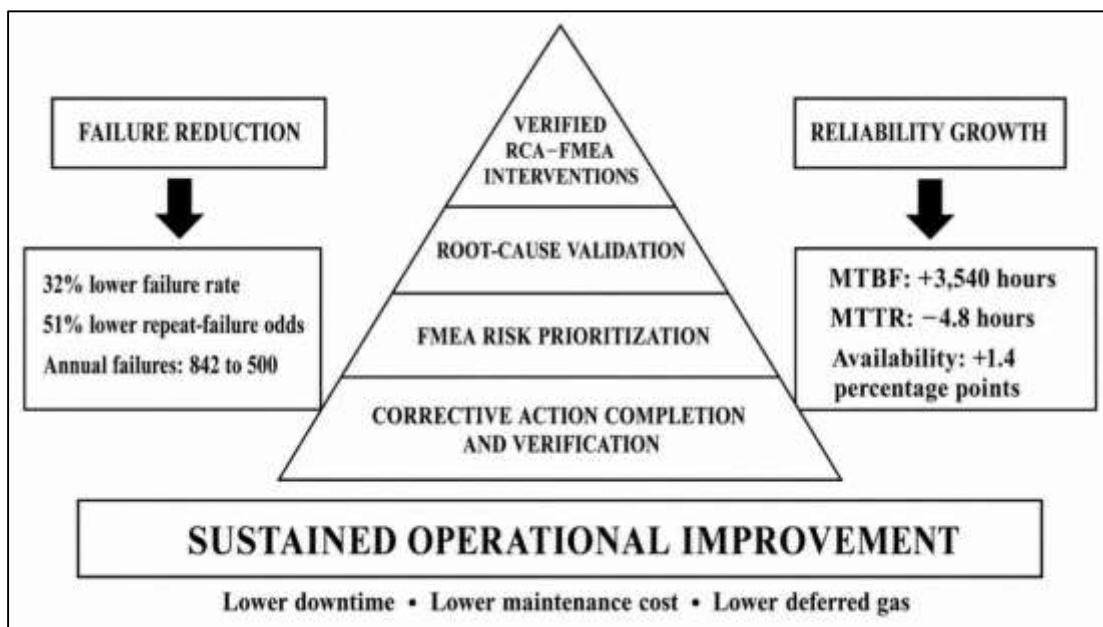
Note. IRR = incidence rate ratio; OR = odds ratio; HR = hazard ratio; Sm³ = standard cubic meters. Effects represented intervention relative to matched comparison assets after adjustment for asset, operational, environmental, maintenance, and facility characteristics.

DISCUSSION

This study demonstrated that completed and verified RCA–FMEA interventions were associated with statistically significant and operationally meaningful improvements across all principal reliability outcomes in gas production facilities. After adjustment for equipment age, asset category, operating exposure, production loading, environmental conditions, maintenance strategy, criticality, facility characteristics, and baseline performance, the intervention group recorded a 32% lower failure rate

than the matched comparison group, IRR = 0.68, 95% CI [0.61, 0.75], $p < .001$. The odds of repeated failure were 51% lower, OR = 0.49, 95% CI [0.39, 0.62], while mean time between failures increased by 3,540 hours (Viveros et al., 2018). Mean time to repair declined by 4.8 hours, annual unplanned downtime decreased by 6.7 hours per asset, and operational availability increased by 1.4 percentage points. These outcomes showed that the intervention influenced both the frequency of equipment failure and the efficiency with which failed assets were restored. Earlier studies of reliability-centered maintenance, FMEA, and structured failure investigation similarly reported reductions in breakdown frequency, maintenance delay, equipment unavailability, and repeated technical defects. Much of that research focused on individual compressors, pumps, pipelines, or refinery units and commonly relied on short observation periods or unadjusted before-and-after comparisons. This study extended that evidence by examining several interconnected asset categories across multiple facilities and operating years (Liu, 2019). The findings were also consistent with previous research showing that integrating failure histories with risk prioritization produced stronger maintenance decisions than scheduling activities solely according to fixed intervals or immediate operational pressure. The reduction of USD 1,970 in annual maintenance expenditure per asset and the decrease of 8.4 thousand standard cubic meters in deferred gas production demonstrated that the measured reliability changes had corresponding economic and production dimensions. Earlier industrial investigations frequently treated technical reliability, maintenance expenditure, and production continuity as separate outcomes. The present findings showed that these measures changed in a coordinated direction when verified root causes were transferred into FMEA registers, corrective actions were prioritized, and implementation was technically confirmed (Sharma & Sharma, 2014). The moderate standardized effect sizes further showed that the intervention effects were large enough to carry operational importance without representing statistically inflated changes produced solely by the substantial number of asset-month observations.

