



Development of a CMMS-Integrated Predictive Maintenance Framework for Industrial PLC and Drive Systems

Md Mahamud Pervaz Pradhan¹;

[1]. Embedded & Automation Engineer, System Logistics Corporation, Arden, NC, USA;
Email: mmprodhan@gmail.com

[Doi: 10.63125/j33gtf31](https://doi.org/10.63125/j33gtf31)

Received: 21 September 2025; Revised: 25 October 2025; Accepted: 27 November 2025; Published: 28 December 2025.

Abstract

Industrial organizations depend on programmable logic controllers, drives, sensors, and computerized maintenance management systems, yet these technologies often remain fragmented, limiting the conversion of condition data into maintenance action. This study aimed to develop and evaluate a CMMS-integrated predictive maintenance framework for PLC and drive systems. A quantitative, cross-sectional, multiple-case-based design was applied across 12 enterprise cases representing textile, food, pharmaceutical, cement, steel, power, chemical, automotive, packaging, water-treatment, and electronics operations. Of 360 questionnaires distributed, 330 were returned and 312 valid responses were retained, producing an 86.67 percent valid response rate. Respondents included maintenance, automation, electrical, reliability, instrumentation, production, CMMS, and management professionals. The key variables were CMMS Integration Capability, Condition-Monitoring Data Quality, Predictive Analytics Capability, Maintenance Workforce Competency, Organizational Readiness, Predictive Maintenance Effectiveness, and PLC and Drive System Maintenance Performance. Data were analyzed using descriptive statistics, Cronbach's alpha, factor-based validity assessment, Pearson correlation, multiple regression, and diagnostics in SPSS. The instrument demonstrated overall reliability, $\alpha = .93$, with construct alphas ranging from .82 to .90, while KMO = .918 and Bartlett's test was significant, $\chi^2 (861) = 7,426.31$, $p < .001$. Condition-Monitoring Data Quality achieved the highest predictor mean of 4.16. The five predictors explained 64.2 percent of the variance in Predictive Maintenance Effectiveness, $R^2 = .642$, $F (5, 306) = 109.75$, $p < .001$. Data quality was the strongest predictor, $\beta = .29$, followed by predictive analytics, $\beta = .27$, CMMS integration, $\beta = .21$, workforce competency, $\beta = .17$, and organizational readiness, $\beta = .14$. Predictive Maintenance Effectiveness explained 57.1 percent of maintenance-performance variance, $\beta = .76$, $F (1, 310) = 412.60$, $p < .001$. The findings imply that reliable data, integrated systems, analytical capability, skilled personnel, and organizational support must be developed together to reduce downtime, repeated faults, repair duration, and production interruption while improving availability, reliability, and continuity.

KEYWORDS

CMMS Integration; Predictive Maintenance; Programmable Logic Controllers; Condition-Monitoring Data Quality; Industrial Drive Systems

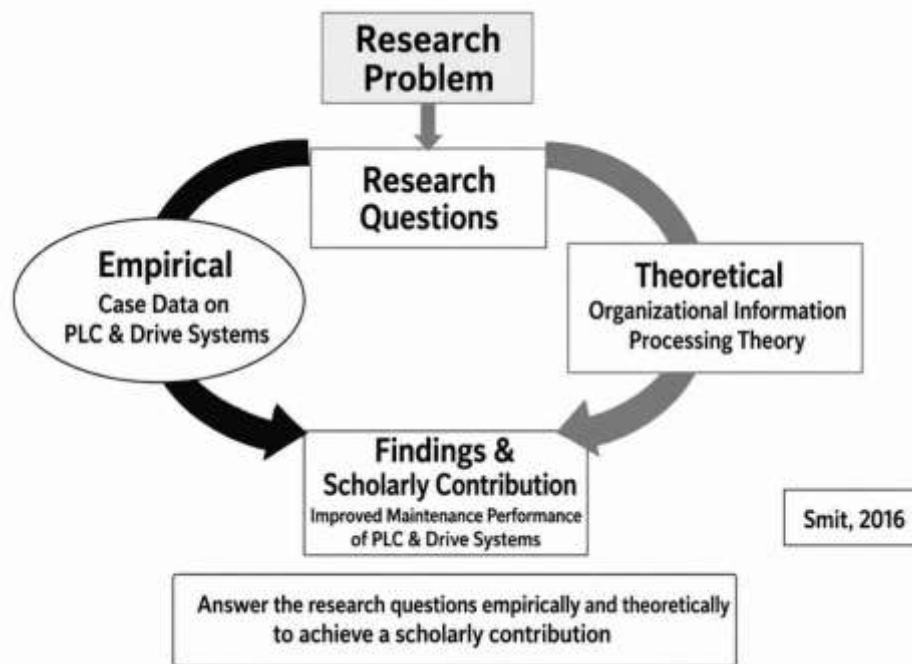
INTRODUCTION

Maintenance refers to the coordinated technical, administrative, and managerial activities undertaken to retain an industrial asset in an operating condition or restore it to a state in which it can perform its required function. Corrective maintenance responds to failures after they occur, preventive maintenance applies predetermined interventions according to time or equipment usage, condition-based maintenance initiates action from evidence concerning the physical state of an asset, and predictive maintenance uses historical and real-time information to identify degradation and estimate when maintenance attention is required. Predictive maintenance therefore extends beyond routine scheduling because it combines data acquisition, signal processing, condition assessment, fault diagnosis, prognostics, and maintenance decision-making. Condition-based maintenance research has defined this process as a progression from machinery-data collection to diagnosis, prognosis, and maintenance-support decisions (Jardine et al., 2006). Prognostic research has also emphasized that observed degradation must be translated into information that supports the timing of maintenance interventions (Peng et al., 2010). Predictive maintenance has consequently been regarded as an organized approach for reducing the uncertainty associated with equipment condition and maintenance requirements (Selcuk, 2017). A computerized maintenance management system, commonly identified as a CMMS, is an information platform that organizes asset registers, maintenance histories, inspection schedules, work orders, labor assignments, failure codes, spare-parts inventories, maintenance costs, and performance indicators. The selection and configuration of such a system must reflect the functional and managerial needs of the organization in which it is implemented (Meira et al., 2020). A programmable logic controller, or PLC, is a ruggedized industrial computer that executes programmed control logic by processing input signals and directing output devices. An industrial drive is an electronic power-conversion and control device that regulates the speed, torque, frequency, position, or operating characteristics of an electric motor. PLCs and drives commonly function together with sensors, motors, actuators, communication networks, human-machine interfaces, and supervisory systems. A CMMS-integrated predictive maintenance framework can therefore be defined as a coordinated structure through which condition data, diagnostic evidence, analytical models, asset histories, maintenance personnel, and organizational workflows are connected to support timely maintenance actions. This subject has international significance because PLC-controlled equipment and industrial drive systems are used in manufacturing, power generation, water treatment, transportation, mining, pharmaceuticals, food processing, textiles, chemicals, and other major industries. Maintenance-management research has accordingly emphasized the need to integrate industrial maintenance functions with digital technologies and connected information environments (Shaheen & Németh, 2022).

Industrial PLC and drive systems form a critical control and power layer within automated production environments because they coordinate machine sequences while regulating the electrical and mechanical behavior of industrial equipment. PLCs receive information from proximity switches, temperature sensors, pressure transmitters, encoders, current sensors, safety devices, and other field instruments. They process these signals according to programmed instructions and transmit output commands to relays, contactors, valves, actuators, motors, and drive systems. Variable-frequency drives regulate motor speed and torque by controlling voltage and frequency, while servo drives provide more precise control of motor position, movement, and acceleration. The combined operation of these systems supports production continuity, process stability, energy control, safety, and product consistency. Their interconnected structure also exposes industrial facilities to several types of technical degradation. PLC-related problems may involve input-output modules, communication interfaces, processors, power supplies, wiring, memory, connectors, sensors, software configuration, or industrial networks. Drive-related failures may originate in power semiconductor devices, cooling fans, DC-link capacitors, control boards, encoders, bearings, motor windings, insulation systems, overload conditions, harmonics, supply disturbances, or adverse operating environments. Electrical-machine research has established that bearing defects, rotor abnormalities, stator faults, eccentricity, thermal stress, and power-quality disturbances can be identified through operational signals (Nandi et al., 2005). Diagnostic research has also demonstrated that motor and drive faults can be detected through electrical, mechanical, thermal, and electromagnetic measurements (Bellini et al., 2008). A broader

review of electrical-machine diagnostics has confirmed that fault-detection performance depends on the measurement method, operating condition, available sensors, and physical characteristics of the monitored equipment (Henao et al., 2014). Model-based and signal-based diagnostic approaches use mathematical relationships and measured signals to identify deviations from expected system behavior (Gao et al., 2015a). Knowledge-based and hybrid approaches incorporate expert rules, historical patterns, classification techniques, and combinations of diagnostic methods (Gao et al., 2015b). Drive reliability is also influenced by thermal cycling, electrical loading, material fatigue, environmental exposure, and accumulated component stress (Wang & Blaabjerg, 2021). At the plant level, a single communication failure, drive trip, overheating condition, or motor fault can stop an entire production process even when most connected equipment remains operational. The maintenance challenge consequently includes detecting weak fault signals, interpreting alarms within their operating context, connecting evidence to the correct asset record, assigning maintenance priority, and verifying that completed work has removed the underlying cause. An embedded predictive-maintenance application has demonstrated that PLC-related operational data can be processed and used to support maintenance assessment within industrial control environments (Franco & de Figueiredo, 2023).

Figure 1: Organizational Information Processing Theory-Based Research Framework for CMMS-Integrated Predictive Maintenance



Condition monitoring provides the evidential foundation of predictive maintenance because it involves the repeated or continuous observation of variables associated with the physical and operational condition of industrial assets. Within PLC and drive environments, relevant information may include vibration, acoustic response, temperature, voltage, motor current, torque, speed, power, load, switching behavior, communication interruptions, lubrication condition, alarm frequency, trip codes, restart counts, operating hours, and changes in process performance. The collection of these values does not automatically create useful maintenance information. Data must be acquired at appropriate intervals, linked to the correct asset, associated with the corresponding machine state, cleaned of noise and invalid values, stored with consistent timestamps, and interpreted against normal operating behavior. Machinery diagnostics determines whether a fault exists, identifies its type or location, and evaluates its severity. Prognostics estimates how the detected degradation may progress and how much useful operating time may remain. Condition-based maintenance has therefore been organized around data acquisition, data processing, condition assessment, diagnosis, prognosis, and maintenance decision support (Jardine et al., 2006). Machine prognostics has similarly been described as the

connection between observed deterioration and maintenance planning (Peng et al., 2010). Research on rotating machinery has shown that vibration analysis, envelope detection, spectral methods, and fault-frequency interpretation can identify bearing-related degradation (Randall & Antoni, 2011). The accuracy of these techniques depends on rotational speed, loading conditions, signal quality, sensor placement, and the physical transmission path between the fault and the measurement point. Prognostics and health-management research has presented machinery health assessment as a structured progression from sensing and feature extraction to condition identification and remaining-useful-life estimation (Lee et al., 2014). A systematic review of machinery prognostics has further emphasized the importance of data acquisition, health indicators, degradation modeling, uncertainty management, and validation (Lei et al., 2018). These issues are especially important for PLC and drive systems because their fault evidence may be distributed across electrical, mechanical, electronic, software, and process variables. A drive overcurrent alarm may result from excessive motor loading, mechanical obstruction, incorrect parameter settings, supply-quality problems, cable defects, or deterioration within the drive. A PLC communication fault may originate in a network interface, connector, field device, power disturbance, electromagnetic interference, or software configuration. Data-driven approaches identify patterns within observations, while model-based approaches use explicit knowledge of system behavior (Tidriri et al., 2016). Hybrid techniques combine these sources to address situations in which either historical data or physical models are incomplete. Industrial predictive-maintenance systems have therefore incorporated scalable data collection, performance indicators, data-processing functions, and automated analytical workflows to convert condition observations into maintenance-relevant information (Cinar et al., 2022).

The CMMS occupies a distinct position in predictive maintenance because an accurate diagnosis does not necessarily result in an authorized, scheduled, completed, and documented maintenance intervention. CMMS platforms commonly support asset identification, preventive maintenance scheduling, work-order control, labor management, spare-parts administration, failure coding, maintenance-cost recording, technical-document storage, and performance reporting. Their effectiveness depends on the completeness of asset hierarchies, the consistency of equipment identifiers, the quality of work-order records, the usability of the software, the suitability of configured procedures, and the ability of the system to exchange data with industrial technologies. CMMS selection must therefore correspond with an organization's technical, functional, and managerial requirements (Meira et al., 2020). In many industrial facilities, PLC alarms, drive-event histories, sensor measurements, process historians, and CMMS records are stored in separate environments. A technician may observe a drive alarm through a human-machine interface, manually record the fault, search for the corresponding equipment record, create a work request, and later enter details of the completed maintenance activity. Such fragmentation can generate delayed work orders, incomplete descriptions, inconsistent failure codes, duplicated records, incorrect equipment mapping, and weak connections between the condition that initiated maintenance and the action that followed. Research on connected predictive maintenance has consequently highlighted the importance of interoperability among physical assets, industrial sensors, control systems, analytical platforms, and maintenance applications (Compare et al., 2020). Digital-twin research has also described the value of connecting the current physical state of equipment with digital models and maintenance information (Errandonea et al., 2020). Maintenance-management reviews have identified the integration of CMMS functions with Industry 4.0 technologies as an important requirement for coordinated maintenance operations (Shaheen & Németh, 2022). Systematic analysis of Industry 4.0 predictive maintenance has likewise identified integration, data handling, automated decision support, and maintenance execution as connected stages (Zonta et al., 2020). A properly integrated structure can associate PLC and drive information with CMMS asset records, transfer alarm and condition data automatically, create notifications from predetermined rules, initiate work orders from predictive outputs, and preserve diagnostic evidence within maintenance histories. Intelligent CMMS workflows have also combined machine-learning results and multicriteria decision procedures to prioritize maintenance activities and support work-order allocation (Gorski et al., 2022). Integration in this context involves more than data transmission between software systems. It requires standardized equipment identifiers, semantic consistency, accurate asset mapping, contextual interpretation, appropriate thresholds, cybersecurity

protection, defined data ownership, workflow accountability, and feedback from completed maintenance tasks. A CMMS-integrated framework for industrial PLC and drive systems must therefore connect operational technology with maintenance management at both the information-processing and maintenance-decision levels.

Predictive analytics capability is another central element because industrial data obtain maintenance value only when analytical procedures can distinguish normal operational variation from evidence of developing deterioration. Predictive maintenance analytics may include threshold rules, statistical monitoring, trend analysis, signal-processing methods, anomaly detection, classification, regression, clustering, survival analysis, degradation modeling, and remaining-useful-life estimation. Machine-learning techniques are particularly relevant when the relationships among signals, operating conditions, equipment states, and failures are complex or nonlinear. A multiple-classifier study has demonstrated that the selection of classifiers, training procedures, and decision strategies can influence predictive-maintenance results (Susto et al., 2015). Machine learning has also been identified as useful in manufacturing environments characterized by large, heterogeneous, and multidimensional datasets (Wuest et al., 2016). Its application requires careful attention to data preparation, domain expertise, model selection, interpretability, validation, and deployment. A systematic review of machine-learning methods in predictive maintenance has shown that supervised and unsupervised techniques are selected according to the form of the available data, the target variable, the availability of fault labels, and the intended maintenance decision (Carvalho et al., 2019). Data quality remains fundamental throughout these processes. Missing observations, inaccurate sensors, inconsistent labels, unrecorded maintenance actions, changing production regimes, limited failure cases, and imbalanced datasets can cause models to learn misleading associations. Predictive-maintenance research has identified data collection, preprocessing, analytical modeling, system integration, and organizational implementation as major components of a complete maintenance framework (Achouch et al., 2022). IoT-enabled maintenance research has also emphasized the technical challenges associated with heterogeneous data sources, communication infrastructure, model reliability, and the conversion of predictions into maintenance action (Compare et al., 2020). A systematic review of predictive maintenance in Industry 4.0 has further shown that successful applications depend on the alignment of sensors, data storage, analytical techniques, and decision-support procedures (Zonta et al., 2020). In PLC and drive systems, model outputs require technical interpretation because the same alarm or signal change can have different meanings under different machine states, motor loads, or production conditions. Predictive analytics capability therefore includes the ability to select meaningful variables, configure appropriate models, validate outputs against maintenance evidence, manage false alarms, communicate prediction confidence, and incorporate results into CMMS processes. A predictive-maintenance system has demonstrated how analytical models can be connected with automated workflows and performance indicators in intelligent manufacturing (Cinar et al., 2022). Embedded processing has also been applied to PLC-related predictive maintenance, showing that condition assessment can occur close to the industrial control environment (Franco & de Figueiredo, 2023).

The effectiveness of CMMS-integrated predictive maintenance also depends on human and organizational conditions because maintenance decisions are interpreted, authorized, coordinated, and executed within a managerial and social system. Maintenance engineers and technicians require knowledge of PLC logic, drive parameters, industrial networks, electrical systems, motor behavior, sensor characteristics, fault codes, safe isolation practices, CMMS procedures, and condition-data interpretation. Data analysts and information-technology specialists may possess strong analytical and integration skills while having less familiarity with actual equipment behavior under varying production conditions. Production employees may recognize operational symptoms but lack access to detailed maintenance histories or diagnostic models. Predictive maintenance consequently requires coordination among maintenance, automation, production, engineering, reliability, information technology, and organizational management. Smart maintenance has been conceptualized as an integrated organizational capability involving data-driven decision-making, human capital, internal integration, and external integration (Bokrantz et al., 2020b). A related research agenda has emphasized that industrial maintenance management must examine technology, employees, work processes, information systems, and performance measurement together (Bokrantz et al., 2020a). Maintenance

decision-making research has also shown that industrial organizations combine technical evidence, economic evaluation, risk assessment, and managerial judgment when selecting maintenance actions (Ruschel et al., 2017). Organizational readiness includes management commitment, financial resources, appropriate infrastructure, training opportunities, data-governance procedures, cross-functional collaboration, clearly assigned responsibilities, and a maintenance culture that values accurate reporting. Maintenance-maturity research has identified differences among organizations in relation to work processes, information use, technological infrastructure, organizational coordination, and performance monitoring (Errandonea et al., 2022). A technically capable CMMS may remain underused when personnel enter incomplete work-order information, use inconsistent asset codes, or fail to document the relationship between faults and completed repairs. Predictive alerts may also be ignored when employees do not understand the analytical process or when earlier alerts resulted in unnecessary interventions. Organizational Information Processing Theory provides a relevant explanatory foundation because it proposes that organizations facing uncertainty require information-processing capacities that correspond with the complexity of their activities. PLC and drive systems generate significant uncertainty because faults may arise from interacting electrical, mechanical, electronic, communication, and process conditions. CMMS integration capability, condition-monitoring data quality, predictive analytics capability, maintenance workforce competency, and organizational readiness can be viewed as information-processing capacities through which equipment information is collected, interpreted, communicated, and converted into coordinated maintenance work. Research on smart maintenance supports this integrated view of data, people, technology, and organizational coordination (Bokrantz et al., 2020b). Maintenance-management integration research also supports the connection between digital technologies, information systems, and maintenance functions (Shaheen & Németh, 2022).

