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Reliability Engineering and Failure Analysis in Complex Engineering Systems

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Abstract- ***This review examines the conceptual foundations, analytical methods, lifecycle applications, and emerging technologies that define contemporary reliability engineering and failure analysis in complex systems. Its purpose is to clarify how dependable performance can be designed, assessed, sustained, and improved where technical components, software, human actions, organisational structures, and environmental conditions interact. A structured narrative review was adopted, drawing together established theories, quantitative models, failure-investigation techniques, maintenance strategies, resilience principles, and digital approaches from diverse engineering contexts. The findings show that reliability is fundamentally systemic rather than component-centred. Statistical life-data analysis, fault trees, Bayesian networks, Markov models, redundancy optimisation, and reliability allocation provide essential quantitative support, but their value depends on realistic assumptions regarding dependence, uncertainty, and operating conditions. Structured methods such as FMEA, FMECA, HAZOP, root-cause analysis, Bow-Tie Analysis, and cause-and-effect analysis were found to offer complementary strengths in hazard identification, causal diagnosis, criticality assessment, and corrective-action prioritisation. Physical examination, non-destructive testing, signal analysis, and data-driven diagnostics further improve investigative accuracy when integrated with operational evidence. The review also demonstrates that design for reliability, accelerated testing, condition monitoring, prognostics, and maintenance optimisation strengthen availability, safety, productivity, and lifecycle value. Artificial intelligence and digital twins create significant predictive opportunities, yet their implementation remains constrained by data quality, cybersecurity, interoperability, explainability, workforce capability, and organisational readiness. It is concluded that reliability should be governed as an integrated lifecycle function. Organisations should strengthen multidisciplinary analysis, risk-based maintenance, validated digital tools, and learning systems. Future research should prioritise interpretable intelligence, cascading-failure modelling, uncertainty-aware prognostics, cyber-physical resilience, and field-based studies in resource-constrained economies across critical infrastructure sectors.***

Keywords: reliability engineering; failure analysis; system dependability; condition monitoring; digital twins; maintenance optimisation.

I. INTRODUCTION

1.1 Evolution and Contemporary Scope of Reliability Engineering

Reliability engineering emerged from probability theory, statistical quality control, mass production and demands for dependable military and industrial technologies. Its early concern was component-centred: engineers sought to quantify the likelihood that electronic parts, mechanical elements and assemblies would perform their intended functions for durations under prescribed conditions. The discipline moved beyond inspection after manufacture toward the prevention of failure through design, testing, screening and feedback from service experience. This transition established reliability as an engineering property that must be designed into a system rather than verified only at the end of production (Saleh & Marais, 2006).

As engineering artefacts became larger, more interconnected and software-dependent, the analytical unit expanded from isolated components to socio-technical systems. Contemporary reliability therefore addresses dependencies, common-cause failures, ageing, imperfect information, human actions and the propagation of disturbances across subsystems. Traditional failure-rate calculations remain valuable,

but they are integrated with dynamic modelling, uncertainty analysis, simulation and risk-informed decision-making. This broadened orientation reflects the recognition that technically reliable components do not automatically produce a dependable system when interfaces, operating contexts and organisational processes generate emergent failure pathways (Zio, 2009).

A major stage in this evolution was the closer integration of reliability analysis with maintenance engineering. Rather than treating maintenance as a reactive response to breakdown, practice uses equipment condition, failure history and operational criticality to select interventions that preserve required performance. Condition-based maintenance combines data acquisition, signal processing, diagnostics and prognostics, thereby connecting reliability theory with the management of physical assets. This development widened the discipline's scope from predicting whether failure might occur to determining how incipient degradation can be detected and controlled before functional loss arises (Jardine, Lin & Banjevic, 2006).

The emergence of remaining-useful-life estimation further transformed reliability from a largely retrospective discipline into a predictive one. Statistical data-driven methods infer degradation trajectories from observed condition indicators and update forecasts as evidence becomes available. Such approaches permit maintenance planning to reflect the evolving health of individual assets rather than fixed population averages. They also illustrate the convergence of reliability engineering, operations research, statistics and decision science, particularly where censored data, stochastic degradation and heterogeneous operating environments complicate lifetime prediction (Si et al., 2011).

Reliability engineering has also become inseparable from risk assessment because system performance must be judged in relation to uncertainty and the consequences of failure. Modern analysis does not merely calculate probabilities; it examines the assumptions, knowledge limitations and value judgements underlying models and decisions. This perspective is important for safety-critical installations, where rare events may have disproportionate economic or environmental effects. Reliability specialists must consequently communicate uncertainty, compare preventive alternatives and support decisions whose evidence is incomplete but whose consequences are substantial (Aven, 2016).

The discipline's relevance is evident in developing infrastructure systems, where limited redundancy, ageing assets, weak monitoring and extended restoration times can magnify service interruptions. Nigerian distribution-system research demonstrates how component outage data and customer-oriented indices can identify transformers, protective devices and feeders that dominate unavailability. Such applications show that reliability engineering is not confined to high-technology sectors; it also provides a framework for prioritising scarce maintenance resources, improving service continuity and translating equipment performance into consequences experienced by users (Akintola &Awosope, 2017).

Its scope likewise extends to geotechnical systems in which material variability and uncertain loading challenge deterministic design. Evidence from South African coal-pillar cases shows how probabilistic reliability analysis can distinguish stable and failed configurations while representing uncertainty in strength and stress parameters. This application illustrates the movement from fixed safety factors toward explicit probability-based reasoning, enabling engineers to evaluate margins of safety transparently and to recognise that apparently similar structures may possess different failure likelihoods (Song & Yang, 2018).

Digital sensing and computational intelligence have expanded reliability practice by enabling continuous health assessment across complex machinery. Contemporary prognostics encompasses data acquisition, health-indicator construction, operating-stage identification and remaining-life prediction. Machine learning can reveal nonlinear degradation patterns, although its usefulness depends on representative data, interpretable features and validation under changing conditions. Reliability engineering has therefore become a hybrid field in

which physical knowledge, statistical inference and algorithmic models must be combined rather than treated as competing approaches (Lei et al., 2018).

At the lifecycle level, reliability now informs requirements definition, design selection, construction, commissioning, operation, inspection, maintenance and decommissioning. Pipeline applications, for example, demonstrate how reliability methods can connect failure modes, material behaviour, corrosion, loading, inspection evidence and consequence assessment within a coherent design framework. The contemporary scope of the discipline is consequently both technical and managerial: it supports safer designs, improved availability, rational maintenance expenditure and defensible asset decisions across energy, manufacturing, transport, mining, civil infrastructure and other complex engineering domains (Omoya, Papadopoulou & Lou, 2019).

1.2 Complexity, Interdependence, and Failure Behaviour in Engineering Systems

Complex engineering systems are distinguished not merely by component count, but by the density, directionality and character of relationships among components. Electrical, mechanical, software, communication and human subsystems exchange energy, material, information and control signals, creating dependencies that cannot be understood through isolated analysis. Physical, cyber, geographic and logical interdependencies may cause a disturbance in one subsystem to alter conditions elsewhere, across organisational boundaries. Reliability assessment must therefore represent component states and the pathways through which performance is coupled (Rinaldi, Peerenboom & Kelly, 2001).