Figure 12: RCA-FMEA reliability improvement framework



The multi-year findings showed a sustained pattern of reliability growth rather than an isolated improvement immediately following intervention. Annual failure events declined from 842 in the first operating year to 500 in the fifth year, representing a reduction of 40.6%. The exposure-adjusted failure rate decreased from 0.147 to 0.082 failures per 1,000 operating hours, while failures per asset declined from 0.975 to 0.579. This distinction was important because total operating exposure increased by 7.0%

during the study period (Balakrishnan et al., 2019). The reduction in failures therefore occurred while the assets collectively accumulated more operating hours, which strengthened the interpretation that improved performance was associated with reliability management rather than reduced equipment utilization. Earlier longitudinal studies of industrial maintenance reported that reliability growth was normally reflected in declining failure intensity, longer operating intervals, and reduced recurrence after successive corrective actions. The present study displayed the same pattern, as mean time between failures increased by 80.2%, from 6,793 to 12,240 hours. Mean time to repair declined by 38.7%, and total unplanned downtime fell by 63.6%. Previous gas-processing and petrochemical studies also identified mean time between failures and mean time to repair as complementary indicators because equipment can experience fewer failures without achieving meaningful availability improvement when repair duration remains excessive (Shaqdan et al., 2014). The simultaneous improvement of both measures in this study explained the increase in operational availability from 96.4% to 98.7%. Annual maintenance expenditure decreased from USD 6.84 million to USD 4.11 million, and deferred gas production declined from 18.7 million to 7.9 million standard cubic meters. These patterns were consistent with earlier evidence connecting preventive and risk-based maintenance with lower emergency-work demand, reduced production interruption, and more stable resource utilization. The interrupted time-series analysis added further support by identifying both an immediate reduction at the intervention point and a continuing favorable monthly trend. Earlier studies based on single pre-intervention and post-intervention measurements could not distinguish an immediate change from an ongoing trend or a temporary maintenance effect (Filho et al., 2017). The repeated monthly and annual observations used in this study provided a clearer representation of how RCA-FMEA interventions were associated with progressive changes in failure occurrence, repair performance, production continuity, and maintenance expenditure.

The distribution of verified root causes showed that mechanical, electrical, and process failures generated the largest combined reliability burden. These three categories accounted for 64.5% of recorded failures, 71.7% of downtime, 70.9% of maintenance expenditure, and 71.6% of deferred gas production. Mechanical causes alone represented 32.0% of events and 37.3% of downtime, reflecting the operational importance of bearings, seals, shafts, couplings, lubrication systems, pistons, and other rotating components (Corvaro et al., 2017). Earlier studies of compressors, pumps, turbines, and process machinery similarly identified wear, misalignment, inadequate lubrication, vibration, seal deterioration, and component fatigue as leading sources of repeated breakdowns. Pipeline and pressure-equipment research placed greater emphasis on corrosion, erosion, containment loss, and pressure deviation, while process-control studies commonly identified transmitter error, actuator malfunction, alarm failure, and unstable control loops. The present study brought these failure groups into a common facility-level dataset and demonstrated that frequently occurring events and high-consequence events were not always identical. Instrumentation failures were relatively frequent but generally created shorter interruptions, whereas process and environmental failures occurred less often and produced substantial downtime or production consequences. RCA quality helped explain why some investigated events produced stronger post-action results than others (Omoya et al., 2019). The mean causal depth was 3.8 levels, evidence completeness reached 86.4%, documentation completeness reached 91.2%, and 82.7% of investigations received technical verification. Earlier root-cause studies repeatedly found that investigations remained ineffective when immediate symptoms, such as vibration, leakage, overheating, or operator error, were incorrectly treated as fundamental causes. Research applying five-whys, fault-tree, cause-and-effect, and barrier analysis also showed that effective investigation required evidence linking equipment conditions with procedural, maintenance, design, and organizational factors. The recurrence findings supported this distinction. Identical failure-mode recurrence affected 10.9% of intervention assets and 22.8% of comparison assets, while recurrence of the same verified root cause affected 8.7% and 19.6%, respectively (Tsarouhas, 2018). These differences showed that deeper causal identification and technically verified action were associated with lower recurrence. Human and organizational causes represented 17.0% of failures collectively, confirming earlier research that treated maintenance planning, training, communication, supervision, inspection delay, and action backlog as measurable reliability factors rather than secondary contextual

