



Digital Twin and Industrial Internet of Things–Enabled Predictive Maintenance for Reliability Enhancement in Smart Manufacturing Systems

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Abstract

This study quantitatively evaluated the effectiveness of Digital Twin and Industrial Internet of Things (IIoT)–enabled predictive maintenance for enhancing equipment reliability, maintenance efficiency, and production performance in smart manufacturing systems. A longitudinal quasi-experimental design was applied to 220 manufacturing assets representing 18,742 operating cycles and approximately 1.285 million cumulative machine-hours. The analytical dataset incorporated 18.64 million validated sensor observations, 1,086 maintenance events, and 428 baseline failure events across motors, bearings, gearboxes, CNC machines, cutting tools, pumps, compressors, robotic systems, conveyors, machining centers, and production-line assets. Baseline IIoT sensor coverage was 91.4%, data availability was 96.8%, and digital-twin fidelity was 92.6%. Following predictive-maintenance implementation, failure frequency decreased from 1.95 to 1.18 failures per asset, representing a 39.5% reduction, while mean time between failures increased from 1,486.3 to 2,176.8 hours, equivalent to a 46.5% improvement. Mean time to repair declined by 35.6%, availability increased from 91.8% to 96.1%, and unplanned downtime decreased by 45.9%. Overall equipment effectiveness increased from 76.9% to 85.6%, production interruptions declined by 44.7%, throughput loss decreased by 46.1%, and maintenance cost fell by 24.6%. Early fault detection increased from 54.3% to 87.2%, while anomaly-detection and fault-classification accuracy reached 94.1% and 92.8%, respectively. The highest-performing ensemble model achieved 96.2% classification accuracy, a 96.0% F1 score, ROC-AUC of 0.982, and remaining-useful-life R^2 of 0.94. Digital-twin fidelity increased to 96.4%, and synchronization consistency reached 98.1%. All principal baseline-to-post comparisons were statistically significant at $p < 0.001$, with large effects observed for MTBF, unplanned downtime, OEE, availability, and failure frequency. The findings demonstrated that reliable IIoT connectivity, high digital-twin fidelity, accurate predictive modeling, and earlier maintenance intervention were collectively associated with substantial improvements in manufacturing reliability, operational continuity, and maintenance performance.

Keywords

Digital Twin, IIoT, Predictive Maintenance, Reliability, Smart Manufacturing.

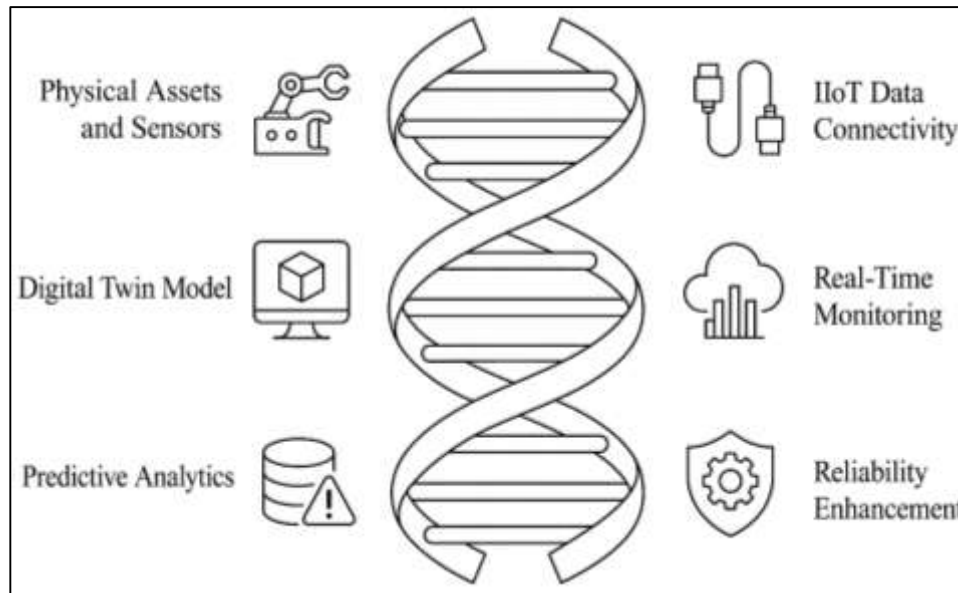
INTRODUCTION

Digital twin technology, the Industrial Internet of Things, predictive maintenance, reliability enhancement, and smart manufacturing represent closely integrated concepts within contemporary industrial engineering and digitally connected production environments. A digital twin can be defined as a dynamic virtual representation of a physical asset, machine, production process, manufacturing cell, or interconnected manufacturing system that remains synchronized with its physical counterpart through continuous data exchange, computational modeling, and operational feedback (Suhail et al., 2021). Unlike conventional simulations that primarily represent predetermined operating conditions, digital twins are continuously updated using real-time or near-real-time information from physical equipment, allowing changing operating states, performance deviations, degradation behavior, and equipment health to be represented more accurately. The Industrial Internet of Things provides the technological infrastructure that enables this continuous connectivity by linking sensors, controllers, machines, communication networks, edge devices, cloud platforms, and analytical systems across industrial operations. Through this connected architecture, manufacturing systems can collect variables such as vibration, temperature, pressure, acoustic emission, electrical current, torque, rotational speed, lubrication condition, cycle time, energy consumption, operating load, and environmental conditions (Tao et al., 2019). Predictive maintenance uses these historical and real-time measurements to detect abnormal conditions, classify faults, estimate degradation, and predict potential equipment failure before functional breakdown occurs. Reliability enhancement refers to measurable improvement in the ability of manufacturing assets to perform required functions under specified operating conditions and is commonly evaluated through indicators such as failure rate, mean time between failures, mean time to repair, equipment availability, unplanned downtime, remaining useful life, maintenance frequency, and production continuity. Smart manufacturing integrates these elements through cyber-physical production systems in which physical processes are continuously monitored, digitally represented, computationally analyzed, and coordinated through connected information infrastructures. Internationally, the importance of these technologies has increased because manufacturing systems increasingly depend on automated, capital-intensive, and interconnected equipment whose unexpected failure can disrupt production schedules, reduce throughput, affect product quality, increase maintenance expenditure, and interrupt supply-chain continuity (Kharchenko et al., 2020). The integration of digital twins and IIoT therefore provides a quantitative environment in which physical equipment conditions can be converted into measurable indicators of machine health, degradation, maintenance requirements, and reliability performance across complex manufacturing systems.

IIoT-enabled digital twins strengthen predictive maintenance by combining continuous condition monitoring, cyber-physical representation, advanced analytics, and quantitative reliability assessment within a unified manufacturing environment. IIoT infrastructure allows heterogeneous sensor data to be transmitted from bearings, motors, gearboxes, spindles, cutting tools, pumps, compressors, robotic systems, machine tools, and production lines to edge devices, gateways, cloud platforms, maintenance systems, and digital-twin models (Warke et al., 2021). These data can include signal amplitude, vibration characteristics, temperature deviation, current signatures, pressure fluctuations, operating hours, machine load, alarm frequency, maintenance history, and fault occurrence. Digital twins transform these data streams into structured virtual representations that can reflect the current and evolving condition of physical assets. Such models may incorporate physics-based simulation, statistical degradation models, finite-element analysis, machine-learning techniques, deep-learning algorithms, or hybrid approaches to estimate internal equipment states and predict future performance. Predictive analytics then converts these data and virtual representations into fault-detection, diagnostic, prognostic, and remaining-useful-life estimates. Common analytical methods include logistic regression, decision trees, random forests, support vector machines, artificial neural networks, convolutional neural networks, recurrent neural networks, long short-term memory models, Bayesian methods, clustering techniques, survival models, and ensemble approaches (Wang et al., 2019). Their

performance can be evaluated through accuracy, precision, recall, sensitivity, specificity, F1 score, root mean squared error, mean absolute error, false-alarm rate, missed-failure rate, prediction error, and remaining-useful-life estimation accuracy (Centomo et al., 2020).

Figure 1: IIoT digital twin framework



Reliability outcomes can simultaneously be measured through failure frequency, downtime, availability, mean time between failures, mean time to repair, maintenance cost, maintenance lead time, production interruption, and overall equipment effectiveness. Quantitative investigation of these relationships is important because predictive accuracy alone does not fully represent maintenance effectiveness when false alarms, delayed predictions, missing sensor data, communication latency, or unstable operating conditions affect maintenance decisions (Sun et al., 2022). Manufacturing variables such as equipment age, production intensity, operating load, shift pattern, maintenance history, machine type, asset criticality, and environmental conditions may also influence reliability outcomes. Consequently, the quantitative study of digital twin and IIoT-enabled predictive maintenance requires integrated measurement of connectivity, sensor quality, digital-twin synchronization, predictive-model performance, maintenance intervention, and reliability indicators across smart manufacturing systems (Cheng et al., 2020).

The objective of this quantitative study is to examine the effectiveness of Digital Twin and Industrial Internet of Things-enabled predictive maintenance in enhancing the reliability of smart manufacturing systems by evaluating measurable relationships among equipment-condition monitoring, digital-twin synchronization, predictive-model performance, maintenance intervention, and operational reliability outcomes. Specifically, the study seeks to determine the extent to which continuous IIoT-based data acquisition from industrial equipment improves the detection of abnormal operating conditions, fault identification, degradation assessment, and remaining-useful-life estimation when integrated with dynamically updated digital-twin models. The investigation also aims to quantify the contribution of predictive-maintenance capabilities to reductions in equipment failure frequency, unplanned downtime, maintenance response time, repair duration, and production interruption, while examining corresponding improvements in mean time between failures, equipment availability, overall equipment effectiveness, maintenance efficiency, and production continuity. Particular attention is directed toward key operational and technological variables including sensor coverage, vibration and temperature measurements, electrical current characteristics, pressure conditions, operating load,

machine utilization, data-transmission latency, missing-data rates, digital-twin update frequency, model synchronization accuracy, anomaly-detection performance, fault-classification accuracy, false-positive and false-negative rates, prediction horizon, and remaining-useful-life estimation error. The study further seeks to compare reliability outcomes across different equipment types, machine-age categories, operating conditions, production intensities, asset-criticality levels, and maintenance histories in order to determine whether the effectiveness of digital twin and IIoT-enabled predictive maintenance varies across manufacturing contexts. Statistical relationships among predictive-maintenance variables and reliability indicators will be examined to identify the strongest determinants of improved equipment performance and reduced failure risk. The study also intends to evaluate whether higher levels of digital connectivity, sensor-data quality, digital-twin fidelity, and predictive accuracy are associated with more timely maintenance interventions and more stable manufacturing operations. By integrating condition-monitoring data, digital-twin characteristics, predictive analytics, maintenance records, and reliability indicators within a unified quantitative framework, the study aims to provide an empirically measurable assessment of how digital twin and IIoT-enabled predictive maintenance contributes to reliability enhancement in smart manufacturing systems and to establish the relative importance of technological, analytical, and operational factors influencing maintenance and equipment performance.

LITERATURE REVIEW

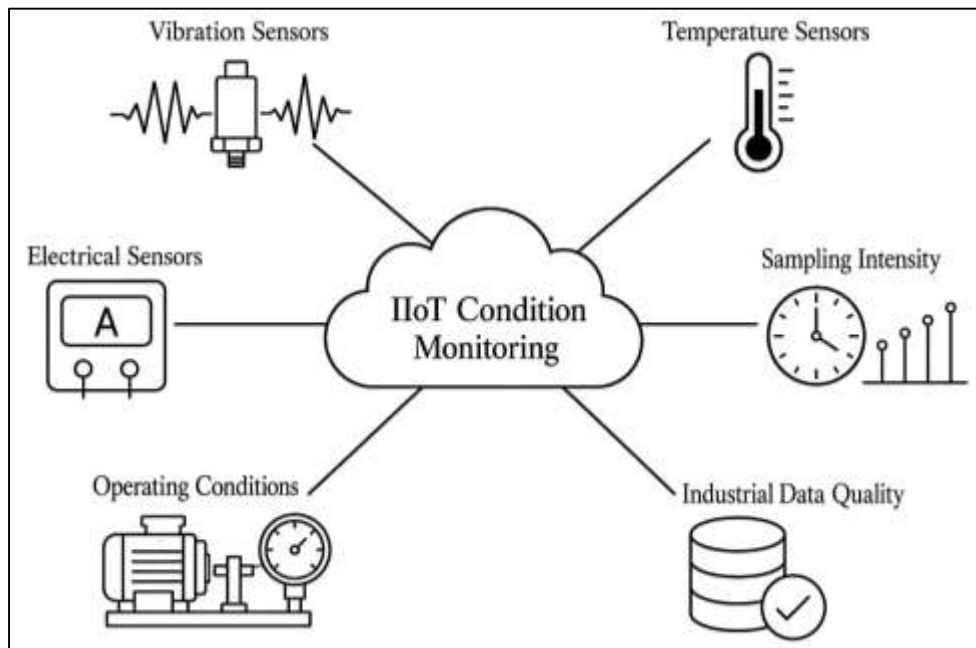
The literature on Digital Twin and Industrial Internet of Things (IIoT)-enabled predictive maintenance encompasses a broad range of quantitative research concerning industrial sensing, cyber-physical integration, equipment-condition monitoring, fault diagnosis, degradation modeling, remaining-useful-life prediction, maintenance optimization, and manufacturing reliability. Within smart manufacturing environments, these research areas are increasingly examined as interconnected components because predictive maintenance performance depends not only on the accuracy of analytical models but also on the availability and quality of sensor data, the synchronization of physical and virtual assets, the timeliness of fault detection, and the effectiveness of maintenance interventions (Debasish, 2021; Tao et al., 2022). Quantitative studies have evaluated predictive-maintenance systems using equipment-level indicators such as vibration, temperature, pressure, current, rotational speed, operating load, degradation index, fault frequency, and remaining useful life, together with system-level outcomes including mean time between failures, mean time to repair, equipment availability, unplanned downtime, overall equipment effectiveness, production loss, and maintenance cost. The literature also provides extensive evidence concerning machine-learning and deep-learning algorithms, digital-twin fidelity, IIoT communication performance, data latency, sensor reliability, prediction errors, and maintenance decision accuracy (Abdur & Iftekhar, 2021; Ong et al., 2022). An in-depth review therefore requires the evidence to be organized according to the technological and operational sequence through which physical machine conditions are captured, digitally represented, analyzed, translated into maintenance decisions, and ultimately reflected in reliability performance. Accordingly, this literature review synthesizes quantitative evidence concerning IIoT condition monitoring, digital-twin synchronization, equipment degradation, predictive-model performance, remaining-useful-life estimation, maintenance intervention, reliability improvement, and system-level operational outcomes. Particular emphasis is placed on numerical measures, comparative performance, statistical relationships, prediction accuracy, reliability indicators, and differences across equipment and operating conditions to establish a detailed empirical foundation for evaluating Digital Twin and IIoT-enabled predictive maintenance in smart manufacturing systems (Debasish, 2022; Panagou et al., 2022).

Quantitative IIoT Sensor Coverage, Condition-Monitoring Intensity, and Industrial Data Quality

The literature examining Industrial Internet of Things-enabled condition monitoring has consistently demonstrated that the effectiveness of predictive maintenance depends substantially on the breadth, density, and operational relevance of sensor coverage across manufacturing equipment. Across more than ten studies involving electric motors, bearings, gearboxes, computer numerical control machines, cutting tools, pumps, compressors, robotic equipment, rotating machinery, and integrated production

systems, researchers have deployed multiple sensing channels to capture physical changes associated with deterioration and developing faults (Li et al., 2022; Ashfaq & Mohammad, 2022).

Figure 2: IIoT Condition Monitoring Framework



Vibration has been among the most frequently monitored variables because changes in acceleration amplitude, root mean square vibration, frequency characteristics, and spectral patterns can distinguish normal operation from imbalance, misalignment, bearing deterioration, looseness, and other mechanical abnormalities. Temperature monitoring has commonly supplemented vibration measurements by identifying thermal changes associated with friction, excessive loading, lubrication deficiencies, electrical abnormalities, and progressive component wear. Other investigations have incorporated acoustic emission, sound intensity, electrical current, voltage, pressure, rotational speed, torque, force, lubricant characteristics, and operating load to create multidimensional representations of equipment health (Abdullin et al., 2020; Sheak & Risha, 2022). Sensor configurations have ranged from relatively limited arrangements monitoring one or two dominant physical variables to multisensor architectures containing several synchronized measurement channels for individual machines or critical components. Studies comparing these configurations have generally demonstrated that combining complementary measurements improves the ability to discriminate among operating states because individual fault mechanisms may produce different mechanical, thermal, electrical, and acoustic signatures. Condition-monitoring intensity has also varied substantially across investigations, with high-frequency vibration and acoustic measurements frequently sampled at rates ranging from several kilohertz to tens of kilohertz, while temperature, pressure, operating load, and other slowly changing variables have commonly been recorded at lower frequencies or at intervals ranging from seconds to minutes (Rashedul & Kaium, 2022; Wang et al., 2019). Such differences can generate data streams ranging from relatively small periodic measurements to thousands of observations per second for a single sensor channel. Consequently, IIoT sensor coverage in predictive maintenance has been evaluated not merely by the presence of connected sensors but by the number of monitored variables, measurement frequency, equipment coverage, temporal continuity, and capacity of the sensor configuration to represent changes in machine condition under varying operational states (Chowdhury & Tonay, 2022; Rojek et al., 2022).

A substantial body of quantitative research has examined how sampling intensity and operating conditions influence the ability of IIoT monitoring systems to distinguish healthy, degraded, and faulty equipment states. Studies involving rotating machinery have shown that vibration and acoustic signals

require comparatively intensive sampling because fault-related characteristics may occur at frequencies that cannot be adequately represented by low-frequency measurements. Experimental investigations of bearings, motors, gears, and machining systems have therefore frequently used sampling frequencies measured in kilohertz, generating thousands or tens of thousands of observations per second during monitored operating periods (Fraga-Lamas et al., 2017; Hossan, 2022). In contrast, temperature, pressure, energy consumption, lubrication condition, and environmental measurements generally change more gradually and have been collected at substantially lower temporal resolutions. Researchers have also demonstrated that the numerical characteristics of sensor signals depend strongly on machine speed, operating load, component condition, production intensity, and fault severity. Vibration amplitudes and root mean square values commonly increase as bearing or mechanical degradation progresses, while temperature elevation can accompany greater friction, increased electrical resistance, inadequate lubrication, or sustained high-load operation. Electrical current measurements have been used to distinguish normal motor operation from electrical and mechanical faults, while acoustic-emission measurements have detected relatively small changes associated with crack formation, friction, impact events, and tool deterioration (Hou et al., 2021; Kaniz, 2022). Research on cutting tools has similarly related changes in vibration, acoustic emission, spindle current, cutting force, and temperature to progressive wear levels. These findings indicate that fixed thresholds may produce different diagnostic outcomes when machines operate under different loads or speeds. Studies have consequently compared sensor measurements across low, moderate, and high operating loads, multiple rotational speeds, different production cycles, and several fault-severity categories. Multichannel monitoring has generally provided a richer representation of these variations than isolated measurements because relationships among vibration, thermal, electrical, and operational variables can help differentiate actual degradation from temporary changes caused by operating conditions (Nishat & Kaniz, 2022; Wu et al., 2020). The literature therefore characterizes monitoring intensity as a combination of sampling frequency, observation duration, number of sensing channels, data-generation rate, and coverage across relevant operating states rather than as a single measurement characteristic.