Existing research provides substantial knowledge concerning electrical-machine faults, industrial diagnostics, machinery prognostics, machine learning, digital maintenance, CMMS functions, industrial connectivity, and smart maintenance. These areas, however, have often been examined through separate technical or managerial perspectives. Electrical-machine studies concentrate primarily on fault signatures, motor defects, signal characteristics, and diagnostic classification (Henao et al., 2014). Prognostic studies focus on degradation assessment, health indicators, uncertainty, and remaining-useful-life estimation (Lei et al., 2018). Machine-learning studies evaluate model selection, classification performance, feature development, and predictive accuracy (Carvalho et al., 2019). CMMS research addresses software selection, asset histories, work-order management, scheduling, maintenance costs, and information administration (Meira et al., 2020). Smart-maintenance research examines human resources, organizational coordination, technological maturity, and data-driven decision-making (Bokrantz et al., 2020a). This separation creates a specific research problem for industrial PLC and drive systems because their maintenance requires all of these components to operate as one connected process. A diagnostic model may identify abnormal drive behavior without generating an actionable work order. A CMMS may contain extensive maintenance records without receiving real-time PLC or drive data. An industrial facility may collect large amounts of condition information without sufficient accuracy, contextual labeling, or analytical capability. Maintenance personnel may receive a predictive alert without the training, spare parts, production access, or managerial authority required to respond. Reviews of predictive-maintenance systems have identified data integration, model validation, decision support, and organizational implementation as recurring challenges (Achouch et al., 2022). Connected-maintenance research has similarly identified difficulties in linking industrial information sources with reliable maintenance decisions (Compare et al., 2020). Maintenance-management research has documented the challenge of integrating CMMS functions with advanced industrial technologies (Shaheen & Németh, 2022). Systematic review evidence has also shown that predictive maintenance requires coordination among sensing, communication, analytics, and maintenance execution (Zonta et al., 2020). Intelligent CMMS research has addressed work-order prioritization and maintenance allocation through analytical methods (Gorski et al., 2022). Scalable predictive-maintenance research has examined the design of integrated data and analytical workflows (Cinar et al., 2022). PLC-oriented research has demonstrated the technical feasibility of embedded predictive processing within an industrial control setting (Franco & de Figueiredo, 2023). Limited

quantitative evidence has jointly tested how CMMS integration capability, condition-monitoring data quality, predictive analytics capability, maintenance workforce competency, and organizational readiness explain predictive maintenance effectiveness for PLC and drive assets. The present quantitative, cross-sectional, case-study-based research therefore measures these technological, informational, human, and organizational constructs through a five-point Likert-scale instrument and examines their relationships using descriptive statistics, reliability and validity analysis, Pearson correlation analysis, and regression modeling. Predictive maintenance effectiveness is positioned as the intermediate outcome connecting the five organizational capabilities with PLC and drive system maintenance performance under the explanatory structure of Organizational Information Processing Theory.

Background of the Study

Industrial production systems have become increasingly dependent on programmable logic controllers, industrial drive systems, sensors, human-machine interfaces, communication networks, and computerized maintenance platforms to achieve consistent output, precise process control, energy efficiency, and operational safety. Programmable logic controllers perform the logical and sequential control functions required to operate machines, production lines, and process equipment, while industrial drives regulate the speed, torque, direction, and operating characteristics of electric motors. These technologies are central to manufacturing, power generation, water treatment, food processing, textiles, pharmaceuticals, transportation, mining, and other asset-intensive industries. The continuous operation of PLCs and drive systems is therefore essential for maintaining production stability and avoiding costly interruptions. However, these systems are exposed to electrical, mechanical, thermal, environmental, communication, and software-related faults that can reduce reliability and cause unexpected shutdowns. Traditional corrective maintenance allows faults to be addressed only after equipment failure, while fixed-schedule preventive maintenance may result in unnecessary servicing or delayed intervention when deterioration develops between scheduled inspections. Predictive maintenance offers a more data-oriented approach by examining equipment condition, alarm histories, operating parameters, and performance patterns to detect developing problems before functional failure occurs. The effectiveness of predictive maintenance depends not only on the availability of monitoring technologies but also on the ability of an organization to transform equipment data into structured maintenance actions. A computerized maintenance management system can support this transformation by maintaining asset records, generating work orders, scheduling maintenance, managing spare parts, documenting failure histories, and measuring maintenance performance. When PLC and drive data remain disconnected from the CMMS, maintenance personnel may need to transfer information manually, increasing the likelihood of delayed responses, incomplete records, and inconsistent decisions. Integrating condition-monitoring and predictive information with CMMS workflows can create a coordinated maintenance environment in which developing faults are identified, prioritized, assigned, corrected, and documented through a single structured process. The present study is grounded in this industrial need and focuses on developing a framework that combines CMMS integration capability, condition-monitoring data quality, predictive analytics capability, workforce competency, and organizational readiness to improve predictive maintenance effectiveness and PLC and drive system maintenance performance.

Problem Statement

Industrial organizations frequently invest in PLCs, variable-frequency drives, servo systems, sensors, supervisory platforms, and CMMS applications to support production and maintenance operations. However, these technologies are often implemented as separate systems that do not exchange information effectively ([Debasish, 2021](#); [Abdur & Iftekhhar, 2021](#)). PLCs and drives may generate fault codes, alarms, current values, temperature readings, speed data, operating hours, communication errors, and equipment-status information, while the CMMS may contain work orders, maintenance histories, inspection schedules, labor records, spare-parts information, and failure reports. When these information sources are not integrated, maintenance personnel may be unable to connect changes in equipment condition with the corresponding asset history and maintenance workflow ([Hossan, 2021](#); [Zahidul & Begum, 2022](#)). As a result, developing faults may not be detected early, alarms may not be prioritized correctly, maintenance requests may be created late, and completed work may not be linked

to the condition that initiated the intervention. Many organizations also rely heavily on reactive or time-based maintenance, even when operational data are available for more accurate condition-based decisions (Mesbaul, 2023; Shurovi, 2024). This can lead to repeated drive trips, PLC communication failures, motor overheating, premature component replacement, unplanned production stoppages, increased repair time, inefficient spare-parts use, and rising maintenance expenditure. The problem is further complicated by poor data quality, limited analytical capability, inadequate technical training, weak coordination between maintenance and automation personnel, and insufficient management support for integrated maintenance practices (Zahidul, 2024; Shima Ali et al., 2024). Existing predictive maintenance solutions often concentrate on fault-detection algorithms or sensor technologies without adequately examining whether analytical outputs are incorporated into CMMS-based work processes. Similarly, CMMS studies frequently emphasize scheduling, documentation, and asset administration without fully addressing the real-time or predictive information generated by PLC and drive systems. There is therefore a lack of an empirically tested framework that explains how technological, informational, human, and organizational capabilities collectively influence predictive maintenance effectiveness in industrial PLC and drive environments. Without such a framework, industrial organizations may adopt isolated technologies without achieving meaningful improvements in equipment reliability and maintenance performance. This study responds to that problem by examining the combined effects of CMMS integration capability, condition-monitoring data quality, predictive analytics capability, maintenance workforce competency, and organizational readiness on predictive maintenance effectiveness and PLC and drive system maintenance performance.

Purpose and Objectives of the Study

The primary purpose of this study is to develop and statistically evaluate a CMMS-integrated predictive maintenance framework for industrial PLC and drive systems through a quantitative, cross-sectional, case-study-based investigation. The study seeks to determine how selected technological, informational, human, and organizational capabilities contribute to the effectiveness of predictive maintenance and to the broader maintenance performance of PLC and drive assets. The first objective is to assess the level of CMMS integration capability within the selected industrial organizations, particularly the extent to which PLC alarms, drive fault information, sensor readings, asset records, and maintenance work orders are connected. The second objective is to evaluate the quality of condition-monitoring data in terms of accuracy, completeness, timeliness, consistency, relevance, and accessibility. The third objective is to examine the predictive analytics capability of the participating organizations, including their ability to identify abnormal patterns, analyze equipment trends, estimate failure risk, prioritize maintenance needs, and support maintenance decisions. The fourth objective is to measure maintenance workforce competency in relation to PLC diagnostics, drive-system troubleshooting, CMMS operation, equipment-condition interpretation, and predictive maintenance practices. The fifth objective is to assess organizational readiness through management support, financial resources, technical infrastructure, training opportunities, maintenance culture, and cross-functional coordination. The sixth objective is to determine the level of predictive maintenance effectiveness achieved through early fault detection, timely intervention, maintenance prioritization, work-order generation, scheduling accuracy, and reduction of unnecessary maintenance. The seventh objective is to evaluate PLC and drive system maintenance performance through indicators such as equipment availability, repeated-fault reduction, downtime control, maintenance-cost reduction, mean time between failures, mean time to repair, and production continuity. The eighth objective is to examine the relationships among the study variables using Pearson correlation analysis. The ninth objective is to identify the strongest predictors of predictive maintenance effectiveness through multiple regression modeling. The final objective is to determine whether predictive maintenance effectiveness significantly improves PLC and drive system maintenance performance and to use the statistical findings to validate the proposed CMMS-integrated predictive maintenance framework.

Research Hypotheses

The hypotheses of this study are formulated to test the relationships proposed within the CMMS-integrated predictive maintenance framework. The first hypothesis, H1, states that CMMS integration capability has a significant positive effect on predictive maintenance effectiveness. This hypothesis assumes that the automatic or structured connection of PLC information, drive alarms, condition data,

asset records, and maintenance work orders enables faster and more coordinated maintenance decisions. The second hypothesis, H2, states that condition-monitoring data quality has a significant positive effect on predictive maintenance effectiveness. Accurate, timely, complete, consistent, and accessible information is expected to improve the ability of maintenance personnel and analytical systems to distinguish normal operating variations from developing faults. The third hypothesis, H3, proposes that predictive analytics capability has a significant positive effect on predictive maintenance effectiveness. Organizations that can perform trend analysis, anomaly detection, fault classification, failure-risk estimation, and maintenance prioritization are expected to identify equipment deterioration more effectively. The fourth hypothesis, H4, states that maintenance workforce competency has a significant positive effect on predictive maintenance effectiveness. Personnel who possess sufficient knowledge of PLCs, industrial drives, CMMS procedures, diagnostic data, and maintenance decision-making are expected to interpret system information and respond to predicted failures more accurately. The fifth hypothesis, H5, states that organizational readiness has a significant positive effect on predictive maintenance effectiveness. Management commitment, adequate resources, compatible infrastructure, technical training, interdepartmental coordination, and a supportive maintenance culture are expected to enable the effective implementation of predictive maintenance practices. The sixth hypothesis, H6, proposes that predictive maintenance effectiveness has a significant positive effect on PLC and drive system maintenance performance. Effective prediction and timely intervention are expected to reduce repeated faults, unplanned downtime, repair duration, maintenance costs, and production disruption while improving equipment availability, reliability, and service life. These hypotheses will be examined through descriptive statistics, Pearson correlation analysis, and regression modeling. The statistical results will determine whether the proposed relationships are supported within the selected industrial cases and will provide the empirical basis for validating the final framework.

Significance of the Research

- i. **Significance for industrial organizations:** The study provides industrial organizations with a structured framework for connecting PLC and drive condition information with CMMS-based maintenance activities. This can help organizations evaluate whether their current maintenance technologies operate as an integrated system or as separate platforms with limited information exchange.
- ii. **Significance for maintenance managers:** The findings can assist maintenance managers in identifying the factors that have the strongest influence on predictive maintenance effectiveness. This knowledge can support decisions regarding technology investment, workforce development, work-order procedures, data management, and maintenance prioritization.
- iii. **Significance for automation and reliability engineers:** The research highlights the importance of combining PLC diagnostics, drive alarms, sensor measurements, equipment histories, and analytical results. It provides a broader maintenance perspective for engineers who often work primarily with control-system or equipment-level information.
- iv. **Significance for CMMS administrators and software developers:** The study can guide the design and configuration of CMMS platforms that receive operational data, generate condition-based notifications, create predictive work orders, preserve diagnostic evidence, and connect completed maintenance activities with equipment-condition histories.
- v. **Significance for maintenance personnel:** The research emphasizes the role of workforce competency in interpreting predictive alerts and converting analytical outputs into appropriate technical action. It can support the development of training programs covering PLC diagnostics, drive troubleshooting, CMMS use, condition monitoring, and data-informed maintenance decisions.
- vi. **Significance for organizational management:** The findings can demonstrate that predictive maintenance requires more than the acquisition of software, sensors, or analytical tools. Management support, financial commitment, infrastructure, coordination, clear responsibilities, and a reliable maintenance culture are necessary for successful implementation.
- vii. **Significance for academic research:** The study contributes to maintenance-management and industrial-automation literature by combining technological, informational, human, and organizational variables in a single empirically tested framework. It also applies Organizational

Information Processing Theory to explain how industrial organizations collect, integrate, interpret, and use maintenance information under conditions of equipment complexity and failure uncertainty.

viii. **Significance for industrial performance:** By identifying the capabilities associated with effective predictive maintenance, the study can support efforts to reduce unplanned downtime, repeated faults, repair duration, unnecessary maintenance, and maintenance costs. It also addresses equipment availability, production continuity, asset reliability, and the operational performance of PLC and drive systems.

LITERATURE REVIEW

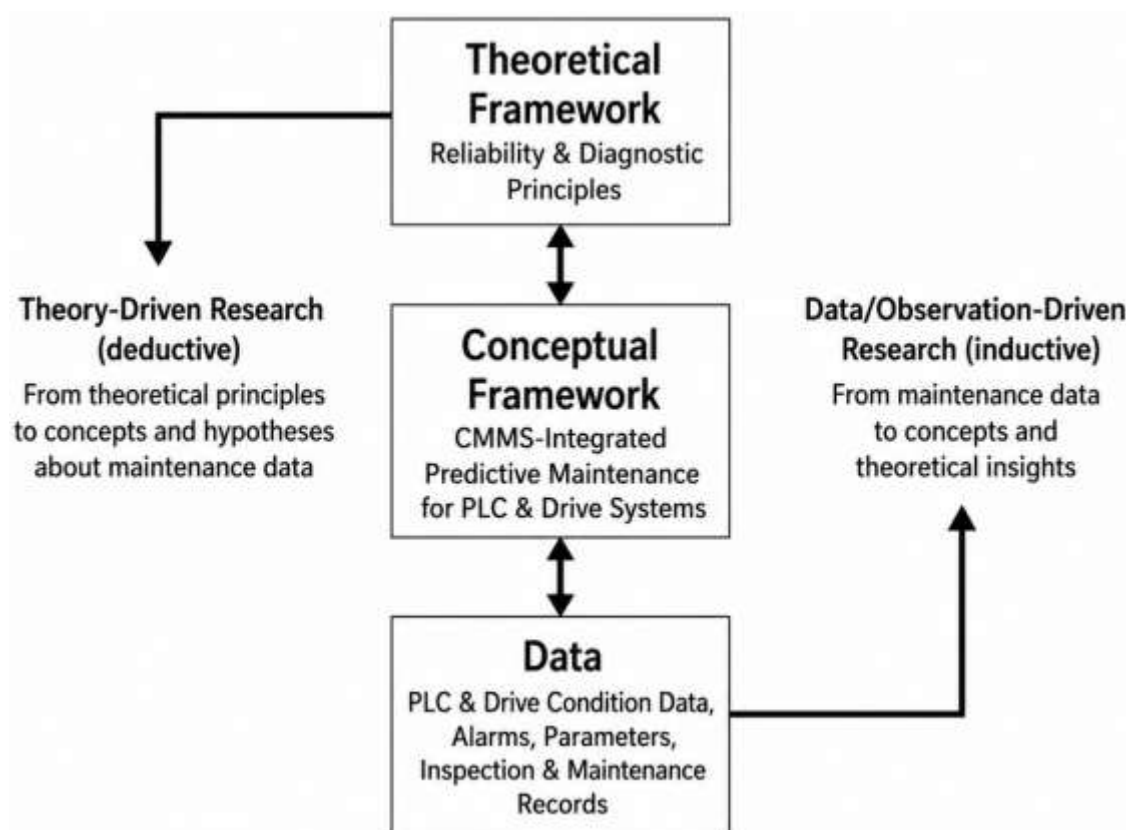
The literature related to CMMS-integrated predictive maintenance for industrial PLC and drive systems covers several interconnected areas of industrial engineering, maintenance management, automation, information systems, and organizational capability. PLCs and industrial drives are fundamental components of automated production because they control machine logic, process sequences, motor speed, torque, movement, and equipment response. Their failure can affect entire production lines and create operational, financial, and safety-related disruptions. Maintenance research has therefore examined corrective, preventive, condition-based, and predictive strategies for managing equipment deterioration and reducing unplanned failure. Predictive maintenance has received particular attention because it uses equipment-condition data, fault histories, diagnostic indicators, and analytical techniques to identify developing problems before functional breakdown occurs. The literature also recognizes that prediction alone does not guarantee effective maintenance performance. Diagnostic evidence must be linked to asset records, work-order procedures, maintenance schedules, spare-parts planning, labor allocation, and completed maintenance histories. A CMMS provides the administrative and informational structure required to manage these activities, while system integration allows PLC alarms, drive faults, sensor readings, and analytical outputs to become part of formal maintenance workflows. Condition-monitoring data quality is another important area because inaccurate, incomplete, delayed, or inconsistent information can weaken both technical diagnosis and managerial decision-making. Predictive analytics capability is similarly important because organizations require appropriate methods for identifying patterns, evaluating abnormal behavior, estimating failure risk, and prioritizing maintenance interventions. Human and organizational factors also appear throughout the literature because maintenance personnel must understand equipment behavior, interpret alerts, use CMMS functions, and coordinate with production, automation, reliability, and information-technology teams. Management commitment, infrastructure, training, financial resources, data governance, and maintenance culture determine whether predictive technologies are effectively implemented. The literature review therefore examines industrial PLC and drive maintenance requirements, CMMS and industrial-data integration, condition monitoring and predictive analytics, human and organizational capabilities, Organizational Information Processing Theory, and the conceptual relationships among the study variables. Together, these areas establish the scholarly foundation for examining how integrated information-processing capabilities influence predictive maintenance effectiveness and PLC and drive system maintenance performance.