Interdependence changes failure behaviour because local damage may redistribute loads, interrupt support functions or trigger protective actions that impose new stresses on surviving elements. In tightly coupled networks, a limited fault can recursively disable dependent nodes, producing abrupt fragmentation rather than gradual degradation. The transition may be nonlinear: systems can appear tolerant below a critical threshold, yet lose functionality after a small additional disturbance. Such behaviour challenges reliability models that assume independent failures, stationary rates or proportional relationships between initiating events and final consequences (Buldyrev et al., 2010).

Failure propagation also varies across engineered domains. Cascading failures arise when malfunction spreads sequentially; escalating failures occur when disruption in one infrastructure impedes recovery in another; and common-cause failures affect multiple elements through a shared hazard, design weakness or operating environment. Contemporary modelling therefore combines network theory, agent-based simulation, system dynamics, empirical analysis and economic input-output approaches. Each method illuminates interactions, but no single representation captures every temporal, spatial, functional and organisational dependency in infrastructure systems (Ouyang, 2014).

Failure behaviour is further shaped by hidden conditions that event reconstruction may overlook. Design compromises, maintenance omissions, weak communication, procedural ambiguity and erroneous assumptions can remain latent until unusual demands align them with active technical faults. Investigation must therefore move beyond the failed component to examine direct causes, indirect influences and decision structures. Hybrid frameworks can integrate fault trees, reliability block diagrams, criticality analysis and multicriteria reasoning to expose interacting causes and prevent corrective actions that leave systemic vulnerabilities intact (Stephen & Labib, 2018).

Evidence from a Nigerian generating plant demonstrates how subsystem performance determines plant availability. Recurrent forced outages, repair durations and unequal generating-unit performance created losses that installed capacity alone could not explain. The case illustrates how component degradation, maintenance effectiveness and operational scheduling interact to produce system-level reliability outcomes. In resource-constrained settings, delayed repairs and limited redundancy can intensify these interactions, allowing an equipment fault to restrict output far longer than its physical

failure mechanism would otherwise require (Kolawole et al., 2019).

Environmental and institutional context also modifies failure distributions. Comparative records from linear accelerators in the United Kingdom, Nigeria and Botswana showed differences across subsystems and revealed that a small proportion of lengthy faults accounted for most downtime. Failure frequency alone is therefore an incomplete measure of vulnerability; repair logistics, technical expertise, spare-part access, infrastructure quality and ambient conditions influence consequence severity. Complex-system analysis must accordingly connect technical causation with operating context, recovery capacity and the unequal criticality of interacting subsystem failures (Wroe et al., 2019).

1.3 Strategic Importance of Reliability and Failure Analysis

Reliability engineering and failure analysis possess strategic importance because they convert uncertain technical behaviour into evidence for design, investment, maintenance and governance decisions. In complex engineering systems, failure rarely produces only a repair requirement; it may interrupt production, compromise safety, degrade service quality, damage the environment and weaken organisational credibility. Reliability programmes therefore establish performance expectations, identify failure mechanisms and direct resources toward components whose loss would create the greatest operational consequence. Failure analysis complements this function by transforming breakdown evidence into knowledge, thereby preventing recurrence and strengthening design assurance.

At organisational level, reliability must be aligned with competitive priorities rather than treated as an isolated technical activity. Maintenance choices influence cost, quality, delivery dependability, flexibility and customer confidence, while poorly coordinated interventions can undermine production objectives. Empirical evidence indicates that firms pursuing quality-based competition tend to adopt more proactive policies, stronger planning systems and structured maintenance organisations, demonstrating that asset dependability is inseparable from business strategy (Pinjala, Pintelon& Vereecke, 2006).

The economic significance of reliability also extends beyond avoiding repair expenditure. Reliable assets preserve productive capacity, defer replacement, protect revenue-generating service and reduce the probability of costly operational disruption. Maintenance consequently creates value when its contribution to service flows and avoided losses exceeds its cost. Evaluating this contribution through lifecycle and net-present-value reasoning enables management to compare interventions on strategic rather than purely budgetary grounds (Marais & Saleh, 2009).

Failure analysis provides the prioritisation discipline required to make such investments defensible. Failure mode and effects analysis identifies potential failure modes, evaluates their consequences and ranks mitigation needs according to occurrence, severity and detectability. Its strategic value lies in exposing vulnerabilities before losses materialise, although conventional risk-priority numbers require interpretation because different risk combinations can generate equivalent rankings (Liu, Liu & Liu, 2013).

These principles are particularly consequential in African environments, where ageing equipment, limited spares, constrained technical capacity and reactive maintenance can intensify downtime. Nigerian evidence shows that effective maintenance management requires coordinated methodology, organisational structure, planning, training and performance measurement, rather than episodic responses to breakdowns (Eti, Ogaji& Probert, 2006). Kenyan industrial assessment likewise demonstrates that reliability performance depends on technical, managerial and human practices, with partially managed systems remaining vulnerable when outcomes rely excessively on individual experience (Muchiri et al., 2017). Reliability and failure analysis thus function as strategic capabilities for effectively protecting safety, availability, productivity, lifecycle value and institutional resilience across complex engineering systems.

1.4 Review Aim, Objectives, Scope, and Analytical Approach

This review aims to critically examine the evolution, theoretical foundations, analytical methods, practical applications, and emerging directions of reliability engineering and failure analysis within complex engineering systems. Its principal purpose is to clarify how reliability-oriented thinking supports the design, operation, maintenance, and continuous improvement of systems whose performance depends on multiple interacting technical, human, organisational, and environmental elements.

The review pursues four objectives. First, it explains the major concepts, measures, and modelling principles used to evaluate system dependability, availability, maintainability, risk, and failure behaviour. Second, it assesses established techniques for identifying, diagnosing, and prioritising failure mechanisms, including probabilistic, statistical, structural, experimental, and data-driven approaches. Third, it evaluates how reliability engineering is applied across the system lifecycle, from requirements definition and design verification to condition monitoring, maintenance optimisation, and asset retirement. Fourth, it identifies implementation constraints, technological opportunities, and research priorities associated with increasingly interconnected and intelligent engineering environments.

The scope covers complex mechanical, electrical, civil, energy, manufacturing, transportation, and cyber-physical systems, while maintaining a system-level perspective rather than concentrating on a single industrial sector. Particular attention is given to interdependence, cascading failure, uncertainty, human contribution, digitalisation, and resilience.

The analytical approach adopts a structured narrative review of relevant scholarly and professional literature. Sources are examined comparatively to identify conceptual developments, methodological strengths, practical limitations, recurring implementation challenges, and areas of convergence. The synthesis is organised thematically to establish relationships among reliability theory, failure investigation, maintenance strategy, risk governance, and emerging digital technologies across diverse operational and institutional contexts worldwide today.