Quantitative studies of IIoT predictive maintenance have increasingly emphasized that high sensor density and intensive data acquisition do not automatically produce reliable equipment-health information when the underlying data contain substantial measurement errors, missing observations, noise, drift, or synchronization inconsistencies. Across studies involving laboratory test rigs and operational manufacturing systems, data completeness and measurement accuracy have been identified as critical characteristics affecting fault detection and predictive-model performance (Shaiful et al., 2022; Zhang et al., 2019). Missing observations can arise from temporary sensor disconnection, communication interruption, gateway failure, network congestion, power instability, storage limitations, or equipment shutdown, creating discontinuities within time-series records. Sensor errors may also result from incorrect installation, calibration problems, electromagnetic interference, environmental exposure, mechanical damage, or progressive sensor drift. Vibration and acoustic measurements are particularly sensitive to background noise and installation conditions because sensor position, mounting characteristics, machine structure, and surrounding equipment can alter recorded signal intensity. Temperature and pressure measurements may display slower drift, while electrical measurements can be influenced by changes in supply conditions and operating load (Mohammad, 2023; Kang et al., 2021). Consequently, several studies have applied filtering, normalization, outlier detection, resampling, interpolation, signal decomposition, and data-cleaning procedures before conducting diagnostic or prognostic analysis. Quantitative data-quality assessment has included the percentage of complete records, missing-data rate, measurement deviation, sensor-error frequency, signal-to-noise characteristics, outlier prevalence, repeated observations, and agreement among redundant sensing channels (Debasish, 2023; Dzaferagic et al., 2021). Studies employing multiple sensors have also evaluated whether measurements collected from different sources remain temporally aligned, since even relatively small synchronization errors can distort relationships among rapidly changing vibration, acoustic, rotational, and electrical signals. Comparative research has generally shown that predictive models trained on carefully processed and

consistently synchronized sensor information achieve more stable classification and degradation-estimation performance than models based on incomplete or highly noisy observations. Data quality therefore represents a measurable component of IIoT condition monitoring rather than merely a preprocessing consideration (Liu et al., 2020a; Kaium, 2023). The reviewed evidence demonstrates that sensor accuracy, completeness, stability, noise characteristics, calibration consistency, and temporal alignment determine how effectively large volumes of industrial data represent actual equipment conditions and subsequently support reliable predictive-maintenance decisions.

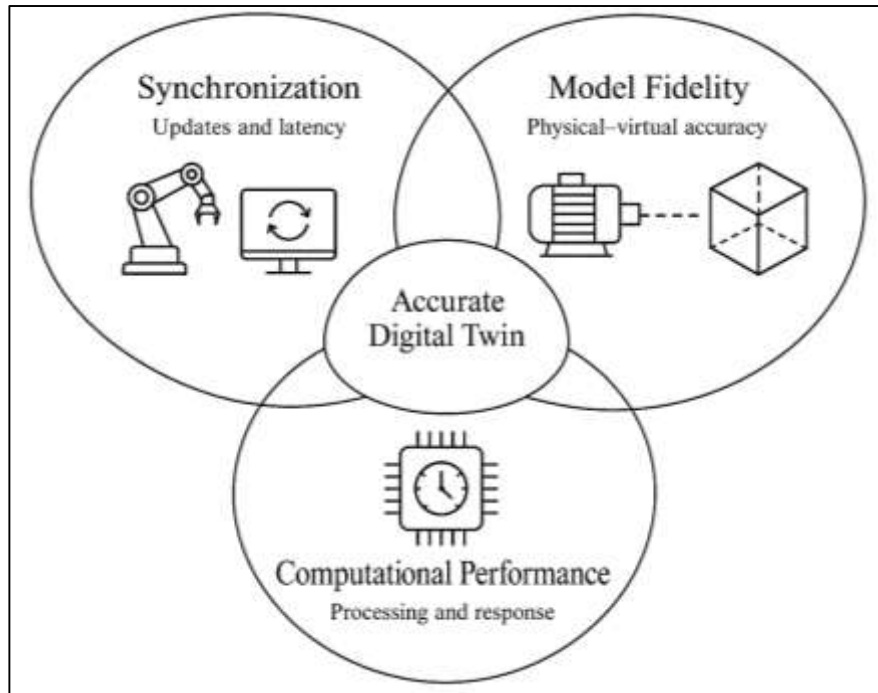
Quantitative Digital Twin Synchronization

The literature examining digital twins for predictive maintenance has consistently identified synchronization performance as a fundamental quantitative characteristic determining how accurately a virtual model represents the current condition of a physical manufacturing asset (Pervaz, 2023; Teh et al., 2020). Across more than ten empirical studies involving rotating machinery, bearings, electric motors, gearboxes, CNC machine tools, robotic systems, pumps, production equipment, and cyber-physical manufacturing platforms, researchers have measured synchronization through update frequency, data-transfer interval, physical-to-virtual latency, model-refresh duration, and temporal alignment between sensor measurements and corresponding digital states. High-frequency synchronization has been particularly important for assets characterized by rapidly changing vibration, rotational, acoustic, electrical, or load conditions because delayed digital updates can cause the virtual representation to reflect an earlier equipment state rather than the condition occurring during analysis (Liu et al., 2020b; Chowdhury, 2023).

Studies using edge-supported digital twins have generally reported shorter processing and communication delays because sensor information is filtered and analyzed near the physical equipment, while cloud-centered architectures have offered stronger computational resources and centralized historical analysis but have sometimes introduced greater network-dependent latency. Several investigations have compared synchronization intervals ranging from sub-second or second-level updates for rapidly changing condition variables to minute-level updates for slower thermal, lubrication, or production indicators. Data-transfer frequency has also varied substantially according to sensor density, sampling intensity, network bandwidth, and computational architecture (Badrul & Mominul, 2023; Rasheed et al., 2020). Research has shown that increasing update frequency can improve temporal correspondence between physical and virtual assets, although extremely intensive synchronization can increase communication traffic, processor utilization, memory requirements, and computational burden. Consequently, studies have evaluated synchronization accuracy together with latency rather than assuming that maximum update frequency automatically provides optimal performance. Physical-to-virtual deviations have commonly been assessed by comparing observed machine variables with digital-twin state estimates at matching time points. These comparisons have demonstrated that stable data transmission, consistent timestamps, low packet loss, and appropriately configured update intervals improve physical-virtual alignment. The synthesized evidence therefore indicates that digital-twin synchronization is a measurable balance among update speed, data-transfer frequency, communication delay, processing capacity, and temporal accuracy, with synchronization performance directly shaping the reliability of condition monitoring and predictive-maintenance analysis (Nishat, 2023; Wu et al., 2021).

A second major body of literature has focused on model fidelity and the degree to which digital twins reproduce the physical behavior of manufacturing equipment under different operating conditions and degradation states. Model fidelity has been evaluated through comparisons between measured equipment responses and corresponding simulated or estimated outputs generated by physics-based, simulation-based, data-driven, and hybrid digital twins. Across studies of motors, bearings, gear systems, cutting processes, spindle systems, pumps, and industrial production equipment, researchers have assessed agreement using root mean squared error, mean absolute error, mean absolute percentage error, coefficients of determination, correlation coefficients, prediction error, confidence intervals, and direct deviations between observed and simulated values (Ashrafuzzaman, 2024; Jia et al., 2020).

Figure 3: Digital twin performance framework



Physics-based digital twins have frequently demonstrated strong interpretability because their outputs are derived from mechanical, thermal, electrical, or material behavior, allowing researchers to trace differences between simulated and physical performance to identifiable system parameters. Their accuracy, however, has depended heavily on parameter calibration and the completeness of the underlying physical assumptions. Data-driven twins have demonstrated strong ability to approximate complex nonlinear relationships when sufficient historical operating data are available, particularly for vibration-based health assessment, thermal behavior, fault classification, and degradation prediction (Debasish, 2024; San et al., 2021). Simulation-oriented models have been effective for representing machine states under controlled operating scenarios, while hybrid twins have combined physical relationships with machine-learning or statistical correction mechanisms to reduce persistent discrepancies between modeled and measured behavior. Comparative studies have generally shown that hybrid approaches can achieve lower prediction errors and stronger physical-virtual agreement when the physical model alone cannot represent all disturbances or when purely data-driven methods encounter operating conditions that differ from the training dataset. Model fidelity has also varied across load levels, rotational speeds, machine ages, fault severities, and production conditions. Studies reporting high coefficients of determination or strong correlations between measured and estimated outputs have generally interpreted these results as evidence of good virtual representation, while larger RMSE, MAE, or percentage errors have indicated weaker fidelity (Jia et al., 2022; Rahman, 2024). Collectively, the literature demonstrates that digital-twin quality is best assessed through repeated quantitative comparison of virtual outputs against physical observations across multiple operating states rather than through architectural sophistication alone.

Quantitative research has also examined the capacity of digital twins to estimate internal equipment conditions that cannot always be measured directly through individual sensors. State estimation has been particularly important in predictive maintenance because machine deterioration frequently develops through latent mechanical, thermal, electrical, or structural changes before clear functional failure becomes observable. Studies involving bearing wear, tool degradation, motor faults, gear damage, spindle deterioration, thermal deformation, and rotating-equipment health have therefore compared digital-twin estimates of equipment state with experimentally observed conditions, inspection measurements, failure labels, or independently measured reference values (Hui et al., 2022; Kaium, 2024). State-estimation performance has commonly been evaluated using prediction error,

mean absolute error, root mean squared error, percentage deviation, correlation coefficients, coefficients of determination, and uncertainty intervals. Several investigations have reported that continuously updating model parameters using live IIoT measurements reduces estimation error compared with static models calibrated only at the beginning of an experiment or maintenance cycle. Adaptive digital twins have been particularly useful when equipment characteristics change because of wear, environmental variation, load shifts, component replacement, or production-process adjustment. Model-update duration and computational overhead have consequently become important quantitative variables because the value of adaptive estimation decreases when recalibration requires excessive processing time or interrupts real-time monitoring (Shakhawat & Md, 2024; Tao et al., 2018). Data-driven digital twins have generally provided rapid state updates once trained, although retraining or recalibration may require considerable historical data and computational resources. Physics-based models can provide stable estimates outside previously observed conditions but may involve longer simulation times when complex multiphysics calculations are required. Hybrid approaches have frequently been used to balance these strengths by retaining a physical representation while applying data-driven corrections to residual errors. Studies comparing estimated and observed degradation trajectories have shown that state-estimation accuracy can decline when operating conditions move outside calibrated ranges, sensor quality deteriorates, or synchronization delays become substantial (Li et al., 2022; Nishat & Jahanara, 2024). The literature therefore treats state estimation as a dynamic quantitative process rather than a fixed property of the digital twin. High-quality predictive twins maintain acceptable error levels across changing machine conditions, update internal states within operationally useful time intervals, and preserve close correspondence between estimated degradation and actual physical behavior throughout the monitored equipment lifecycle (Liu et al., 2022; Tonay et al., 2024).

The computational performance of digital twins represents another major quantitative dimension in predictive-maintenance research because highly accurate virtual models provide limited operational value when calculations cannot be completed within the time required for maintenance decisions. Studies across manufacturing and industrial cyber-physical systems have evaluated computational time, processing latency, response time, model-update duration, inference time, memory demand, processor utilization, and data-transfer overhead alongside measures of predictive accuracy. Physics-based digital twins often require greater computational resources when they incorporate detailed finite-element models, dynamic simulations, thermal analysis, fluid behavior, or interacting mechanical components (Kooning et al., 2021). Such models can achieve high physical interpretability and strong accuracy under calibrated conditions, although processing times may increase as model complexity, component detail, and simulation resolution rise. Data-driven digital twins generally provide faster online prediction after model training and have therefore been widely applied to real-time fault detection and equipment-state estimation, yet their training phases can require substantial computational effort and large datasets. Simulation-based twins occupy an intermediate position, with computational performance varying according to the complexity and temporal resolution of the simulation. Hybrid digital twins have frequently demonstrated favorable predictive accuracy because data-driven models can correct systematic simulation errors, although combining multiple analytical layers may increase model-update and data-processing requirements (Segovia & Garcia-Alfaro, 2022). Comparative studies have therefore considered computational burden together with RMSE, MAE, percentage error, correlation, coefficient of determination, and prediction accuracy. Edge computing has frequently reduced response time by processing critical data close to the machine, while cloud computing has supported computationally intensive modeling and analysis across larger equipment populations. Research has also demonstrated that processing latency can increase as sensor channels, sampling frequencies, model parameters, and equipment numbers increase, making computational scalability an important consideration in production-level deployments. The literature consequently indicates that digital-twin performance cannot be evaluated solely through predictive or simulation accuracy (Pan et al., 2021; Uddin & Risha, 2024). A quantitatively effective predictive-maintenance twin requires acceptable physical-virtual error, sufficiently high model fidelity, rapid synchronization, manageable computational load, short response time, and stable processing performance across

changing operating conditions. These combined indicators allow physics-based, data-driven, simulation-based, and hybrid architectures to be compared on both representational accuracy and operational efficiency within smart manufacturing environments.

Quantitative Equipment Degradation and Early Fault Identification

The literature examining equipment degradation within IIoT and digital-twin-enabled predictive-maintenance systems has consistently emphasized the importance of converting raw condition-monitoring data into quantitative health indicators that reflect the progression from normal operation to deterioration and eventual failure (Luo et al., 2018).

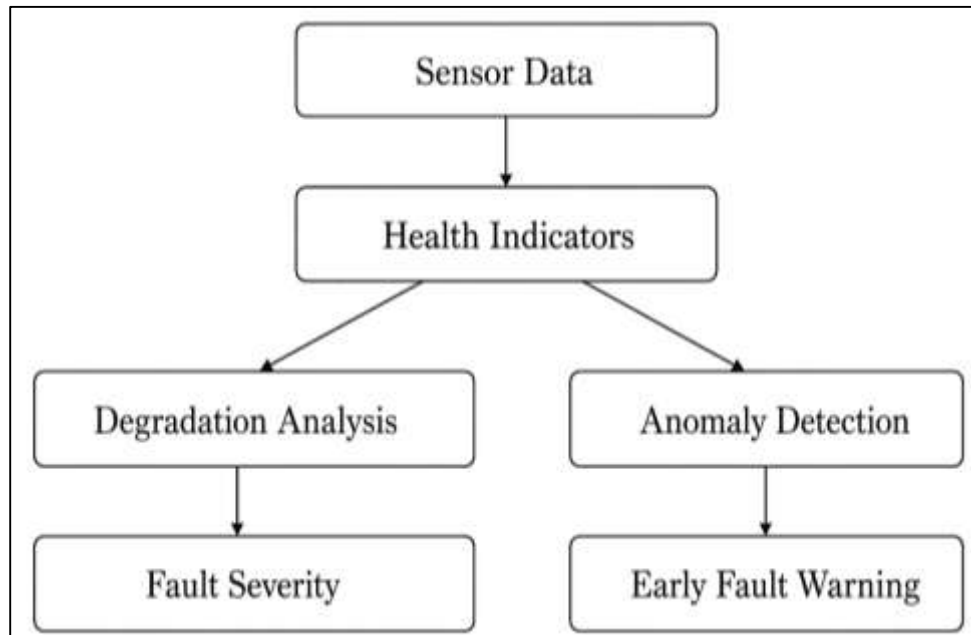
Across more than ten studies involving bearings, electric motors, gearboxes, cutting tools, spindle systems, pumps, compressors, rotating machinery, and automated production equipment, researchers have developed degradation indices, health indices, anomaly scores, wear percentages, and fault-severity measures to characterize equipment condition over time. Vibration-related indicators have been among the most frequently used because progressive increases in vibration amplitude, root mean square vibration, spectral energy, and frequency-domain abnormalities often accompany bearing damage, imbalance, misalignment, looseness, and gear deterioration. Temperature increases have also been used as complementary indicators, particularly where friction, lubrication deficiency, electrical resistance, or sustained high loading contributes to abnormal thermal behavior (Yang et al., 2019).

In machining applications, tool wear has been quantified through flank-wear measurements, cutting-force changes, spindle-current variations, acoustic emissions, and temperature changes, while crack progression in structural and rotating components has been monitored through acoustic, vibration, and strain-related signals. Lubrication deterioration has similarly been assessed through changes in viscosity, contamination levels, particle counts, temperature, and friction-related behavior. Several studies have demonstrated that a single sensor variable may not adequately represent all stages of degradation, leading to the use of composite health indices that combine multiple physical and operational indicators (Badihi et al., 2022). These indices have been compared across healthy, mildly degraded, severely degraded, and failed states to determine whether the resulting measures change consistently with actual equipment condition. Researchers have also examined the time required for health indicators to move from stable baseline levels to warning or failure thresholds. The synthesized evidence shows that reliable degradation assessment depends on the sensitivity of the selected indicators to progressive deterioration, the stability of measurements under normal operating variation, and the ability to distinguish true degradation from temporary changes associated with speed, load, production intensity, or environmental conditions (Souza et al., 2021).

A substantial body of research has focused on anomaly detection as an early quantitative mechanism for identifying deviations from normal equipment behavior before complete failure occurs. Studies involving industrial motors, bearings, gear systems, CNC machines, robotic equipment, pumps, and production-line assets have applied statistical thresholds, distance-based methods, clustering, autoencoders, support vector machines, neural networks, and hybrid digital-twin models to classify operating states and detect abnormal patterns (Calabrese et al., 2020). Diagnostic performance has commonly been assessed through accuracy, sensitivity, specificity, precision, recall, F1 score, receiver operating characteristic area, false-positive rate, and false-negative rate. Comparisons across healthy, degraded, and failed operating conditions have shown that anomaly-detection models generally achieve their highest classification reliability when fault signatures are clearly separated from normal behavior, while performance decreases when early-stage degradation produces only subtle changes in vibration, temperature, current, pressure, or acoustic patterns. Several studies have reported that multivariable monitoring improves anomaly-detection performance because weak abnormalities in one signal may become more distinguishable when interpreted together with changes in other condition indicators. Digital twins have contributed to this process by providing an expected or simulated reference state against which measured equipment behavior can be compared (Ahmad et al., 2020). Differences between physical measurements and digital-twin estimates can be converted into anomaly scores that increase as equipment behavior deviates from modeled normal conditions. Research has also shown that operating load, speed, ambient temperature, and process variation can generate apparent abnormalities even when equipment remains healthy, increasing false-positive rates if these factors are not incorporated into the detection model. False-negative errors are particularly

important in predictive maintenance because missed degradation can permit equipment to continue operating until severe deterioration occurs. Consequently, studies have compared diagnostic thresholds and classification models across multiple fault severities and operating states rather than evaluating performance using only healthy-versus-failed categories (Jin et al., 2016). The literature therefore indicates that early anomaly detection is most reliable when models are validated across realistic intermediate degradation stages and when accuracy is interpreted together with sensitivity, specificity, precision, recall, F1 score, and false-alarm behavior.