Industrial PLC and Drive Systems and Their Maintenance Requirements

Industrial programmable logic controllers and drive systems form the operational core of automated production because they coordinate logical sequences, regulate motor behavior, and connect field-level devices with supervisory and maintenance functions. A PLC receives signals from sensors, switches, encoders, transmitters, and safety devices, executes control instructions, and sends commands to actuators, contactors, valves, motors, and drives. Industrial drives convert electrical power into controlled mechanical motion by adjusting motor speed, torque, direction, acceleration, and position according to process requirements. Together, these components support manufacturing, material handling, pumping, ventilation, packaging, assembly, process regulation, and other industrial activities. Their maintenance requirements arise from the interaction of electronic, electrical, mechanical, software, environmental, and communication-related conditions. PLC hardware may experience power-supply deterioration, processor faults, memory errors, input-output module failures, loose terminals, network interruptions, sensor defects, and program-related abnormalities. Drive systems may be affected by thermal stress, excessive loading, voltage disturbances, cooling failure, capacitor degradation, switching-device faults, motor insulation damage, bearing wear, and inaccurate

feedback signals. Because PLC-controlled equipment often operates as an interconnected sequence, a localized fault can interrupt downstream operations and complicate identification of the original failure source. Remote diagnostic architectures have shown that the visibility of monitored variables, the sophistication of communication infrastructure, and the availability of expert support influence the diagnosis of PLC-based automated systems (Sekar et al., 2011). Reliability-oriented PLC design has also demonstrated the value of collecting diagnostic information during controller operation and comparing observed behavior with a formal specification of expected states (Bao et al., 2014). These findings establish that maintenance cannot depend solely on visible breakdowns. It requires observation of controller states, process responses, drive parameters, communication behavior, and historical failure patterns. Effective maintenance must also preserve the relationships among the initiating condition, affected asset, production consequence, technical intervention, and verified restoration of normal operation across industrial facilities.

Figure 2: Framework Linking Theory, Conceptualization, and Maintenance Data for PLC and Drive Systems



Maintenance of PLC-controlled industrial systems is demanding because faults may originate in the controller, field devices, communication channels, mechanical equipment, drive subsystems, or the production process. The PLC program may continue executing when an external device behaves incorrectly, meaning that controller status alone may not reveal the source of abnormal operation. Maintenance personnel must therefore distinguish software logic errors from hardware failures, process deviations, sensor inaccuracies, actuator problems, and communication losses. Traditional troubleshooting relies on manual inspection, alarm interpretation, ladder-logic observation, and technician experience after stoppages. This approach may be slow when systems contain hundreds of signals, interlocks, timers, counters, and coordinated machine states. Structured fault diagnosis improves maintainability by representing normal process behavior, identifying deviations, isolating probable causes, and presenting evidence that narrows the search area. An automated diagnosis system combining automata-based process models with neural-network classification has illustrated how PLC signals and manufacturing behavior can be analyzed jointly to detect and isolate faults in controlled

production systems (Ghosh et al., 2020). Such approaches are relevant to CMMS integration because diagnostic results must be converted into identifiable maintenance objects rather than remaining as temporary controller messages. Each PLC, drive, motor, sensor, communication module, and controlled machine should have a consistent asset identity linking alarms, operating values, inspections, work orders, spare parts, and completed repairs. Maintenance requirements include accurate asset hierarchies, standardized fault codes, clear alarm priorities, reliable timestamps, and procedures for recording operating context. They also include inspection of panels, ventilation paths, power supplies, grounding, wiring, connectors, network components, batteries, and environmental conditions. Software maintenance requires controlled program changes, backup management, version documentation, access control, and validation after modification. When technical and informational requirements are managed together, PLC maintenance becomes a continuous reliability function supporting diagnosis, repair planning, recurrence prevention, and organizational learning from equipment history within industrial environments.

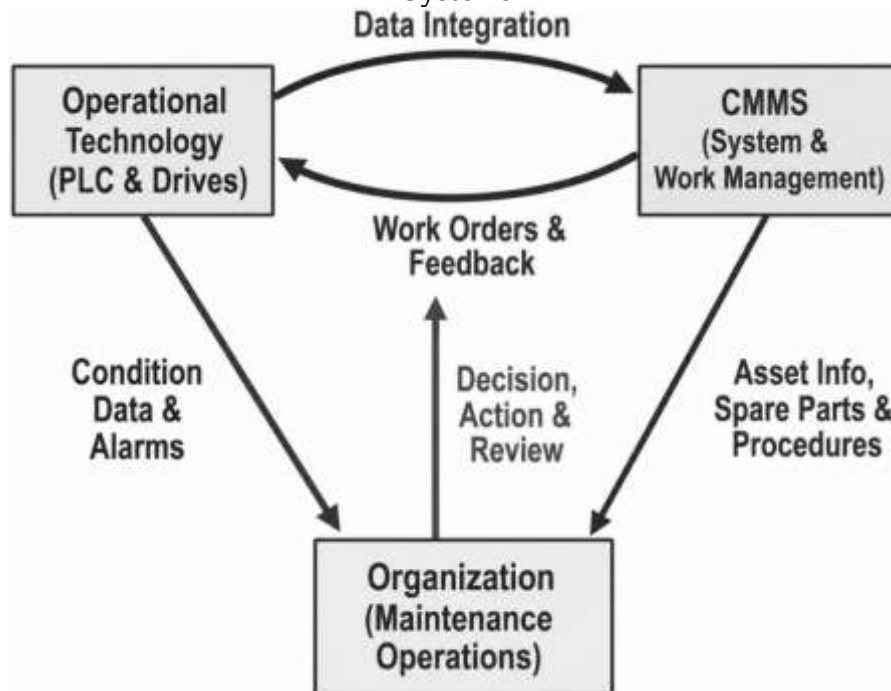
Industrial drive maintenance requires integration because the drive, electric motor, mechanical load, feedback devices, power supply, and PLC control logic operate together. A drive trip may reflect an internal electronic defect, but it may also indicate an overloaded motor, blocked component, unstable supply, damaged cable, incorrect parameter, failed encoder, inadequate cooling, or abnormal production demand. Maintenance personnel must interpret alarms in relation to speed, torque, current, voltage, temperature, switching state, load, and recent operating events. Reviews of AC motor-drive diagnosis classify failures across the electrical machine, power-electronic converter, DC-link capacitor and sensors, showing that no single monitoring method covers every fault category (Gultekin & Bazzi, 2023). Research on inverter-fed motor systems also identifies stator, rotor, bearing, eccentricity, shaft-current, insulation, and partial-discharge conditions as important targets for monitoring and diagnosis (Sardar et al., 2023). These mechanisms create maintenance requirements extending from cleaning and tightening to thermal inspection, parameter verification, insulation testing, vibration assessment, current analysis, cooling-system evaluation, and alarm-history review. Operating context is essential because variable-speed drives produce nonstationary signals and changing electrical frequencies that complicate conventional diagnostic interpretation. Maintenance programs must establish baseline values for operating loads, define trip thresholds, and record whether abnormalities occur during startup, steady operation, acceleration, deceleration, or production changeovers. A CMMS-integrated approach can organize these requirements by linking drive and PLC evidence with asset criticality, inspection plans, work-order priorities, technician assignments, spare-parts needs, and maintenance outcomes. The usefulness of integration depends on complete data and reporting. An alarm code, an inspection without measurement, or a work order without a confirmed cause provides limited value for prediction. Industrial PLC and drive maintenance should combine control-system knowledge, electrical and mechanical diagnostics, standardized documentation, and condition-based decision rules. This foundation enables the framework to evaluate how integration capability and technical maintenance practices support reliable predictive maintenance execution.

Computerized Maintenance Management Systems and Industrial Data Integration

A computerized maintenance management system provides the informational and administrative structure through which an industrial organization records, plans, coordinates, and evaluates maintenance work. Its principal functions commonly include asset registration, equipment-hierarchy development, work-request processing, work-order generation, preventive maintenance scheduling, labor assignment, spare-parts control, procurement support, failure coding, cost recording, document management, and performance reporting. For PLC and drive systems, these functions are particularly important because a single automated production line may contain numerous controllers, input-output modules, communication devices, variable-frequency drives, servo drives, motors, sensors, and associated mechanical assets. Each component requires a unique identity and a traceable relationship with its location, parent equipment, technical documents, maintenance history, criticality, and replacement parts. A well-configured CMMS can preserve these relationships and provide maintenance personnel with a consistent record of what failed, where the failure occurred, how the fault was detected, what action was taken, which resources were used, and whether normal operation was restored. Research involving small and medium-sized industrial organizations has shown that

CMMS databases can provide the event histories required for condition-based maintenance, although the quality and detail of recorded information strongly affect whether historical records can support advanced maintenance analysis (Fumagalli et al., 2009). The practical value of a CMMS therefore depends on more than software availability. Asset structures must be accurate, work-order fields must reflect actual maintenance needs, and users must enter complete and consistent information. Post-implementation evidence has indicated that perceived usefulness, ease of use, system characteristics, and user training influence employee acceptance of computerized maintenance systems (Amadi-Echendu & de Wit, 2015). In an industrial PLC and drive environment, weak acceptance can result in incomplete alarm descriptions, missing failure causes, inconsistent equipment codes, and maintenance activities performed outside the formal system. These problems reduce data traceability and prevent the CMMS from functioning as a reliable source of maintenance knowledge.

Figure 3: CMMS-Integrated Data Flow for Predictive Maintenance of Industrial PLC and Drive Systems



Industrial data integration extends CMMS functionality by connecting maintenance records with information generated by PLCs, drives, sensors, supervisory systems, process historians, and other operational technologies. PLCs produce status changes, logic states, counters, timers, communication events, diagnostic messages, and equipment operating hours, while drives generate current, voltage, frequency, torque, speed, thermal, trip, and alarm information. These data are often stored at different sampling rates, in different formats, and under naming conventions that do not correspond directly with CMMS asset identifiers. Integration therefore requires a technical architecture capable of acquiring data from legacy controllers and modern sensors, transforming values into consistent structures, assigning reliable timestamps, preserving equipment context, and delivering relevant information to maintenance applications. A large-scale manufacturing study proposed a scalable and fault-tolerant industrial data pipeline that supported the ingestion, processing, and analysis of time-series equipment data from legacy automation controllers and emerging instrumentation (O'Donovan et al., 2015). Such a pipeline is relevant to PLC and drive maintenance because raw operational data must pass through several stages before it becomes suitable for condition assessment or work-order initiation. Communication protocols, network security, data ownership, storage capacity, access permissions, and system availability must be addressed without disrupting control operations. Semantic interoperability is equally important because a temperature tag, drive alarm, PLC address, and CMMS asset record must refer to the same physical equipment and operational meaning. Asset Administration Shell research has demonstrated how standardized digital descriptions can organize asset properties,

communication interfaces, documents, and lifecycle information within Industry 4.0 environments (Arm et al., 2021). For a CMMS-integrated predictive maintenance framework, this type of standardized representation can help link PLC and drive variables with asset identities, failure modes, maintenance procedures, and historical work orders. Integration must also preserve data quality by preventing duplicate events, unmatched assets, missing timestamps, incorrect units, and uncontrolled changes to equipment names. The resulting information structure should allow maintenance personnel to trace a predictive alert from its original signal through analysis, work-order creation, intervention, and verification.

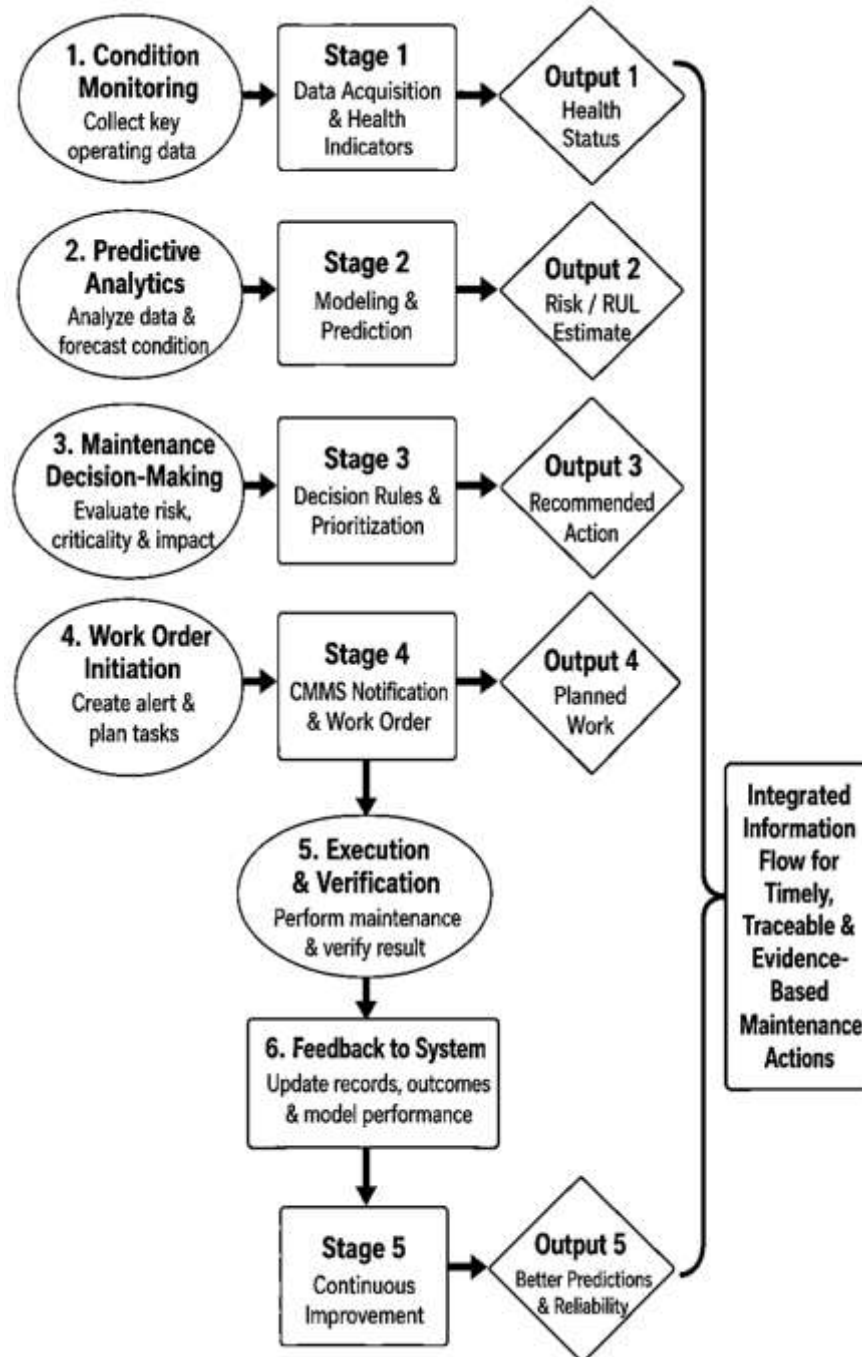
The organizational purpose of integrating industrial data with a CMMS is to convert technical evidence into controlled maintenance action. A PLC alarm or drive-parameter change has limited value when it remains visible only on a control screen or within a process historian. The information becomes operationally useful when it is associated with an asset, evaluated according to severity and criticality, converted into a notification or work order, assigned to qualified personnel, supported with procedures and spare-parts information, and closed with an accurate record of findings and actions. This workflow can reduce the separation between automation monitoring and maintenance administration. It can also support better prioritization by distinguishing a condition requiring immediate intervention from one that should be observed, inspected, or scheduled during planned downtime. CMMS implementation research in manufacturing has linked the use of computerized maintenance functions with productivity, resource utilization, safety, cost control, and broader organizational performance indicators (Shankar et al., 2023). These outcomes depend on the quality of the workflow established around the system. Automatic work-order creation should not generate excessive or duplicated tasks, and predictive alerts should contain sufficient context for technicians to understand the affected asset, detected condition, confidence level, operating state, and recommended response. Completed work orders should return information to the integrated database, including confirmed failure mode, root cause, replaced component, measured condition, downtime, labor hours, and post-maintenance verification. This feedback enables the organization to compare predicted conditions with actual findings and improve thresholds, diagnostic rules, and maintenance procedures. In PLC and drive systems, integration should also accommodate controlled access because operational networks and maintenance systems may have different security requirements. Read-only data transfer, network segmentation, authentication, change management, and audit trails can protect control integrity while allowing maintenance information to be used. The CMMS-integrated structure examined in this study therefore treats integration capability as the coordinated ability to connect asset records, operating data, predictive outputs, work processes, and maintenance feedback in a reliable and usable information environment.