concerns.

The FMEA results demonstrated that structured risk prioritization corresponded meaningfully with observed operational consequences. Failure-mode coverage reached 93.6%, while 24.1% of assessed modes were classified as high or critical priority, 44.3% were classified as moderate priority, and 31.6% were classified as low priority (Liu et al., 2018). Severity was positively associated with downtime and deferred gas production, occurrence was associated with failure frequency and recurrence, and detectability was associated with missed pre-failure identification. The correlation between occurrence and observed failure frequency reached $\rho=.63$, $\rho=.63$, while criticality and production loss produced the strongest association, $\rho=.67$, $\rho=.67$. These relationships were consistent with earlier FMEA studies showing that severity, occurrence, and detectability represented different dimensions of operational risk and should not be interpreted as interchangeable measures. Previous research also criticized conventional risk-priority values because different combinations of ratings can generate the same total score while representing substantially different consequences. The present study addressed this limitation by examining each FMEA dimension separately and validating combined classifications against failure frequency, downtime, maintenance cost, recurrence, and production loss (Yousefi et al., 2018). Receiver-operating-characteristic analysis showed that severity alone provided acceptable discrimination of high-consequence failures, AUC = 0.76, while overall risk priority produced better discrimination, AUC = 0.82. Criticality classification reached an AUC of 0.86, and combined action priority produced the strongest performance, AUC = 0.89. These findings were aligned with earlier studies that incorporated asset importance, consequence magnitude, operating exposure, and system dependency into FMEA-based decisions. The results also supported research using weighted, fuzzy, and multicriteria FMEA approaches to improve ranking accuracy when conventional scoring did not adequately represent uncertainty or unequal consequence importance. Inter-rater reliability strengthened confidence in the resulting classifications (Faught et al., 2017). Severity ratings achieved an ICC of .84, overall risk priority reached .81, occurrence reached .79, and detectability reached .76. Earlier studies reported that disagreement often arose because operations personnel emphasized production, maintenance personnel emphasized repair complexity, and safety professionals emphasized hazardous consequences. The acceptable-to-strong agreement observed in this study reflected the use of standardized definitions, documented evidence, interdisciplinary assessment, and structured reconciliation. FMEA therefore operated as an empirically connected reliability instrument rather than an isolated expert-scoring exercise (Kerk et al., 2015).

The subgroup findings demonstrated that intervention effectiveness varied according to asset type, criticality, operating condition, environmental exposure, maintenance strategy, and baseline failure history. Compressors recorded the largest equipment-specific reduction in failure rate, IRR = 0.58, followed by pumps and electrical equipment. Compressor downtime declined by 9.2 hours, and availability increased by 1.9 percentage points. Earlier compressor studies emphasized that these machines are exposed to interacting degradation processes involving vibration, lubrication, bearings, seals, valves, pressure instability, and operating-load variation. Such complexity creates several opportunities for RCA-informed redesign, monitoring, and maintenance revision, which may explain the comparatively strong improvement (Shafiee et al., 2019). Pump studies similarly documented the reliability effects of cavitation, seal leakage, bearing failure, misalignment, flow deviation, and motor-current variation. Pipeline and flowline assets demonstrated a smaller but significant effect, IRR = 0.75. This pattern was consistent with earlier integrity research showing that corrosion, erosion, and wall-thickness loss often develop over longer periods and may not respond as rapidly as rotating-equipment failures to short-term maintenance changes. High-criticality assets experienced a larger reduction than low-criticality assets, with failure-rate ratios of 0.56 and 0.81, respectively. High-criticality equipment also recorded a 9.8-hour reduction in downtime and a 2.1-percentage-point increase in availability. Earlier risk-based maintenance research similarly reported stronger measured returns when technical resources were concentrated on equipment with high production contribution, limited redundancy, severe consequences, or extensive system dependencies. Greater effects were also observed for equipment operating above 80% of rated capacity, assets exposed to corrosive or environmentally severe conditions, and equipment with elevated baseline failure histories (Chang et al., 2019). These