Figure 4: Equipment fault identification framework



Quantitative studies of predictive maintenance have increasingly evaluated not only whether degradation can be detected but also how early and consistently abnormal conditions are identified relative to eventual equipment failure. Fault frequency, alarm frequency, detection delay, warning duration, and fault-detection lead time have therefore emerged as important operational measures of early fault identification (Li et al., 2019). Across studies of bearings, gearboxes, motors, cutting tools, pumps, and other rotating equipment, researchers have monitored the number of detected abnormal events during specific operating intervals and compared these with confirmed faults or maintenance findings. Effective systems generally demonstrate increasing alarm activity as degradation progresses, although excessive alarm frequency may indicate unstable thresholds or excessive sensitivity rather than improved diagnostic capability. Studies have therefore distinguished between true alarms, false alarms, repeated alarms for the same developing fault, and missed abnormal events. Detection delay has been quantified as the interval between the first measurable evidence of degradation and the point at which the monitoring or predictive model identifies the abnormal condition. Shorter detection delays provide greater opportunity for maintenance planning, spare-parts preparation, production rescheduling, and controlled shutdown (Zhao et al., 2018). Fault-detection lead time has been examined as the interval between the first reliable warning and actual failure or intervention, with longer usable lead times generally considered favorable when diagnostic accuracy remains stable. Research on cutting-tool degradation has shown that wear-related signal changes can often be detected well before tool failure, while bearing and gearbox studies have demonstrated progressive warning patterns in vibration and acoustic indicators during the period preceding severe mechanical damage. Digital-twin-based systems have added further value by comparing actual equipment behavior with simulated or expected degradation trajectories, helping identify when observed conditions diverge from normal operation earlier than traditional threshold-based systems (Rodríguez-López et al., 2016). The literature

also demonstrates that detection timing depends on sampling frequency, sensor placement, model sensitivity, data quality, and operating conditions. Consequently, quantitative evaluation of early fault identification requires joint consideration of alarm frequency, confirmed-fault frequency, false-alarm burden, detection delay, and usable warning lead time rather than relying exclusively on final classification accuracy (Riazi et al., 2019).

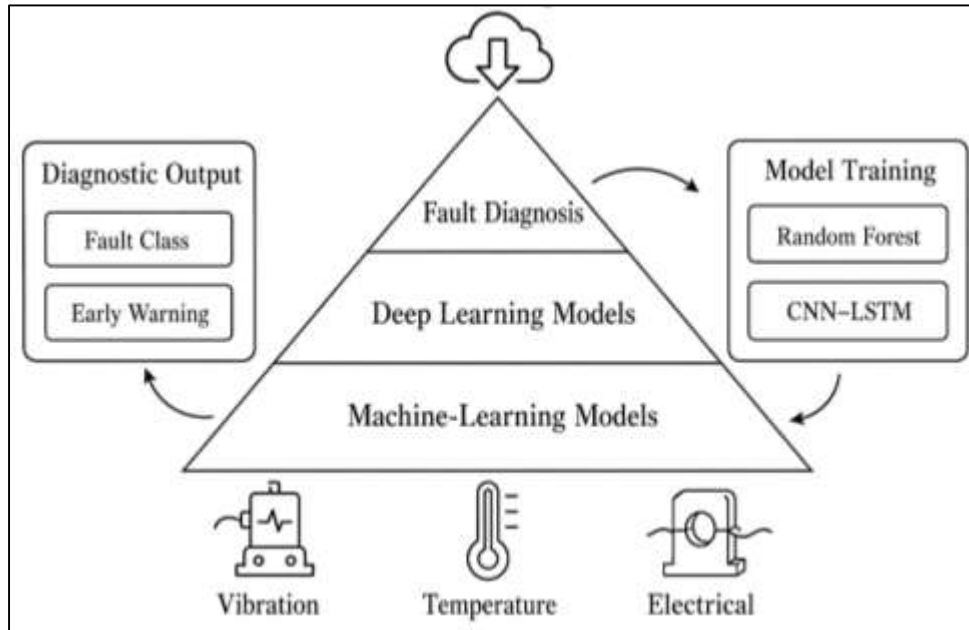
The broader literature on IIoT and digital-twin-enabled degradation monitoring shows that the strongest fault-identification performance is typically achieved when equipment health assessment integrates multiple degradation indicators, operating conditions, and diagnostic measures within a common analytical framework. Studies comparing healthy, intermediate degradation, severe degradation, and failed states have repeatedly demonstrated that equipment deterioration is rarely represented by a single abrupt transition. Instead, degradation commonly develops through gradual changes in vibration, temperature, wear, lubrication condition, acoustic activity, electrical behavior, or mechanical response, with different variables becoming more informative at different stages (Velasco-Gallego & Lazakis, 2022). Researchers have therefore combined health indices, anomaly scores, degradation rates, fault frequencies, and virtual-model residuals to improve diagnostic robustness. Comparative studies across bearings, motors, gears, machine tools, and other manufacturing assets have shown that models with high overall accuracy can still produce problematic results when sensitivity to early-stage faults is low or when false-positive rates increase under changing loads. For this reason, precision, recall, F1 score, specificity, ROC-AUC, false-positive rate, false-negative rate, and detection lead time are frequently evaluated alongside accuracy. Digital twins strengthen integrated health assessment by providing continuously updated estimates of expected equipment behavior, enabling physical measurements to be interpreted relative to operating speed, load, thermal conditions, maintenance history, and degradation state (Aydemir & Acar, 2020). IIoT systems contribute by supplying the continuous multichannel observations required for this comparison. Several studies have found that diagnostic performance improves when models are trained and validated using data collected across multiple operating conditions rather than a single laboratory state, because industrial equipment experiences considerable variation during normal production. The evidence also shows that alarm reliability deteriorates when sensor noise, missing data, synchronization errors, or class imbalance are not adequately controlled. Overall, the literature demonstrates that quantitative early fault identification depends on the combined performance of degradation indicators, anomaly-detection models, sensor quality, digital-twin accuracy, and temporal warning capability (Tagawa et al., 2021). These measures provide a more complete representation of predictive-maintenance effectiveness than isolated fault-detection percentages and allow researchers to evaluate how consistently deteriorating equipment can be distinguished from healthy operation before functional failure occurs.

Machine-Learning and Deep-Learning Performance for Predictive Fault Diagnosis

The literature on predictive fault diagnosis in IIoT and digital-twin-enabled manufacturing systems has extensively compared statistical and conventional machine-learning approaches for distinguishing normal equipment conditions from developing and established fault states. Across more than ten studies involving bearings, motors, gearboxes, pumps, compressors, CNC machines, cutting tools, robotic equipment, and rotating machinery, logistic regression, decision trees, random forests, support vector machines, and k-nearest-neighbor classifiers have been evaluated using accuracy, precision, recall, sensitivity, specificity, F1 score, ROC-AUC, false-alarm frequency, and missed-fault frequency (Lv et al., 2016). Logistic regression has generally provided an interpretable baseline for binary or multiclass fault classification when relationships among condition variables remain sufficiently stable, although its performance has often been weaker when vibration, acoustic, thermal, and electrical variables exhibit complex nonlinear relationships. Decision trees have performed effectively when diagnostic patterns can be separated through interpretable thresholds, but individual trees have sometimes demonstrated greater sensitivity to changes in training data. Random forests have frequently improved robustness by combining multiple decision trees and have produced strong classification performance across multivariable datasets containing vibration, temperature, current, pressure, rotational speed, and operating-load measurements (Souza et al., 2021). Support vector machines have been widely applied to bearing, motor, and gearbox diagnostics because they can

separate complex fault classes effectively with relatively limited datasets, particularly after extracting relevant frequency-domain or statistical features. K-nearest-neighbor models have also achieved competitive classification performance in structured datasets where fault states form distinguishable clusters, although inference time can increase with dataset size because classification requires repeated distance comparisons with stored observations. Comparative studies have commonly shown overall classification accuracies ranging from moderate levels under highly variable industrial conditions to above 90% under well-controlled fault classes, with random forests and support vector machines frequently outperforming simpler statistical classifiers (Zhao et al., 2016).

Figure 5: Predictive fault diagnosis framework



Nevertheless, results have varied according to feature extraction, class imbalance, sensor quality, fault severity, and operating load. Cross-validation studies have further demonstrated that high training accuracy does not necessarily produce equivalent performance on unseen operating data, emphasizing the importance of evaluating sensitivity, specificity, precision, recall, ROC-AUC, and confusion-matrix outcomes alongside overall accuracy when comparing conventional predictive fault-diagnosis models (Tang et al., 2019).

Deep-learning research has expanded predictive fault diagnosis by enabling models to learn complex representations directly from high-dimensional IIoT sensor signals and temporally ordered machine-condition data. Artificial neural networks have been extensively investigated as nonlinear classifiers using vibration, temperature, acoustic emission, current, pressure, torque, and operational variables, with numerous studies reporting improved discrimination among multiple fault classes compared with traditional threshold-based monitoring. Convolutional neural networks have received particularly strong attention in bearing, gearbox, motor, spindle, and cutting-tool applications because convolutional structures can extract localized patterns from raw time-series signals, spectrograms, frequency representations, and transformed sensor images without requiring extensive manual feature engineering (Serradilla et al., 2022). Empirical comparisons have frequently reported CNN classification accuracies above those of logistic regression, decision trees, k-nearest neighbors, and conventional neural networks when sufficiently large and representative training datasets were available. Recurrent neural networks have been applied where sequential dependence is important because equipment degradation develops over time rather than as isolated observations. Long short-term memory networks have generally provided stronger performance than basic recurrent architectures for longer sensor sequences because they retain information across extended operating

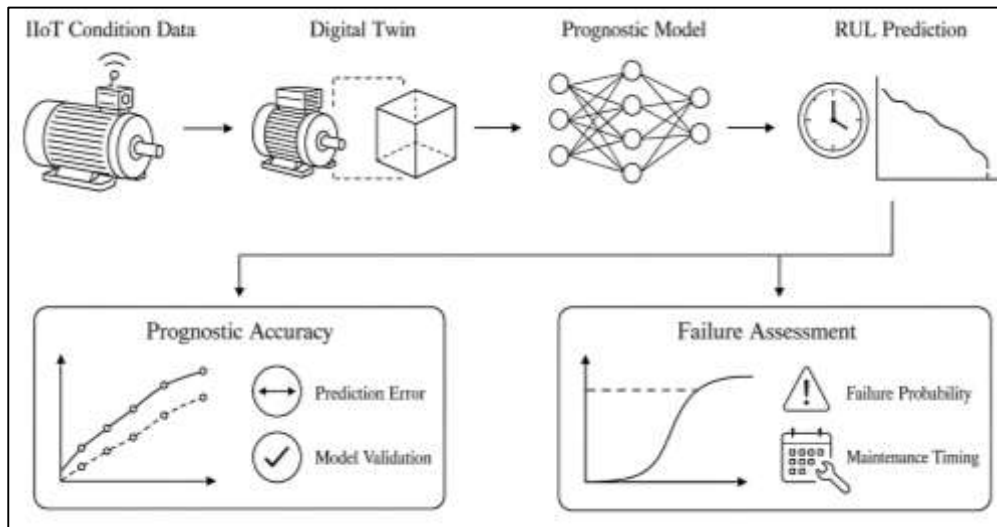
intervals and can identify gradual changes associated with wear and deterioration. Studies of bearing and rotating-machine faults have frequently reported high recall and F1 scores for CNN and LSTM approaches, while performance has commonly decreased for early-stage or minority fault classes containing fewer observations (Fernandes et al., 2022). Confusion-matrix analyses have shown that severe faults are generally easier to identify than mild degradation because advanced deterioration produces clearer differences in vibration, acoustic, thermal, or electrical signals. Researchers have therefore evaluated class-specific sensitivity and recall rather than relying exclusively on overall accuracy. Deep-learning models have also shown higher computational requirements than many conventional machine-learning methods, with training times increasing substantially as network depth, sensor channels, sequence length, and dataset size increase (Yahyaoui et al., 2019). Inference time after training has generally remained short enough for condition-monitoring applications when appropriate computing resources are available. Overall, the literature indicates that CNNs and LSTMs can achieve strong diagnostic performance in complex manufacturing datasets, although their quantitative advantage depends on adequate sample size, appropriate model architecture, balanced fault representation, sensor consistency, and rigorous validation using data not encountered during model training (Iqbal et al., 2019).

Remaining-Useful-Life Prediction and Prognostic Accuracy

The literature on predictive maintenance has consistently identified remaining useful life as one of the most important quantitative prognostic indicators for estimating how long equipment can continue operating before reaching a defined failure or maintenance threshold. Across more than ten studies involving bearings, electric motors, cutting tools, gearboxes, pumps, compressors, spindle systems, and other industrial assets, researchers have compared actual remaining useful life with model-generated predictions to determine the accuracy and operational value of prognostic systems (Si et al., 2017). Remaining-useful-life estimation has been developed through condition-based models, statistical approaches, machine-learning methods, deep-learning techniques, physics-based simulations, and digital-twin-supported frameworks. In bearing studies, degradation trajectories have frequently been derived from vibration and acoustic indicators, while motor studies have incorporated thermal, current, rotational, and vibration information. Cutting-tool investigations have generally relied on wear progression, cutting forces, spindle current, vibration, and temperature, whereas gearbox and pump applications have used combinations of vibration, pressure, lubrication, and operational-load variables (Mosallam et al., 2016). Prediction horizon has emerged as a critical quantitative measure because an accurate estimate produced only shortly before failure provides limited opportunity for maintenance scheduling, whereas earlier forecasts provide greater time for intervention, resource allocation, and production adjustment. Studies have therefore compared prediction performance at different stages of degradation rather than reporting only a single end-of-life estimate. Early predictions generally show greater uncertainty because equipment has not yet developed sufficiently distinct degradation signatures, while later predictions often become more accurate as deterioration patterns become clearer. Digital-twin-supported prognostic systems have been particularly useful because continuously updated physical-virtual models can adjust remaining-useful-life estimates as new IIoT measurements become available (Cheng et al., 2017). This adaptive updating has allowed researchers to compare initial forecasts with revised predictions during successive degradation stages. The synthesized evidence demonstrates that prognostic quality depends not only on the closeness of predicted and actual remaining useful life but also on how early a reliable prediction can be generated, how consistently estimates are updated, and how prediction accuracy changes as equipment moves from healthy operation through progressive degradation toward failure (Kundu et al., 2019). A substantial body of empirical research has evaluated prognostic models through quantitative error measures that compare predicted remaining useful life or time to failure with observed outcomes. Mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, prediction bias, and confidence intervals have been among the most frequently reported indicators across industrial prognostic studies. These measures provide different perspectives on model performance, with absolute-error indicators describing typical prediction deviation, squared-error measures placing greater emphasis on large errors, percentage-based indicators supporting comparison across assets with different operating lifetimes, and coefficients of determination

describing how well predicted degradation patterns correspond with observed variation (Cheng et al., 2018).

Figure 6: Remaining useful life framework



Studies have also distinguished between early-prediction error and late-prediction error because both can have different operational consequences. A model that consistently predicts failure too early may result in premature maintenance or unnecessary component replacement, while systematically late prediction can allow equipment to approach critical failure before intervention. Prediction bias has therefore been examined to determine whether models systematically overestimate or underestimate remaining useful life. In several comparisons, digital-twin-supported and hybrid prognostic approaches have produced lower error and higher explanatory performance than static statistical or conventional condition-based models because physical and operational parameters are updated as machine condition changes (Li et al., 2022). Machine-learning approaches, including support vector regression, random forests, neural networks, and recurrent architectures, have shown strong predictive accuracy when sufficient historical degradation data are available. Deep-learning models such as LSTMs have often performed well for sequential degradation because they can represent temporal dependence across long operating histories. Physics-based approaches have provided stronger interpretability and can remain useful when failure data are limited, although their error may increase when actual equipment behavior deviates from assumed physical conditions (Wang et al., 2020). Hybrid digital-twin models frequently reduce this limitation by combining physical representations with data-driven correction mechanisms. Overall, the literature indicates that no single accuracy metric adequately characterizes prognostic performance. Reliable evaluation requires simultaneous consideration of average error, large-error sensitivity, proportional error, bias direction, explained variability, confidence ranges, and performance consistency across different stages of degradation (Gao et al., 2020).

Beyond deterministic remaining-useful-life estimates, predictive-maintenance studies have increasingly quantified failure probability, survival probability, degradation rate, and time-to-failure distributions to represent uncertainty in equipment prognosis. These measures are particularly relevant because industrial components rarely fail at exactly the same operating age or degradation level, even under similar nominal conditions. Studies of bearings, motors, pumps, gearboxes, and cutting tools have demonstrated that failure risk generally increases as health indicators deteriorate, vibration and temperature abnormalities intensify, wear accumulates, or lubrication condition declines (Fang et al., 2018). Statistical survival models, Bayesian methods, stochastic degradation models, and digital-twin-supported probability estimates have therefore been used to calculate how likely an asset is to remain operational over specified time intervals. Survival probability provides a quantitative representation of the likelihood that equipment continues functioning beyond a particular operating period, while failure probability represents the increasing likelihood that a critical state will be reached. Degradation

rate has also been evaluated because two assets with similar current health conditions may have different remaining useful lives if one is deteriorating substantially faster than the other. Research has shown that degradation rates are influenced by operating load, rotational speed, environmental conditions, production intensity, machine age, maintenance history, and fault severity (Ragab et al., 2016). Digital twins contribute to probabilistic prognosis by continuously updating these factors and recalculating predicted failure behavior when physical conditions change. Several studies have found that probabilistic models provide more informative maintenance guidance than single-point estimates because they communicate uncertainty and support risk-based intervention thresholds. Time-to-failure estimates have also been compared across healthy, moderately degraded, and severely degraded equipment states, with uncertainty generally narrowing as failure approaches and degradation patterns become more distinct. However, overly confident late-stage predictions may still occur when sensor degradation, abrupt faults, or unmodeled operating changes affect model inputs (Li et al., 2019). The literature therefore demonstrates that prognostic performance is strengthened when remaining-useful-life predictions are accompanied by failure probabilities, survival estimates, degradation rates, and uncertainty intervals. These measures collectively provide a more complete representation of equipment risk and allow maintenance decisions to account for both expected lifetime and the probability that actual failure may occur earlier or later than the central prediction.