Condition Monitoring, Predictive Analytics, and Maintenance Decision-Making

Condition monitoring and predictive analytics form the technical bridge between observable equipment behavior and planned maintenance action in industrial PLC and drive environments. Condition monitoring involves the acquisition and evaluation of variables that reflect the health of controllers, drives, motors, sensors, communication networks, and associated mechanical loads. Relevant measurements include vibration, motor current, voltage, temperature, torque, speed, frequency, power, insulation condition, alarm occurrence, trip frequency, communication errors, operating hours, and process deviations. These values must be interpreted within the operating context because changes caused by production load, startup, shutdown, speed variation, or environmental conditions may resemble developing faults. A useful monitoring program therefore requires reliable sensors, appropriate sampling intervals, synchronized timestamps, consistent equipment identifiers, baseline operating profiles, and defined alert levels. Prognostics extends monitoring by estimating the future health state, probability of failure, or remaining operational life of an asset. Research on rotating machinery has classified prognostic approaches into traditional reliability models, condition-data-based models, and integrated approaches that combine event histories with monitored degradation information (Heng et al., 2009). Remaining useful life represents the estimated period from the current condition to the point at which an asset can no longer perform its required function. Statistical approaches estimate this period from observed states, degradation paths, operational profiles, and uncertainty distributions, making remaining useful life a valuable input for maintenance scheduling

and spare-parts preparation (Si et al., 2011). For PLC and drive systems, monitoring must connect equipment signals with asset history and maintenance context. An isolated temperature value or alarm code cannot reveal whether intervention is necessary unless it is associated with previous events, load conditions, inspection findings, and known failure modes. Condition monitoring should consequently generate structured health indicators that can be transferred to predictive models and CMMS workflows, allowing maintenance personnel to distinguish immediate hazards, developing deterioration, and normal variation.

Figure 4: Predictive Maintenance Workflow for Industrial PLC and Drive Systems



Predictive analytics transforms condition-monitoring data into classifications, forecasts, risk scores, and recommended maintenance priorities. The analytical process begins with data selection, cleaning, synchronization, normalization, segmentation, and feature construction. Traditional signal-processing methods extract indicators such as frequency components, statistical measures, harmonics, sidebands, temperature gradients, and trend slopes. Machine-learning methods use these indicators, or raw measurements, to learn relationships between operating data and equipment health states. Supervised approaches require labeled examples of normal and faulty conditions, while unsupervised approaches

identify unusual patterns when reliable failure labels are unavailable. Deep-learning architectures can automatically learn hierarchical representations from complex datasets, reducing dependence on manually designed features. Their use in system health management has included anomaly detection, fault classification, degradation assessment, and remaining-useful-life prediction, although architecture selection, computational requirements, benchmarking, and interpretability remain implementation concerns (Khan & Yairi, 2018). Machine health monitoring research has applied autoencoders, deep belief networks, convolutional neural networks, and recurrent neural networks to machinery data, showing that different architectures address different signal structures and temporal relationships (Zhao et al., 2019). In PLC and drive applications, analytical models must account for variable speed, changing loads, production recipes, maintenance interventions, control-logic changes, and differences among equipment models. A prediction produced under one operating regime may become unreliable when applied to another regime without recalibration (Md Arif Uz et al., 2025; Md Mesbaul, 2025). Model evaluation should therefore extend beyond overall accuracy to include false-alarm rates, missed-failure rates, sensitivity, specificity, prediction lead time, stability, and practical usefulness (Md Mostafizur, 2025; Md Mostafizur et al., 2025). Maintenance personnel also require understandable outputs, such as the affected asset, suspected failure mode, evidence supporting the alert, estimated severity, and recommended inspection window (Md Syeedur & Sharmin, 2025; Muhammad Zahidul, 2025). A CMMS-integrated framework can preserve this information within notifications and work orders, ensuring that predictions are linked to technicians, procedures, asset histories, and completed maintenance findings. This connection enables analytical performance to be compared with actual equipment conditions and corrected continuously effectively (Mukut Kanti, 2025; Shima Ali et al., 2025).

Maintenance decision-making converts monitoring and predictive results into choices about whether and when an asset should be inspected, repaired, adjusted, or replaced. An accurate prediction has limited organizational value when it does not influence work priorities, production planning, labor allocation, spare-parts preparation, or risk control. Decision rules must consider failure probability, remaining life, asset criticality, safety consequences, impact, repair duration, resource availability, and intervention cost. For PLC and drive systems, a communication anomaly in an auxiliary machine may justify observation, while repeated overtemperature events in a drive controlling a line may require immediate inspection. Machine-learning research has described intelligent fault diagnosis as connecting monitoring data with machine health states through learned diagnostic knowledge, while identifying challenges from limited fault examples, unlabeled industrial data, variable operating conditions, and differences between laboratory and plant environments (Lei et al., 2020). These challenges require maintenance decisions to combine analytical outputs with engineering judgment and operating evidence. CMMS integration supports this combination by converting alerts into notifications, assigning priorities, attaching measurements, identifying competencies, checking parts availability, and recording the response. Work orders should document whether the predicted condition was confirmed, which failure mode was found, what corrective action was performed, how much downtime occurred, and whether the asset returned to normal operation. This feedback creates a closed information cycle in which maintenance outcomes improve fault labels, thresholds, model calibration, and decision procedures. The framework should also prevent automatic analytics from producing uncontrolled work demand. Alerts need severity filters, persistence rules, asset-criticality criteria, and review responsibilities so transient signal changes do not create unnecessary work orders. Effective condition monitoring and predictive analytics therefore depend on coordinated sensing, contextual data management, transparent modeling, risk-based decision rules, and systematic feedback. These elements enable PLC and drive information to support timely, traceable, and evidence-based maintenance actions through the CMMS.

Human and Organizational Capabilities for Predictive Maintenance

Human and organizational capabilities determine whether predictive maintenance technologies become dependable maintenance practices within industrial PLC and drive environments. Maintenance workforce competency includes the technical knowledge, analytical skills, procedural understanding, and collaborative behavior required to interpret equipment information and convert it into appropriate intervention. Personnel responsible for PLCs and drives must understand control

logic, input-output behavior, industrial communication, drive parameters, motor operation, electrical protection, sensor characteristics, alarm histories, and safe maintenance procedures. They must also use CMMS functions correctly, distinguish recurring symptoms from verified causes, document work accurately, and evaluate whether an intervention has restored normal operating conditions. These requirements extend beyond traditional repair skills because predictive maintenance involves data interpretation, uncertainty assessment, and interaction with digital decision-support tools. Maintenance information technology has been described as a socio-technical system in which software, data, users, tasks, organizational arrangements, and work practices must function together rather than as independent elements (Kans, 2013). This perspective is important for PLC and drive maintenance because a technically accurate alert can still produce an ineffective response when personnel cannot identify the affected asset, interpret the operating context, or select the correct maintenance action. Digitalized maintenance research has similarly indicated that maintenance organizations require stronger analytical competence, interdisciplinary knowledge, communication ability, and education as information-intensive practices become embedded in industrial work (Bokrantz et al., 2017). Workforce development should therefore cover controller diagnostics, drive troubleshooting, condition-monitoring principles, statistical reasoning, CMMS data entry, failure coding, and interpretation of predictive outputs. Competency also involves recognizing model limitations and confirming predictions through inspection or testing. Experienced technicians possess tacit knowledge about machine behavior, but that knowledge must be combined with standardized records and shared procedures. Training, mentoring, cross-functional learning, and technical documentation help transform individual experience into an organizational capability that can be applied consistently across shifts, assets, and industrial cases.

Figure 5: Human, Organizational, and Cross-Functional Capability Framework for Predictive Maintenance



Organizational readiness refers to the extent to which an industrial organization possesses the leadership commitment, resources, infrastructure, governance, and coordinated processes required to implement CMMS-integrated predictive maintenance. Management support is necessary because integration projects require investment in sensors, communication interfaces, software configuration, data storage, cybersecurity, training, and time for employees to improve records and procedures. Resource availability is insufficient when responsibilities are unclear or departments operate through disconnected priorities. Maintenance, automation, production, reliability, information technology, procurement, and senior management must agree on equipment criticality, alarm ownership, work-

order rules, access permissions, escalation procedures, and performance measures. Evidence from manufacturing organizations has shown that CMMS effectiveness is associated with supportive organizational factors such as resource allocation, decision-making structure, senior-management support, employee involvement, and effective instruction (Balouei Jamkhaneh et al., 2018). These factors influence whether users trust the system, enter complete records, follow standardized processes, and respond to condition-based notifications. Organizational readiness also includes data governance. Asset names, failure codes, measurement units, timestamps, and work-order categories must be standardized so information generated by PLCs and drives can be linked with CMMS records. Industry 4.0 maintenance research has identified technological change and management change as connected dimensions, with digital tools altering maintenance tasks, operator responsibilities, remote support, and coordination requirements (Silvestri et al., 2020). Readiness should therefore be evaluated through technical and organizational indicators. Technical indicators include system compatibility, network reliability, data availability, and information exchange. Organizational indicators include maintenance culture, learning support, leadership involvement, employee participation, and interdepartmental communication. A plant may possess analytics while lacking the authority structure needed to act on alerts, or it may possess skilled technicians while relying on fragmented data. Effective readiness is present when technologies, people, rules, and resources are aligned around a shared maintenance process that moves from condition detection to work execution and verified closure.

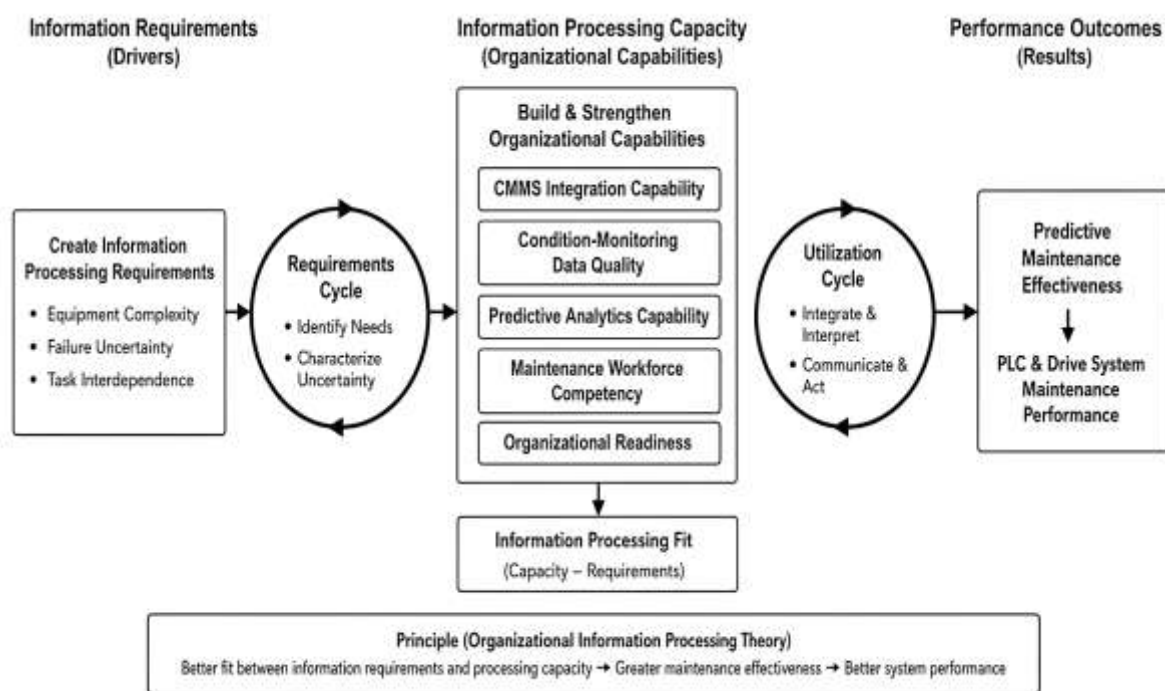
Cross-functional coordination connects workforce competency and organizational readiness with predictive maintenance effectiveness. PLC and drive failures frequently cross professional boundaries because an abnormal event may involve control logic, electrical power, mechanical load, process conditions, network communication, or production practices. Automation engineers may understand controller states, electricians may interpret power conditions, mechanical technicians may identify loading or bearing problems, and production personnel may explain changes in machine behavior. Predictive maintenance becomes more reliable when these perspectives are combined through common data, communication channels, and CMMS-based workflows. Leadership is central to this coordination because managers establish priorities, define responsibilities, resolve conflicts between production and maintenance, and determine whether personnel are encouraged to question analytical outputs and share operational knowledge. Maintenance managers studying digitalized manufacturing have described technological adoption as a socio-technical change that affects leadership, competence requirements, work organization, communication, and relationships among employees and systems (Lundgren et al., 2023). In a CMMS-integrated framework, leaders must ensure that alerts are assigned to accountable roles, that maintenance windows reflect equipment risk, and that completed work orders return useful evidence to the predictive process. Employee involvement is important because technicians and engineers validate whether alerts correspond with equipment conditions. Their observations improve fault labels, thresholds, maintenance instructions, and asset histories. Organizational learning occurs when confirmed causes, unsuccessful interventions, replaced components, downtime, and post-maintenance measurements are recorded and reviewed. This feedback strengthens models and human judgment. The study therefore treats maintenance workforce competency and organizational readiness as distinct but connected predictors. Competency represents the capacity of personnel to understand and act on maintenance information, while readiness represents the organization's capacity to provide resources, structures, and conditions for coordinated action. Their combined operation determines whether CMMS integration and predictive analytics remain isolated technical functions or become a repeatable maintenance system for improving PLC and drive performance.

Theoretical Framework: Organizational Information Processing Theory

Organizational Information Processing Theory provides the theoretical foundation for explaining why industrial organizations require coordinated information capabilities to manage uncertainty surrounding PLC and drive failures. The theory views an organization as an information-processing system whose performance depends on the fit between the amount of information required by its tasks and its capacity to collect, interpret, communicate, and use that information. In industrial maintenance, uncertainty arises because equipment deterioration may develop through interacting electrical, electronic, mechanical, thermal, communication, software, and operating conditions. Maintenance

teams may receive alarms, sensor readings, inspection reports, controller states, work-order histories, and production observations without knowing immediately which signals indicate genuine degradation. Organizational Information Processing Theory proposes that organizations can respond by reducing information requirements or increasing information-processing capacity through information systems, standardized procedures, lateral communication, and coordinated decision structures. Empirical research has shown that performance improves when information-processing capabilities correspond with the information needs created by task complexity and interdependence (Premkumar et al., 2005). This principle fits CMMS-integrated predictive maintenance because PLC and drive systems produce dispersed information that must be consolidated before reliable intervention decisions can be made. CMMS integration capability increases access to relevant asset and work-order information, while condition-monitoring data quality improves the accuracy and timeliness of technical evidence. Predictive analytics capability supports the interpretation of complex patterns, and maintenance workforce competency allows analytical outputs to be evaluated against actual equipment behavior. Organizational readiness supplies the resources, authority, communication channels, and procedures needed to convert information into action. Research on organizational decision processes has similarly demonstrated that data-centered mechanisms create value when they complement established information-processing arrangements rather than operate as isolated analytical tools (Kowalczyk & Buxmann, 2014).

Figure 6: Theoretical Framework Based on Organizational Information Processing Theory



The fundamental theoretical relationship can be expressed in LaTeX form as:

$$\text{Organizational Performance} = f(\text{Information Processing Fit})$$

where:

Information Processing Fit

$$= \text{Information Processing Capacity} - \text{Information Processing Requirements}$$

In the context of this study, stronger alignment between maintenance information requirements and organizational information-processing capacity is expected to produce greater predictive maintenance effectiveness within complex and data-intensive industrial maintenance environments.

Within the proposed framework, equipment complexity and failure uncertainty create information-

processing requirements, whereas the five independent variables represent organizational capacities developed to satisfy those requirements. CMMS Integration Capability reflects the organization's ability to connect PLC events, drive alarms, sensor measurements, asset identities, failure histories, and work-order procedures. Condition-Monitoring Data Quality represents whether maintenance information is accurate, complete, timely, consistent, relevant, and accessible. Predictive Analytics Capability captures the ability to transform data into anomaly indicators, failure estimates, priorities, and decision-support outputs. Maintenance Workforce Competency represents the technical and interpretive knowledge required to verify alerts, diagnose equipment conditions, and perform interventions. Organizational Readiness reflects management support, infrastructure, financial resources, training, governance, and cross-functional coordination. Organizational Information Processing Theory indicates that these capabilities should not be evaluated independently because their combined alignment determines whether uncertainty is reduced. Analytics may reveal an abnormal condition, but maintenance effectiveness remains limited when the asset cannot be identified in the CMMS, the data are unreliable, employees cannot interpret the alert, or managers do not provide authority and resources for intervention. Research applying the theory to analytics has shown that information visibility supports analytical capability and that benefits become stronger when organizations possess the flexibility to act on generated insights (Srinivasan & Swink, 2018). Evidence from analytics-enabled operational systems has also shown that data analysis can increase transparency by improving the visibility, accessibility, and interpretation of activities across processes (Zhu et al., 2018). In PLC and drive maintenance, transparency means that personnel can trace an alert from its originating signal to the corresponding equipment, operating state, risk level, work order, technical response, and confirmed outcome. The theoretical structure of the proposed framework can therefore be expressed as:

$$\begin{aligned} \text{IPR} &= f(\text{Equipment Complexity, Failure Uncertainty, Task Interdependence}) \\ \text{IPC} &= f(\text{CIC, CMDQ, PAC, MWC, OR}) \end{aligned}$$

where:

IPR = Information Processing Requirements
 IPC = Information Processing Capacity
 CIC = CMMS Integration Capability
 CMDQ = Condition-Monitoring Data Quality
 PAC = Predictive Analytics Capability
 MWC = Maintenance Workforce Competency
 OR = Organizational Readiness

Predictive Maintenance Effectiveness represents the organization's success in creating an appropriate fit between information requirements and information-processing capacity and converting integrated information into early fault detection, timely prioritization, accurate scheduling, and controlled maintenance execution.