groups possessed higher initial risk and greater potential for measurable improvement. Maintenance strategy also modified the intervention effect. Assets supported by reliability-centered or condition-based maintenance achieved a failure-rate ratio of 0.60, compared with 0.78 among assets managed predominantly through corrective maintenance. Previous studies reached comparable findings when vibration monitoring, oil analysis, thermography, corrosion monitoring, and performance trending allowed developing defects to be identified before functional loss. Equipment redesign produced the strongest action-specific effect, followed by condition monitoring and component replacement, demonstrating that interventions addressing structural causes or detection limitations produced greater changes than actions limited to documentation or administrative control (Mascia et al., 2020). The survival and recurrent-event findings provided additional evidence that RCA-FMEA intervention was associated with longer and more stable equipment operation. At 24 months, the failure-free survival probability was 0.74 among intervention assets and 0.56 among comparison assets. Median time to first failure reached 38.6 months in the intervention group and 24.7 months in the comparison group. After adjustment for asset and operating characteristics, intervention assets experienced a 38% lower hazard of first failure, $HR = 0.62$, 95% CI [0.54, 0.71]. Recurrent-event modeling produced a rate ratio of 0.57, corresponding to a 43% reduction in multiple-failure occurrence. Earlier reliability studies using survival and time-to-failure models reported that maintenance effectiveness could be underestimated when analysis was restricted to annual failure counts. Survival analysis incorporated operating duration and the contribution of equipment that remained functional without experiencing an event. The present findings were therefore consistent with previous research showing that maintenance and design changes extended equipment operating life and altered the timing of recurrent failures. Corrective-action status further differentiated reliability performance. Of the 1,487 corrective actions, 1,246 were documented as completed, while 1,091 received technical verification. Assets connected with verified actions recorded 0.064 failures per 1,000 operating hours, compared with 0.086 for completed but unverified actions and 0.101 for incomplete actions (Lapan & Poynton, 2020). Earlier incident-management studies similarly found that administrative closure did not necessarily establish that a hazard, defect, or root cause had been controlled. Verification through functional testing, inspection, monitoring, or engineering review provided stronger evidence that the intended corrective mechanism had become operational. Mediation analysis clarified this process by showing that corrective-action completion and verification jointly explained 39.2% of the association between RCA-FMEA quality and reliability improvement. Technical verification produced the strongest individual indirect pathway, $\beta = .093$, followed by completion, $\beta = .064$, and the sequential completion-to-verification pathway, $\beta = .028$. The direct effect remained statistically significant after the mediators were included, demonstrating partial rather than complete mediation (Mansour et al., 2019). This pattern corresponded with earlier reliability research in which analytical quality influenced outcomes partly through action implementation while also improving failure classification, maintenance prioritization, monitoring, communication, and technical decision-making.

The consistency of results across multiple statistical procedures strengthened the interpretation of RCA-FMEA-driven reliability improvement. Mixed-effects regression accounted for repeated observations and clustering within equipment and facilities, while difference-in-differences analysis compared changes among intervention assets with changes among matched comparison assets (Luu, 2018). Interrupted time-series analysis separated immediate intervention effects from continuing monthly trend changes, and survival models examined the timing of first and recurrent failures. Earlier industrial reliability studies frequently used descriptive failure counts, Pareto rankings, or single-period before-and-after comparisons. These approaches provided useful operational descriptions but offered limited control for asset age, operating exposure, production load, environmental conditions, maintenance strategy, and pre-existing reliability differences. This study incorporated these factors and obtained directionally consistent estimates across all analytical approaches. Matching produced a maximum standardized mean difference of 0.04, the pre-intervention trend test was nonsignificant, and the maximum variance-inflation factor was 2.84. Count-model dispersion remained acceptable, time-series residuals showed no material autocorrelation, and the proportional-hazards condition was