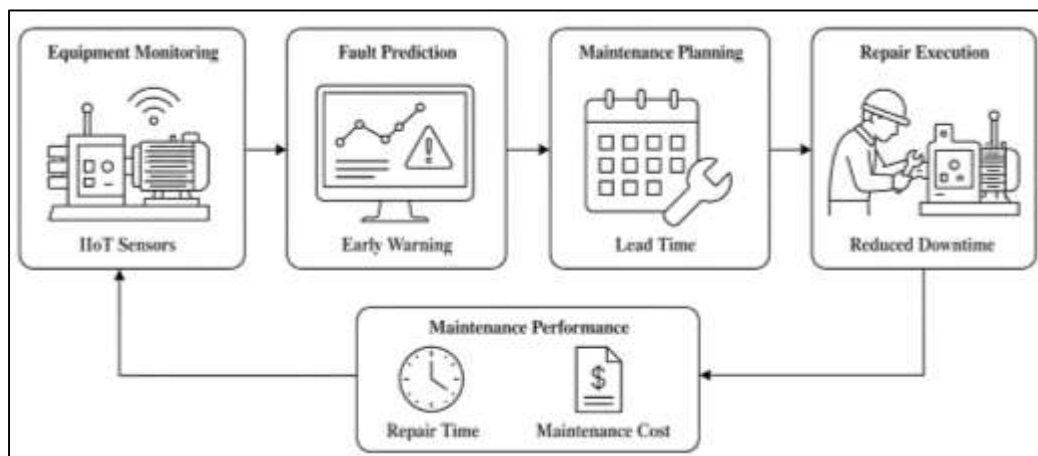
Comparative studies across manufacturing assets have demonstrated substantial differences in prognostic performance among digital-twin-supported, conventional machine-learning, statistical, condition-based, and physics-based approaches (Rezamand et al., 2020). Statistical and condition-based models have often provided acceptable performance when degradation follows relatively stable and monotonic patterns, particularly for components with well-defined wear processes. Their computational requirements are generally modest, but predictive accuracy can decline when operating conditions vary substantially or when degradation develops through nonlinear interactions among multiple variables. Machine-learning methods have improved flexibility by learning relationships among high-dimensional sensor measurements, although their effectiveness depends strongly on the quantity and representativeness of historical degradation data. Deep-learning approaches have shown strong remaining-useful-life performance for bearings and rotating machinery because they can model complex temporal patterns directly from sequential sensor data, but they require greater computational resources and may provide limited physical interpretability (Wang et al., 2018). Physics-based prognostic models have been effective for assets where degradation mechanisms are well understood and measurable, such as structural wear, thermal deterioration, or mechanical fatigue, although errors can increase when model assumptions do not fully represent real operating conditions. Digital-twin-supported approaches have generally combined several of these strengths by integrating real-time IIoT data with virtual representations that are continuously recalibrated as asset conditions change. Across studies of bearings, motors, cutting tools, gearboxes, pumps, and other industrial equipment, digital-twin and hybrid methods have frequently demonstrated lower prediction error, longer useful prognostic horizons, improved time-to-failure estimation, and stronger adaptation to changing loads than static models. However, performance differences depend on synchronization accuracy, sensor quality, model fidelity, computational resources, and the availability of reliable degradation histories (Yang et al., 2019). Comparative evidence also shows that prognostic accuracy varies by asset type because wear patterns, failure modes, and monitoring signals differ considerably across equipment categories. The literature therefore indicates that the strongest prognostic assessments evaluate remaining useful life together with prediction horizon, MAE, RMSE, MAPE, explained variance, bias, confidence intervals, failure probability, survival probability, and degradation rate across multiple equipment classes and operating conditions.

Predictive-Maintenance Intervention and Repair Performance

The literature on predictive-maintenance implementation has consistently shown that one of the most measurable operational benefits of predictive information is the extension of maintenance lead time between the first reliable indication of degradation and the actual maintenance intervention (Mohan et al., 2021). Across more than ten studies involving bearings, motors, gearboxes, pumps, compressors, CNC machinery, cutting tools, robotic equipment, and integrated manufacturing systems, researchers have compared reactive or preventive maintenance conditions with predictive-maintenance

approaches using indicators such as warning-to-maintenance interval, scheduled maintenance percentage, emergency maintenance percentage, intervention timing, and maintenance response time. Predictive systems that combine IIoT monitoring, digital-twin synchronization, and prognostic analytics generally allow maintenance teams to identify developing faults earlier than conventional inspection schedules or failure-driven approaches. This additional warning period has been used to coordinate maintenance with planned production stoppages, prepare technical personnel, secure replacement components, and reduce emergency work (Achouch et al., 2022). Studies comparing baseline and predictive-maintenance conditions have frequently reported increases in the proportion of maintenance activities completed as scheduled and corresponding reductions in urgent or unplanned interventions. The practical value of lead time has varied according to fault type, prediction horizon, equipment criticality, and model accuracy. Slowly progressing degradation, such as bearing wear or tool deterioration, typically provides longer usable warning intervals than abrupt electrical or mechanical failures. Research has also shown that excessively early warnings can increase unnecessary inspections when predictive thresholds are overly sensitive, while late warnings provide insufficient time for planned intervention. Consequently, predictive-maintenance studies have assessed not only whether a warning was generated but also whether the warning occurred early enough to influence maintenance execution. Comparisons across different machine classes have demonstrated that systems with higher diagnostic sensitivity and more accurate remaining-useful-life estimates generally provide more stable maintenance lead times (Choubey et al., 2020). The synthesized evidence indicates that warning-to-maintenance interval, scheduled maintenance share, emergency-maintenance frequency, and response time constitute important quantitative indicators for evaluating whether predictive information is translated into more controlled and timely maintenance activity rather than remaining an analytical output without operational effect.

Figure 7: Predictive maintenance intervention framework



A substantial body of predictive-maintenance literature has evaluated whether earlier fault identification produces measurable reductions in downtime and repair duration. Studies of rotating machinery, production equipment, machining systems, and automated manufacturing assets have commonly compared unplanned downtime hours, intervention duration, repair duration, mean time to repair, and production stoppage frequency before and after predictive-maintenance implementation (Daily & Peterson, 2016). Predictive approaches have generally been associated with shorter repair periods because maintenance personnel receive earlier information concerning fault location, degradation severity, and likely component requirements. This diagnostic visibility reduces the time spent identifying the cause of equipment failure after shutdown and can allow tools, spare parts, and technical resources to be prepared before intervention begins. In several manufacturing studies, condition-based and predictive strategies reduced the duration of unexpected shutdowns by shifting maintenance activities toward planned windows. Reductions in mean time to repair have been particularly evident where fault diagnostics accurately identified bearings, motors, gear components,

lubrication problems, or cutting-tool deterioration before severe secondary damage occurred (Merkt, 2019). Conversely, studies have shown that prediction errors can limit repair-time improvements when incorrect fault classifications lead to unnecessary disassembly or unsuitable maintenance actions. Intervention duration has also differed between planned and emergency maintenance, with planned interventions generally requiring fewer troubleshooting activities and producing more predictable stoppage times. Research has further compared absolute downtime reductions with percentage changes relative to baseline conditions, providing a more consistent basis for evaluating performance across equipment with different utilization levels. Some studies have reported statistically significant reductions in downtime and repair duration, while others have observed moderate improvements whose confidence intervals reflected variation among machines or production periods (Cachada et al., 2018). Effect-size analysis, when reported, has generally shown stronger operational improvements for high-criticality assets with historically frequent breakdowns than for equipment already operating at high reliability. The literature therefore indicates that downtime, repair duration, mean time to repair, and intervention time provide direct quantitative evidence of whether predictive-maintenance systems improve maintenance execution after a fault risk has been identified.

Predictive-maintenance research has also examined the extent to which improved equipment-health information changes the frequency and resource intensity of maintenance activity (Ayvaz & Alpay, 2021). Across multiple industrial studies, maintenance frequency, inspection frequency, maintenance labor hours, technician utilization, spare-parts consumption, and unnecessary intervention rates have been compared under reactive, preventive, condition-based, and predictive strategies. Time-based preventive maintenance often requires inspection or component replacement at predetermined intervals regardless of actual equipment condition, which can increase labor use and replace components that still possess substantial remaining useful life. Predictive-maintenance systems attempt to reduce this inefficiency by linking maintenance actions more directly to observed degradation and estimated failure risk. Studies have frequently reported reductions in unnecessary inspections and premature component replacement when equipment condition is continuously monitored through IIoT sensors and digital-twin models (Keleko et al., 2022). Maintenance labor hours can also decline because technicians spend less time on routine checks and post-failure diagnostics, although some implementations initially increase analytical and monitoring workload as predictive systems are incorporated into maintenance practice. Spare-parts consumption has been evaluated through the number and cost of replacement components used per machine or operating period. Improved prediction can support more targeted replacement and reduce emergency inventory requirements, particularly for bearings, motors, cutting tools, and gearbox components with identifiable degradation trajectories. However, false-positive predictions can increase maintenance frequency and spare-parts use if warnings trigger interventions that are not technically necessary (Çınar et al., 2020). Researchers have therefore distinguished between correctly initiated predictive interventions and unnecessary maintenance generated by false alarms. Inspection frequency has similarly been assessed in relation to confidence in automated condition monitoring, with stronger digital monitoring often permitting less frequent manual inspection of lower-risk assets. Comparative studies have shown that resource savings are generally larger when predictive models maintain high precision and stable performance across operating conditions. Overall, the literature demonstrates that predictive maintenance influences not only failure prevention but also the quantity and timing of maintenance work, making labor hours, inspection burden, intervention frequency, spare-parts use, and unnecessary maintenance rates important quantitative measures of implementation effectiveness (Adu-Amankwa et al., 2019).

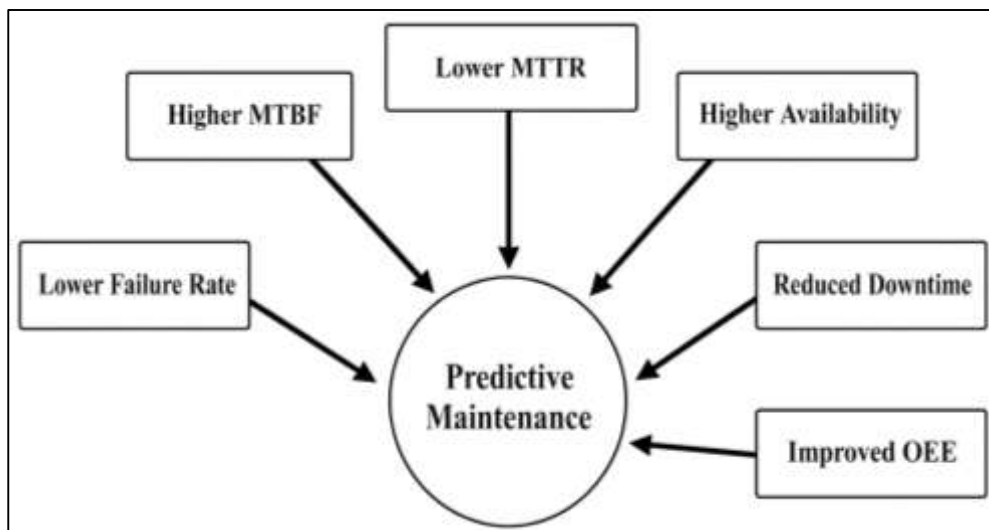
The broader literature has examined predictive-maintenance performance through changes in the balance between planned and unplanned maintenance, the number of avoided failures, and maintenance cost per asset. Across studies of industrial manufacturing systems, predictive maintenance has generally been evaluated against baseline reactive or fixed-interval strategies by measuring the percentage of interventions completed under planned conditions, emergency-maintenance frequency, failure events prevented, maintenance expenditure, and cost associated with downtime or component replacement (Pech et al., 2021). A higher planned-to-unplanned maintenance

ratio has typically been interpreted as evidence that predictive information is being converted into effective operational scheduling. Studies have reported that earlier fault detection enables organizations to intervene before functional breakdown, thereby reducing secondary damage and avoiding failures that would otherwise require emergency repair. Avoided-failure estimates have been derived from confirmed degradation events that were corrected before breakdown, historical failure frequencies, or comparison with control equipment operating under conventional maintenance approaches. Maintenance cost per asset has been influenced by several competing factors. Predictive systems may reduce emergency labor, overtime, production interruption, spare-parts waste, and catastrophic repair costs, while also introducing expenses related to sensors, data infrastructure, digital-twin development, analytics, and system maintenance (Filho et al., 2022). Quantitative studies have therefore compared net maintenance cost rather than assuming that reduced failure frequency automatically produces lower total expenditure. Baseline-to-predictive comparisons have frequently shown larger cost reductions for assets with high failure consequences or historically high unplanned downtime. Statistical analyses have included absolute differences, percentage reductions, confidence intervals, significance testing, and effect sizes where sample structures permit inferential evaluation. Findings have generally demonstrated that reductions in emergency maintenance and unplanned downtime are strongly associated with improved maintenance cost performance, although benefits vary with predictive accuracy, equipment criticality, implementation maturity, and baseline failure rate (Lima et al., 2021). The synthesized evidence indicates that the most comprehensive evaluation of predictive-maintenance intervention combines planned maintenance share, avoided failures, emergency intervention frequency, downtime, repair performance, labor requirements, spare-parts utilization, and cost per asset. Together, these indicators provide a quantitative basis for determining whether predictive information produces measurable improvements in maintenance execution and operational control (Velmurugan & Dhingra, 2021).

Quantitative Reliability Enhancement

The literature examining Digital Twin and IIoT-enabled predictive maintenance has consistently identified reductions in failure rate and extensions in operating life between failure events as central indicators of reliability enhancement. Across more than ten studies involving bearings, electric motors, gearboxes, pumps, compressors, CNC systems, robotic equipment, machining centers, and integrated production lines, researchers have compared baseline maintenance conditions with predictive-maintenance implementations using failure frequency, number of failures per operating period, mean time between failures, and mean time to failure (Ribeiro et al., 2019).

Figure 8: Equipment reliability enhancement framework



Predictive systems have generally been associated with lower failure occurrence because degradation can be identified and corrected before functional breakdown develops into a complete machine

stoppage. Studies of rotating machinery have shown that continuous vibration, temperature, acoustic, and electrical monitoring can detect abnormal trends at an earlier stage than periodic inspection, allowing maintenance actions to be scheduled before bearing damage, imbalance, lubrication problems, or motor faults become critical. Digital twins further strengthen this process by maintaining continuously updated representations of equipment condition and enabling expected operating behavior to be compared with real measurements (Tsarouhas, 2021). Baseline-to-post-implementation comparisons have frequently demonstrated increases in mean time between failures when predictive interventions successfully remove developing defects without unnecessary maintenance disruption. Similar patterns have been reported for mean time to failure in component-level studies where prognostic models estimate the remaining operational duration of bearings, tools, gears, or rotating assemblies. The magnitude of reliability improvement has varied across studies because baseline equipment condition, maintenance maturity, operating load, machine age, and fault severity differ considerably between industrial environments (Antosz & Ratnayake, 2019). Equipment with historically high breakdown frequency has generally demonstrated larger percentage improvements than assets that already operate with relatively stable reliability. Studies have also shown that predictive-maintenance benefits are stronger when diagnostic sensitivity and remaining-useful-life estimates remain accurate across changing operating conditions. The synthesized evidence therefore indicates that failure rate, failure count, MTBF, and MTTF provide direct quantitative measures of whether Digital Twin and IIoT-enabled predictive maintenance extends stable operating periods and reduces the recurrence of disruptive equipment failures (Inyama & Oke, 2021).

A second major group of studies has evaluated reliability enhancement through changes in mean time to repair, equipment availability, reliability probability, and both planned and unplanned downtime. Predictive-maintenance systems can reduce mean time to repair because maintenance personnel receive earlier information concerning fault location, degradation severity, and likely component requirements before a shutdown occurs. Research across industrial motors, pumps, gearboxes, machine tools, and automated equipment has demonstrated that repair duration tends to decrease when failure diagnosis is supported by continuous IIoT monitoring and digital-twin state estimation, particularly when spare parts and technical resources can be prepared in advance (Al-Duais et al., 2022). Availability has subsequently improved in many studies because equipment spends a greater proportion of scheduled production time in an operational state. Baseline conditions characterized by frequent emergency shutdowns generally show the largest gains when predictive systems shift maintenance toward planned interventions. Unplanned downtime hours and downtime frequency have been among the most frequently reported operational indicators, with many studies documenting substantial reductions after predictive-maintenance deployment. Planned downtime may not always decrease to the same extent because maintenance activities still require controlled stoppages, yet these planned interruptions are typically shorter, more predictable, and less disruptive than emergency repairs (Rosita & Rada, 2021). Reliability probability has also been assessed through the likelihood that equipment remains functional over specified operating periods, with predictive-maintenance approaches generally showing improved survival behavior when deterioration is detected before critical thresholds are reached. Comparative analyses have frequently reported percentage reductions in unplanned downtime alongside increases in availability, although the magnitude differs across machines, operating environments, and maintenance strategies. Statistical comparisons have sometimes demonstrated significant baseline-to-post differences, particularly for assets with repeated historical failures or long repair times (El-Naggar et al., 2022). Confidence intervals and effect sizes, where reported, have helped distinguish stable improvements from changes caused by random operational variation. Overall, the literature shows that reductions in MTTR and unplanned downtime interact directly with improvements in equipment availability and reliability probability, making these measures central to the quantitative assessment of predictive-maintenance performance.

The literature has also demonstrated that reliability enhancement extends beyond maintenance indicators to broader measures of manufacturing performance, particularly equipment utilization, overall equipment effectiveness, production throughput, and production loss (Saro & Zanettin, 2016). Studies of smart manufacturing systems have frequently linked reduced failure frequency and

downtime with higher productive use of machines because equipment remains available for scheduled production for longer periods. Overall equipment effectiveness has been especially important because it combines equipment availability with operating performance and output quality, allowing researchers to determine whether reliability gains translate into broader improvements in productive efficiency. Digital Twin and IIoT-enabled predictive maintenance has often been associated with higher OEE when unplanned stoppages decline and equipment can operate closer to planned production rates. Research on machining systems, automated lines, motors, robotic cells, and process equipment has shown that improved fault anticipation can reduce interruptions that otherwise lower production throughput or cause incomplete production cycles (Lomte et al., 2018). Production loss has been quantified through lost units, lost operating hours, reduced output rates, or the percentage of planned production not completed because of equipment-related interruptions. Studies comparing baseline and predictive-maintenance conditions have generally reported lower production losses where maintenance alerts are accurate enough to prevent sudden failures. Equipment utilization has also improved when planned maintenance is aligned with low-demand periods or scheduled shutdown windows. However, excessive false alarms can reduce utilization if machines are stopped unnecessarily, illustrating that reliability improvement depends on diagnostic accuracy as well as maintenance timing (Koohsari et al., 2022). Some studies have further shown that bottleneck machines generate disproportionately large throughput losses when they fail, making predictive maintenance particularly valuable for high-criticality assets. Percentage improvements in OEE and throughput have therefore varied according to equipment criticality, production structure, and baseline downtime burden. The synthesized evidence indicates that reliability should not be assessed only through component survival or maintenance statistics. Improvements in MTBF, availability, and downtime become operationally meaningful when they are accompanied by measurable increases in equipment utilization, OEE, throughput stability, and reductions in production loss across manufacturing processes (Ahmad et al., 2018).