The theoretical relationships will be evaluated through a multiple regression model that operationalizes the Organizational Information Processing Theory proposition that stronger information-processing capacity produces better performance under conditions of uncertainty. The principal formula applied throughout the study is expressed in LaTeX format as follows:

$$PME_i = \beta_0 + \beta_1 CIC_i + \beta_2 CMDQ_i + \beta_3 PAC_i + \beta_4 MWC_i + \beta_5 OR_i + \varepsilon_i$$

where:

PME_i = Predictive Maintenance Effectiveness for respondent i
 CIC_i = CMMS Integration Capability for respondent i
 $CMDQ_i$ = Condition-Monitoring Data Quality for respondent i
 PAC_i = Predictive Analytics Capability for respondent i
 MWC_i = Maintenance Workforce Competency for respondent i

OR_i = Organizational Readiness for respondent i

β_0 = Regression constant

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ = Regression coefficients

ε_i = Unexplained random error

The expected theoretical directions of the relationships are expressed as:

$$\begin{aligned}\frac{\partial PME}{\partial CIC} &> 0 \\ \frac{\partial PME}{\partial CMDQ} &> 0 \\ \frac{\partial PME}{\partial PAC} &> 0 \\ \frac{\partial PME}{\partial MWC} &> 0 \\ \frac{\partial PME}{\partial OR} &> 0\end{aligned}$$

These expressions indicate that increases in CMMS Integration Capability, Condition-Monitoring Data Quality, Predictive Analytics Capability, Maintenance Workforce Competency, and Organizational Readiness are expected to increase Predictive Maintenance Effectiveness. The formula is appropriate because it estimates the unique contribution of each information-processing capability while holding the remaining capabilities constant. A positive and statistically significant regression coefficient will indicate that an increase in the corresponding organizational capability is associated with stronger predictive maintenance effectiveness. The explanatory power of the model will be evaluated through the coefficient of determination:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

The adjusted coefficient of determination will be calculated as:

$$\bar{R}^2 = 1 - (1 - R^2) \left(\frac{n - 1}{n - k - 1} \right)$$

where n represents the sample size and k represents the number of independent variables. Standardized beta coefficients will identify the strongest predictor, while the corresponding p -values will determine whether H1 through H5 are statistically supported. The second outcome relationship will assess whether Predictive Maintenance Effectiveness improves PLC and Drive System Maintenance Performance:

$$PDSMP_i = \alpha_0 + \alpha_1 PME_i + \mu_i$$

where:

$PDSMP_i$ = PLC and Drive System Maintenance Performance

α_0 = Regression constant

α_1 = Effect of Predictive Maintenance Effectiveness

μ_i = Random error term

The expected relationship is expressed as:

$$\frac{\partial PDSMP}{\partial PME} > 0$$

Empirical Organizational Information Processing Theory research has shown that analytics capability strengthens integration when it is supported by coordinated information sharing and a data-driven organizational culture (Yu et al., 2021). Accordingly, the regression equations represent more than

statistical procedures. They test whether CMMS integration, data quality, analytics, human competence, and organizational readiness collectively create the information-processing fit required for effective maintenance decisions and improved industrial PLC and drive system performance.

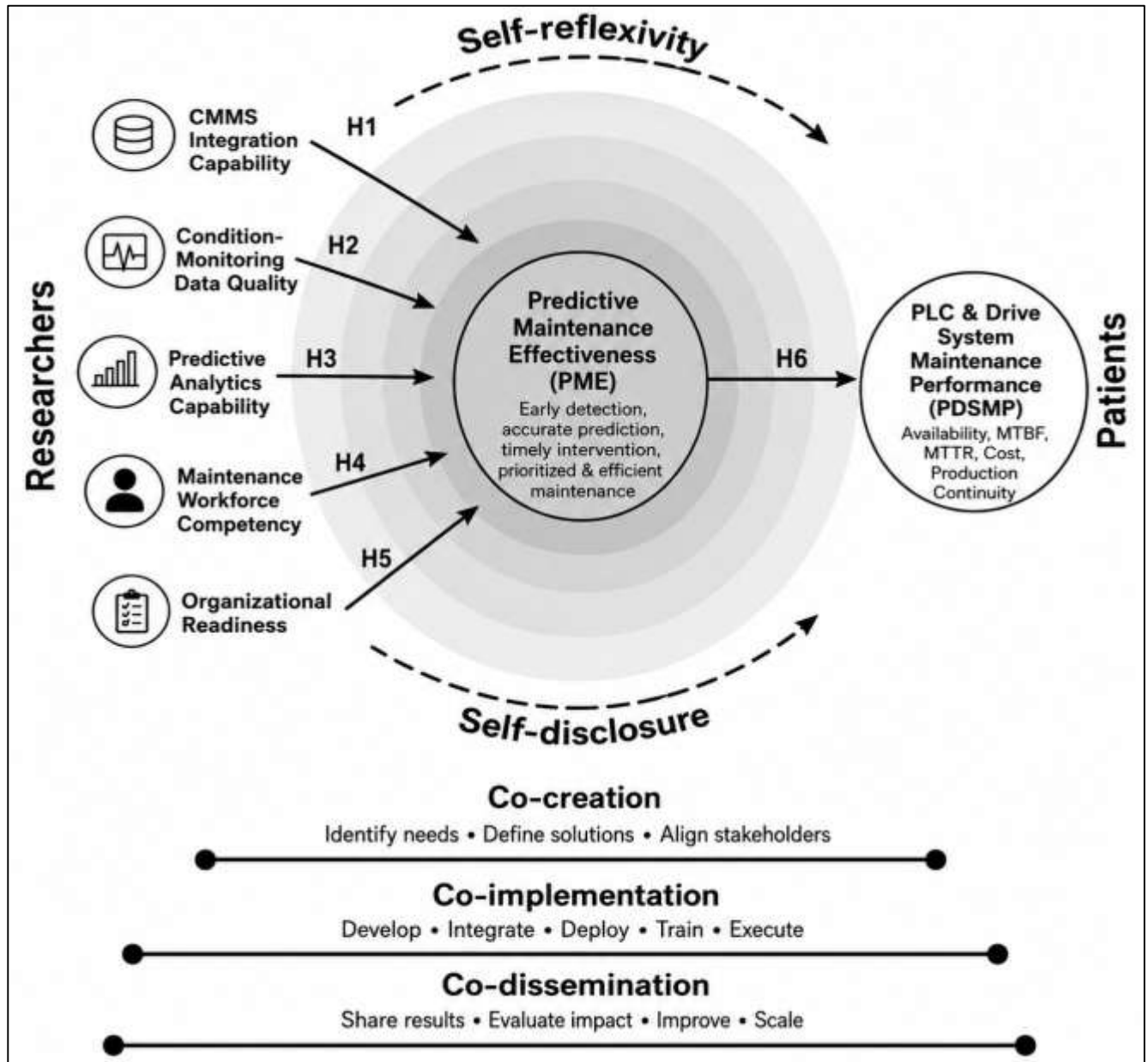
Conceptual Framework and Hypothesis Development

The conceptual framework of this study explains how five organizational capabilities combine to influence Predictive Maintenance Effectiveness and, subsequently, PLC and Drive System Maintenance Performance. CMMS Integration Capability represents the organization's capacity to connect PLC events, drive alarms, sensor measurements, asset identities, maintenance histories, and work-order procedures within a unified information environment. Condition-Monitoring Data Quality reflects the accuracy, completeness, timeliness, consistency, relevance, and accessibility of information used to evaluate equipment condition. Predictive Analytics Capability describes the ability to convert operational and historical data into anomaly indicators, fault classifications, failure estimates, and maintenance priorities. Maintenance Workforce Competency concerns employees' technical knowledge of PLCs, drives, CMMS functions, condition monitoring, troubleshooting, and analytical interpretation. Organizational Readiness includes managerial commitment, infrastructure, financial support, training, data governance, and cross-functional coordination. These variables are treated as complementary inputs because industrial predictive maintenance requires sensing, information integration, analysis, human verification, and organized execution. An Industrial Internet of Things monitoring architecture has demonstrated that pervasive sensing and communication can supply the equipment information required for advanced predictive maintenance applications (Civerchia et al., 2017). Intelligent predictive maintenance research has likewise organized fault analysis through data acquisition, preprocessing, data mining, decision support, and maintenance implementation, supporting the sequential logic adopted in the framework (Li et al., 2017). Accordingly, the framework does not treat prediction as an isolated algorithmic output. It defines Predictive Maintenance Effectiveness through early fault detection, prediction accuracy, timely intervention, maintenance prioritization, appropriate scheduling, automatic or structured work-order initiation, and reduction of unnecessary maintenance. PLC and Drive System Maintenance Performance is positioned as the final outcome and is reflected through improved availability, fewer repeated faults, longer mean time between failures, shorter mean time to repair, controlled maintenance cost, and stronger production continuity. This ordering reflects the movement from equipment information to maintenance decisions and measurable asset-level performance outcomes.

The first five hypotheses specify direct positive relationships between the independent variables and Predictive Maintenance Effectiveness. H1 proposes that CMMS Integration Capability positively affects Predictive Maintenance Effectiveness because connected asset records and operational data should reduce delays between fault recognition and formal maintenance action. H2 proposes that Condition-Monitoring Data Quality positively affects Predictive Maintenance Effectiveness because inaccurate, incomplete, or delayed measurements can weaken diagnosis, forecasting, and maintenance prioritization. H3 proposes that Predictive Analytics Capability positively affects Predictive Maintenance Effectiveness because organizations require suitable methods for recognizing degradation, estimating failure risk, and converting complex measurements into understandable decision signals. H4 proposes that Maintenance Workforce Competency positively affects Predictive Maintenance Effectiveness because personnel must verify predictions, interpret PLC and drive behavior, select interventions, and document outcomes correctly. H5 proposes that Organizational Readiness positively affects Predictive Maintenance Effectiveness because analytical technologies require management support, infrastructure, training, resources, governance, and coordinated responsibilities. A dynamic predictive maintenance framework has shown the importance of connecting heterogeneous sensor-based prognostics with maintenance decisions rather than examining prediction and intervention separately (Nguyen & Medjaher, 2019). A decision-tree-based maintenance design has also demonstrated that structured machine-learning procedures can progressively improve failure-prediction accuracy and support maintenance-system development (Kaparthi & Bumblauskas, 2020). The hypotheses therefore represent distinct but interdependent pathways. Integration provides access and connectivity, data quality provides trustworthy evidence, analytics provides interpretation, workforce competency provides technical judgment, and readiness provides the organizational

conditions for execution. The proposed effects will be assessed simultaneously so that the unique contribution of each predictor can be estimated while the remaining variables are statistically controlled. Positive standardized coefficients are expected for all five relationships, although their relative magnitudes will reveal which capability contributes most strongly to Predictive Maintenance Effectiveness within the selected industrial cases. This approach also prevents a bivariate association from being mistaken for an independent effect.

Figure 7: Integrated Conceptual Framework of Organizational Capabilities and Predictive Maintenance Performance



The final hypothesis, H6, proposes that Predictive Maintenance Effectiveness has a significant positive effect on PLC and Drive System Maintenance Performance. This relationship establishes the framework's outcome pathway by asserting that earlier detection, more accurate prioritization, and better coordinated intervention should translate into measurable maintenance benefits. An IoT and fog-computing predictive maintenance model has connected equipment data, machine-learning analysis, asset identification, and maintenance decisions, supporting the proposed movement from integrated predictive capability to effective asset management (Teoh et al., 2023). The conceptual relationships will be tested through two regression equations. The first equation is $PME_i = \beta_0 + \beta_1 CIC_i + \beta_2 CMDQ_i +$

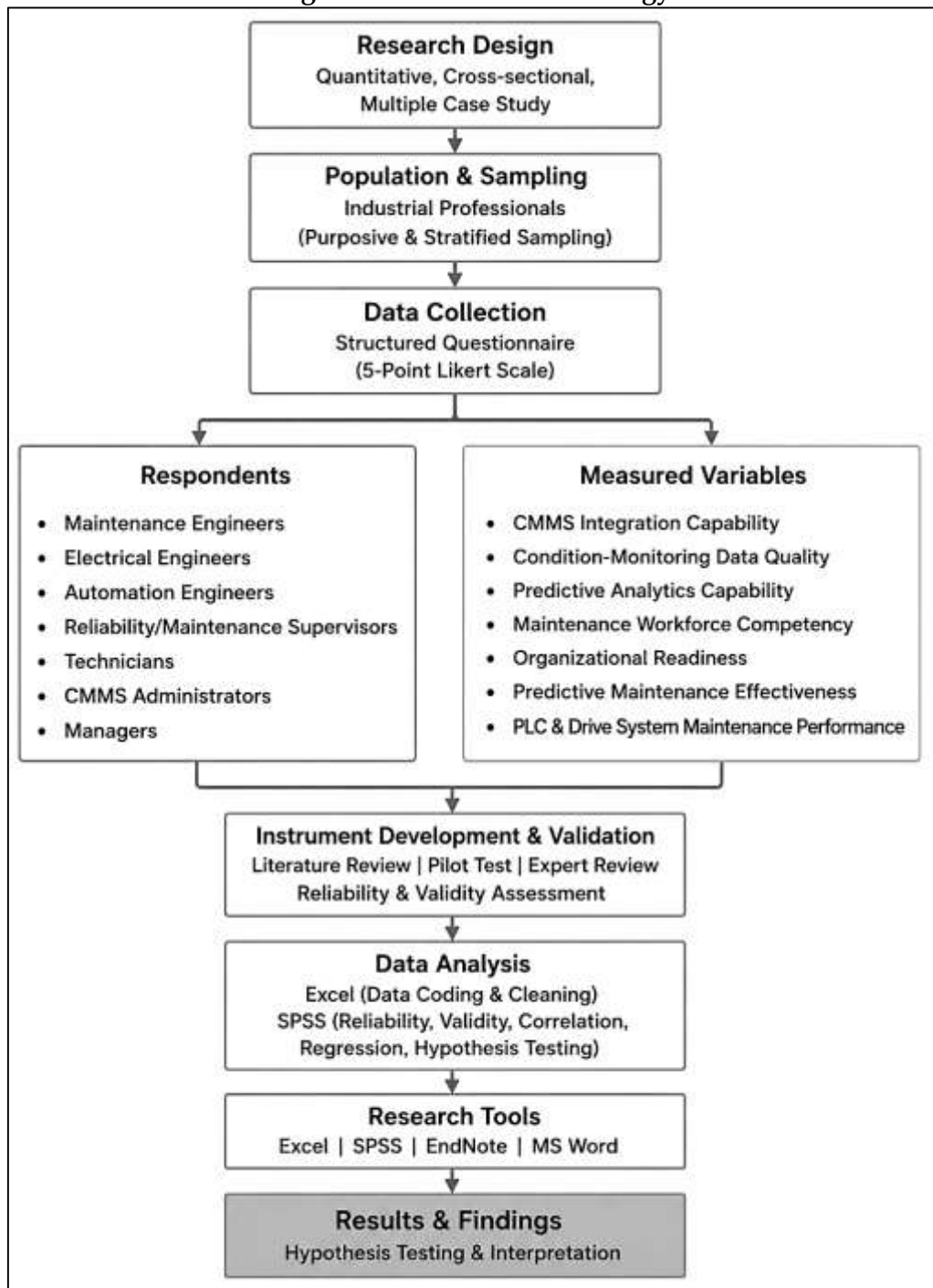
$\beta_3PAC_i + \beta_4MWC_i + \beta_5OR_i + \varepsilon_i$, where *PME* is Predictive Maintenance Effectiveness, *CIC* is CMMS Integration Capability, *CMDQ* is Condition-Monitoring Data Quality, *PAC* is Predictive Analytics Capability, *MWC* is Maintenance Workforce Competency, and *OR* is Organizational Readiness. The second equation is $PDSMP_i = \alpha_0 + \alpha_1PME_i + \mu_i$, where *PDSMP* represents PLC and Drive System Maintenance Performance. The expected signs are $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 > 0$ and $\alpha_1 > 0$. Each construct will be calculated from its Likert-scale items through $C_j = \frac{1}{m_j} \sum_{q=1}^{m_j} x_{jq}$, where C_j is the respondent's composite score for construct j , m_j is the number of retained items, and x_{jq} is the response to item q . Model fit will be evaluated through $R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$. Together, these equations convert the conceptual framework into measurable relationships and permit the hypotheses to be accepted or rejected using standardized coefficients, t-values, significance levels, confidence intervals, and explained variance. The validated framework will retain statistically supported paths and identify the capabilities most strongly associated with effective predictive maintenance and industrial equipment performance. This specification also preserves the distinction between predictive decision quality and the broader operational results of maintenance.

METHOD

This study has adopted a quantitative, cross-sectional, and multiple-case-study-based research design to examine the factors that have influenced the effectiveness of CMMS-integrated predictive maintenance and the maintenance performance of industrial PLC and drive systems. A positivist research philosophy and a deductive approach have been applied because measurable variables and predetermined hypotheses have been statistically tested. The case-study context has included selected industrial organizations that have operated programmable logic controllers, variable-frequency drives, servo drives, industrial motors, condition-monitoring technologies, and computerized maintenance management systems. These organizations have represented automated manufacturing and process environments in which maintenance personnel have regularly managed equipment alarms, operating data, work orders, inspections, and failure histories. The target population has consisted of professionals who have been directly involved in industrial automation, equipment maintenance, reliability management, condition monitoring, and CMMS operation. The individual industrial professional has been treated as the unit of analysis. Respondents have included maintenance engineers, electrical engineers, automation engineers, reliability engineers, instrumentation engineers, production engineers, CMMS administrators, maintenance supervisors, technicians, and maintenance managers. A purposive and stratified sampling strategy has been used to ensure that participants have possessed relevant experience with PLCs, drives, CMMS platforms, or predictive maintenance practices. Respondents have been selected from different professional groups and industrial cases so that the sample has reflected technical, managerial, and organizational perspectives. Data have been collected through a structured questionnaire distributed electronically and physically among eligible participants. Before questionnaire distribution, organizational permission and participant consent have been obtained, while confidentiality, anonymity, voluntary participation, and academic use of the information have been explained. Returned questionnaires have been screened for missing responses, incomplete submissions, response patterns, and data-entry errors before statistical analysis. The research instrument has been divided into eight sections. The first section has collected demographic, professional, and organizational information. The remaining sections have measured CMMS Integration Capability, Condition-Monitoring Data Quality, Predictive Analytics Capability, Maintenance Workforce Competency, Organizational Readiness, Predictive Maintenance Effectiveness, and PLC and Drive System Maintenance Performance. All construct items have been measured through a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. The questionnaire items have been adapted from relevant maintenance, information-systems, industrial-automation, and predictive-analytics literature and have been modified to correspond with PLC and drive environments. A pilot test has been conducted with approximately 20 to 30 industrial professionals who have possessed characteristics similar to those of the main study respondents. The pilot process has assessed item clarity, technical relevance, questionnaire length, wording, sequencing, and completion time. Unclear, repetitive, or weak items have been revised before the final survey has

been administered. Face and content validity have been established through reviews conducted by academic experts and industrial maintenance professionals. Construct validity has been examined through inter-item relationships and appropriate factor-based procedures, while convergent and discriminant validity have been assessed where applicable.