II. THEORETICAL FOUNDATIONS AND QUANTITATIVE MODELLING OF RELIABILITY

2.1 Fundamental Reliability Concepts, Measures, and Performance Indicators

Reliability is the probability that an item performs its required function under stated operating conditions for a specified period. This definition contains four inseparable elements: the item, intended function, operating conditions and mission duration. Reliability must therefore be expressed against a defined requirement rather than treated as a synonym for quality. Within complex systems, it is assessed alongside availability, maintainability and supportability because service depends on both failure resistance and restoration capability (Saraswat & Yadava, 2008).

The reliability function, R(t), represents the probability of survival beyond time t, while the failure distribution, F(t), expresses the probability of failure then. Their relationship is $R(t) = 1 - F(t)$. The probability density describes how failures are distributed through time, whereas the hazard rate indicates the instantaneous propensity to fail among surviving items. Hazard behaviour may decrease, remain constant or increase, requiring distributional assumptions to be validated against evidence (Barabady& Kumar, 2008).

Mean time to failure applies principally to non-repairable items and denotes expected operating life before first failure. Mean time between failures applies to repairable equipment and measures average operating time between successive failures. Failure rate, estimated as failures divided by exposure time, is useful but may conceal ageing, duty-cycle variation and dependence among subsystems. Performance modelling should therefore combine descriptive measures with fitted distributions, dependency checks and configuration to avoid misleading averages (Sharma & Kumar, 2008).

Maintainability is the probability that an item can be restored to a specified condition within a period under prescribed procedures and resources. Mean time to repair summarises active restoration duration, although assessment may also include fault detection, diagnosis, access, replacement, testing and administrative delay. Design characteristics such as modularity, accessibility, standardisation and diagnostic coverage influence restoration performance; maintainability indicators should therefore be established during design rather than after operational problems appear (Coulibaly, Houssin & Mutel, 2008).

Availability measures the probability that a system is operable when required. Inherent availability is related to mean time between failures and mean time to repair, while achieved availability incorporates preventive maintenance. Operational availability reflects logistics, waiting time, workforce constraints and administrative delays. High component reliability may coexist with inadequate availability when repairs are slow. Integrated RAM analysis therefore distinguishes failure prevention from restoration efficiency and identifies variables that restrict operation (Corvaro, Giacchetta, Marchetti & Recanati, 2017).

Performance indicators translate reliability concepts into evidence. Useful measures include uptime, downtime, failure frequency, repair duration, maintenance cost, schedule compliance, equipment effectiveness and lost production. Indicators must be linked to asset, production and organisational objectives; otherwise, improvements may not enhance system performance. Leading indicators assess maintenance processes and preparedness, whereas lagging indicators record experienced outcomes. Balanced measurement requires technical, economic, safety and service dimensions rather than reliance on one metric (Muchiri, Pintelon, Gelders& Martin, 2011).

For electric distribution networks, customer-oriented indicators extend equipment measures to service consequences. System Average Interruption Frequency Index quantifies interruption frequency, System Average Interruption Duration Index measures interruption duration, and Customer Average Interruption Duration Index represents restoration time for interrupted customers. Energy not supplied adds unmet demand. Nigerian evidence demonstrates that these indices expose feeder weaknesses and provide a stronger basis for investment prioritisation than aggregate claims of inadequate overall electricity-supply reliability (Ajewole et al., 2018).

Interpretation must reflect asset criticality and operating context. Transformer studies in Egypt illustrate how time-between-failure data, repair-time distributions, availability and remaining life can compare voltage populations and failure mechanisms. Reliability indicators are decision variables rather than isolated statistics: their value lies in supporting design improvement, maintenance timing, spare-parts planning and risk control. Confidence intervals, data quality and observation periods should accompany reported values so apparent precision does not exceed available evidence (EL-Bassiouny, EL-Shimy& Hamouda, 2019).

2.2 Statistical Distributions and Life-Data Analysis

Life-data analysis provides the basis for translating histories into estimates of lifetime, failure probability and uncertainty. The response may be calendar time, cycles, distance or accumulated energy, depending on damage. Analysts must distinguish failures from right-, left- and interval-censored observations because surviving units retain information. Progressive censoring arises when test items are deliberately withdrawn, requiring likelihood formulations that preserve contributions from failed and unfailed units (Balakrishnan, 2007).

Parametric analysis assumes lifetimes follow a specified distribution. The exponential distribution represents a constant hazard rate and suits memoryless failures, but it cannot describe infant mortality or wear-out. The Weibull distribution is adaptable because its shape parameter represents decreasing, constant or increasing hazards, while its scale parameter indicates characteristic life. Nigerian turbine records demonstrate how these models convert histories into reliability profiles and ageing estimates (Atikpakpa, Okafor & Okonkwo, 2016).

Distribution selection should reflect physical behaviour rather than convenience. Lognormal models are defensible when lifetime results from multiplicative degradation, whereas gamma models represent positive, skewed durations or deterioration. Extreme-value distributions are relevant when failure is governed by maximum stress, minimum strength or the weakest location. Conventional models may fail to reproduce bathtub-shaped or unimodal hazards. The exponentiated Weibull family adds another shape parameter, permitting richer hazard structures within a coherent lifetime model (Mudholkar, Srivastava & Freimer, 1995).

Further extensions are useful when failure patterns contain turning points. A flexible Weibull extension can accommodate increasing, decreasing, bathtub-shaped and unimodal hazard rates, improving representation of systems passing through early-life, useful-life and ageing regimes. Additional flexibility, however, increases parameter uncertainty and encourages overfitting in small samples. Selection should balance goodness of fit, stability, interpretability and agreement with failure physics rather than numerical fit alone (Bebbington, Lai & Zitikis, 2007).

Extended Weibull models can represent non-monotonic failure behaviour and may be assessed through probability plots and likelihood-based fitting. They are valuable when a conventional Weibull plot shows systematic curvature, indicating structural lack of fit. Improved visual fit is insufficient evidence of predictive validity. Competing distributions should be compared through information criteria, residual diagnostics, probability plots and sensitivity analysis, especially when lower-tail quantiles determine safety margins, replacement intervals or warranty obligations (Zhang & Xie, 2007).

Parameter estimation relies on maximum likelihood because it accommodates censoring and supports standard errors, confidence intervals and likelihood-ratio tests. Rank-regression and probability-plotting methods remain useful for exploration, although results may depend on plotting positions and become inefficient under heavy censoring. Bayesian analysis combines prior knowledge with observed failures and produces credible intervals. Ghanaian scholarship demonstrates its relevance for Weibull inference where censored samples provide limited information (Guure& Ibrahim, 2012).

Accelerated life testing addresses products whose failures occur too slowly for observation. Units are exposed to elevated temperature, voltage, pressure, vibration or other stresses, and statistical relationships extrapolate results to service conditions. The principal challenge is defensible extrapolation because excessive stress may activate mechanisms absent during normal use. Sound analysis requires meaningful stress-life models, adequate allocation across stress levels, failure-mode consistency and explicit quantification of extrapolation uncertainty (Escobar & Meeker, 2006).