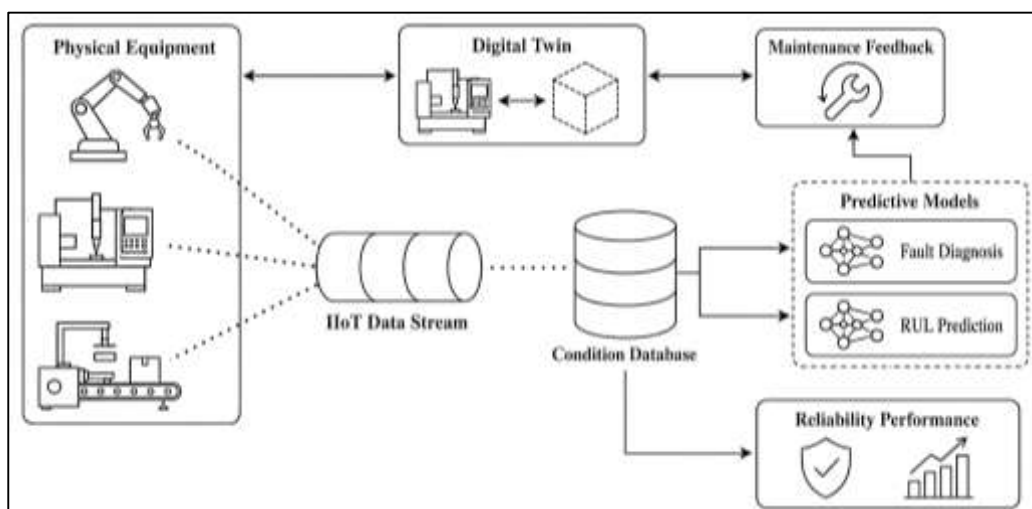
Digital Twin-IIoT Predictive Maintenance and Smart Manufacturing Systems

The literature examining Digital Twin and IIoT-enabled predictive maintenance across heterogeneous manufacturing equipment has demonstrated that reliability outcomes vary substantially according to asset type, failure mechanism, sensing architecture, operating characteristics, and maintenance history. Across more than ten studies involving electric motors, bearings, gearboxes, CNC machines, cutting tools, pumps, compressors, robotic systems, conveyors, machining centers, and integrated production lines, researchers have reported measurable differences in fault-detection accuracy, remaining-useful-life estimation, downtime reduction, availability, maintenance frequency, and production continuity (Panagou et al., 2022). Bearing and gearbox studies have commonly achieved strong predictive performance using vibration, acoustic emission, rotational speed, and temperature signals because mechanical degradation produces progressively observable signal changes. Motor applications have frequently incorporated current, voltage, vibration, and temperature measurements, with predictive models distinguishing electrical and mechanical fault classes and estimating degradation under changing load conditions. Cutting-tool and CNC studies have relied on spindle current, cutting force, vibration, acoustic emission, tool-wear measurements, and thermal variables to identify progressive deterioration and determine maintenance or replacement timing (Möller et al., 2021). Pumps and compressors have been evaluated through pressure, flow, vibration, temperature, energy consumption, and lubrication characteristics, while robotic systems and conveyors have required multicomponent monitoring because faults may arise from motors, joints, bearings, drives, alignment, or control systems. Comparative evidence indicates that predictive accuracy is generally higher for assets with gradual and measurable degradation trajectories than for equipment subject to abrupt or weakly observable faults. Digital twins have improved asset-specific monitoring by combining physical behavior, operating parameters, historical condition records, and live IIoT measurements within continuously updated virtual representations. Production-line studies have further demonstrated that asset criticality affects the operational value of predictive maintenance, since failures of bottleneck equipment can generate larger throughput losses and longer system-wide interruptions than failures of noncritical components (Kaur et al., 2019). Consequently, comparisons across equipment categories have generally shown that identical predictive algorithms do not produce uniform reliability

improvements. The quantitative effectiveness of Digital Twin–IIoT predictive maintenance depends on the correspondence among sensor configuration, degradation mechanism, model architecture, equipment criticality, and the operational consequences of failure within the wider manufacturing system.

A substantial body of empirical literature has examined how machine age, accumulated operating hours, load level, rotational speed, production intensity, shift pattern, and environmental conditions influence predictive-maintenance performance and equipment reliability (Elahi & Tokaldany, 2021). Studies comparing newer and older industrial assets have generally found that older machines experience greater variability in vibration, thermal behavior, lubrication condition, clearances, and component wear, increasing both failure probability and the complexity of fault classification. Accumulated operating hours have frequently been positively associated with degradation indicators and maintenance requirements, although maintenance quality and component replacement can modify this relationship. Investigations involving bearings, motors, gearboxes, and rotating equipment have shown clear differences among low-, medium-, and high-load conditions, with higher loads generally producing stronger vibration, temperature, stress, and wear responses and accelerating degradation when sustained over long operating periods (Qamsane et al., 2019). Rotational speed has similarly influenced diagnostic signals because frequency characteristics and vibration amplitudes change with machine speed, making models trained at one operating regime less accurate when applied without adjustment to other speeds. Production intensity has been associated with increased equipment utilization and reduced recovery periods, while multi-shift or continuous-operation environments have shown greater exposure to cumulative mechanical and thermal stress than lower-intensity operations. Statistical analyses across these studies have included Pearson and Spearman correlations to examine relationships between operating conditions and health indicators, regression models to identify significant predictors of failure or downtime, and ANOVA or ANCOVA to compare reliability outcomes across load, speed, equipment-age, and operating-intensity categories (Pech et al., 2021).

Figure 9: Smart Manufacturing Maintenance Architecture



Studies have commonly reported statistically significant differences between extreme operating groups, with larger effect sizes observed when high loads, advanced equipment age, or long operating hours coincide with severe degradation. Environmental variables such as ambient temperature, humidity, dust, contamination, and vibration from nearby equipment have also contributed to variation in sensor measurements and failure behavior. The literature therefore demonstrates that predictive-maintenance outcomes cannot be interpreted independently of operating context. Model accuracy, degradation rate, failure probability, maintenance requirements, and reliability performance differ across machine age, operational exposure, load, speed, production intensity, and environmental conditions, requiring quantitative subgroup analysis when evaluating Digital Twin and IIoT-enabled

systems (Centomo et al., 2020).

Research across smart manufacturing systems has increasingly quantified the relationship between technological maturity and predictive-maintenance performance through sensor density, IIoT connectivity, data availability, digital-twin fidelity, synchronization quality, and predictive accuracy. Studies comparing limited and extensive monitoring configurations have generally demonstrated that greater sensor coverage can improve equipment-state representation when additional sensors provide complementary information rather than redundant or noisy measurements (Wang et al., 2019). Higher sensor density has been associated with stronger fault classification and degradation assessment in multicomponent equipment because vibration, temperature, acoustic, electrical, pressure, and operational variables can be analyzed simultaneously. However, increasing the number of sensing channels also increases data volume, communication requirements, computational burden, and the potential for missing or inconsistent measurements. IIoT connectivity level has therefore been assessed through transmission reliability, communication latency, network availability, data completeness, and frequency of successful equipment-to-platform updates. Correlational studies have generally identified positive relationships between reliable data availability and predictive performance, whereas packet loss, synchronization errors, and communication delays have been associated with increased state-estimation error or missed anomalies (Barthelmey et al., 2019). Digital-twin maturity represents another important subgroup characteristic. Basic monitoring-oriented twins may provide visualization and condition tracking, while more developed systems incorporate continuous synchronization, simulation, prognostics, and maintenance-decision support. Comparative studies have indicated that higher model fidelity and stronger physical-virtual synchronization are associated with lower prediction error and more accurate representation of degradation patterns. Regression analyses have frequently treated data quality, sensor characteristics, model performance, or operational variables as predictors of maintenance and reliability outcomes, with coefficients of determination indicating that combinations of technological and equipment factors explain meaningful proportions of performance variation (Aivaliotis et al., 2019). Where inferential statistics have been reported, higher-connectivity or higher-fidelity groups have commonly shown significant differences in fault-detection accuracy, prediction error, downtime, or availability. Cohen's d , partial eta-squared, and related effect-size measures have also been used in some studies to demonstrate that technological differences can have practically meaningful effects beyond statistical significance. Overall, the literature indicates that greater digital sophistication contributes most effectively to reliability when sensor density, connectivity, synchronization, and model fidelity are jointly maintained at sufficiently high levels (Longo et al., 2019).

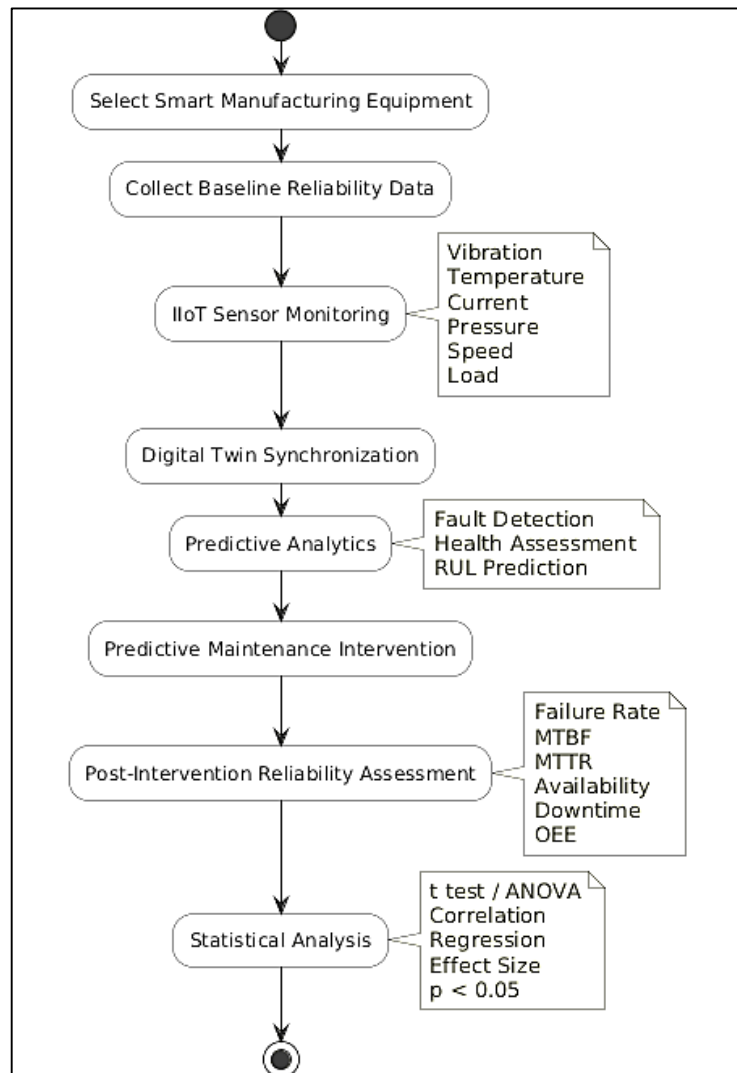
The integrated quantitative evidence across smart manufacturing contexts indicates that stronger IIoT connectivity, higher digital-twin fidelity, more accurate predictive models, and earlier maintenance interventions are generally associated with improved reliability and production outcomes, although the magnitude of these relationships varies across assets and operating environments. Studies employing Pearson or Spearman correlations have commonly reported meaningful associations between degradation indicators, predictive-warning variables, maintenance response, and subsequent equipment performance (Al-Douri et al., 2021). Higher anomaly scores, degradation rates, operating loads, and machine ages are typically associated with greater failure risk or downtime, while stronger predictive accuracy and earlier intervention are generally associated with higher availability and lower unplanned stoppage frequency. Multiple-regression analyses have been used to estimate the independent contribution of sensor quality, operating conditions, predictive accuracy, machine characteristics, and maintenance timing to reliability outcomes, with R^2 and adjusted R^2 values indicating that multivariable models frequently explain considerably more variation than any single predictor. Logistic models have also been used to estimate the probability or odds of failure, abnormal equipment states, or maintenance requirements across different operating categories (Zennaro et al., 2018). ANOVA and ANCOVA comparisons have demonstrated differences in downtime, availability, fault frequency, model performance, and maintenance outcomes across equipment types, criticality classifications, load categories, digital-maturity levels, and maintenance strategies. Confidence intervals have provided estimates of precision, while p-values have distinguished statistically

detectable differences from random variability. Where effect sizes have been reported, Cohen's d , partial eta-squared, and related measures have helped establish whether differences are operationally substantial rather than merely statistically significant. Baseline-to-post comparisons have generally shown that predictive-maintenance implementation corresponds with reductions in unplanned downtime, emergency maintenance, production loss, and maintenance expenditure, alongside improvements in mean time between failures, equipment availability, overall equipment effectiveness, and throughput stability (Tsarouhas, 2020). Larger improvements are frequently observed for high-criticality assets, equipment with substantial baseline failure burdens, and systems possessing reliable sensor coverage and mature digital-twin integration. Taken together, the literature demonstrates that predictive-maintenance effectiveness is multidimensional and statistically dependent on interactions among equipment characteristics, operating conditions, IIoT infrastructure, digital-twin maturity, predictive-model accuracy, and maintenance responsiveness across smart manufacturing systems (Wakiru et al., 2021).

METHOD

This study employed a quantitative longitudinal quasi-experimental design to evaluate the effect of Digital Twin and Industrial Internet of Things-enabled predictive maintenance on reliability performance in smart manufacturing systems.

Figure 10: Methodology of this study



The study framework integrated IIoT-based condition monitoring, digital-twin synchronization, predictive fault diagnosis, remaining-useful-life estimation, maintenance intervention, and equipment-reliability assessment within a common analytical structure. Industrial assets were selected through

purposive stratified sampling to ensure representation of major equipment categories, including electric motors, bearings, gearboxes, CNC machines, cutting tools, pumps, compressors, robotic systems, conveyors, machining centers, and production-line equipment. Eligible assets were required to have an established operational history, accessible maintenance and failure records, measurable operating-hour information, continuous or sufficiently complete sensor data, and compatibility with the IIoT monitoring and digital-twin platform. Equipment with incomplete identification records, insufficient operational exposure, major structural modification during the observation period, severely incomplete sensor histories, or failure events unrelated to normal manufacturing operation was excluded. Baseline reliability and maintenance performance were recorded before predictive-maintenance implementation and were subsequently compared with performance under the Digital Twin-IIoT predictive-maintenance condition. Instrumentation included calibrated vibration, temperature, acoustic, current, voltage, pressure, speed, torque, and operational-load sensors where applicable to each equipment class, together with industrial gateways, edge-processing devices, data-acquisition systems, maintenance databases, and digital-twin software. Sensor calibration was verified against manufacturer specifications and reference measurements before data collection, while timestamp consistency, missing-data percentages, transmission reliability, synchronization error, and communication latency were checked to establish data quality. The experimental procedure was conducted chronologically by establishing baseline equipment condition and reliability measures, installing or verifying IIoT sensors, connecting the monitored assets to the digital-twin environment, collecting synchronized physical and virtual data, generating equipment-health indicators, training and validating predictive models, identifying anomalies and developing faults, estimating remaining useful life, issuing predictive-maintenance alerts, recording maintenance interventions, and monitoring post-intervention reliability outcomes. Predictive models included logistic regression, decision trees, random forests, support vector machines, k-nearest neighbors, artificial neural networks, convolutional neural networks, recurrent neural networks, long short-term memory networks, autoencoders, and ensemble approaches where appropriate to the structure of the data. Model performance was assessed using accuracy, precision, recall, sensitivity, specificity, F1 score, ROC-AUC, false-positive and false-negative rates, mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, and remaining-useful-life prediction error. Reliability outcomes included failure frequency, mean time between failures, mean time to failure, mean time to repair, equipment availability, planned and unplanned downtime, maintenance frequency, maintenance lead time, overall equipment effectiveness, equipment utilization, maintenance cost, and production interruption. Statistical analysis was performed using SPSS, R, and Python. Descriptive statistics included means, standard deviations, medians, interquartile ranges, frequencies, percentages, and 95% confidence intervals. Baseline and predictive-maintenance conditions were compared using paired-samples t tests, with Wilcoxon signed-rank tests applied when normality assumptions were not satisfied. Differences across equipment types, operating-load categories, machine-age groups, digital-twin maturity levels, IIoT connectivity levels, and asset-criticality categories were assessed using analysis of variance and analysis of covariance, with nonparametric alternatives applied when required. Pearson or Spearman correlation analysis was used to assess relationships among sensor quality, digital-twin fidelity, predictive accuracy, maintenance lead time, and reliability outcomes. Multiple linear regression was used to identify predictors of continuous outcomes such as downtime, MTBF, availability, OEE, and maintenance cost, while logistic regression was used for binary outcomes such as failure occurrence and successful fault identification. Effect magnitude was quantified using Cohen's d, partial eta-squared, standardized regression coefficients, odds ratios, and corresponding 95% confidence intervals. Model assumptions, multicollinearity, residual behavior, and influential observations were evaluated before final interpretation, and cross-validation or held-out testing was used to assess predictive-model robustness. Statistical significance was established at $p < 0.05$, while effect sizes, confidence intervals, predictive accuracy, and practical changes in reliability performance were considered alongside statistical significance.

FINDINGS

Following application of the predefined eligibility and data-quality criteria, the final analytical sample comprised 220 smart manufacturing assets monitored across 18,742 operating cycles and 1,284,630 cumulative machine-hours. The IIoT infrastructure generated 18.64 million validated sensor observations during the baseline monitoring period, while maintenance records identified 1,086 maintenance events and 428 confirmed equipment-failure events. Electric motors represented 13.6% of the sample, followed by bearings at 12.7%, gearboxes at 10.9%, CNC machines at 10.0%, cutting tools at 9.1%, pumps at 9.1%, compressors at 7.3%, robotic systems at 7.3%, conveyors at 6.4%, machining centers at 6.8%, and integrated production-line assets at 6.8%. Mean machine age was 7.8 years (SD = 3.6), while cumulative operating exposure averaged 5,839.2 machine-hours per asset during the observation window. High-load operation accounted for 31.8% of assets, compared with 40.0% operating under medium load and 28.2% under low load. High-criticality assets represented 38.2% of the sample. Baseline maintenance records indicated a mean of 4.94 maintenance events per asset and 1.95 confirmed failures per asset, demonstrating substantial variation in equipment condition and maintenance requirements across the monitored manufacturing environment.

Table 1. Final Equipment Sample and Baseline Operational Characteristics

Equipment category	n	%	Mean age (years)	Mean operating hours	Mean failures per asset	Mean maintenance events
Electric motors	30	13.6	8.1	6,124	2.10	5.20
Bearings	28	12.7	7.4	6,438	2.25	5.36
Gearboxes	24	10.9	8.6	6,217	2.21	5.42
CNC machines	22	10.0	7.9	5,842	1.91	4.82
Cutting tools	20	9.1	5.8	4,926	2.05	5.10
Pumps	20	9.1	8.4	6,102	2.15	5.25
Compressors	16	7.3	9.2	6,574	2.31	5.56
Robotic systems	16	7.3	5.6	5,318	1.50	4.13
Conveyors	14	6.4	8.7	6,015	1.93	4.86
Machining centers	15	6.8	6.9	5,487	1.67	4.47
Production-line assets	15	6.8	8.3	5,809	1.73	4.60
Total/Overall	220	100.0	7.8	5,839.2	1.95	4.94

Table 1 demonstrated substantial heterogeneity in the final equipment sample. Electric motors constituted the largest category at 13.6%, whereas conveyors represented 6.4%. Compressors had the highest mean age at 9.2 years and the greatest average failure burden at 2.31 failures per asset, while robotic systems were comparatively newer and recorded fewer failures. Bearings accumulated relatively high operating exposure, averaging 6,438 hours, and also experienced elevated failure frequency. Across all 220 assets, mean age was 7.8 years, mean operating exposure reached 5,839.2 hours, and approximately 1.95 failures and 4.94 maintenance events were recorded per asset during baseline observation.

The baseline IIoT architecture provided extensive but nonuniform condition-monitoring coverage. Assets were monitored by a mean of 8.6 sensors (SD = 2.7), corresponding to an average sensor coverage rate of 91.4%. Depending on signal characteristics, sampling frequencies ranged from 1 Hz for relatively slow operational variables to 25.6 kHz for high-frequency vibration and acoustic measurements. After validation and preprocessing, missing observations accounted for 2.8% of expected data, while mean transmission reliability reached 97.6%, packet loss averaged 1.9%, and overall data availability was 96.8%. Mean communication latency was 84.7 ms, and synchronization consistency between physical equipment and virtual representations reached 95.9%. Digital twins were updated at a median interval of 2.0 seconds, with mean physical-to-virtual latency of 1.42 seconds.