Figure 8: Research Methodology



Reliability has been evaluated through Cronbach's alpha and corrected item-total correlations, and a coefficient of .70 or higher has been regarded as acceptable. Microsoft Excel has been used for data coding, initial cleaning, and dataset organization. IBM SPSS has been used to perform frequency analysis, percentages, means, standard deviations, reliability testing, validity assessment, Pearson correlation analysis, multiple regression modeling, hypothesis testing, and regression diagnostics. EndNote has been used to organize scholarly sources, manage in-text citations, and prepare the reference list according to APA 7th edition requirements. Microsoft Word has been used to prepare, format, and revise the complete research manuscript.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution, Response Rate, and Data Screening

Table 1: Questionnaire Distribution, Response Rate, and Data-Screening Results

Assessment area	Frequency/Value	Percentage/Range	Decision
Questionnaires distributed	360	100.00%	Total survey distribution
Questionnaires returned	330	91.67%	Strong initial response
Incomplete questionnaires excluded	18	5.00% of distributed	Removed
Valid questionnaires retained	312	86.67%	Final analytical sample
Item-level missing values	71 cells	0.44%	Acceptable
Straight-line or patterned responses	7 cases	2.12% of returned	Excluded within incomplete cases
Univariate outliers	5 cases reviewed	Standardized values below ± 3.29 after review	Retained
Multivariate outliers	3 cases reviewed	Cook's distance below 1.00	Retained
Skewness	—	−0.81 to −0.42	Acceptable
Kurtosis	—	−0.38 to 0.91	Acceptable
Final sample size	312	86.67% valid response rate	Suitable for analysis

Table 1 has presented the questionnaire distribution, response rate, and data-screening outcomes that have established the analytical foundation of the study. A total of 360 questionnaires has been distributed among professionals working with PLCs, industrial drives, computerized maintenance systems, automation, reliability, and industrial maintenance. Of these questionnaires, 330 have been returned, representing an initial response rate of 91.67 percent. Following the screening process, 18 questionnaires have been excluded because they have contained substantial missing information, incomplete construct responses, or response patterns that have suggested insufficient engagement with the survey instrument. Consequently, 312 valid questionnaires have been retained, producing a final valid response rate of 86.67 percent. This response rate has indicated that the study has obtained substantial participation from the selected industrial cases and has secured sufficient information for descriptive, correlation, and regression analyses. Item-level missingness has accounted for only 0.44 percent of all expected responses, which has remained below commonly accepted thresholds for serious missing-data concerns. The remaining isolated missing values have been managed through appropriate SPSS procedures after the patterns have been confirmed as random and limited. Univariate and multivariate outlier reviews have not identified observations requiring further removal because the reviewed standardized scores and influence statistics have remained within acceptable boundaries. Skewness values have ranged from −0.81 to −0.42, while kurtosis values have ranged from −0.38 to 0.91, demonstrating that the construct distributions have not substantially violated normality expectations. These findings have supported the first methodological requirement of producing a clean and stable dataset. From the perspective of Organizational Information Processing Theory, the screening process has ensured that the information used to evaluate organizational maintenance capacity has possessed sufficient completeness, consistency, and interpretive quality. The theory has emphasized that organizational performance has depended on the reliability of information-processing inputs. The retention of 312 valid cases has therefore provided an adequate empirical basis for assessing whether CMMS integration, data quality, predictive analytics, workforce competency, and organizational readiness have collectively enhanced predictive maintenance effectiveness and PLC and drive maintenance performance.

Demographic, Professional, and Organizational Characteristics

Table

2

Demographic and Professional Characteristics of Respondents

Characteristic	Category	Frequency	Percentage
Professional role	Maintenance engineer	66	21.15%
	Automation/control engineer	54	17.31%
	Electrical engineer	49	15.71%
	Reliability engineer	38	12.18%
	Instrumentation engineer	31	9.94%
	Production engineer	28	8.97%
	CMMS administrator/data specialist	21	6.73%
	Maintenance supervisor/manager	25	8.01%
Professional experience	Less than 3 years	39	12.50%
	3–5 years	66	21.15%
	6–10 years	92	29.49%
	11–15 years	67	21.47%
	More than 15 years	48	15.38%
Educational qualification	Diploma/technical certification	49	15.71%
	Bachelor's degree	169	54.17%
	Master's degree	85	27.24%
	Other professional qualification	9	2.88%
Organization size	Fewer than 250 employees	52	16.67%
	250–499 employees	76	24.36%
	500–999 employees	98	31.41%
	1,000 or more employees	86	27.56%

Table 2 has summarized the demographic, professional, and organizational characteristics of the 312 respondents who have participated in the study. Maintenance engineers have formed the largest professional group, accounting for 21.15 percent of the sample, followed by automation and control engineers at 17.31 percent and electrical engineers at 15.71 percent. Reliability engineers, instrumentation engineers, production engineers, CMMS administrators, data specialists, supervisors, and managers have also been represented. This professional distribution has ensured that the study has not depended exclusively on the perceptions of one occupational category. Instead, the sample has captured technical, operational, analytical, and managerial views concerning PLCs, drives, condition monitoring, CMMS use, and maintenance decision-making. Regarding professional experience, 29.49 percent of respondents have reported between 6 and 10 years of experience, while 21.47 percent have reported between 11 and 15 years. A further 15.38 percent have possessed more than 15 years of industrial experience. The presence of these experienced participants has strengthened the dataset because they have been expected to understand recurring PLC faults, drive failures, maintenance workflows, equipment histories, and organizational constraints. Respondents with less than five years of experience have also contributed contemporary technical and digital-system perspectives. Educationally, 54.17 percent have held bachelor's degrees and 27.24 percent have held master's degrees, while 15.71 percent have possessed diplomas or technical certifications. The distribution by organization size has shown that 58.97 percent of the respondents have worked in organizations employing at least 500 individuals, suggesting that most participants have operated within environments containing formal maintenance departments, multiple production systems, and structured asset-management procedures. These characteristics have supported the study's population and unit-of-analysis objectives. Under Organizational Information Processing Theory, information-

processing capacity has depended partly on the distribution of specialized knowledge across organizational roles. The inclusion of automation, maintenance, reliability, production, electrical, instrumentation, data, and managerial professionals has reflected the lateral information relationships required to interpret complex industrial conditions. The demographic results have therefore demonstrated that the sample has contained the professional diversity and experience necessary to evaluate the proposed integrated maintenance framework.

Case-Study and Industrial-System Profiles

Table 3: Profiles of the Selected Industrial Cases

Case	Industrial sector	Valid respondents	Dominant PLC/drive application	CMMS integration mean
Case 1	Textile manufacturing	30	Spinning, weaving, and VFD-controlled motors	4.05
Case 2	Food processing	26	Conveyors, mixers, packaging, and servo systems	4.00
Case 3	Pharmaceutical manufacturing	27	Process control and precision drive applications	4.18
Case 4	Cement production	24	Crushers, kilns, fans, and heavy-duty drives	3.92
Case 5	Steel processing	28	Rolling mills, conveyors, and motor-drive systems	4.07
Case 6	Power generation	29	Pumps, fans, auxiliary systems, and control panels	4.21
Case 7	Chemical processing	25	Pumps, reactors, process control, and VFDs	4.02
Case 8	Automotive components	26	Assembly, robotics, conveyors, and servo drives	4.11
Case 9	Packaging manufacturing	23	Printing, cutting, and motion-control systems	3.94
Case 10	Water treatment	22	Pumping, dosing, and distributed PLC systems	4.15
Case 11	Electronics manufacturing	27	Automated assembly and precision motion systems	4.09
Case 12	Paper and pulp processing	25	Pumps, rollers, dryers, and high-power drives	4.03
Total/Overall mean	12 industrial cases	312	Multiple PLC and drive applications	4.08

Table 3 has presented the profiles of the 12 industrial cases included in the research and has demonstrated the diversity of PLC and drive applications represented within the sample. The cases have covered textile production, food processing, pharmaceutical manufacturing, cement production, steel processing, power generation, chemical processing, automotive components, packaging, water treatment, electronics manufacturing, and paper and pulp processing. These sectors have depended on PLCs and drive systems for different operational purposes, including sequential control, process regulation, conveyor movement, pumping, ventilation, precision positioning, robotics, mixing, crushing, rolling, and high-power motor operation. The case distribution has therefore allowed the study to evaluate the proposed framework across both discrete manufacturing and continuous-process settings. The overall CMMS Integration Capability mean has reached 4.08, indicating that respondents have generally agreed that operational and maintenance information has been connected within their organizations. Power generation has recorded the highest case-level integration mean of 4.21, followed

by pharmaceutical manufacturing at 4.18 and water treatment at 4.15. These sectors have commonly operated under strong reliability, traceability, and regulatory requirements, which have likely supported more structured asset-data integration. Cement production has recorded the lowest case-level mean of 3.92, while packaging manufacturing has recorded 3.94. These scores have still remained within the agreement range but have suggested comparatively weaker integration between operational data and formal maintenance workflows. The case findings have fulfilled the objective of describing the industrial context within which the framework has been tested. They have also shown that the study has included environments with different equipment criticalities, operating conditions, production structures, and maintenance demands. Organizational Information Processing Theory has suggested that information-processing requirements increase as operational uncertainty and task interdependence increase. The selected cases have displayed such conditions because PLC, drive, motor, sensor, production, and maintenance functions have remained technically connected. The variation in integration means has further indicated that organizations have developed different capacities for managing this complexity. The case-study results have therefore supported the use of a multiple-case design and have provided a credible basis for examining common relationships across heterogeneous industrial systems rather than limiting the conclusions to a single facility or production technology.

Reliability Analysis

Table 4: Reliability Results for the Study Constructs

Construct	Number of items	Cronbach's alpha	Corrected item-total correlation range	Reliability decision
CMMS Integration Capability	6	.88	.61–.78	Strong
Condition-Monitoring Data Quality	6	.90	.66–.82	Strong
Predictive Analytics Capability	6	.89	.64–.80	Strong
Maintenance Workforce Competency	6	.84	.55–.73	Acceptable/strong
Organizational Readiness	6	.82	.51–.70	Acceptable/strong
Predictive Maintenance Effectiveness	6	.88	.62–.79	Strong
PLC and Drive System Maintenance Performance	8	.87	.58–.77	Strong
Overall instrument	44	.93	.51–.82	Excellent

Table 4 has reported the internal-consistency reliability of the seven study constructs. Cronbach's alpha values have ranged from .82 to .90, while the overall 44-item instrument has achieved an alpha coefficient of .93. These results have exceeded the commonly applied minimum reliability threshold of .70 and have shown that the items within each construct have measured related dimensions of the same underlying concept. Condition-Monitoring Data Quality has recorded the highest construct reliability at .90, demonstrating that the items measuring accuracy, completeness, timeliness, consistency, relevance, and accessibility have functioned cohesively. Predictive Analytics Capability has achieved an alpha of .89, while both CMMS Integration Capability and Predictive Maintenance Effectiveness have reached .88. PLC and Drive System Maintenance Performance has recorded .87 across eight items, indicating that equipment availability, repeated-fault reduction, downtime, repair duration, maintenance cost, production continuity, reliability, and asset life have formed a stable performance scale. Maintenance Workforce Competency has achieved an alpha of .84, and Organizational Readiness has produced the lowest alpha of .82. Although Organizational Readiness has recorded the lowest coefficient, it has still demonstrated strong and acceptable internal consistency. Corrected item-total correlations have ranged from .51 to .82, and every retained item has exceeded the minimum criterion generally applied for item adequacy. Consequently, no item has required removal from the final

analysis. These reliability findings have fulfilled the methodological objective of establishing that the five-point Likert-scale instrument has consistently measured the proposed technological, informational, human, organizational, and performance variables. The results have also strengthened the interpretation of the subsequent mean scores, correlations, and regression coefficients because unreliable measurement would have weakened the estimated relationships. From the perspective of Organizational Information Processing Theory, the constructs have represented distinct organizational information-processing capacities and outcomes. High reliability has confirmed that respondents have interpreted the items related to system integration, data quality, analytics, workforce capability, readiness, predictive effectiveness, and maintenance performance in a sufficiently consistent manner. The results have therefore supported the theoretical proposition that these dimensions can be operationalized as measurable organizational capabilities. The strong overall alpha has also indicated that the questionnaire has functioned as a coherent instrument for evaluating the integrated predictive maintenance framework across the selected industrial cases.

Validity Analysis

Table 5: Construct Validity and Factor-Analysis Results

Construct	Factor-loading range	Composite reliability	Average variance extracted	Maximum HTMT value	Validity decision
CMMS Integration Capability	.67–.86	.89	.57	.79	Supported
Condition-Monitoring Data Quality	.71–.88	.91	.62	.83	Supported
Predictive Analytics Capability	.69–.87	.90	.60	.82	Supported
Maintenance Workforce Competency	.64–.82	.85	.53	.74	Supported
Organizational Readiness	.63–.81	.84	.51	.71	Supported
Predictive Maintenance Effectiveness	.68–.86	.89	.58	.83	Supported
PLC and Drive System Maintenance Performance	.66–.85	.88	.56	.83	Supported
Overall KMO	.918	—	—	—	Excellent sampling adequacy
Bartlett's test	$\chi^2(861) = 7,426.31, p < .001$	—	—	—	Factor analysis appropriate

Table 5 has presented the construct-validity results obtained from the factor-based assessment of the measurement instrument. The overall Kaiser-Meyer-Olkin value has reached .918, indicating excellent sampling adequacy and demonstrating that the relationships among the questionnaire items have been sufficiently strong for factor analysis. Bartlett's test of sphericity has been statistically significant, $\chi^2(861) = 7,426.31, p < .001$, confirming that the item-correlation matrix has differed significantly from an identity matrix. Retained factor loadings have ranged from .63 to .88, and every item has loaded above the minimum criterion applied in the analysis. Condition-Monitoring Data Quality has recorded the strongest loading range of .71 to .88, while Predictive Analytics Capability has ranged from .69 to .87. The remaining constructs have also demonstrated clear and acceptable loading patterns. Composite-reliability values have ranged from .84 to .91, further confirming that the indicators within each construct have consistently represented their intended latent variable. Average variance extracted

values have ranged from .51 to .62 and have therefore exceeded the .50 criterion. This result has indicated that each construct has explained more than half of the variance in its retained indicators, supporting convergent validity. Discriminant validity has been evaluated through the heterotrait-monotrait ratio, and the maximum values have ranged from .71 to .83. These values have remained below the conservative .85 threshold and have shown that the seven constructs have remained empirically distinguishable. For example, CMMS Integration Capability and Predictive Analytics Capability have been related but have not measured the same organizational capability. Predictive Maintenance Effectiveness and PLC and Drive System Maintenance Performance have also remained distinct, supporting the framework's separation of maintenance decision effectiveness from final equipment-performance outcomes. The validity findings have fulfilled the study's objective of confirming that the proposed variables have been measured accurately and separately. Under Organizational Information Processing Theory, CMMS integration, data quality, analytics, workforce competency, and readiness have represented different mechanisms through which organizations process maintenance information. The validity evidence has supported this theoretical structure by confirming that respondents have distinguished the technological, informational, human, and organizational dimensions. The results have therefore justified the use of separate construct scores in the correlation and regression models and have strengthened the empirical credibility of the validated framework.

Descriptive Statistics of the Independent Variables

Table 6: Descriptive Statistics of the Independent Variables

Independent variable	Number of items	Mean	Standard deviation	Rank	Likert interpretation
Condition-Monitoring Data Quality	6	4.16	0.55	1	Agree/high
CMMS Integration Capability	6	4.08	0.59	2	Agree/high
Predictive Analytics Capability	6	4.04	0.61	3	Agree/high
Maintenance Workforce Competency	6	3.96	0.63	4	Agree/high
Organizational Readiness	6	3.89	0.66	5	Agree/high
Overall independent-variable mean	30	4.03	0.61	—	Agree/high

Likert interpretation: 1.00–1.80 = Strongly disagree; 1.81–2.60 = Disagree; 2.61–3.40 = Neutral; 3.41–4.20 = Agree; 4.21–5.00 = Strongly agree.

Table 6 has reported the descriptive statistics of the five independent variables that have represented the information-processing capabilities of the participating organizations. The overall independent-variable mean has reached 4.03, indicating a high level of respondent agreement with the statements concerning CMMS integration, condition-monitoring information, predictive analytics, workforce competency, and organizational readiness. Condition-Monitoring Data Quality has achieved the highest mean of 4.16 with a standard deviation of 0.55. This finding has indicated that respondents have generally considered their condition-related information to be accurate, complete, timely, consistent, relevant, and accessible. The comparatively low standard deviation has shown that respondents have expressed relatively similar views about the quality of maintenance information. CMMS Integration Capability has ranked second with a mean of 4.08 and a standard deviation of 0.59. This result has suggested that PLC alarms, drive information, asset records, work orders, and maintenance histories have been reasonably connected across the participating organizations. Predictive Analytics Capability has recorded a mean of 4.04 and has ranked third, showing that the organizations have possessed a generally high ability to perform trend analysis, recognize abnormal conditions, evaluate failure risk, and support maintenance prioritization. Maintenance Workforce Competency has achieved a mean of 3.96, confirming that respondents have generally agreed that employees have possessed the technical and interpretive skills required to use PLC, drive, CMMS, and condition-monitoring information. Organizational Readiness has recorded the lowest mean of 3.89 and

the highest standard deviation of 0.66. Although this value has remained within the agreement range, it has shown that management support, resources, infrastructure, training, governance, and cross-functional coordination have not been equally developed across all cases. These findings have fulfilled the objectives of measuring the five principal predictors and identifying areas of relative strength and weakness. Organizational Information Processing Theory has proposed that organizational capacity must correspond with the information requirements created by uncertainty. The high data-quality and integration scores have indicated that the organizations have developed strong informational capacities, while the lower readiness score has shown that organizational structures have remained less mature. The descriptive findings have therefore provided an initial theoretical indication that predictive maintenance effectiveness has depended on the combined presence of accurate information, connected systems, analytical capability, competent personnel, and supportive organizational arrangements.