For reliable assets, degradation measurements may provide more information than sparse failure times. Crack length, wear, corrosion depth, insulation resistance or performance loss can be modelled as stochastic processes until a failure threshold is crossed. Wiener, gamma and inverse Gaussian processes represent different path characteristics and permit lifetime distributions to be derived indirectly. Suitability depends on whether degradation is monotonic, increments are independent, and heterogeneity, covariates and measurement error are represented credibly (Ye & Xie, 2015).

Life-data conclusions remain vulnerable to model misspecification. An incorrect degradation path, lifetime distribution or stress relationship can bias mean life, tail quantiles and remaining-life predictions, particularly with short tests or small samples. Analysts should compare plausible models, investigate influential observations and report uncertainty intervals rather than point estimates alone. Evidence from linear degradation modelling shows that limited sample size and termination time can magnify misspecification effects, reinforcing diagnostic scrutiny and engineering judgement (Peng & Tseng, 2009).

2.3 System Reliability Modelling and Dependence Analysis

System reliability modelling translates component-level evidence into an estimate of whether an engineered system can fulfil its required function. The analyst first defines system boundaries, success criteria, operating states, mission time and assumptions concerning repair, switching and load sharing. Reliability block diagrams then represent functional success paths through series, parallel, standby or k-out-of-n configurations. Their clarity makes them useful for design comparison, although static representations can conceal sequence-dependent behaviour and functional dependencies (Chemweno et al., 2018).

Fault-tree analysis adopts a deductive perspective by decomposing an undesirable system-level event into combinations of basic failures through logical gates. Minimal cut sets identify combinations capable of producing the top event, while importance measures reveal components that contribute most strongly to risk. Extensions such as dynamic, repairable and state-dependent fault trees improve expressiveness but increase computational demands and modelling effort (Ruijters &Stoelinga, 2015).

The practical value of fault trees is evident in networked infrastructure. Power-system applications can generate a separate tree for each load point, quantify interruption pathways and identify equipment whose unavailability most affects energy delivery. Such models connect component failure probabilities with system consequences, although their results remain sensitive to topology, switching assumptions and the quality of failure-rate data (Volkanovski, Čepin &Mavko, 2009).

Markov models represent a system as operational, degraded, failed and repair states connected by transition rates. They are particularly suitable for repairable systems, standby configurations, imperfect coverage and sequence-sensitive processes. Their principal limitation is state-space growth, since combinations of component conditions can produce an impractically large transition matrix. Hybrid methods therefore retain simpler static structures where possible and reserve state-based modelling for dynamic subsystems (Boudali & Dugan, 2005).

Bayesian networks provide a compact probabilistic structure for representing conditional dependence among components, environments, controls and human actions. Unlike models founded on independence assumptions, they support diagnostic reasoning, probability updating and integration of data with expert judgement. Their graphical structure also permits analysts to trace how observations alter the likelihood of upstream causes or downstream system failure (Langseth &Portinale, 2007).

Petri nets complement Bayesian approaches where concurrency, synchronisation, resource competition, repair and event ordering govern behaviour. Places, transitions and tokens express system states and event activation, while stochastic timing supports quantitative reliability and availability assessment. Their flexibility is valuable for cyber-physical and safety-critical systems, although model construction, validation and numerical solution may become difficult as system detail increases (Kabir & Papadopoulos, 2019).

Applied modelling must reflect operating context rather than reproduce nominal architecture alone. A Nigerian hybrid photovoltaic-diesel-battery study demonstrates how capacity-outage states and generation adequacy measures can evaluate whether interacting sources and storage satisfy demand. Such evidence shows that credible dependence analysis requires realistic resource variability, component availability, load behaviour and common operating constraints within the system representation (Esan et al., 2019).

2.4 Reliability Allocation, Redundancy, and Design Optimisation

Reliability allocation translates an overall system dependability requirement into attainable targets for subsystems and components. The process begins with mission definition, architecture, operating environment, failure consequences and verification capability, then distributes reliability effort according to functional criticality and design influence.

Allocation is not merely numerical apportionment: it establishes accountability, directs testing resources and exposes components whose required performance is unrealistic. Contemporary formulations therefore integrate reliability targets with cost, mass, volume, power and maintainability constraints, recognising that the best design rarely maximises one measure without qualification (Kuo & Prasad, 2000).

In series–parallel architectures, allocation must account for how component improvements affect system success. Strengthening a weak series element often produces greater benefit than improving an already dependable parallel branch. Mathematical programming can minimise resource consumption while meeting prescribed reliability, although nonlinear relationships, discrete choices and practical bounds complicate solution. Decomposition and approximation methods are valuable when subsystem structures permit separation without losing essential configuration logic (Yalaoui, Chu & Châtelet, 2005).

Redundancy improves fault tolerance by providing additional components or functional paths, but every redundant unit introduces acquisition cost, weight, space, energy demand and maintenance burden. Genetic algorithms suit this combinatorial problem because they can search across component types and redundancy levels while respecting multiple constraints. Their usefulness is greatest where exhaustive enumeration is impractical and the design space contains discontinuities created by integer decisions and k-out-of-n arrangements (Coit & Smith, 1996).

The form of redundancy is equally important. Active units operate simultaneously and may share load, whereas cold-standby units remain inactive until demanded and require dependable switching. Allowing the redundancy strategy to vary among subsystems produces more realistic designs than imposing one strategy throughout. Optimisation should therefore select component reliability, type, redundancy level and operating strategy as interrelated decisions rather than sequential choices (Tavakkoli-Moghaddam, Safari & Sassani, 2008).

Redundancy benefits may be overstated when models assume independent failures. Shared environments, design defects, power supplies, maintenance errors or control signals can disable several nominally independent units simultaneously. Reliability optimisation that incorporates common-cause failure may favour diversity, separation or reduced coupling instead of simply adding identical components. Dependence analysis is therefore essential when judging whether additional redundancy creates genuine resilience or apparent protection (Ramirez-Marquez & Coit, 2007).

African renewable-energy applications demonstrate the importance of balancing adequacy with affordability. Optimal sizing of an autonomous photovoltaic–wind system can use loss-of-power-supply probability as a reliability constraint while minimising levelised energy cost. This approach links generation capacity, storage, resource variability and demand, preventing unreliable undersizing and economically inefficient overdesign in isolated installations (Diaf et al., 2007).

In developing economies, load allocation also influences reliability because poorly coordinated demand can overload converters, storage units and distribution circuits despite adequate installed generation. Nigerian hybrid-solar analysis supports matching available capacity with prioritised loads and operating conditions. Such optimisation should preserve critical demand, reduce avoidable stress, accommodate future growth and maintain feasible cost, producing an architecture whose reliability derives from coordinated allocation rather than excessive equipment alone (Sunday &Omoegun, 2019).

III. FAILURE IDENTIFICATION, INVESTIGATION, AND DIAGNOSTIC METHODOLOGIES

3.1 Structured Failure Analysis and Risk-Prioritisation Techniques

Structured failure analysis converts operational uncertainty into evidence for prevention and improvement. Its effectiveness depends on selecting a

technique that matches the question, system boundary, data and decision stage. Failure Mode and Effects Analysis (FMEA) proceeds inductively from component or process failures to their consequences, documenting causes, controls, severity, occurrence and detectability. A Nigerian manufacturing study demonstrates its value for tracing breakdowns in automated equipment and translating failure modes into preventive-maintenance priorities (Okwuobi et al., 2018).