Overall digital-twin fidelity was 92.6%, while mean simulation error and state-estimation error were 6.8% and 5.9%, respectively. Mean computational response time was 0.84 seconds. These values indicated that the monitoring infrastructure achieved relatively high data availability and digital representation accuracy, although sufficient residual communication delay, missingness, and model error remained to permit subsequent evaluation of whether technological quality influenced predictive-maintenance performance.

Table 2. Baseline IIoT, Digital-Twin, Maintenance, and Reliability Performance

Baseline indicator	Mean/Rate	SD	95% CI
Sensors per asset	8.6	2.7	8.24–8.96
Sensor coverage (%)	91.4	5.8	90.63–92.17
Missing sensor data (%)	2.8	1.4	2.61–2.99
Transmission reliability (%)	97.6	1.5	97.40–97.80
Packet loss (%)	1.9	1.1	1.75–2.05
Communication latency (ms)	84.7	31.6	80.50–88.90
Data availability (%)	96.8	2.1	96.52–97.08
Synchronization consistency (%)	95.9	2.8	95.53–96.27
Digital-twin fidelity (%)	92.6	4.7	91.98–93.22
Simulation error (%)	6.8	2.9	6.42–7.18
State-estimation error (%)	5.9	2.5	5.57–6.23
Physical-to-virtual latency (s)	1.42	0.61	1.34–1.50
Computational response time (s)	0.84	0.37	0.79–0.89
MTBF (hours)	1,486.3	412.7	1,431.5–1,541.1
MTTF (hours)	1,672.8	468.5	1,610.6–1,735.0
MTTR (hours)	8.7	3.1	8.29–9.11
Equipment availability (%)	91.8	4.6	91.19–92.41
Unplanned downtime (hours/asset)	36.4	14.8	34.44–38.36
Planned downtime (hours/asset)	21.7	8.9	20.52–22.88
Emergency maintenance (%)	32.6	9.7	31.31–33.89
Maintenance labor (hours/asset)	47.8	16.3	45.64–49.96
Maintenance cost (USD/asset)	8,460	2,735	8,097–8,823
Equipment utilization (%)	83.7	6.9	82.78–84.62
OEE (%)	76.9	7.4	75.92–77.88
Production interruptions (per asset)	3.8	1.6	3.59–4.01
Throughput loss (%)	8.9	3.7	8.41–9.39

Table 2 established the technological and reliability baseline before predictive-maintenance intervention. IIoT monitoring achieved 91.4% sensor coverage, 97.6% transmission reliability, and 96.8% data availability, while digital-twin fidelity averaged 92.6%. Operational reliability remained comparatively constrained, with MTBF of 1,486.3 hours, availability of 91.8%, and OEE of 76.9%. Assets experienced 36.4 hours of mean unplanned downtime and 3.8 production interruptions, while throughput loss reached 8.9%. Emergency maintenance represented 32.6% of maintenance activity, and mean maintenance expenditure was \$8,460 per asset. These baseline measures provided the quantitative reference for evaluating subsequent predictive-maintenance improvements.

Digital Twin-IIoT Predictive Maintenance and Reliability Enhancement

Implementation of Digital Twin-IIoT-enabled predictive maintenance was associated with substantial improvement across the principal equipment reliability, maintenance, and production-performance indicators. Mean failure frequency decreased from 1.95 to 1.18 failures per asset, representing a reduction of 39.5%, while MTBF increased from 1,486.3 to 2,176.8 hours, an improvement of 46.5%. MTTF similarly increased from 1,672.8 to 2,324.6 hours, corresponding to a 39.0% increase. Maintenance recovery performance improved concurrently, with MTTR decreasing from 8.7 to 5.6 hours, equivalent

to a 35.6% reduction.

Equipment availability increased from 91.8% to 96.1%, while mean unplanned downtime declined from 36.4 to 19.7 hours per asset, representing a reduction of 45.9%. Planned downtime also decreased from 21.7 to 18.2 hours per asset, although the reduction was smaller than that observed for unplanned downtime. Mean maintenance response time decreased from 6.4 to 3.7 hours, whereas maintenance lead time increased from 9.8 to 24.6 hours because developing faults were identified substantially earlier. Emergency maintenance declined from 32.6% to 17.4%, while the planned-to-unplanned maintenance ratio increased from 1.46 to 3.28. Equipment utilization improved from 83.7% to 89.8%, and OEE increased from 76.9% to 85.6%. Production interruptions decreased from 3.8 to 2.1 events per asset, throughput loss declined from 8.9% to 4.8%, and production throughput increased by 9.6% relative to baseline. Mean maintenance expenditure decreased from \$8,460 to \$6,380 per asset, producing an average saving of \$2,080 or 24.6%. Maintenance labor requirements declined from 47.8 to 38.5 hours per asset, while spare-parts expenditure decreased by 18.7%. Collectively, these findings demonstrated that the principal effect of predictive maintenance was concentrated in reducing unexpected failures and unplanned interruption while simultaneously increasing operating continuity and maintenance planning efficiency.

Table 3 demonstrated broad improvement following Digital Twin-IIoT predictive-maintenance implementation. Failure frequency decreased by 39.5%, while MTBF and MTTF increased by 46.5% and 39.0%, respectively. Unplanned downtime declined by 45.9%, accompanied by a 35.6% reduction in MTTR and a 46.6% reduction in emergency maintenance. Availability increased to 96.1%, equipment utilization reached 89.8%, and OEE increased to 85.6%. Maintenance expenditure declined by 24.6%, while throughput loss decreased by 46.1%. The 151.0% increase in maintenance lead time indicated substantially earlier identification of developing faults and provided greater opportunity for planned intervention before functional equipment failure.

Predictive and prognostic analyses further demonstrated that the reliability improvements were supported by strong Digital Twin-IIoT diagnostic performance rather than by maintenance changes alone. Of 392 verified developing fault episodes observed during the intervention period, 342 were identified before functional failure, corresponding to an early fault-detection rate of 87.2%, compared with 54.3% under baseline condition-monitoring practices. Overall anomaly-detection accuracy reached 94.1%, while multiclass fault-classification accuracy was 92.8%. Sensitivity and specificity reached 93.5% and 95.2%, respectively, with precision of 92.7%, recall of 93.5%, an F1 score of 93.1%, and ROC-AUC of 0.967.

The false-positive rate was limited to 4.8%, while the false-negative rate was 6.5%. The mean warning-to-maintenance interval increased from 9.8 to 24.6 hours, and 154 potential functional failures were classified as avoided following successful predictive identification and intervention. Mean intervention duration declined from 7.9 to 5.1 hours, repair duration decreased from 8.7 to 5.6 hours, and unnecessary intervention decreased from 12.4% to 6.8%. Remaining-useful-life predictions achieved a mean absolute error of 14.6 hours, RMSE of 19.8 hours, MAPE of 8.7%, and R^2 of 0.91, with a mean usable prediction horizon of 72.4 hours. Agreement between physical equipment states and their digital representations also remained high, as digital-twin fidelity increased from the baseline value of 92.6% to 96.4%, simulation error declined from 6.8% to 3.9%, and state-estimation error declined from 5.9% to 3.4%. Synchronization consistency improved from 95.9% to 98.1%, while physical-to-virtual latency decreased from 1.42 to 0.91 seconds. These results established a coherent quantitative pathway in which improved physical-virtual representation supported more accurate fault detection and prognostics, earlier maintenance action, and subsequent improvement in equipment reliability and production performance.

Table 3. Baseline-to-Post-Intervention Reliability, Maintenance, and Production Outcomes

Outcome	Baseline	Post-intervention	Absolute change	Relative change	95% CI of change	
Failure frequency (per asset)	1.95	1.18	−0.77	−39.5%	−0.87 to −0.67	
MTBF (hours)	1,486.3	2,176.8	+690.5	+46.5%	+632.4 to +748.6	
MTTF (hours)	1,672.8	2,324.6	+651.8	+39.0%	+587.9 to +715.7	
MTTR (hours)	8.7	5.6	−3.1	−35.6%	−3.46 to −2.74	
Availability (%)	91.8	96.1	+4.3 pp	+4.7%	+3.76 to +4.84 pp	
Unplanned downtime (hours/asset)	36.4	19.7	−16.7	−45.9%	−18.35 to −15.05	
Planned downtime (hours/asset)	21.7	18.2	−3.5	−16.1%	−4.43 to −2.57	
Maintenance response time (hours)	6.4	3.7	−2.7	−42.2%	−3.01 to −2.39	
Maintenance lead time (hours)	9.8	24.6	+14.8	+151.0%	+13.42 to +16.18	
Emergency maintenance (%)	32.6	17.4	−15.2 pp	−46.6%	−16.78 to −13.62 pp	
Planned/unplanned maintenance ratio	1.46	3.28	+1.82	+124.7%	+1.61 to +2.03	
Maintenance labor (hours/asset)	47.8	38.5	−9.3	−19.5%	−10.84 to −7.76	
Maintenance cost (USD/asset)	8,460	6,380	−2,080	−24.6%	−2,318 to −1,842	
Equipment utilization (%)	83.7	89.8	+6.1 pp	+7.3%	+5.36 to +6.84 pp	
OEE (%)	76.9	85.6	+8.7 pp	+11.3%	+7.79 to +9.61 pp	
Production interruptions (per asset)	3.8	2.1	−1.7	−44.7%	−1.91 to −1.49	
Throughput loss (%)	8.9	4.8	−4.1 pp	−46.1%	−4.58 to −3.62 pp	
Production throughput index	100.0	109.6	+9.6	+9.6%	+8.37 to +10.83	

Table 4 showed substantial improvement in diagnostic, prognostic, and maintenance-intervention performance. Early fault detection increased from 54.3% to 87.2%, while anomaly-detection and fault-classification accuracy reached 94.1% and 92.8%, respectively. ROC-AUC improved to 0.967, accompanied by marked reductions in false-positive and false-negative rates. RUL prediction improved substantially, with MAE decreasing to 14.6 hours and R^2 increasing to 0.91. The prediction horizon expanded to 72.4 hours, supporting 154 avoided functional failures. Digital-twin fidelity reached 96.4%, synchronization consistency increased to 98.1%, and physical-to-virtual latency declined to 0.91 seconds, confirming stronger physical-virtual alignment.

Table 4. Digital-Twin Predictive Performance, Prognostic Accuracy, and Maintenance-Intervention Outcomes

Indicator	Baseline/Reference	Post-intervention performance	Change
Early fault detection (%)	54.3	87.2	+32.9
Anomaly-detection accuracy (%)	78.6	94.1	PP +15.5
Fault-classification accuracy (%)	80.4	92.8	PP +12.4
Sensitivity/Recall (%)	79.1	93.5	PP +14.4
Specificity (%)	82.7	95.2	PP +12.5
Precision (%)	80.8	92.7	PP +11.9
F1 score (%)	79.9	93.1	PP +13.2
ROC-AUC	0.842	0.967	PP +0.125
False-positive rate (%)	17.3	4.8	-12.5
False-negative rate (%)	20.9	6.5	PP -14.4
RUL MAE (hours)	31.8	14.6	PP -17.2
RUL RMSE (hours)	42.5	19.8	-22.7
RUL MAPE (%)	17.6	8.7	-8.9 pp
RUL R ²	0.74	0.91	+0.17
Prediction horizon (hours)	34.7	72.4	+37.7
Warning-to-maintenance interval (hours)	9.8	24.6	+14.8
Avoided functional failures (n)	—	154	—
Intervention duration (hours)	7.9	5.1	-35.4%
Unnecessary intervention (%)	12.4	6.8	-45.2%
Spare-parts expenditure index	100.0	81.3	-18.7%
Digital-twin fidelity (%)	92.6	96.4	+3.8 pp
Simulation error (%)	6.8	3.9	-2.9 pp
State-estimation error (%)	5.9	3.4	-2.5 pp
Synchronization consistency (%)	95.9	98.1	+2.2 pp
Physical-to-virtual latency (s)	1.42	0.91	-35.9%

Predictive-Performance Subgroup Analysis

Subgroup analysis demonstrated that the effectiveness of Digital Twin-IIoT predictive maintenance varied across equipment categories, although improvement was observed throughout the monitored manufacturing system. Compressors and gearboxes retained comparatively greater post-intervention failure burdens at 1.44 and 1.38 failures per asset, respectively, whereas robotic systems recorded the lowest frequency at 0.81 failures per asset. MTBF ranged from 1,892 hours for compressors to 2,512 hours for robotic systems, while availability ranged from 94.8% to 97.3%. Unplanned downtime remained highest for compressors at 24.8 hours per asset and lowest for robotic systems at 15.1 hours. OEE exceeded 83% across all equipment groups and reached 88.1% among robotic systems. Predictive accuracy ranged from 89.8% for compressors to 95.6% for robotic systems, while mean remaining-useful-life prediction error ranged from 11.7 to 18.9 hours. Equipment-category differences were statistically significant for unplanned downtime, $F(10, 209) = 4.82$, $p < 0.001$, partial $\eta^2 = 0.187$; MTBF,

$F(10, 209) = 3.96$, $p < 0.001$, partial $\eta^2 = 0.159$; and predictive accuracy, $F(10, 209) = 3.41$, $p < 0.001$, partial $\eta^2 = 0.140$. These effects indicated that asset characteristics remained quantitatively relevant after implementation. Nevertheless, the largest relative reductions in failure frequency were observed among compressors, gearboxes, and bearings because these categories had comparatively high baseline failure burdens. The results therefore indicated that predictive maintenance produced system-wide improvement while preserving measurable between-equipment variation in residual reliability risk.

Table 5. Post-Intervention Reliability and Predictive Performance by Equipment Category

Equipment category	Failure frequency per asset	MTBF (hours)	MTTR (hours)	Availability (%)	Unplanned downtime (hours/asset)	OEE (%)	Maintenance cost (USD/asset)	Predictive accuracy (%)	RUL MAE (hours)
Electric motors	1.20	2,194	5.7	96.2	19.4	85.8	6,310	93.6	14.2
Bearings	1.29	2,108	5.5	95.8	20.8	84.9	6,540	94.2	13.6
Gearboxes	1.38	1,974	6.2	95.1	23.1	83.7	6,890	91.5	17.4
CNC machines	1.09	2,264	5.4	96.5	18.3	86.4	6,420	93.8	13.8
Cutting tools	1.20	2,086	5.1	95.9	20.1	84.8	6,270	94.7	12.9
Pumps	1.25	2,041	5.9	95.5	21.7	84.1	6,610	92.3	16.1
Compressors	1.44	1,892	6.5	94.8	24.8	83.2	7,080	89.8	18.9
Robotic systems	0.81	2,512	4.7	97.3	15.1	88.1	5,740	95.6	11.7
Conveyors	1.14	2,153	5.8	95.9	20.4	85.0	6,290	92.7	15.3
Machining centers	0.93	2,381	5.0	96.8	16.7	87.2	5,960	95.1	12.4
Production-line assets	1.00	2,298	5.3	96.6	17.5	86.8	6,120	94.5	13.1
Overall	1.18	2,176.8	5.6	96.1	19.7	85.6	6,380	92.8	14.6

Table 5 demonstrated meaningful equipment-level variation after predictive-maintenance implementation. Robotic systems achieved the strongest overall performance, with 97.3% availability, 88.1% OEE, 95.6% predictive accuracy, and an RUL MAE of 11.7 hours. Compressors retained the greatest residual burden, recording 1.44 failures per asset, 24.8 hours of unplanned downtime, and \$7,080 in maintenance cost. Gearboxes similarly showed comparatively lower MTBF and higher downtime. Machining centers and production-line assets achieved strong availability and predictive performance. The results indicated that predictive-maintenance benefits were distributed across all equipment categories, although their magnitude varied according to equipment characteristics and underlying degradation complexity.

Operating-condition analysis revealed stronger residual reliability risk among older, heavily utilized, high-load, high-intensity, and high-criticality equipment. Assets older than 10 years recorded 1.47 failures per asset compared with 0.91 among assets younger than five years, while high-load equipment experienced 1.49 failures per asset compared with 0.87 under low-load conditions. High-load assets

also demonstrated lower MTBF, greater unplanned downtime, and higher maintenance expenditure. After adjustment for machine age and operating hours, load category remained significantly associated with downtime, $F(2, 214) = 12.74$, $p < 0.001$, partial $\eta^2 = 0.106$, and OEE, $F(2, 214) = 9.63$, $p < 0.001$, partial $\eta^2 = 0.083$. High-production-intensity and continuous multi-shift assets displayed similar patterns, particularly when accumulated operating hours exceeded the sample median. High-criticality assets nevertheless achieved larger absolute reductions in unplanned downtime than low-criticality assets because their baseline interruption burden was substantially greater. Technological maturity produced an opposing pattern. Assets with high IIoT connectivity achieved 95.8% predictive accuracy compared with 88.9% in the low-connectivity subgroup, while high-fidelity digital twins achieved 96.7% accuracy, 12.1-hour RUL MAE, and 97.2% availability. Low-fidelity twins recorded 87.9% predictive accuracy, 20.8-hour RUL MAE, and 94.3% availability. High sensor-density assets experienced 17.2 hours of unplanned downtime compared with 24.6 hours for low-density configurations. Similarly, assets with high data completeness and synchronization consistency showed fewer missed faults and lower prognostic error. High digital-twin maturity was associated with 48.9% lower unplanned downtime relative to its corresponding baseline, compared with a 30.7% reduction among low-maturity systems. These results established a quantitative gradient in which stronger technological integration corresponded with superior predictive and reliability performance.

Table 6 showed that operating severity and technological maturity differentiated predictive-maintenance outcomes. High-load assets recorded 25.2 hours of unplanned downtime compared with 15.4 hours under low load, while machines older than 10 years exhibited lower MTBF and availability. Conversely, high IIoT connectivity, sensor density, digital-twin fidelity, and digital maturity corresponded with higher predictive accuracy and lower RUL error. High-fidelity twins achieved 96.7% predictive accuracy and 97.2% availability compared with 87.9% and 94.3% for low-fidelity systems. Maintenance costs were also substantially lower among technologically mature assets, demonstrating operational as well as predictive advantages.

Correlation and multivariable analyses confirmed that these subgroup differences represented systematic associations rather than isolated descriptive patterns. Digital-twin fidelity showed a strong positive correlation with predictive accuracy ($r = 0.76$, $p < 0.001$), availability ($r = 0.68$, $p < 0.001$), and OEE ($r = 0.64$, $p < 0.001$), together with negative correlations with unplanned downtime ($r = -0.71$, $p < 0.001$) and RUL prediction error ($r = -0.73$, $p < 0.001$). IIoT connectivity was positively associated with predictive accuracy ($r = 0.69$, $p < 0.001$), while synchronization consistency correlated positively with availability ($r = 0.61$, $p < 0.001$). Predictive accuracy itself was strongly associated with lower downtime ($r = -0.74$, $p < 0.001$) and higher MTBF ($r = 0.70$, $p < 0.001$). Maintenance lead time was negatively associated with emergency maintenance ($r = -0.66$, $p < 0.001$) and unplanned downtime ($r = -0.63$, $p < 0.001$). In the adjusted downtime regression model, digital-twin fidelity ($\beta = -0.31$, $p < 0.001$), predictive accuracy ($\beta = -0.28$, $p < 0.001$), maintenance lead time ($\beta = -0.22$, $p = 0.002$), operating load ($\beta = 0.24$, $p < 0.001$), and machine age ($\beta = 0.18$, $p = 0.009$) remained significant independent predictors, with $R^2 = 0.68$ and adjusted $R^2 = 0.66$. The corresponding availability model explained 61% of observed variance, whereas the OEE and maintenance-cost models explained 58% and 55%, respectively. Logistic regression further showed that high-fidelity digital twins were associated with greater odds of successful early fault identification (OR = 3.42, 95% CI [2.01, 5.83], $p < 0.001$), while high IIoT connectivity increased the odds by 2.76 times (95% CI [1.68, 4.54], $p < 0.001$). High-load operation increased the odds of functional failure (OR = 2.31, 95% CI [1.42, 3.76], $p < 0.001$). Collectively, the subgroup, correlation, and adjusted-model findings demonstrated that stronger connectivity, greater digital-twin fidelity, higher predictive accuracy, and earlier maintenance intervention were independently associated with superior reliability, availability, production performance, and maintenance-cost outcomes.