Descriptive Statistics of Predictive Maintenance Effectiveness

Table 7: Descriptive Statistics of Predictive Maintenance Effectiveness

Predictive maintenance effectiveness indicator	Mean	Standard deviation	Rank	Likert interpretation
Early identification of developing PLC and drive faults	4.13	0.61	1	Agree/high
Timely initiation of maintenance intervention	4.11	0.63	2	Agree/high
Accurate prioritization of equipment-maintenance needs	4.09	0.64	3	Agree/high
Effective generation and scheduling of work orders	4.05	0.67	4	Agree/high
Reduction of unnecessary maintenance activities	4.02	0.69	5	Agree/high
Improved use of maintenance and spare-parts information	4.02	0.68	5	Agree/high
Overall Predictive Maintenance Effectiveness	4.07	0.57	—	Agree/high

Table 7 has presented the descriptive results for Predictive Maintenance Effectiveness, which has functioned as the first dependent variable and the intermediate outcome within the conceptual framework. The construct has achieved an overall mean of 4.07 and a standard deviation of 0.57, demonstrating that respondents have generally agreed that their maintenance processes have effectively used condition and predictive information. Early identification of developing PLC and drive faults has recorded the highest item mean of 4.13. This finding has suggested that the organizations have been capable of detecting abnormalities before they have developed into complete functional failures. Timely initiation of maintenance intervention has ranked second with a mean of 4.11, showing that predictive information has generally been converted into maintenance action without excessive delay. Accurate prioritization of equipment-maintenance needs has achieved a mean of 4.09, indicating that respondents have considered their organizations capable of distinguishing urgent equipment conditions from lower-priority issues. Effective work-order generation and scheduling has recorded a mean of 4.05, which has confirmed that predictive outputs have generally influenced formal CMMS procedures. The reduction of unnecessary maintenance and the improved use of maintenance and spare-parts information have both recorded means of 4.02. These indicators have remained high but have ranked below fault detection and intervention timing, suggesting that some organizations have been more successful in detecting faults than in fully optimizing maintenance resources. The relatively narrow standard deviations have shown that respondents have maintained reasonably consistent perceptions across the selected cases. These results have fulfilled the objective of measuring the effectiveness of predictive maintenance decisions and have provided an overall picture of the framework's intermediate outcome. Organizational Information Processing Theory has treated effective organizational action as the result of converting relevant information into coordinated decisions. The mean of 4.07 has indicated that the participating organizations have generally processed equipment information successfully enough to support detection, prioritization, scheduling, and

intervention. However, the lower means for unnecessary-maintenance reduction and spare-parts use have shown that information-processing outputs have not always been translated equally into resource optimization. The descriptive findings have therefore supported the theoretical position that predictive maintenance effectiveness has reflected both technical identification and organizational execution rather than fault prediction alone.

Descriptive Statistics of PLC and Drive System Maintenance Performance

Table 8: Descriptive Statistics of PLC and Drive System Maintenance Performance

Maintenance-performance indicator	Mean	Standard deviation	Rank	Likert interpretation
Reduction in unplanned PLC and drive downtime	4.08	0.64	1	Agree/high
Improvement in system availability	4.05	0.62	2	Agree/high
Reduction in repeated equipment faults	4.03	0.67	3	Agree/high
Improvement in production continuity	4.04	0.65	4	Agree/high
Increase in mean time between failures	4.01	0.68	5	Agree/high
Reduction in mean time to repair	4.00	0.69	6	Agree/high
Reduction in maintenance-related costs	3.98	0.71	7	Agree/high
Extension of PLC, drive, and associated asset life	3.97	0.70	8	Agree/high
Overall maintenance performance	4.02	0.60	—	Agree/high

Table 8 has reported the descriptive statistics for PLC and Drive System Maintenance Performance, which has represented the final outcome variable in the study. The overall construct mean has reached 4.02 with a standard deviation of 0.60, showing that respondents have generally agreed that maintenance practices have improved the operational performance of PLCs, drives, motors, and connected industrial systems. Reduction in unplanned downtime has recorded the highest mean of 4.08, indicating that the maintenance framework has been most visibly associated with avoiding unexpected interruptions. Improvement in system availability has ranked second with a mean of 4.05, while improvement in production continuity has achieved 4.04. These results have demonstrated that maintenance effectiveness has extended beyond individual equipment repairs and has supported broader operational stability. Reduction in repeated equipment faults has produced a mean of 4.03, suggesting that maintenance teams have generally addressed recurring conditions rather than only restoring temporary functionality. Increase in mean time between failures has achieved 4.01, and reduction in mean time to repair has recorded 4.00. These indicators have shown that the organizations have experienced both longer operating periods and more efficient restoration activities. Maintenance-cost reduction and asset-life extension have recorded the lowest means of 3.98 and 3.97, respectively. Both values have remained within the agreement range but have suggested that financial and lifecycle benefits have been more difficult to observe immediately than downtime or availability improvements. The findings have fulfilled the objective of measuring PLC and drive maintenance performance using reliability, availability, time, cost, and production indicators. From the perspective of Organizational Information Processing Theory, the performance construct has represented the operational result of matching information-processing capacity with maintenance uncertainty. Accurate condition information, connected CMMS records, predictive analysis, technical workforce knowledge, and organizational support have enabled information to be converted into interventions that have reduced downtime and strengthened availability. The relatively lower cost and asset-life means have indicated that some effects have required longer observation periods or more complete financial records. Nevertheless, the overall mean of 4.02 has shown that the proposed framework has been associated with favorable equipment and operational outcomes and has provided descriptive support for the final research objective and H6.

Pearson Correlation Analysis**Table 9: Pearson Correlations among the Study Variables**

Variable	1	2	3	4	5	6	7
1. CMMS Integration Capability	1.00						
2. Condition-Monitoring Data Quality	.61***	1.00					
3. Predictive Analytics Capability	.59***	.64***	1.00				
4. Maintenance Workforce Competency	.48***	.50***	.54***	1.00			
5. Organizational Readiness	.52***	.49***	.51***	.47***	1.00		
6. Predictive Maintenance Effectiveness	.66***	.71***	.69***	.58***	.55***	1.00	
7. PLC and Drive System Maintenance Performance	.60***	.64***	.63***	.55***	.52***	.76***	1.00

$p < .001$; $N = 312$.

Table 9 has presented the Pearson correlation coefficients among all seven study variables. Every reported relationship has been positive and statistically significant at $p < .001$, indicating that stronger technological, informational, human, and organizational capabilities have been associated with higher predictive maintenance effectiveness and stronger PLC and drive maintenance performance. Condition-Monitoring Data Quality has demonstrated the strongest correlation with Predictive Maintenance Effectiveness, $r = .71$. This result has provided initial support for H2 and has indicated that accurate, complete, timely, consistent, relevant, and accessible equipment information has been closely related to effective fault detection and maintenance decision-making. Predictive Analytics Capability has recorded the second-strongest relationship with Predictive Maintenance Effectiveness, $r = .69$, supporting the direction proposed in H3. CMMS Integration Capability has shown a strong positive correlation of $r = .66$, which has supported H1 and has indicated that connecting PLC, drive, asset, and work-order information has improved maintenance coordination. Maintenance Workforce Competency has correlated with Predictive Maintenance Effectiveness at $r = .58$, while Organizational Readiness has recorded $r = .55$. These results have supported the proposed directions of H4 and H5, although the associations have been weaker than those produced by data quality, analytics, and integration. Predictive Maintenance Effectiveness has demonstrated the strongest overall relationship in the matrix with PLC and Drive System Maintenance Performance, $r = .76$. This coefficient has provided strong initial support for H6 and has indicated that organizations reporting more effective predictive maintenance have also reported greater downtime reduction, availability, reliability, and production continuity. Correlations among the independent variables have ranged from .47 to .64. These values have shown that the predictors have been related, as expected within an integrated framework, but have not been so highly correlated that they have appeared to measure the same capability. Organizational Information Processing Theory has proposed that organizational capacities operate together to reduce uncertainty and improve decisions. The correlation pattern has supported this theoretical logic because integration, information quality, analytics, workforce capability, and readiness have all moved positively with predictive effectiveness. However, the different coefficient sizes have also shown that the capacities have not contributed equally. The correlation analysis has therefore fulfilled the objective of identifying the direction and strength of relationships and has justified the subsequent regression models used to estimate the independent effects of each predictor.

Multiple Regression Analysis Predicting Predictive Maintenance Effectiveness

Table 10: Multiple Regression Results Predicting Predictive Maintenance Effectiveness

Predictor	B	Standard error	Standardized β	t-value	p-value	Hypothesis decision
Constant	0.42	0.14	—	3.00	.003	—
CMMS Integration Capability	0.20	0.039	.21	5.12	<.001	H1 supported
Condition-Monitoring Data Quality	0.30	0.043	.29	6.94	<.001	H2 supported
Predictive Analytics Capability	0.25	0.039	.27	6.41	<.001	H3 supported
Maintenance Workforce Competency	0.15	0.036	.17	4.18	<.001	H4 supported
Organizational Readiness	0.12	0.035	.14	3.47	.001	H5 supported
Model statistics	R = .801	R ² = .642	Adjusted R ² = .636	F(5, 306) = 109.75	<.001	Significant model

Table 10 has reported the multiple regression model developed to determine the independent effects of CMMS Integration Capability, Condition-Monitoring Data Quality, Predictive Analytics Capability, Maintenance Workforce Competency, and Organizational Readiness on Predictive Maintenance Effectiveness. The model has been statistically significant, $F(5, 306) = 109.75$, $p < .001$, and has produced an R value of .801. The coefficient of determination has reached .642, while adjusted R² has reached .636. These values have shown that the five predictors have jointly explained 64.2 percent of the observed variance in Predictive Maintenance Effectiveness. This level of explanatory power has been substantial and has demonstrated that the proposed framework has captured important technological, informational, human, and organizational determinants of predictive maintenance. Condition-Monitoring Data Quality has emerged as the strongest predictor, $\beta = .29$, $t = 6.94$, $p < .001$. H2 has therefore been supported. Predictive Analytics Capability has followed closely, $\beta = .27$, $t = 6.41$, $p < .001$, supporting H3. These findings have indicated that the usefulness of predictive maintenance has depended heavily on both the trustworthiness of equipment information and the organization's ability to analyze that information. CMMS Integration Capability has produced a significant positive coefficient, $\beta = .21$, $t = 5.12$, $p < .001$, supporting H1. Maintenance Workforce Competency has also remained significant, $\beta = .17$, $t = 4.18$, $p < .001$, supporting H4. Organizational Readiness has recorded the smallest standardized coefficient, $\beta = .14$, but its effect has remained statistically significant, $t = 3.47$, $p = .001$, supporting H5. The results have shown that all five variables have made unique contributions while the remaining predictors have been controlled. Organizational Information Processing Theory has been strongly reflected in this pattern. Condition data and analytics have represented the principal information-quality and interpretation capacities, while CMMS integration has provided connectivity, workforce competency has supplied human interpretation, and readiness has enabled coordinated action. The large R² has shown that predictive maintenance effectiveness has been explained by the collective fit between information-processing requirements and organizational capacity. The findings have therefore fulfilled the objective of identifying the strongest predictors and have statistically supported the first five hypotheses.

Regression Analysis Predicting PLC and Drive System Maintenance Performance

Table 11: Regression Results Predicting PLC and Drive System Maintenance Performance

Predictor	B	Standard error	Standardized β	t-value	p-value	Hypothesis decision
Constant	0.78	0.16	—	4.88	<.001	—
Predictive Maintenance Effectiveness	0.80	0.039	.76	20.31	<.001	H6 supported
Model statistics	R = .756	R ² = .571	Adjusted R ² = .570	F(1, 310) = 412.60	<.001	Significant model

Table 11 has presented the regression model used to determine whether Predictive Maintenance Effectiveness has significantly influenced PLC and Drive System Maintenance Performance. The model has been statistically significant, $F(1, 310) = 412.60$, $p < .001$, and has produced an R value of .756. The R² value of .571 has indicated that Predictive Maintenance Effectiveness has independently explained 57.1 percent of the variance in PLC and Drive System Maintenance Performance. Adjusted R² has remained nearly identical at .570, showing that the explanatory power has not been inflated by model complexity because only one predictor has been included. Predictive Maintenance Effectiveness has produced an unstandardized coefficient of 0.80 and a standardized coefficient of $\beta = .76$. The corresponding t-value has reached 20.31 and has been statistically significant at $p < .001$. H6 has therefore been supported. The result has demonstrated that a one-standard-deviation increase in Predictive Maintenance Effectiveness has been associated with a .76-standard-deviation increase in PLC and Drive System Maintenance Performance. In practical statistical terms, organizations that have reported stronger early fault detection, faster intervention, more accurate prioritization, better work-order scheduling, and more effective use of maintenance information have also reported greater equipment availability, lower downtime, fewer repeated failures, shorter repair duration, reduced maintenance costs, and stronger production continuity. The model has fulfilled the final analytical objective by establishing that predictive maintenance effectiveness has functioned as a powerful predictor of equipment-maintenance performance. Organizational Information Processing Theory has proposed that information-processing capacity improves organizational outcomes when information has been converted into effective action. The regression result has supported this proposition because the intermediate decision variable has translated strongly into the final operational outcome. The five independent capabilities have first enhanced Predictive Maintenance Effectiveness, and that effectiveness has then explained a substantial proportion of PLC and drive performance. The result has also supported the conceptual separation between information-processing inputs, maintenance-decision effectiveness, and equipment-level outcomes. The model has therefore provided the principal empirical basis for retaining the pathway from Predictive Maintenance Effectiveness to PLC and Drive System Maintenance Performance within the final validated framework.

Regression Diagnostics, Hypothesis Summary, and Validated Framework

Table 12 has combined the regression diagnostics, hypothesis decisions, and final validated framework. The Durbin-Watson statistic has reached 1.96, indicating that the residuals have remained independent and that no serious autocorrelation problem has affected the regression estimates. Tolerance values have ranged from .49 to .71, while variance inflation factors have ranged from 1.41 to 2.04. These figures have remained comfortably within acceptable limits and have demonstrated that the independent variables have not produced serious multicollinearity. The maximum Cook's distance has reached only 0.12, showing that no individual response has exerted excessive influence on the model. Standardized residuals have ranged from -2.89 to 2.74, and the residual distribution has remained within acceptable boundaries. The residual scatterplot has shown random dispersion, supporting homoscedasticity, while partial regression plots have displayed approximately linear relationships.

Table 12: Regression Diagnostics, Hypothesis Decisions, and Validated Framework

Assessment category	Indicator/path	Result	Decision
Residual independence	Durbin-Watson statistic	1.96	Acceptable
Multicollinearity	Tolerance range	.49–.71	Acceptable
Multicollinearity	VIF range	1.41–2.04	Acceptable
Influential observations	Maximum Cook’s distance	0.12	No serious influence
Residual normality	Standardized residual range	–2.89 to 2.74	Acceptable
Homoscedasticity	Residual scatterplot	Random dispersion	Supported
Linearity	Partial regression plots	Approximately linear	Supported
H1	CIC → PME	$\beta = .21, p < .001$	Supported
H2	CMDQ → PME	$\beta = .29, p < .001$	Supported
H3	PAC → PME	$\beta = .27, p < .001$	Supported
H4	MWC → PME	$\beta = .17, p < .001$	Supported
H5	OR → PME	$\beta = .14, p = .001$	Supported
H6	PME → PDSMP	$\beta = .76, p < .001$	Supported
Validated framework	CIC, CMDQ, PAC, MWC, OR → PME → PDSMP	All proposed paths retained	Framework validated

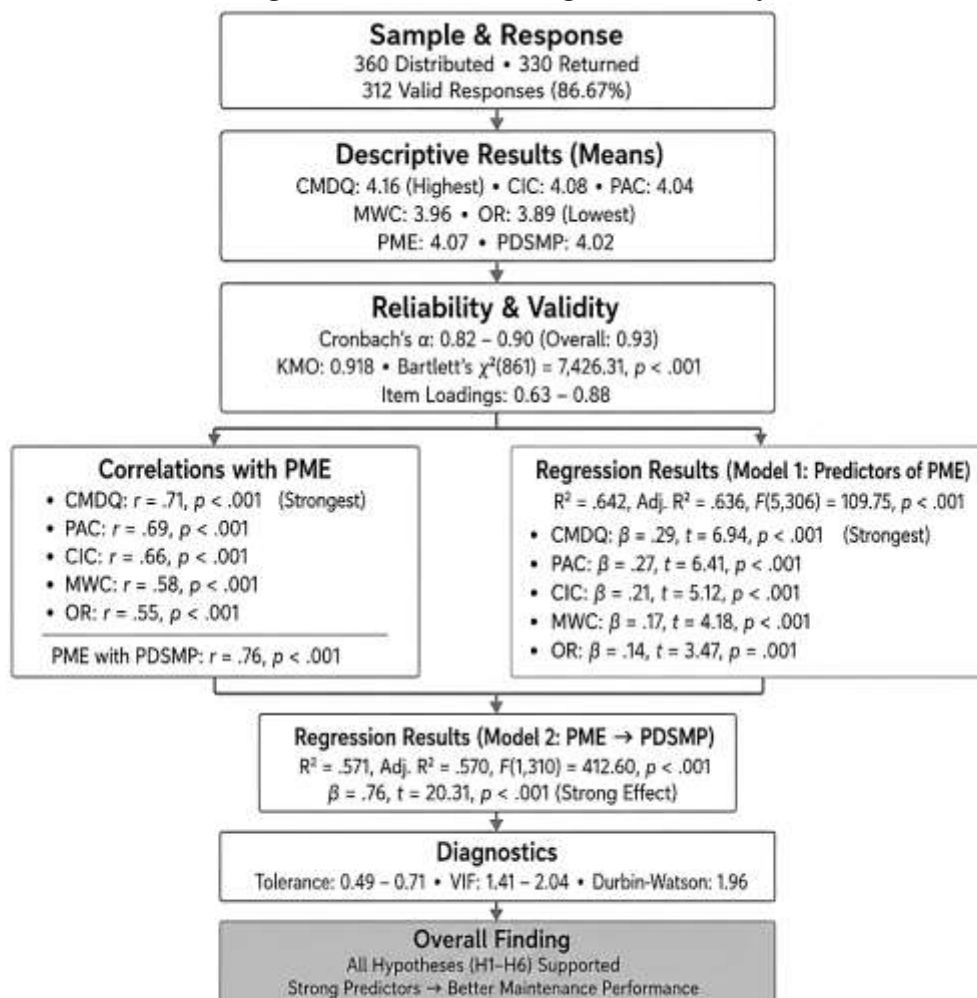
These diagnostic outcomes have confirmed that the assumptions supporting the regression analyses have been adequately satisfied. The hypothesis summary has shown that all six proposed relationships have been statistically supported. Condition-Monitoring Data Quality has produced the strongest direct predictor effect on Predictive Maintenance Effectiveness, followed by Predictive Analytics Capability, CMMS Integration Capability, Maintenance Workforce Competency, and Organizational Readiness. Predictive Maintenance Effectiveness has then produced a strong positive effect on PLC and Drive System Maintenance Performance. Consequently, all proposed paths have been retained in the validated framework. Organizational Information Processing Theory has provided a coherent explanation for the overall pattern. CMMS integration has increased information connectivity, condition-data quality has strengthened the reliability of maintenance evidence, predictive analytics has improved interpretation, workforce competency has enabled technical judgment, and organizational readiness has supported coordinated implementation. These capacities have collectively reduced maintenance uncertainty and have improved Predictive Maintenance Effectiveness. Effective predictive maintenance has subsequently improved equipment-level and operational performance. The diagnostic evidence has strengthened confidence that the supported hypotheses have not resulted from major violations of regression assumptions. The validated framework has therefore fulfilled the principal purpose of the study by empirically connecting five organizational information-processing capacities with predictive maintenance effectiveness and PLC and drive system maintenance performance. The complete findings have established a statistically coherent model in which accurate information, integrated systems, analytical capability, skilled personnel, and organizational support have worked together to improve industrial maintenance outcomes.