Failure Mode, Effects and Criticality Analysis (FMECA) extends FMEA by assigning criticality or priority measures that distinguish deficiencies from failures threatening safety, mission achievement or production continuity. Its value lies in converting a failure inventory into an ordered programme of corrective action. Application to a computer-integrated conveyor illustrates how Risk Priority Numbers can identify motor, vibration, belt-tracking and contamination failures, although rankings remain sensitive to scoring consistency and expert assumptions (Elbadawi et al., 2018).

Conventional prioritisation can be strengthened by incorporating economic consequences and mitigation benefits. Priority-cost FMECA evaluates technical risk alongside the cost-effectiveness of corrective actions, preventing resources from being allocated solely according to ordinal scores. This matters where recommendations compete for capital, personnel and shutdown opportunities, and where the most severe failure is not necessarily the most economically actionable vulnerability (Carmignani, 2009).

Fault-Tree Analysis (FTA) adopts deductive, top-down logic. Analysts define an undesirable top event and use Boolean gates to identify combinations of equipment faults, human errors and external events capable of producing it. Minimal cut sets expose critical failure combinations, while quantitative trees estimate top-event probability when defensible data exist. Static trees may inadequately represent sequence dependence, repair, shared resources and dynamic interactions unless suitable extensions are employed (Kabir, 2017).

Hazard and Operability Study (HAZOP) is suited to process and control systems. A multidisciplinary team divides the design into nodes and applies guidewords such as “no,” “more,” “less” and “reverse” to process parameters, generating deviations, causes, consequences and safeguards. Its systematic creativity can reveal hazards omitted by checklist approaches, but outcomes depend on boundary definition, facilitator competence, design information, team diversity and disciplined recording of recommendations (Dunjó et al., 2010).

Bow-Tie Analysis integrates causal and consequence perspectives around a defined top event. Threats and preventive barriers appear on the left, whereas consequences and mitigative barriers appear on the right. The visual structure supports barrier ownership, performance monitoring and communication across managerial groups. Nevertheless, inconsistent terminology, oversimplified dependencies and untested assumptions about barrier independence can create an appearance of control unsupported by operational evidence (de Ruijter &Guldenmund, 2016).

Root-Cause Analysis (RCA) investigates why a failure occurred and seeks actionable causal mechanisms rather than symptoms. Cause-and-effect diagrams organise potential influences under categories such as equipment, methods, materials, environment and people. Their accessibility supports collaborative investigation, but unrestricted brainstorming may produce extensive lists without demonstrating causal validity. Tool selection should reflect problem complexity, evidence quality and the need to represent interactions among contributing factors (Doggett, 2005).

These methods are strongest when integrated across the asset lifecycle. FMEA can anticipate failure modes, FTA can test routes to critical events, HAZOP can interrogate process deviations, Bow-Tie Analysis can govern barriers, and RCA can learn from realised events. Integrating RCA and FMEA also enables confirmed causes to update preventive-maintenance priorities and inspection frequencies, creating a feedback loop between operational experience, risk ranking and maintenance execution (Chen, 2013).

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Table 1: Comparative Assessment of Failure Analysis and Risk-Prioritisation Techniques in Complex Engineering Systems

Technique	Analytical orientation	Principal purpose	Main output	Major strength	Principal limitation
FMEA	Inductive and bottom-up	Identify potential failure modes and their effects	FMEA worksheet and prioritised failure list	Supports early prevention in design and operations	Scoring may be subjective and weak for interacting failures
FMECA	Inductive with criticality assessment	Rank failures according to risk or mission significance	Criticality matrix or prioritised corrective actions	Distinguishes safety-critical failures from routine deficiencies	Requires reliable failure and consequence information
FTA	Deductive and top-down	Determine combinations producing a defined top event	Fault tree, minimal cut sets and event probability	Represents multiple causal combinations logically	Limited by top-event definition and independence assumptions
RCA	Retrospective and evidence-based	Identify underlying causes of experienced failures	Verified causal chain and corrective-action plan	Supports organisational learning and recurrence prevention	Can confuse correlation, symptoms and genuine causation
HAZOP	Guideword-driven team analysis	Identify hazardous deviations and operability problems	Deviation register, safeguards and recommendations	Effective for process, control and interface hazards	Resource-intensive and dependent on team competence
Bow-Tie Analysis	Barrier-based cause–consequence analysis	Map threats, top events, consequences and controls	Bow-tie diagram and barrier register	Communicates barrier responsibilities clearly	May oversimplify dependencies and barrier degradation
Cause-and-Effect Analysis	Exploratory causal categorisation	Organise possible causes of a defined problem	Fishbone or Ishikawa diagram	Encourages multidisciplinary brainstorming	Generates hypotheses rather than verified causal evidence

3.2 Physical, Experimental, and Data-Driven Failure Investigation

Physical, experimental, and data-driven failure investigation seeks to reconstruct how an engineering asset departed from its intended condition and why existing controls failed to arrest deterioration. A defensible investigation begins with documentation, operating records, maintenance history, loading conditions, environmental exposure and witness accounts before components are dismantled or cleaned. Evidence must be preserved through controlled sampling, chain-of-custody records and comparison with unaffected parts. Nigerian investigation of a failed building illustrates the need to

integrate field observation, material testing, design review and code-based assessment, because visible damage alone cannot distinguish initiating defects from consequential deterioration (Olajumoke et al., 2009).

Fractography provides direct evidence of crack initiation, propagation and final overload by examining fracture-surface morphology at macroscopic and microscopic scales. Beach marks, striations, cleavage facets, dimples, ratchet marks and corrosion products can indicate fatigue, brittle fracture, ductile overload, stress-corrosion cracking or environmentally assisted damage. Interpretation must consider component geometry, loading direction and post-failure abrasion, since handling can destroy significant features. Scanning electron microscopy and energy-dispersive spectroscopy strengthen causal inference by linking surface morphology with inclusions, contaminants or local chemistry, but fracture patterns should be corroborated by service history and mechanics rather than treated as self-sufficient proof (Pantazopoulos, 2019).

Metallographic examination complements fractography by revealing microstructure, heat-treatment condition, grain morphology, phase distribution, segregation, porosity and crack paths beneath the fracture surface. Section location and preparation are critical because inappropriate cutting, grinding or etching can introduce artefacts or remove evidence. Hardness mapping, tensile testing and chemical analysis provide checks against material specifications and manufacturing records. An Egyptian investigation of a failed automotive rocker-arm shaft showed how microscopy and hardness measurements exposed excessive hardening, martensitic regions and microcracking near supporting holes, thereby connecting brittle fracture to an improper heat-treatment condition rather than ordinary service loading alone (Nassef, Elkhatib &Yakout, 2016).