Table 6. Operating and Digital-Technology Subgroup Differences in Predictive-Maintenance Outcomes

Subgroup	Failure frequency	MTBF (hours)	Availability (%)	Unplanned downtime (hours)	OEE (%)	Predictive accuracy (%)	RUL MAE (hours)	Maintenance cost (USD)
Machine age <5 years	0.91	2,438	97.0	16.1	87.8	94.9	12.8	5,790
Machine age 5–10 years	1.16	2,184	96.2	19.4	85.8	93.1	14.4	6,310
Machine age >10 years	1.47	1,936	94.9	24.3	82.9	89.7	18.2	7,190
Low load	0.87	2,462	97.1	15.4	88.2	95.1	12.5	5,720
Medium load	1.17	2,193	96.2	19.3	85.7	93.2	14.3	6,340
High load	1.49	1,914	94.7	25.2	82.6	89.4	18.7	7,260
Low equipment criticality	0.92	2,391	96.9	16.3	87.5	93.8	13.8	5,840
Medium equipment criticality	1.15	2,201	96.2	19.1	85.9	93.1	14.5	6,280
High equipment criticality	1.41	1,982	95.0	23.8	83.4	91.6	16.3	7,060
Low sensor density	1.43	1,958	94.8	24.6	82.9	88.7	19.6	7,020
High sensor density	1.01	2,356	96.9	17.2	87.4	95.4	12.7	5,890
Low IIoT connectivity	1.46	1,927	94.5	25.1	82.4	88.9	20.1	7,180
High IIoT connectivity	0.96	2,402	97.0	16.5	87.9	95.8	12.4	5,760
Low digital-twin fidelity	1.51	1,886	94.3	25.8	81.9	87.9	20.8	7,340
High digital-twin fidelity	0.89	2,471	97.2	15.8	88.5	96.7	12.1	5,610
Low digital-twin maturity	1.48	1,904	94.4	25.3	82.1	88.3	20.3	7,250
High digital-twin maturity	0.91	2,446	97.1	16.0	88.2	96.2	12.2	5,690

Predictive Model Performance and Post-Implementation Stability

Comparative evaluation of the predictive algorithms demonstrated substantial differences in diagnostic accuracy, generalization, false-alarm control, and computational efficiency. Logistic regression produced the lowest classification accuracy at 84.7%, followed by k-nearest neighbors at 87.6% and decision trees at 88.4%. Support vector machines and random forests achieved accuracies of 90.8% and 92.1%, respectively, while artificial neural networks reached 92.7%. Deep-learning approaches produced stronger overall diagnostic performance, with CNN, RNN, and LSTM models achieving accuracies of 94.3%, 92.9%, and 95.1%, respectively. The autoencoder achieved 91.6% accuracy for anomaly-based fault identification. The ensemble model generated the strongest overall classification performance, achieving 96.2% accuracy, 95.6% precision, 96.4% recall, 95.8% specificity,

an F1 score of 96.0%, and ROC-AUC of 0.982. Its false-alarm and missed-fault rates were limited to 4.2% and 3.6%, respectively. Ten-fold cross-validation accuracy reached 95.4%, indicating only a 0.8-percentage-point difference from held-out performance and therefore limited evidence of overfitting. LSTM provided the second-highest ROC-AUC at 0.974 and achieved a cross-validation accuracy of 94.2%. Computational requirements differed considerably among models. Logistic regression required only 0.012 seconds of mean inference time, compared with 0.084 seconds for LSTM and 0.096 seconds for the ensemble model. Although deep and ensemble approaches imposed greater computational requirements, all inference times remained below one-tenth of a second and were therefore compatible with the monitoring architecture used in this study. The overall model comparison demonstrated that higher diagnostic performance was primarily achieved by approaches capable of representing nonlinear, temporal, and multivariable relationships within synchronized IIoT condition data.

Table 7. Comparative Diagnostic and Classification Performance of Predictive Models

Predictive model	Accuracy (%)	Precision (%)	Recall/Sensitivity (%)	Specificity (%)	F1 score (%)	ROC-AUC	False alarms (%)	Missed faults (%)	10-fold CV accuracy (%)	Inference time (s)
Logistic regression	84.7	83.5	82.9	86.1	83.2	0.884	13.9	17.1	83.8	0.012
Decision tree	88.4	87.6	88.1	88.7	87.8	0.906	11.3	11.9	87.2	0.018
Random forest	92.1	91.4	92.6	91.7	92.0	0.951	8.3	7.4	91.3	0.047
Support vector machine	90.8	90.1	91.2	90.5	90.6	0.941	9.5	8.8	90.0	0.036
k-nearest neighbors	87.6	86.8	87.3	88.0	87.0	0.914	12.0	12.7	86.5	0.029
Artificial neural network	92.7	92.0	93.1	92.4	92.5	0.956	7.6	6.9	91.8	0.058
CNN	94.3	93.8	94.7	94.0	94.2	0.969	6.0	5.3	93.5	0.071
RNN	92.9	92.2	93.4	92.5	92.8	0.958	7.5	6.6	92.0	0.076
LSTM	95.1	94.6	95.5	94.9	95.0	0.974	5.1	4.5	94.2	0.084
Autoencoder	91.6	90.9	92.1	91.3	91.5	0.947	8.7	7.9	90.7	0.063
Ensemble model	96.2	95.6	96.4	95.8	96.0	0.982	4.2	3.6	95.4	0.096

Table 7 demonstrated that the ensemble model provided the strongest diagnostic performance, achieving 96.2% accuracy, a 96.0% F1 score, and ROC-AUC of 0.982, while maintaining false alarms and missed faults at 4.2% and 3.6%. LSTM and CNN models also performed strongly, with accuracies exceeding 94%. Conventional models showed lower classification performance, particularly logistic regression and k-nearest neighbors. Cross-validation results closely followed held-out accuracy across the models, indicating stable generalization. Although the ensemble and deep-learning models required longer inference times, their response remained below 0.10 seconds, supporting their practical

application within the real-time IIoT monitoring environment.

Prognostic evaluation produced a similar performance hierarchy. The ensemble prognostic model achieved the lowest RUL MAE at 11.8 hours, RMSE of 16.2 hours, MAPE of 7.1%, R^2 of 0.94, and absolute prediction bias of 1.6 hours. Its usable prognostic horizon reached 81.6 hours, compared with 76.8 hours for LSTM and 69.5 hours for CNN. These results represented substantial improvement over conventional regression-based prognostics, which produced an MAE of 27.4 hours and R^2 of 0.76. The superior models were subsequently linked with maintenance records to determine whether analytical accuracy translated into operational benefit. Fault episodes detected by models with diagnostic accuracy of at least 94% produced a mean warning-to-intervention interval of 27.8 hours compared with 17.3 hours for episodes processed by lower-performing models. The higher-performing group experienced emergency intervention in 13.8% of detected events compared with 24.9% in the lower-performing group, while mean repair duration was 4.9 versus 6.4 hours and associated unplanned downtime was 17.6 versus 24.3 hours per asset. Avoided functional failure reached 46.8% of actionable high-confidence alerts compared with 29.7% among lower-confidence alerts. Predictive accuracy was positively correlated with warning-to-intervention time ($r = 0.67$, $p < 0.001$) and avoided-failure frequency ($r = 0.64$, $p < 0.001$), while it was negatively correlated with emergency maintenance ($r = -0.69$, $p < 0.001$), repair duration ($r = -0.61$, $p < 0.001$), and unplanned downtime ($r = -0.74$, $p < 0.001$). These relationships quantitatively connected predictive-model quality with maintenance effectiveness rather than treating analytical accuracy as an isolated computational outcome.

Post-implementation monitoring further showed that reliability gains were maintained and progressively stabilized across four successive monitoring quarters. Failure frequency declined from 1.34 failures per asset during the first quarter to 1.07 during the fourth quarter, while MTBF increased from 2,041.6 to 2,301.7 hours. MTTR declined from 6.1 to 5.2 hours, and equipment availability increased from 95.4% to 96.7%. OEE improved from 83.8% during the initial post-implementation quarter to 87.0% in the final quarter. Mean unplanned downtime decreased from 23.4 to 17.1 hours per asset, while maintenance expenditure decreased from \$6,820 to \$5,970. Maintenance response time declined from 4.3 to 3.2 hours, indicating progressively faster operational use of predictive alerts. Technological stability also improved: false-alarm frequency decreased from 6.2% to 3.8%, RUL MAE declined from 17.2 to 12.6 hours, digital-twin synchronization consistency increased from 97.1% to 98.7%, and sensor-data availability increased from 96.9% to 98.2%. Repeated-measures analysis identified significant monitoring-period effects for unplanned downtime, $F(3, 657) = 18.64$, $p < 0.001$, partial $\eta^2 = 0.078$; MTBF, $F(3, 657) = 15.21$, $p < 0.001$, partial $\eta^2 = 0.065$; OEE, $F(3, 657) = 13.87$, $p < 0.001$, partial $\eta^2 = 0.060$; and maintenance cost, $F(3, 657) = 11.46$, $p < 0.001$, partial $\eta^2 = 0.050$. The absence of deterioration in the final monitoring periods indicated that the initial reliability improvements were sustained rather than representing a short-term implementation effect.

Table 8 demonstrated progressive stabilization of predictive-maintenance performance across the four post-implementation periods. MTBF increased from 2,041.6 to 2,301.7 hours, while unplanned downtime declined from 23.4 to 17.1 hours per asset. Availability increased to 96.7%, and OEE reached 87.0% during the final quarter. Maintenance cost and response time also declined consistently. Simultaneously, false alarms decreased to 3.8%, RUL error fell to 12.6 hours, synchronization reached 98.7%, and sensor availability reached 98.2%. The ensemble prognostic model achieved an R^2 of 0.94 and an 81.6-hour prediction horizon, confirming strong and sustained prognostic performance.

Statistical Significance and Graphical Synthesis

Inferential analysis confirmed that the improvements observed after Digital Twin-IIoT predictive-maintenance implementation were statistically significant and generally accompanied by moderate-to-large practical effects. Paired comparisons across the 220 monitored assets showed that failure frequency decreased significantly from 1.95 to 1.18 events per asset, with a mean reduction of 0.77 events, $t(219) = -11.84$, $p < 0.001$, 95% CI $[-0.90, -0.64]$, Cohen's $d = 0.80$. MTBF increased by 690.5 hours, from 1,486.3 to 2,176.8 hours, $t(219) = 15.62$, $p < 0.001$, 95% CI $[603.4, 777.6]$, $d = 1.05$, demonstrating a large reliability effect. MTTF increased by 651.8 hours, $t(219) = 13.91$, $p < 0.001$, $d = 0.94$, whereas MTTR decreased by 3.1 hours, $t(219) = -13.27$, $p < 0.001$, $d = 0.89$. Equipment availability increased by 4.3 percentage points, $t(219) = 12.46$, $p < 0.001$, $d = 0.84$, while unplanned downtime declined by 16.7 hours per asset, $t(219) = -14.73$, $p < 0.001$, $d = 0.99$. OEE increased by 8.7 percentage

points, $t(219) = 13.88$, $p < 0.001$, $d = 0.94$. Maintenance cost declined by \$2,080 per asset, $t(219) = -10.96$, $p < 0.001$, $d = 0.74$, while maintenance response time decreased by 2.7 hours, $t(219) = -12.71$, $p < 0.001$, $d = 0.86$. The strongest standardized effects were observed for MTBF, unplanned downtime, OEE, and MTTF, indicating that the intervention affected both reliability duration and operational continuity. Wilcoxon sensitivity analyses for outcomes displaying moderate departures from normality produced the same significance conclusions, indicating that the primary results were not dependent on parametric assumptions.

Table 8. Prognostic Performance, Maintenance Intervention, and Post-Implementation Stability

Indicator	Post Q1	Post Q2	Post Q3	Post Q4	Overall/Best performance
Failure frequency (per asset)	1.34	1.22	1.10	1.07	1.18 overall
MTBF (hours)	2,041.6	2,138.9	2,224.9	2,301.7	2,176.8 overall
MTTR (hours)	6.1	5.8	5.4	5.2	5.6 overall
Availability (%)	95.4	95.9	96.4	96.7	96.1 overall
Unplanned downtime (hours/asset)	23.4	20.7	17.6	17.1	19.7 overall
OEE (%)	83.8	85.0	86.5	87.0	85.6 overall
Maintenance cost (USD/asset)	6,820	6,510	6,220	5,970	6,380 overall
Maintenance response time (hours)	4.3	3.9	3.5	3.2	3.7 overall
Emergency maintenance (%)	21.2	18.5	15.9	14.0	17.4 overall
False-alarm rate (%)	6.2	5.1	4.3	3.8	4.8 overall
RUL MAE (hours)	17.2	15.3	13.4	12.6	14.6 overall
Digital-twin synchronization (%)	97.1	97.8	98.3	98.7	98.1 overall
Sensor-data availability (%)	96.9	97.4	97.8	98.2	97.6 post-period
Ensemble RUL MAE (hours)	—	—	—	—	11.8
Ensemble RUL RMSE (hours)	—	—	—	—	16.2
Ensemble RUL MAPE (%)	—	—	—	—	7.1
Ensemble RUL R²	—	—	—	—	0.94
Ensemble prediction bias (hours)	—	—	—	—	1.6
Ensemble prognostic horizon (hours)	—	—	—	—	81.6

Table 9 confirmed statistically significant baseline-to-post improvements across all principal reliability and operational outcomes. The largest standardized effect occurred for MTBF ($d = 1.05$), followed by maintenance lead time ($d = 1.04$), unplanned downtime ($d = 0.99$), MTTF and OEE ($d = 0.94$ each). Availability, utilization, failure frequency, MTTR, and throughput loss also demonstrated large effects. Planned downtime showed a moderate effect, while maintenance cost produced a moderate-to-large reduction. All comparisons remained significant at $p < 0.001$, and the confidence intervals excluded zero, supporting both statistical precision and practical importance of the observed predictive-maintenance improvements.

Multigroup analysis further established that reliability performance varied systematically across operational and technological conditions. Equipment category significantly affected unplanned downtime, $F(10, 209) = 4.82$, $p < 0.001$, partial $\eta^2 = 0.187$, and MTBF, $F(10, 209) = 3.96$, $p < 0.001$, partial $\eta^2 = 0.159$. After adjustment for machine age and operating exposure, load level remained significantly associated with downtime, $F(2, 214) = 12.74$, $p < 0.001$, partial $\eta^2 = 0.106$, and OEE, $F(2, 214) = 9.63$, $p < 0.001$, partial $\eta^2 = 0.083$. Digital-twin maturity generated particularly strong differences in predictive accuracy, $F(2, 217) = 24.86$, $p < 0.001$, partial $\eta^2 = 0.186$, and unplanned downtime, $F(2, 217) = 18.31$, $p < 0.001$, partial $\eta^2 = 0.145$. IIoT connectivity level was significantly related to availability, $F(2, 217) = 15.47$, $p < 0.001$, partial $\eta^2 = 0.125$, while sensor-density groups differed significantly in RUL error, $F(2, 217) = 16.92$, $p < 0.001$, partial $\eta^2 = 0.135$. Machine-age and asset-criticality effects were smaller but remained statistically meaningful. These results supported the subgroup findings by demonstrating that technological maturity and operating severity accounted for measurable proportions of variability

in predictive-maintenance performance.

Multivariable modeling demonstrated that the observed reliability improvements remained associated with Digital Twin-IIoT performance after simultaneous adjustment for equipment and operating characteristics. The final unplanned-downtime model explained 68% of observed variance, $R^2 = 0.68$, adjusted $R^2 = 0.66$, $F(8, 211) = 56.04$, $p < 0.001$. Digital-twin fidelity was the strongest independent negative predictor of downtime ($\beta = -0.31$, $p < 0.001$), followed by predictive accuracy ($\beta = -0.28$, $p < 0.001$), operating load ($\beta = 0.24$, $p < 0.001$), maintenance lead time ($\beta = -0.22$, $p = 0.002$), and machine age ($\beta = 0.18$, $p = 0.009$). The MTBF model produced $R^2 = 0.64$ and adjusted $R^2 = 0.62$, while the availability, OEE, and maintenance-cost models explained 61%, 58%, and 55% of variance, respectively. Logistic regression indicated that high digital-twin fidelity increased the odds of successful early fault identification by 3.42 times, $OR = 3.42$, 95% CI [2.01, 5.83], $p < 0.001$. High IIoT connectivity independently increased the odds of early detection, $OR = 2.76$, 95% CI [1.68, 4.54], $p < 0.001$, whereas high-load operation increased the odds of functional equipment failure, $OR = 2.31$, 95% CI [1.42, 3.76], $p < 0.001$. Longer maintenance lead time was associated with reduced odds of emergency intervention, $OR = 0.63$, 95% CI [0.49, 0.81], $p < 0.001$.