satisfied (Mathew, 2018). Conditional model-explanatory values ranged from .39 to .51, demonstrating that the models accounted for meaningful variation without presenting the intervention as the only determinant of reliability. Sensitivity analyses also produced stable estimates after extreme shutdowns, limited-exposure assets, completely replaced equipment, alternative matching procedures, recurrence definitions, and missing-data treatments were considered. The adjusted failure-rate ratio remained between 0.66 and 0.69, while the hazard ratio remained between 0.60 and 0.63. No alternative specification changed the direction or significance of the primary findings. The graphical evidence supported the same interpretation (Luo et al., 2018). Annual failure rates, downtime, maintenance expenditure, and deferred gas production moved downward, while availability and failure-free survival moved upward. Pareto analysis concentrated the operational burden within mechanical, electrical, and process causes, and the subgroup forest plot showed favorable effects across all assessed categories. In comparison with earlier studies, the combined statistical and visual evidence offered a broader account of reliability improvement by connecting causal investigation, risk prioritization, action verification, failure recurrence, maintenance efficiency, production continuity, and financial performance within a single multi-year empirical structure (Narne et al., 2019).

CONCLUSION

This study concluded that the systematic integration of root-cause analysis and Failure Mode and Effects Analysis was associated with substantial, statistically significant, and operationally meaningful reliability improvement across gas production facilities. The multi-year dataset included eight facilities, 864 assets, 3,412 verified failure events, and 51,840 asset-month observations, providing a sufficiently broad empirical foundation for examining equipment performance over time. Annual failures declined from 842 to 500, while the exposure-adjusted failure rate decreased from 0.147 to 0.082 failures per 1,000 operating hours. Mean time between failures increased by 80.2%, mean time to repair declined by 38.7%, and unplanned downtime decreased by 63.6%. Operational availability increased from 96.4% to 98.7%, while maintenance expenditure and deferred gas production declined by 39.9% and 57.8%, respectively. Adjusted models confirmed that intervention assets experienced a 32% lower failure rate, 51% lower odds of repeated failure, 4.8 fewer repair hours, 6.7 fewer annual downtime hours per asset, and a 1.4-percentage-point increase in availability. Mechanical, electrical, and process causes generated most of the recorded failures, downtime, expenditure, and production loss, establishing these categories as the dominant sources of facility-level reliability burden. FMEA severity, occurrence, detectability, risk priority, and criticality ratings corresponded meaningfully with observed operational outcomes, while combined action-priority classification demonstrated strong discrimination of high-consequence failures. Survival analysis showed that intervention assets had a 38% lower hazard of first failure and a 43% lower recurrent-event rate. Equipment redesign, condition monitoring, component replacement, and maintenance revision produced the strongest improvements, particularly among compressors, high-criticality assets, environmentally exposed equipment, and assets with elevated baseline failure histories. Technically verified corrective actions produced stronger outcomes than administrative completion alone, and completion and verification mediated 39.2% of the relationship between RCA-FMEA quality and reliability improvement. The consistency of results across mixed-effects regression, difference-in-differences analysis, interrupted time-series modeling, survival analysis, recurrent-event analysis, matching, imputation, and sensitivity testing demonstrated that the principal findings remained stable under alternative analytical conditions. Overall, the study established RCA-FMEA integration as a measurable reliability-management process connecting verified causal diagnosis, evidence-based risk prioritization, corrective-action control, reduced recurrence, improved equipment availability, lower maintenance demand, and stronger production continuity.