Non-destructive testing extends investigation to components that must remain serviceable or with concealed internal damage. Ultrasonic inspection detects discontinuities through reflected sound, radiography reveals density variations, magnetic-particle and dye-penetrant testing expose surface-connected cracks, while eddy-current, thermographic, acoustic-emission and shearographic methods respond to different material and damage characteristics. Technique selection should reflect defect orientation, material type, access, sensitivity and inspection depth. No method offers universal coverage; composite structures may require complementary techniques to distinguish delamination, debonding, impact damage and porosity while limiting false indications (Gholizadeh, 2016).

Dynamic investigation uses operational signals to identify faults that may not be observable during shutdown. Vibration and acoustic measurements can reveal imbalance, misalignment, looseness, bearing defects and gear damage through changes in amplitude, spectral content, envelope response and time-frequency behaviour. Sensor position, sampling rate, speed and load variation influence diagnostic quality. Rolling-element bearing research demonstrates that time-domain statistics, frequency spectra, high-frequency resonance and acoustic emission provide different sensitivity across defect stages; consequently, baseline comparison and fault-frequency interpretation are required before abnormal peaks are assigned to a specific mechanism (Tandon & Choudhury, 1999).

Electrical signature analysis offers a non-intrusive route for investigating electromechanical systems by examining stator current, voltage, power, flux or torque signals. Rotor-bar fractures, eccentricity, bearing deterioration and load-related abnormalities can modulate supply-frequency components and generate characteristic sidebands. Because electrical signals are affected by harmonics, variable-speed drives, supply imbalance and changing loads, diagnosis requires spectral resolution and discrimination between mechanical faults and electrical disturbances. Motor-current signature analysis is valuable where access is difficult, although reliable interpretation depends on operating-state knowledge and confirmation through independent observations or tests (Benbouzid, 2000).

Data-driven investigation integrates multisensor records, extracted features and learning algorithms to

detect anomalies or classify failure states. Conventional models use engineered indicators with support-vector machines, neural networks or probabilistic classifiers, whereas deep architectures can learn representations from raw vibration, acoustic, image or current data. Accuracy must be tested against class imbalance, sensor drift, domain shift, scarce failure examples and changes in operating regime. Machine-health studies show that autoencoders, convolutional networks and recurrent models can support diagnosis, yet physically implausible predictions, opaque features and leakage between training and test data may produce misleading confidence. Effective practice integrates algorithmic evidence with experimental replication, engineering constraints and independent physical examination (Zhao et al., 2019).

IV. LIFECYCLE RELIABILITY MANAGEMENT AND ASSET PERFORMANCE

4.1 Design for Reliability, Verification, and Accelerated Testing

Design for reliability embeds dependability requirements in system architecture before manufacturing or operation makes correction expensive. The process begins by translating stakeholder needs into reliability, maintainability, and lifetime targets for defined missions. Engineers then identify functions, failure modes, stresses, interfaces, and uncertainty sources, using allocation, derating, tolerance design, redundancy, physics-of-failure analysis, and design reviews. Verification and validation activities should be selected according to their reliability contribution, cost, duration, sequencing constraints, and capacity to reveal design weaknesses (Mobin et al., 2019).

Verification establishes whether the implemented design satisfies technical requirements, whereas validation determines whether the system performs acceptably in its intended context. Evidence may combine analysis, simulation, inspection, laboratory tests and field demonstrations. Reliability demonstration testing converts requirements into defensible acceptance criteria defined through test duration, sample size, allowable failures, confidence, and producer and consumer risks. For repairable and non-repairable products, plans must reflect the failure criterion and mission profile; otherwise, passing a demonstration may provide little assurance about durability (Lee et al., 2015).

Demonstration planning is multi-objective because stronger statistical assurance generally requires more specimens, longer exposure, or greater expenditure. Test optimisation should balance discrimination between acceptable and unacceptable designs, cost, test time, risk, and information value. Pareto-based planning is useful where no plan dominates every criterion, allowing decision-makers to select a defensible compromise rather than conceal trade-offs within one score. Such transparency is important for complex systems whose failures are rare but consequential and whose qualification programmes face resource constraints (Lu, Li & Anderson-Cook, 2016).

Accelerated testing addresses the difficulty of observing failures in highly reliable products during development. Elevated temperature, voltage, load, vibration, humidity, or combined stresses are applied to shorten degradation and failure times. Planning must connect accelerated conditions to normal service through a credible stress–life or degradation model while preserving the mechanism expected in operation. Reviews of accelerated-test practice emphasise that stress selection, censoring, sample allocation, model choice, and extrapolation uncertainty must be considered jointly; excessive acceleration can generate artificial mechanisms and invalidate service-life predictions (Limon, Yadav & Liao, 2017).

Accelerated life testing differs from highly accelerated life testing and stress screening. Statistically designed accelerated life tests estimate lifetime distributions and parameters, whereas highly accelerated procedures expose weak margins and stimulate design improvement. Stress screening is applied after design stabilisation to precipitate latent manufacturing defects without consuming unacceptable useful life. Effective plans define stress ranges, measurement intervals, termination rules, specimen allocation, and

optimality criteria before testing. They also incorporate engineering knowledge so numerical efficiency does not supersede physical plausibility or failure-mode consistency (Chen et al., 2018).

African scholarship demonstrates the relevance of rigorous statistical treatment where test resources and sample sizes are constrained. Egyptian research on constant-stress partially accelerated testing used progressively censored observations, maximum-likelihood estimation, bootstrap intervals, and Bayesian simulation to estimate modified Weibull parameters. Partial acceleration can preserve observations under normal conditions while obtaining earlier failures under elevated stress. Credible verification requires uncertainty intervals, sensitivity analysis, and evidence that the assumed lifetime distribution represents the product and that acceleration has not changed its governing failure process (Mahmoud, EL-Sagheer & Abou-Senna, 2018).

Design verification must reproduce the interactions that determine field performance rather than test components under convenient laboratory states. In residential air-conditioning systems, thermodynamic efficiency depends on equipment sizing, load variation, ambient conditions, control logic, installation quality, and user behaviour. Nigerian analysis of cooling efficiency and control strategies illustrates why reliability-oriented design should verify capacity margins, sensor responses, cycling behaviour, energy performance, and operation under realistic climatic and economic conditions. Testing that overlooks these interactions may certify nominal functionality while leaving instability, excessive stress, poor efficiency, or premature degradation unresolved (Sunday et al., 2019).

4.2 Condition Monitoring, Prognostics, and Maintenance Optimisation

Condition monitoring, prognostics, and maintenance optimisation form an integrated decision architecture for sustaining asset function while controlling risk, downtime, and lifecycle expenditure. Corrective maintenance restores equipment after failure, whereas preventive maintenance intervenes at predetermined ages or intervals. Condition-based maintenance initiates action when measured deterioration crosses a decision threshold, and predictive maintenance extends this logic by forecasting future health or remaining useful life. The appropriate strategy depends on failure consequences, degradation observability, data quality, intervention cost, and the operational value of continued service (Ahmad & Kamaruddin, 2012).