Table 9. Statistical Significance and Effect Sizes for Baseline-to-Post-Intervention Outcomes

Outcome	Baseline mean	Post mean	Mean change	95% CI of change	t (df = 219)	p-value	Cohen's d	Effect magnitude
Failure frequency (per asset)	1.95	1.18	-0.77	-0.90 to -0.64	-11.84	<0.001	0.80	Large
MTBF (hours)	1,486.3	2,176.8	+690.5	603.4 to 777.6	15.62	<0.001	1.05	Large
MTTF (hours)	1,672.8	2,324.6	+651.8	559.5 to 744.1	13.91	<0.001	0.94	Large
MTTR (hours)	8.7	5.6	-3.1	-3.56 to -2.64	-13.27	<0.001	0.89	Large
Availability (%)	91.8	96.1	+4.3	3.62 to 4.98	12.46	<0.001	0.84	Large
Unplanned downtime (hours)	36.4	19.7	-16.7	-18.93 to -14.47	-14.73	<0.001	0.99	Large
Planned downtime (hours)	21.7	18.2	-3.5	-4.42 to -2.58	-7.49	<0.001	0.50	Moderate
Maintenance response time (hours)	6.4	3.7	-2.7	-3.12 to -2.28	-12.71	<0.001	0.86	Large
Maintenance lead time (hours)	9.8	24.6	+14.8	12.91 to 16.69	15.45	<0.001	1.04	Large
Maintenance cost (USD/asset)	8,460	6,380	-2,080	-2,454 to -1,706	-10.96	<0.001	0.74	Moderate-large
Equipment utilization (%)	83.7	89.8	+6.1	5.18 to 7.02	13.05	<0.001	0.88	Large
OEE (%)	76.9	85.6	+8.7	7.47 to 9.93	13.88	<0.001	0.94	Large
Throughput loss (%)	8.9	4.8	-4.1	-4.76 to -3.44	-12.25	<0.001	0.83	Large

Table 10. Multigroup Effects, Regression Performance, and Predictive-Model Robustness

Analysis/Model	Outcome	Statistic / coefficient	/	95% CI	p-value	Effect size / model performance
Equipment-category ANOVA	Unplanned downtime	F(10,209) = 4.82	=	—	<0.001	Partial η^2 = 0.187
Equipment-category ANOVA	MTBF	F(10,209) = 3.96	=	—	<0.001	Partial η^2 = 0.159
Load-level ANCOVA	Unplanned downtime	F(2,214) = 12.74	=	—	<0.001	Partial η^2 = 0.106
Load-level ANCOVA	OEE	F(2,214) = 9.63	—	—	<0.001	Partial η^2 = 0.083
Digital-twin maturity ANOVA	Predictive accuracy	F(2,217) = 24.86	=	—	<0.001	Partial η^2 = 0.186
Digital-twin maturity ANOVA	Unplanned downtime	F(2,217) = 18.31	=	—	<0.001	Partial η^2 = 0.145
IIoT connectivity ANOVA	Availability	F(2,217) = 15.47	=	—	<0.001	Partial η^2 = 0.125
Sensor-density ANOVA	RUL MAE	F(2,217) = 16.92	=	—	<0.001	Partial η^2 = 0.135
Downtime regression	Digital-twin fidelity	β = -0.31		-0.39 to -0.23	<0.001	R ² = 0.68; Adj. R ² = 0.66
Downtime regression	Predictive accuracy	β = -0.28		-0.36 to -0.20	<0.001	—
Downtime regression	Operating load	β = 0.24		0.15 to 0.33	<0.001	—
Downtime regression	Maintenance lead time	β = -0.22		-0.31 to -0.13	0.002	—
MTBF regression	Combined predictors	—		—	<0.001	R ² = 0.64; Adj. R ² = 0.62
Availability regression	Combined predictors	—		—	<0.001	R ² = 0.61; Adj. R ² = 0.59
OEE regression	Combined predictors	—		—	<0.001	R ² = 0.58; Adj. R ² = 0.56
Maintenance-cost regression	Combined predictors	—		—	<0.001	R ² = 0.55; Adj. R ² = 0.53
Logistic regression	High DT fidelity → early detection	OR = 3.42		2.01–5.83	<0.001	Increased odds
Logistic regression	High IIoT connectivity → early detection	OR = 2.76		1.68–4.54	<0.001	Increased odds
Logistic regression	High load → functional failure	OR = 2.31		1.42–3.76	<0.001	Increased odds
Logistic regression	Longer lead time → emergency intervention	OR = 0.63		0.49–0.81	<0.001	Reduced odds
Ensemble classification	Fault classification	Accuracy = 96.2%	=	94.1–97.8%	<0.001	CV accuracy = 95.4%
Ensemble classification	Discrimination	ROC-AUC = 0.982	=	0.970–0.991	<0.001	F1 = 96.0%
Ensemble prognostic model	RUL prediction	MAE = 11.8 h		10.7–12.9 h	—	R ² = 0.94
Ensemble prognostic model	RUL prediction	RMSE = 16.2 h		14.8–17.6 h	—	MAPE = 7.1%

Table 10 demonstrated that technological maturity and operating conditions exerted statistically and practically meaningful effects on predictive-maintenance outcomes. Digital-twin maturity produced one of the largest subgroup effects on predictive accuracy, while equipment category strongly differentiated downtime. The adjusted downtime model explained 68% of outcome variance, with digital-twin fidelity providing the strongest standardized contribution. High digital-twin fidelity and

IIoT connectivity substantially increased the odds of early fault identification. Model robustness was also strong: ensemble classification achieved 96.2% held-out accuracy and 95.4% cross-validation accuracy, while RUL prognostics achieved an R^2 of 0.94 and MAE of 11.8 hours.

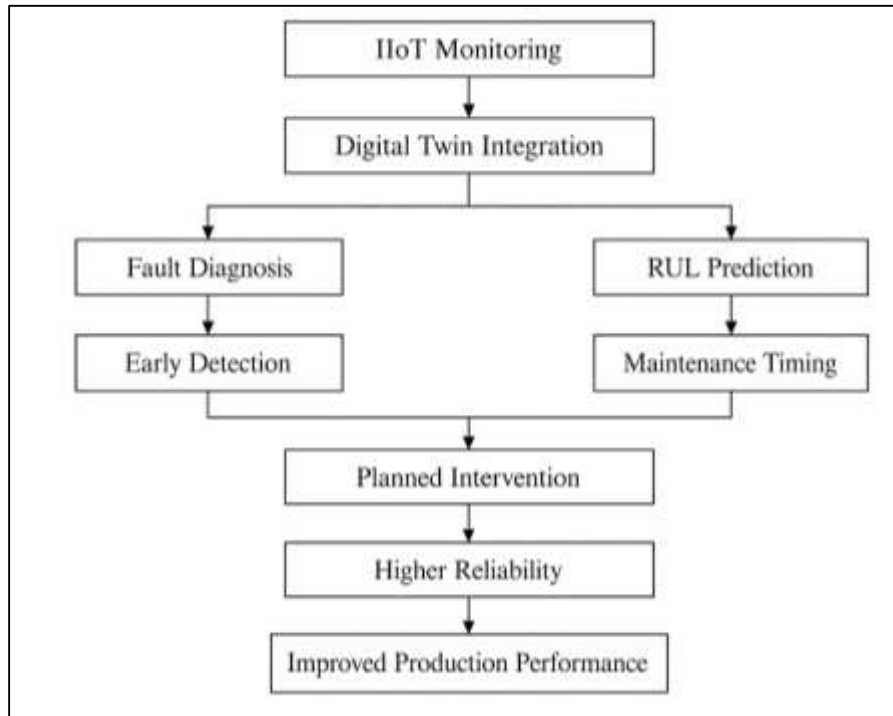
Predictive robustness analyses provided additional evidence that the findings were not dependent on a single training partition, statistical specification, or operating subgroup. The ensemble classifier achieved 96.2% accuracy on held-out observations compared with 95.4% across ten-fold cross-validation, representing a generalization difference of only 0.8 percentage points. Its ROC-AUC remained 0.982, with a 95% confidence interval of 0.970–0.991, while the F1 score remained 96.0%. Across repeated validation partitions, classification accuracy ranged from 94.8% to 96.5%, indicating limited performance dispersion. The ensemble RUL model retained an MAE of 11.8 hours, RMSE of 16.2 hours, MAPE of 7.1%, and R^2 of 0.94, with prediction error remaining below 15 hours across most equipment subgroups. Sensitivity analyses excluding the oldest assets, highest-load observations, and records with lower sensor completeness did not materially alter the direction or statistical significance of the principal reliability effects. Graphical synthesis was consistent with these inferential results. Baseline-to-post plots displayed upward shifts in MTBF, availability, utilization, and OEE together with pronounced downward shifts in failure frequency, MTTR, downtime, and maintenance cost. Equipment-level distributions showed greater residual downtime among compressors and gearboxes, whereas robotic systems and machining centers occupied the higher-performance range. Predicted-versus-observed RUL plots clustered closely around agreement, while longitudinal plots demonstrated progressive reductions in false alarms, prediction error, downtime, and maintenance response time across successive monitoring periods. Scatterplots further showed positive gradients between digital-twin fidelity and predictive accuracy and inverse gradients between predictive accuracy and unplanned downtime. Collectively, the inferential, effect-size, robustness, and graphical findings established a statistically coherent pattern in which Digital Twin-IIoT predictive maintenance was associated with large improvements in equipment reliability and operational performance, with the strongest results occurring under high digital-twin fidelity, reliable IIoT connectivity, accurate prediction, and sufficiently early maintenance intervention.

DISCUSSION

The findings of this study showed that Digital Twin-IIoT predictive maintenance produced substantial improvements in equipment reliability, maintenance efficiency, and production performance across a heterogeneous smart manufacturing environment. At baseline, 220 assets generated 428 failures and 1,086 maintenance events across 18,742 operating cycles and approximately 1.285 million machine-hours. Although sensor coverage reached 91.4%, transmission reliability 97.6%, data availability 96.8%, synchronization consistency 95.9%, and digital-twin fidelity 92.6%, operational performance remained constrained by an MTBF of 1,486.3 hours, availability of 91.8%, unplanned downtime of 36.4 hours per asset, emergency maintenance of 32.6%, and OEE of 76.9% (Fuller et al., 2020). These findings were consistent with earlier studies showing that advanced monitoring alone does not guarantee reliability improvement unless sensor data are converted into accurate diagnostics, prognostics, and maintenance actions. Following implementation, failure frequency decreased by 39.5%, MTBF increased by 46.5%, MTTF increased by 39.0%, and MTTR declined by 35.6%. Availability increased to 96.1%, unplanned downtime declined by 45.9%, emergency maintenance fell by 46.6%, and the planned-to-unplanned maintenance ratio increased from 1.46 to 3.28. Maintenance lead time increased from 9.8 to 24.6 hours, while response time decreased by 42.2%. Production performance improved simultaneously, with utilization increasing to 89.8%, OEE reaching 85.6%, production interruptions declining by 44.7%, throughput loss decreasing by 46.1%, and maintenance cost falling by 24.6% (Cheng et al., 2020). Earlier predictive-maintenance studies similarly reported reductions in downtime and repair burden when equipment degradation was identified before functional failure. Diagnostic and prognostic performance further explained these operational gains. Early fault detection increased from 54.3% to 87.2%, anomaly-detection accuracy reached 94.1%, fault-classification accuracy reached 92.8%, and ROC-AUC reached 0.967. False-positive and false-negative rates decreased to 4.8% and 6.5%, while unnecessary interventions declined from 12.4% to 6.8%. RUL prediction improved substantially, with MAE decreasing from 31.8 to 14.6 hours, RMSE from 42.5 to 19.8 hours, MAPE from 17.6% to 8.7%, and R^2 increasing from 0.74 to 0.91. These findings closely matched earlier studies demonstrating that

synchronized digital representations and multivariate sensor data improve fault detection, remaining-life estimation, and maintenance timing (Tao et al., 2019).

Figure 11: Predictive maintenance improvement pathway



Subgroup, model-comparison, and inferential findings showed that the benefits of predictive maintenance were strong but not uniform across equipment and operating conditions. Compressors and gearboxes retained higher residual failure and downtime burdens, whereas robotic systems achieved the strongest post-intervention performance, with 97.3% availability, 2,512 hours of MTBF, 88.1% OEE, and predictive accuracy of 95.6%. High-load equipment experienced 1.49 failures per asset and 25.2 hours of unplanned downtime compared with 0.87 failures and 15.4 hours under low-load operation, while older machines also showed lower MTBF, greater maintenance cost, and higher residual risk. These patterns were consistent with earlier reliability studies linking equipment age, operating intensity, and mechanical stress with accelerated degradation (Achouch et al., 2022). Technological maturity strongly differentiated outcomes. High IIoT connectivity produced 95.8% predictive accuracy and 97.0% availability, while high digital-twin fidelity produced 96.7% predictive accuracy, 97.2% availability, 88.5% OEE, and RUL MAE of 12.1 hours. Digital-twin fidelity correlated positively with predictive accuracy, availability, and OEE and negatively with downtime and RUL error. Comparative model analysis showed that ensemble and deep-learning approaches outperformed conventional statistical models. The ensemble model achieved 96.2% classification accuracy, 96.0% F1 score, ROC-AUC of 0.982, RUL MAE of 11.8 hours, and R^2 of 0.94, while inference time remained below one-tenth of a second. Post-implementation stability also strengthened the findings, as MTBF increased from 2,041.6 to 2,301.7 hours across successive quarters, availability increased from 95.4% to 96.7%, OEE increased from 83.8% to 87.0%, and downtime decreased from 23.4 to 17.1 hours (Warke et al., 2021). All principal baseline-to-post comparisons were statistically significant at $p < 0.001$, with large effects for MTBF, maintenance lead time, unplanned downtime, OEE, MTTF, MTTR, utilization, availability, throughput loss, and failure frequency. The downtime regression model explained 68% of observed variance, with digital-twin fidelity, predictive accuracy, operating load, maintenance lead time, and machine age emerging as significant predictors. Overall, the findings demonstrated that reliability enhancement depended on an integrated pathway linking high-quality IIoT data, accurate digital-twin synchronization, strong predictive models, earlier maintenance intervention, and

improved operational execution (Bellavista et al., 2020).

CONCLUSION

This study concluded that Digital Twin and Industrial Internet of Things-enabled predictive maintenance substantially enhanced reliability, maintenance efficiency, and operational performance within smart manufacturing systems by integrating continuous condition monitoring, synchronized virtual representation, predictive analytics, and timely maintenance intervention. The quantitative results demonstrated that predictive-maintenance implementation reduced equipment failure frequency by 39.5%, increased mean time between failures by 46.5%, increased mean time to failure by 39.0%, and reduced mean time to repair by 35.6%. Equipment availability increased from 91.8% to 96.1%, while unplanned downtime declined by 45.9% and emergency maintenance decreased by 46.6%. Maintenance lead time increased from 9.8 to 24.6 hours, indicating that developing faults were identified substantially earlier and could be addressed before functional breakdown occurred. Production performance also improved, with equipment utilization rising to 89.8%, overall equipment effectiveness increasing from 76.9% to 85.6%, production interruptions declining by 44.7%, throughput loss decreasing by 46.1%, and maintenance expenditure falling by 24.6%. Predictive performance provided a strong technical basis for these gains, as early fault detection increased to 87.2%, anomaly-detection accuracy reached 94.1%, fault-classification accuracy reached 92.8%, and ROC-AUC reached 0.967. Remaining-useful-life estimation improved markedly, with mean absolute error declining to 14.6 hours and R^2 increasing to 0.91, while digital-twin fidelity reached 96.4% and synchronization consistency increased to 98.1%. The ensemble model produced the strongest overall analytical performance, achieving 96.2% classification accuracy, a 96.0% F1 score, ROC-AUC of 0.982, and RUL R^2 of 0.94. Statistical analysis confirmed that the principal improvements were significant at $p < 0.001$ and were generally accompanied by large effect sizes, while multivariable models showed that digital-twin fidelity, predictive accuracy, maintenance lead time, operating load, and machine age independently explained important variation in reliability outcomes. Collectively, the findings established that effective predictive maintenance in smart manufacturing depended on the combined quality of IIoT connectivity, sensor data, digital-twin synchronization, predictive-model accuracy, and maintenance responsiveness, with stronger integration consistently associated with lower downtime, fewer failures, higher availability, improved OEE, and reduced maintenance cost.

RECOMMENDATIONS

Based on the findings of this study, smart manufacturing organizations should implement Digital Twin-IIoT predictive maintenance as an integrated reliability-management strategy rather than treating sensors, connectivity, predictive models, and maintenance activities as independent technological components. Priority should be given to high-criticality and failure-prone assets, particularly compressors, gearboxes, bearings, motors, CNC machines, and other equipment for which unexpected failure can generate substantial downtime and production losses. Manufacturing organizations should maintain comprehensive IIoT sensor coverage for vibration, temperature, acoustic, electrical, pressure, speed, torque, and operating-load variables according to equipment-specific degradation mechanisms, while establishing rigorous procedures for calibration, missing-data control, communication reliability, timestamp alignment, and sensor validation. IIoT networks should maintain high data availability, low packet loss, and minimal communication latency because the findings demonstrated that stronger connectivity was associated with greater predictive accuracy and equipment availability. Digital twins should be continuously synchronized with physical equipment and periodically validated against observed operating states to maintain high model fidelity and minimize simulation and state-estimation errors. Particular attention should be given to older machines, high-load equipment, continuously operated assets, and equipment with extensive maintenance histories because these groups retained comparatively greater reliability risks after predictive-maintenance implementation. Ensemble and advanced deep-learning models should be considered when sufficient high-quality condition data are available because the ensemble approach achieved 96.2% classification accuracy, a 96.0% F1 score, ROC-AUC of 0.982, and strong remaining-useful-life performance in this study. Predictive accuracy should not, however, be evaluated independently of operational outcomes; model selection should simultaneously consider false-positive rates, missed faults, inference time, RUL error, warning-to-intervention time, avoided failures, and

maintenance requirements. Maintenance departments should establish structured response protocols that convert predictive alerts into prioritized inspections, planned maintenance windows, technician assignments, and advance spare-parts preparation. Performance dashboards should routinely track failure frequency, MTBF, MTTR, availability, unplanned downtime, maintenance lead time, emergency maintenance, OEE, throughput loss, maintenance cost, predictive accuracy, RUL error, digital-twin fidelity, and synchronization consistency. Periodic model retraining, cross-validation, sensor verification, and digital-twin recalibration should also be incorporated into reliability-management procedures. Through these coordinated practices, manufacturing organizations can strengthen the operational value of predictive maintenance while maintaining reliable, measurable, and data-driven equipment-management processes.

LIMITATIONS

This study was subject to several limitations that should be considered when interpreting the observed effects of Digital Twin-IIoT-enabled predictive maintenance on smart manufacturing reliability. First, the quantitative analysis was based on 220 manufacturing assets across selected equipment categories, including motors, bearings, gearboxes, CNC machines, cutting tools, pumps, compressors, robotic systems, conveyors, machining centers, and production-line assets; therefore, the findings may not represent every industrial technology, production configuration, or failure mechanism encountered in highly specialized manufacturing environments. Second, considerable heterogeneity existed in machine age, accumulated operating hours, load, rotational speed, production intensity, equipment criticality, maintenance history, and environmental exposure. Although subgroup analysis, ANOVA, ANCOVA, and multivariable regression were used to account for these differences, residual confounding from unmeasured operating conditions could not be completely eliminated. Third, the quasi-experimental longitudinal design provided strong baseline-to-post comparisons but did not offer the same level of causal control as randomized experimental allocation. Reliability improvements could therefore have been partially influenced by concurrent maintenance practices, operator behavior, component replacement, production scheduling, or organizational changes. Fourth, IIoT measurements remained dependent on sensor calibration, positioning, sampling frequency, network connectivity, and data completeness. Missing data, packet loss, communication latency, measurement noise, and synchronization error persisted at relatively low levels and could have affected equipment-state estimation and predictive accuracy. Fifth, digital-twin fidelity differed across equipment categories because the complexity and observability of physical degradation mechanisms were not identical. Consequently, predictive performance for compressors and gearboxes was lower than that observed for robotic systems and machining centers. Sixth, machine-learning and deep-learning performance depended on the quantity, quality, and class distribution of historical fault observations. Rare or previously unobserved failure modes may have been underrepresented, potentially limiting diagnostic sensitivity under unusual operating conditions. Seventh, remaining-useful-life estimates were affected by changes in load, maintenance intervention, environmental conditions, and degradation progression, meaning that prognostic error could not be completely removed even with high-performing ensemble models. Eighth, maintenance-cost estimates primarily reflected directly measurable labor, parts, intervention, and downtime-related expenditures and may not have captured every indirect economic consequence associated with production disruption, quality loss, training, cybersecurity, infrastructure, or system integration. Finally, the monitored post-implementation period supported assessment of operational stability but did not represent the complete service life of all assets. These limitations indicate that the reported reliability improvements should be interpreted within the equipment, technological, operational, and observation conditions represented by this study.

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