RECOMMENDATIONS

Gas production organizations should institutionalize an integrated RCA-FMEA reliability-management system that connects every significant equipment failure with structured causal investigation, risk reassessment, corrective-action assignment, technical verification, and long-term performance monitoring. Priority should be given to compressors, pumps, electrical equipment, high-criticality assets, heavily loaded systems, environmentally exposed equipment, and assets with repeated failure histories because these categories demonstrated the greatest reliability burden and

strongest response to intervention. Mechanical, electrical, and process failures should receive concentrated engineering attention through improved lubrication control, vibration monitoring, alignment assessment, seal management, electrical testing, corrosion prevention, process-stability monitoring, and operating-limit enforcement. Each RCA investigation should examine technical, human, organizational, and environmental causes, use several evidence sources, involve relevant professional disciplines, and avoid treating visible symptoms as fundamental causes. FMEA registers should be updated immediately after root causes have been verified, and severity, occurrence, detectability, criticality, existing controls, and action priorities should be reassessed using current operational evidence. Organizations should evaluate the individual risk dimensions alongside combined priority values so that high-severity failure modes are not overlooked because of low occurrence. Corrective actions should not be considered effective solely because they have been administratively closed. Completion should be confirmed through inspection, functional testing, process monitoring, condition assessment, or engineering review, with recurrence tracked for an adequate operating period. Equipment redesign, condition-based monitoring, component replacement, inspection improvement, and maintenance-task revision should receive priority when they address verified technical weaknesses. Computerized maintenance systems, process historians, inspection databases, production records, RCA reports, and FMEA registers should use standardized asset identifiers, failure definitions, timestamps, downtime classifications, and production-loss measures. Reliability dashboards should routinely report failure rates, repeated failures, mean time between failures, mean time to repair, downtime, availability, maintenance cost, deferred gas production, action backlogs, and verification status. Maintenance personnel should receive continuing training in causal analysis, FMEA scoring, condition monitoring, evidence documentation, and interdisciplinary decision-making. Management should conduct periodic reliability reviews, allocate resources according to asset criticality and operational consequence, and evaluate improvement through exposure-adjusted multi-year trends rather than isolated annual failure counts. Independent audits should examine data completeness, scoring consistency, overdue actions, recurrence, and the alignment between maintenance expenditure and measured reliability outcomes. These coordinated practices would support sustained failure reduction, stronger production continuity, efficient maintenance allocation, and accountable reliability governance throughout gas production operations.

LIMITATIONS

This study was subject to several limitations that should be considered when interpreting the reported reliability improvements. The retrospective longitudinal quasi-experimental design supported multi-year comparison but did not provide the experimental control available through randomized assignment. Assets receiving RCA–FMEA interventions may have differed from comparison assets in unmeasured characteristics such as management attention, workforce competence, spare-parts availability, maintenance culture, or access to specialist engineering support. Propensity-based matching, mixed-effects modeling, difference-in-differences analysis, and covariate adjustment reduced observable differences but could not eliminate residual confounding. Facility selection depended on the availability of continuous operational records and documented RCA–FMEA activities, which may have favored organizations with more developed maintenance systems and reduced generalizability to smaller, older, or less digitally integrated facilities. The analysis relied on computerized maintenance systems, process historians, inspection records, production databases, and technical reports originally created for operational rather than research purposes. Incomplete timestamps, inconsistent failure descriptions, missing operating hours, duplicate work orders, and differences in coding practices may therefore have introduced measurement error. Standardized extraction procedures and technical verification reduced this risk but could not reconstruct information that had never been recorded. RCA quality and FMEA ratings also contained professional judgment, particularly when evidence was incomplete or several causes interacted. Acceptable inter-rater reliability did not establish perfect agreement among engineering, maintenance, operations, inspection, and safety personnel. Corrective actions varied in technical complexity, implementation time, resource requirements, and expected duration of benefit, limiting direct comparison across action categories. The designated intervention date may not have represented the precise point at which each action became fully operational. Reliability outcomes were influenced by equipment age, production loading,

environmental exposure, shutdown schedules, design differences, and market-related operating decisions that changed across years. Maintenance expenditure and deferred gas production were derived from facility records and valuation procedures that may not have been fully comparable across locations. Survival estimates were affected by censoring, asset replacement, decommissioning, and unequal post-intervention exposure. Rare catastrophic events were insufficiently frequent for detailed subgroup modeling, while aggregation could have concealed component-level failure mechanisms. Finally, the study emphasized measurable equipment and production outcomes and did not fully quantify workforce behavior, safety culture, regulatory performance, environmental consequences, or the organizational costs required to establish and maintain the integrated RCA-FMEA system.

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