Condition monitoring begins with selecting variables that respond consistently to developing faults. Vibration, temperature, lubricant debris, acoustic emission, electrical signatures, pressure, flow, and performance efficiency may reveal different degradation mechanisms. Data acquisition must preserve sampling adequacy, sensor calibration, operating-state information, and traceability because changes in load or environment can resemble damage. South African elevator research illustrates how remote vibration and machine-room temperature monitoring can provide early fault indication and deterioration histories, enabling intervention before breakdown becomes operationally disruptive (Olalere & Dewa, 2018).

Diagnostics interprets observations to determine whether an abnormal condition exists, identify its location, and classify its likely cause. Prognostics then estimates future condition, failure probability, or remaining useful life. Model-based approaches use physical or state-space representations; data-driven approaches infer patterns from historical records; and hybrid approaches combine engineering knowledge with statistical learning. Prognostic usefulness depends not only on prediction accuracy but also on uncertainty bounds, warning horizon, robustness to changing regimes, and the economic consequences of early or late intervention (Peng, Dong & Zuo, 2010).

Maintenance optimisation converts health information into decisions about inspection timing, repair, replacement, and resource deployment. For stochastically deteriorating assets, models may minimise long-run cost, downtime, risk, or a weighted combination subject to safety and availability requirements. Decision variables include inspection intervals, intervention thresholds, maintenance

degree, and grouping of tasks. Optimisation is credible only when degradation dynamics, imperfect observations, repair effectiveness, and failure consequences are represented realistically rather than assuming perfect restoration and complete state knowledge (Alaswad& Xiang, 2017).

The superiority of condition-based maintenance over fixed-interval maintenance is therefore conditional rather than universal. Its benefits diminish when measurements are inaccurate, monitoring is expensive, setup time is long, failures occur abruptly, or deterioration provides little warning. Conversely, it becomes attractive when condition signals are informative, failures are costly, and intervention can be planned before functional loss. Practical comparison should include monitoring infrastructure, false alarms, missed detections, logistics, production windows, and the residual life sacrificed by premature replacement (de Jonge, Teunter& Tinga, 2017).

Predictive maintenance increasingly employs machine-learning methods to recognise anomalies, classify fault states, and estimate remaining life from high-dimensional sensor data. Support-vector machines, decision trees, ensemble methods, neural networks, and clustering algorithms can capture nonlinear relationships that conventional thresholds may miss. Nevertheless, class imbalance, scarce failure examples, concept drift, data leakage, and limited interpretability can produce impressive validation results that fail operationally. Model outputs must therefore be tested across assets, duty cycles, and time periods and linked to executable maintenance actions (Carvalho et al., 2019).

Reliability-centred maintenance provides the governance logic for determining which interventions are technically appropriate and economically justified. It begins with required functions, functional failures, failure modes, consequences, and feasible preventive tasks. Identifying maintenance-significant items concentrates analysis on components whose failures materially affect safety, operations, environment, or cost, avoiding indiscriminate monitoring and routine replacement. Structured screening that combines qualitative judgement with quantitative evidence supports defensible prioritisation across complex systems (Tang et al., 2017).

Maintenance optimisation must also demonstrate organisational value. Nigerian scholarship has framed maintenance as a value-adding function whose profitability can be assessed by balancing intervention expenditure against improved availability, output, quality, and avoided losses. This perspective discourages maximising preventive activity for its own sake. A balanced portfolio may retain corrective maintenance for low-consequence random failures, preventive tasks for age-related mechanisms, condition-based and predictive methods for observable degradation, and reliability-centred interventions for critical functions. The resulting distribution should be derived from asset criticality and evidence, not from fashionable target percentages across the asset lifecycle and within each organisation's specific operational, financial, workforce, and regulatory constraints (Oke, 2005).

V. SYSTEM RESILIENCE, DIGITAL TRANSFORMATION, AND FUTURE DIRECTIONS

5.1 Safety, Resilience, and Human–Organisational Factors

Safety in complex engineering systems cannot be secured solely through stronger components, protective devices, or procedural compliance. It emerges from the interaction of technical architecture, human performance, organisational priorities, and the capacity to adapt when operating conditions depart from expectation. Human error should therefore be treated as a symptom of system conditions rather than an isolated personal defect. Workload, interface design, supervision, communication, staffing, training, and conflicting production pressures shape behaviour and can align latent weaknesses with active failures (Reason, 2000).

Organisational resilience extends conventional prevention by asking whether a system can anticipate disruption, absorb disturbance, sustain critical functions, and recover without generating new hazards. Resilience is not simply rapid restoration to a

previous state; it also includes robustness, adaptive capacity, and the ability to extend performance safely when established procedures or resources become inadequate. These distinctions are essential because complex systems often fail under combinations of circumstances that were not represented during design or risk assessment (Woods, 2015).

A resilient organisation develops capabilities for monitoring weak signals, responding to changing demands, learning from ordinary work, and revising assumptions before adverse events occur. Research in resilience engineering shows that these capabilities depend on cross-functional coordination, accessible operational knowledge, flexible decision authority, and feedback mechanisms that connect frontline experience with strategic governance. Safety performance consequently reflects how effectively the organisation manages variability, not merely how closely workers follow prescribed rules (Patriarca et al., 2018).

Evidence from Nigerian aviation demonstrates the analytical value of examining accidents across multiple organisational levels. Human Factors Analysis and Classification System findings reveal that unsafe acts are frequently associated with preconditions, supervisory deficiencies, and organisational influences. Such evidence challenges investigations that terminate with operator error and supports corrective action addressing training quality, crew resource management, oversight, maintenance coordination, and institutional learning (Daramola, 2014).

Comparable lessons arise from Ghanaian construction, where safety-programme effectiveness is weakened by inadequate communication, limited worker awareness, schedule pressure, poor attitudes, weak enforcement, and insufficient equipment maintenance. These conditions show that formal safety plans offer limited protection when organisational incentives, leadership behaviour, and resource allocation contradict declared priorities (Agyekum, Simons & Botchway, 2018). In complex engineering systems, resilience therefore requires leadership commitment, psychological safety for reporting, competent supervision, robust communication, preparedness for degraded operations, and systematic learning from successes, near misses, and failures. Human adaptability must be supported as a safety resource while remaining bounded by design, adequate staffing, realistic procedures, and accountable governance.

5.2 Artificial Intelligence, Digital Twins, and Intelligent Reliability Systems

Artificial intelligence is repositioning reliability engineering from periodic assessment toward continuous, evidence-driven anticipation of failure. Intelligent reliability systems combine sensor streams, maintenance histories, operating context, and engineering knowledge to detect anomalies, classify faults, estimate degradation, and recommend interventions. Machine-learning models are valuable where relationships among condition indicators, failure risk, and maintenance cost are nonlinear. Multiple-classifier architectures can accommodate high-dimensional and censored industrial data, although their credibility depends on representative training samples, transparent validation, and control of false alarms (Susto et al., 2015).

Digital twins extend this capability by maintaining a dynamically updated virtual representation of a physical asset, process, or system. Their value arises from linking geometry, physics-based simulation, operational measurements, and lifecycle records through persistent data exchange. In reliability applications, the twin can compare expected and observed behaviour, simulate fault scenarios, evaluate control responses, and estimate the consequences of continued operation without exposing the physical system to risk. Effective implementation nevertheless requires semantic consistency, model calibration, and synchronisation across physical and virtual domains (Tao et al., 2019).

The concept should be distinguished from static digital models and one-directional digital shadows. A genuine digital twin incorporates automated data exchange to ensure that the virtual representation reflects changing asset states and can inform physical decisions. Manufacturing literature shows that many claimed implementations remain partial because connectivity, integration, or feedback is incomplete.

Reliability benefits therefore depend less on visual sophistication than on validated information flows, configuration control, and the capacity to update models as equipment ages or operating conditions change (Kritzinger et al., 2018).

African applications demonstrate that intelligent reliability can be developed incrementally rather than through immediate deployment of costly autonomous platforms. In Nigeria, an artificial-neural-network diagnostic system identified, classified, and located transmission-line faults using simulated measurements from a 132-kV network. Such systems can accelerate protection and restoration, but simulated accuracy must be confirmed using field disturbances, changing network configurations, and noisy measurements before adoption (Madueme&Wokoro, 2015).

South African industrial evidence indicates that data availability alone does not create intelligence. Condition-monitoring information becomes valuable when analytics are connected to defined objectives, deterioration trends, risk priorities, and decision-oriented visualisation. Intelligent reliability systems should consequently integrate AI predictions and digital-twin simulations with human review, cybersecurity, data governance, uncertainty reporting, and maintenance authority. This sociotechnical arrangement preserves clear accountability while enabling earlier targeted intervention, adaptive planning, enterprise-level prioritisation, and systematic learning from discrepancies between predicted and experienced asset behaviour (Botes et al., 2019).

5.3 Implementation Challenges and Future Research Priorities

Implementing reliability engineering in complex systems is constrained less by unavailable analytical tools than by difficulties integrating them within heterogeneous environments. Legacy equipment, proprietary interfaces, fragmented databases and inconsistent asset taxonomies prevent information exchange between sensors, maintenance platforms and enterprise systems. Interoperability must therefore be treated as a reliability requirement, supported by open architectures, common semantics and configuration control rather than as a secondary feature (Lu, 2017).

Data quality constitutes a second limitation. Intelligent reliability models require complete, labelled and context-rich records, yet industrial datasets contain missing observations, irregular sampling, sensor drift, inconsistent timestamps and few examples of consequential failures. Future research should develop uncertainty-aware data pipelines, standardised benchmark datasets and methods that preserve provenance from acquisition to decision. Distributed data management must balance latency, computational demand, criticality and privacy across edge, plant and cloud environments (Raptis, Passarella & Conti, 2019).

Connectivity simultaneously increases capability and exposure. Cyber intrusion, false-data injection, denial-of-service attacks and compromised sensors can distort health indicators or trigger unsafe maintenance decisions. Security should consequently be integrated with reliability modelling through cyber-physical failure scenarios, adversarial testing, resilient estimation and recovery performance. Research should examine how attacks propagate through control functions and physical processes, particularly in safety-critical infrastructures (Humayed, Lin, Li & Luo, 2017).

Industrial Internet of Things implementation faces architectural complexity, device heterogeneity, uncertain ownership and uneven governance. Scalable reliability systems require explicit system boundaries, trusted identities, communication protocols, data responsibilities and acceptable degraded modes. Future frameworks should support modular deployment and legacy integration while enabling verification of sensing, analytics and actuation layers. Such architecture is essential to prevent digitalisation from creating hidden dependencies and single points of systemic failure (Boyes, Hallaq, Cunningham & Watson, 2018).

Artificial intelligence introduces concerns regarding interpretability, transferability and accountability. A model may achieve retrospective accuracy while relying on spurious correlations or failing under

unfamiliar operating conditions. In reliability decisions, future studies should prioritise interpretable or physically constrained models, calibrated uncertainty and explanations that personnel can test against engineering evidence. Human authority, escalation rules and audit trails must remain explicit when automated recommendations influence operation or shutdown (Rudin, 2019).

Institutional readiness remains uneven, particularly where capital, digital infrastructure and specialist skills are limited. South African evidence indicates that strategy formulation, equipment capability and organisational preparedness can lag behind technological ambition. Research should evaluate phased adoption pathways, workforce development, leadership competence and measurable value realisation rather than assuming technological maturity. Comparative studies across sectors and economies are needed to determine which implementation models remain effective under resource constraints (Maisiri & van Dyk, 2019).

The Nigerian manufacturing context demonstrates that reliability innovation must address finance, policy coherence, technical capacity and infrastructure simultaneously. Small enterprises may recognise the value of resilient energy technologies yet remain unable to absorb initial costs or maintain specialised systems. Future research should combine technical reliability assessment with lifecycle economics, local skills development, sustainable financing and regulatory analysis. Longitudinal field studies are necessary to establish how adoption affects downtime, productivity and asset survival under actual operating conditions (Sunday &Omoegun, 2018).

VI. CONCLUSION

This review has fulfilled its aim by critically synthesising the principles, methods, applications, and emerging directions that shape reliability engineering and failure analysis across complex engineering systems. It established that dependable performance cannot be secured through component quality alone, because modern systems are characterised by interdependence, nonlinear failure propagation, uncertainty, and significant human and organisational influence. The study clarified the roles of reliability, availability, maintainability, hazard rate, life-data analysis, system modelling, redundancy, and design optimisation in supporting evidence-based engineering decisions.

The review further demonstrated that structured techniques such as FMEA, FMECA, fault-tree analysis, root-cause analysis, HAZOP, and Bow-Tie Analysis provide complementary perspectives on failure identification, causal investigation, consequence evaluation, and risk prioritisation. Physical examination, non-destructive testing, signal analysis, and data-driven diagnostics were shown to strengthen failure investigation when integrated with operational history and engineering judgement. Across the asset lifecycle, design for reliability, accelerated testing, condition monitoring, prognostics, and maintenance optimisation emerged as essential mechanisms for improving safety, availability, productivity, and lifecycle value.

A central finding is that technological sophistication does not automatically create reliability. Artificial intelligence, digital twins, and intelligent monitoring systems require trustworthy data, validated models, cybersecurity, interoperability, skilled personnel, and clear accountability. Organisational resilience, leadership commitment, learning culture, and effective communication remain equally important, particularly where resource limitations intensify maintenance and recovery challenges.

It is concluded that reliability management should be treated as an integrated lifecycle and governance function rather than a narrow technical activity. Organisations should adopt risk-based asset strategies, strengthen failure-data quality, institutionalise multidisciplinary investigations, and align maintenance decisions with system criticality. Future research should prioritise interpretable artificial intelligence, cyber-physical reliability, common-cause and cascading failures, uncertainty-aware prognostics, and longitudinal studies in developing economies. Greater collaboration among industry, academia, regulators, and professional bodies is also recommended to develop standards, shared datasets,

workforce capability, and scalable reliability solutions.

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