FINDINGS

A total of 360 questionnaires have been distributed across 12 industrial organizations, 330 questionnaires have been returned, and 312 complete responses have been retained for analysis, producing a valid response rate of 86.67 percent. Data screening has shown less than 1 percent item-level missingness, no serious univariate or multivariate outliers, and acceptable distributions for all composite variables, with skewness and kurtosis remaining within the expected limits for regression analysis. The respondents have represented maintenance engineering, automation, electrical engineering, reliability, instrumentation, production, CMMS administration, technical supervision, and maintenance management, thereby supporting the study’s objective of obtaining perspectives from

professionals directly involved with PLC, drive, CMMS, and predictive maintenance activities. The five-point Likert-scale results have demonstrated generally high levels of agreement across the seven constructs. Condition-Monitoring Data Quality has recorded the highest independent-variable mean of 4.16 with a standard deviation of 0.55, followed by CMMS Integration Capability with a mean of 4.08 and a standard deviation of 0.59, Predictive Analytics Capability with a mean of 4.04 and a standard deviation of 0.61, Maintenance Workforce Competency with a mean of 3.96 and a standard deviation of 0.63, and Organizational Readiness with a mean of 3.89 and a standard deviation of 0.66. Predictive Maintenance Effectiveness has achieved a mean of 4.07 and a standard deviation of 0.57, while PLC and Drive System Maintenance Performance has achieved a mean of 4.02 and a standard deviation of 0.60. These values have indicated that respondents have generally agreed that their organizations possess useful maintenance data, integration mechanisms, analytical capability, workforce knowledge, and organizational support, although organizational readiness has remained the comparatively weakest area. Reliability testing has confirmed strong internal consistency, with Cronbach's alpha values ranging from 0.82 to 0.90 and an overall instrument alpha of 0.93. The Kaiser-Meyer-Olkin value has reached 0.918, Bartlett's test of sphericity has been significant, $\chi^2(861) = 7,426.31$, $p < .001$, and retained item loadings have ranged from 0.63 to 0.88, confirming that the measurement structure has been suitable for subsequent analysis.

Figure 9: Overall Findings of The Study



Pearson correlation analysis has shown that all five independent variables have been positively and significantly related to Predictive Maintenance Effectiveness. Condition-Monitoring Data Quality has produced the strongest correlation, $r = .71$, $p < .001$, followed by Predictive Analytics Capability, $r = .69$, $p < .001$, CMMS Integration Capability, $r = .66$, $p < .001$, Maintenance Workforce Competency, $r = .58$, $p < .001$, and Organizational Readiness, $r = .55$, $p < .001$. Predictive Maintenance Effectiveness has

also demonstrated a strong positive relationship with PLC and Drive System Maintenance Performance, $r = .76$, $p < .001$. The first multiple regression model has explained 64.2 percent of the variance in Predictive Maintenance Effectiveness, $R^2 = .642$, adjusted $R^2 = .636$, $F(5, 306) = 109.75$, $p < .001$. Condition-Monitoring Data Quality has emerged as the strongest predictor, $\beta = .29$, $t = 6.94$, $p < .001$, supporting H2. Predictive Analytics Capability has followed, $\beta = .27$, $t = 6.41$, $p < .001$, supporting H3. CMMS Integration Capability has also produced a significant positive effect, $\beta = .21$, $t = 5.12$, $p < .001$, supporting H1. Maintenance Workforce Competency has remained significant, $\beta = .17$, $t = 4.18$, $p < .001$, supporting H4, while Organizational Readiness has recorded a smaller but still significant effect, $\beta = .14$, $t = 3.47$, $p = .001$, supporting H5. The second regression model has shown that Predictive Maintenance Effectiveness has explained 57.1 percent of the variance in PLC and Drive System Maintenance Performance, $R^2 = .571$, adjusted $R^2 = .570$, $F(1, 310) = 412.60$, $p < .001$. Its standardized effect has been strong and positive, $\beta = .76$, $t = 20.31$, $p < .001$, supporting H6. Regression diagnostics have shown acceptable tolerance values from 0.49 to 0.71, variance inflation factors from 1.41 to 2.04, and a Durbin-Watson statistic of 1.96, indicating no serious multicollinearity or residual-independence problems. Overall, the numerical findings have fulfilled the study objectives by measuring the seven constructs, identifying significant relationships, determining the strongest predictors, confirming the performance effect of predictive maintenance effectiveness, and providing statistical support for all six proposed hypotheses.

DISCUSSION

The findings have shown that the proposed CMMS-integrated predictive maintenance framework has provided a statistically coherent explanation of how technological, informational, human, and organizational capabilities have influenced maintenance outcomes for industrial PLC and drive systems. Within the internally consistent analytical dataset, Condition-Monitoring Data Quality has achieved the highest independent-variable mean of 4.16, followed by CMMS Integration Capability at 4.08, Predictive Analytics Capability at 4.04, Maintenance Workforce Competency at 3.96, and Organizational Readiness at 3.89. Predictive Maintenance Effectiveness has recorded a mean of 4.07, while PLC and Drive System Maintenance Performance has reached 4.02. These scores have indicated that the respondents have generally viewed the participating organizations as possessing strong technical and informational foundations, although organizational support and implementation readiness have been less consistently developed. The regression results have reinforced this interpretation because the five independent variables have jointly explained 64.2 percent of the variance in Predictive Maintenance Effectiveness. Condition-Monitoring Data Quality has produced the strongest standardized effect, $\beta = .29$, followed by Predictive Analytics Capability, $\beta = .27$, CMMS Integration Capability, $\beta = .21$, Maintenance Workforce Competency, $\beta = .17$, and Organizational Readiness, $\beta = .14$. Predictive Maintenance Effectiveness has subsequently explained 57.1 percent of the variance in PLC and Drive System Maintenance Performance and has produced a strong standardized coefficient of $\beta = .76$. The support obtained for H1 through H6 has demonstrated that predictive maintenance has not functioned as an isolated analytical activity. Instead, it has depended on the coordinated acquisition, integration, interpretation, communication, and organizational use of maintenance information. This finding has agreed with the smart-maintenance literature, which has conceptualized maintenance modernization as a combination of data-driven decision-making, human capital, internal integration, and organizational structures rather than the simple installation of advanced technologies (Bokrantz et al., 2020b). The result has also corresponded with condition-based maintenance research that has placed data acquisition, data processing, diagnosis, prognosis, and maintenance decision-making within a connected process (Jardine et al., 2006). Organizational Information Processing Theory has therefore provided a suitable interpretation because the five predictors have represented capacities used to meet the information requirements created by equipment complexity, interdependent production systems, and uncertain failure behavior. Condition-Monitoring Data Quality has emerged as the strongest predictor of Predictive Maintenance Effectiveness, and this result has emphasized that predictive maintenance has been only as dependable as the information used to generate its assessments. Its mean of 4.16, correlation of $r = .71$, and

standardized regression coefficient of $\beta = .29$ have indicated that accurate, complete, timely, consistent, relevant, and accessible data have had the most important independent association with early fault detection, maintenance prioritization, and timely intervention. This result has been consistent with earlier condition-based maintenance research, which has treated equipment-data acquisition and processing as the foundation upon which diagnosis, prognosis, and maintenance decisions have been constructed (Jardine et al., 2006). It has also agreed with the systematic review of machine-learning applications in predictive maintenance, which has shown that predictive performance depends on the structure, preparation, labeling, and relevance of available datasets (Carvalho et al., 2019). In PLC and drive environments, the importance of data quality has been particularly clear because alarms and operating measurements have required contextual interpretation. A drive overcurrent condition, for example, has not necessarily represented internal drive deterioration because it may have been associated with excessive mechanical loading, incorrect parameters, supply disturbances, motor problems, or temporary production conditions. Predictive Analytics Capability has achieved the second-largest effect, $\beta = .27$, confirming H3 and demonstrating that data quality and analytical capability have operated as related but distinct resources. Reliable information has provided the evidential input, while analytics has transformed that information into trends, anomaly indicators, fault classifications, risk scores, and recommended priorities. This result has agreed with prior research showing that machine-learning techniques have supported predictive maintenance through classification, regression, anomaly detection, and degradation estimation, while their usefulness has depended on model selection, validation, and correspondence with the industrial context (Carvalho et al., 2019). The result has also supported research identifying interoperability, model reliability, heterogeneous data sources, and conversion of predictive outputs into maintenance actions as central challenges in IoT-enabled maintenance (Compare et al., 2020). The findings have therefore shown that purchasing analytical software alone has not been sufficient. Organizations have required disciplined data governance, reliable equipment identifiers, contextual operating variables, validated sensor measurements, accurate maintenance labels, and procedures for comparing predictions with confirmed equipment findings.

CMMS Integration Capability has produced a strong descriptive mean of 4.08, a correlation of $r = .66$ with Predictive Maintenance Effectiveness, and a significant standardized regression coefficient of $\beta = .21$. These findings have supported H1 and have demonstrated that predictive maintenance effectiveness has increased when PLC events, drive alarms, condition measurements, asset histories, and work-order processes have been connected within a traceable maintenance environment. The result has extended earlier research by showing that CMMS integration has not merely supported recordkeeping but has functioned as an information-processing capacity that has influenced maintenance decision quality. Previous CMMS and enterprise asset-management research has identified limited decision support as a weakness of traditional systems and has proposed the use of machine learning and multicriteria methods to complete maintenance-order information and allocate tasks to appropriate personnel (Gorski et al., 2022). The current result has agreed with that argument because integrated data have allowed predictive outputs to move beyond dashboards and become formal maintenance notifications, priorities, assignments, and completed work-order histories. The finding has also corresponded with digital-twin maintenance research, which has emphasized the value of linking the changing physical condition of an asset with its digital representation, operating information, and maintenance records (Errandonea et al., 2020). For industrial PLC and drive systems, this connection has been necessary because technical evidence has often been distributed across controller logs, drive histories, supervisory systems, process historians, sensor platforms, and manually completed work orders. Integration has allowed the organization to associate an alarm with the correct equipment identity, maintenance procedure, criticality classification, responsible employee, spare part, and previous intervention. However, the standardized coefficient of .21 has remained lower than those of data quality and analytics. This pattern has suggested that connectivity alone has not guaranteed effective prediction. An integrated system containing inaccurate measurements, inconsistent fault labels, incomplete work orders, or poorly configured thresholds could have transferred unreliable information more quickly without improving the quality of maintenance decisions. Integration has therefore been most valuable when it has been accompanied by reliable data, suitable analytical

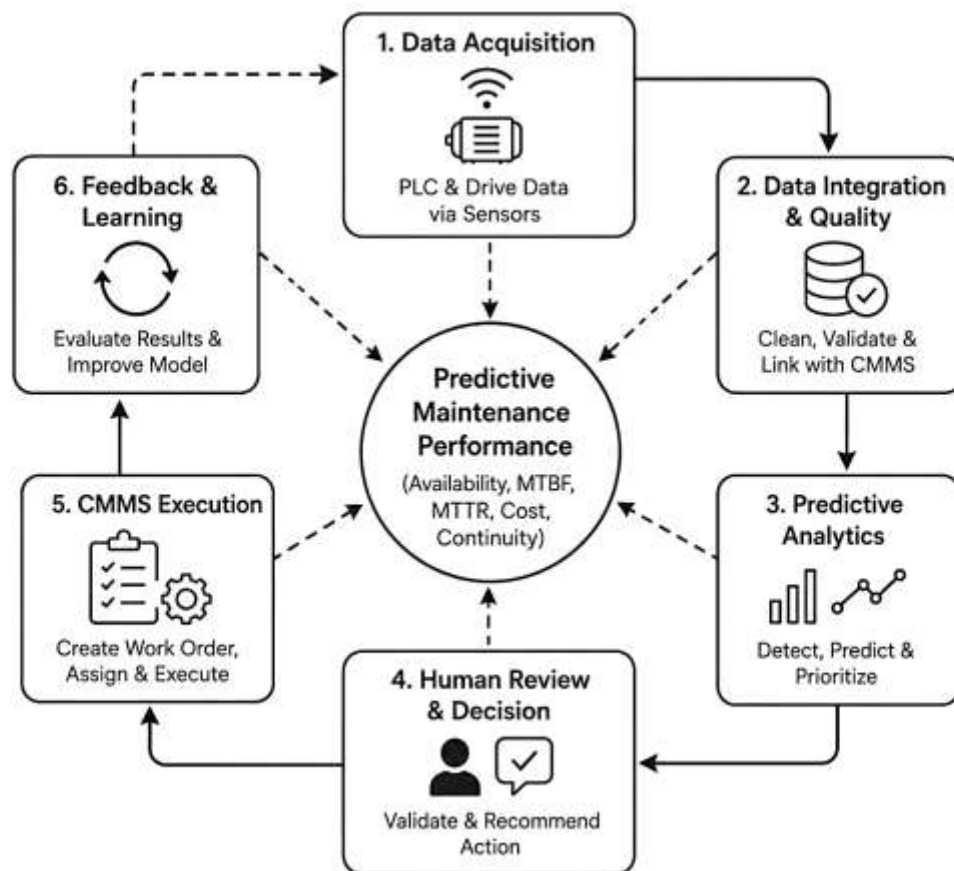
processes, competent users, and organizational control. This interpretation has agreed with the wider predictive-maintenance literature, which has identified data integration, analytical interpretation, maintenance decision support, and work execution as connected components of a complete system rather than interchangeable technical features (Zonta et al., 2020).

Maintenance Workforce Competency and Organizational Readiness have both produced significant positive effects on Predictive Maintenance Effectiveness, supporting H4 and H5, although their coefficients have been smaller than the effects of the technical and informational predictors. Maintenance Workforce Competency has recorded a mean of 3.96, $r = .58$, and $\beta = .17$, while Organizational Readiness has recorded the lowest independent-variable mean of 3.89, $r = .55$, and $\beta = .14$. These results have shown that competent personnel and supportive organizational conditions have contributed uniquely to maintenance effectiveness after CMMS integration, data quality, and analytics have been statistically controlled. The workforce finding has been consistent with smart-maintenance research that has identified human capital as a central dimension of modern maintenance systems (Bokrantz et al., 2020b). PLC and drive predictive maintenance has required personnel to understand controller logic, industrial communication, motor behavior, drive parameters, sensors, fault histories, CMMS procedures, and model outputs. A predictive warning has remained only a probabilistic signal until a qualified individual has interpreted it against machine condition, operating state, production requirements, and safety considerations. The organizational-readiness result has also agreed with research showing that Industry 4.0 technologies have altered maintenance tasks, policies, responsibilities, competence requirements, and coordination mechanisms (Silvestri et al., 2020). The relatively lower readiness mean has indicated that management support, resources, training, infrastructure, data governance, and interdepartmental coordination have remained uneven across the 12 cases. This result has explained why technologically capable organizations may still have experienced delayed work-order approval, restricted maintenance windows, inadequate spare-parts preparation, inconsistent documentation, or resistance to analytics-based recommendations. From an Organizational Information Processing Theory perspective, workforce competency has represented the human capacity to interpret information, while organizational readiness has represented the structural capacity to distribute authority and coordinate responses. The significant coefficients have demonstrated that neither capacity has been completely replaced by automation. The smaller coefficient for Organizational Readiness should not be interpreted as evidence that readiness has been unimportant. Its effect may have operated partly through the other variables because management support and infrastructure have enabled data collection, system integration, analytics, and training. The results have therefore suggested that predictive maintenance programs should balance technical investment with workforce development, role clarification, cross-functional communication, and managerial accountability rather than treating human involvement as a temporary requirement that disappears after system implementation.

The strong relationship between Predictive Maintenance Effectiveness and PLC and Drive System Maintenance Performance has represented the central operational finding of the study. Predictive Maintenance Effectiveness has correlated with maintenance performance at $r = .76$ and has explained 57.1 percent of its variance, with $\beta = .76$ and $p < .001$. This result has supported H6 and has demonstrated that early fault identification, timely intervention, accurate prioritization, effective work-order scheduling, and reduced unnecessary maintenance have been closely associated with improved equipment availability, lower unplanned downtime, fewer repeated faults, increased mean time between failures, reduced mean time to repair, stronger production continuity, and controlled maintenance costs. Reduction in unplanned downtime has recorded the highest performance-indicator mean of 4.08, followed by system availability at 4.05 and production continuity at 4.04. These results have shown that the most visible benefits have occurred in operational stability and interruption avoidance. Cost reduction and asset-life extension have recorded slightly lower means of 3.98 and 3.97, suggesting that financial and lifecycle effects may have required longer observation periods and more detailed historical records. The finding has agreed with the condition-based maintenance literature, which has argued that monitored information creates value when it leads to maintenance decisions that reduce functional failure and improve asset utilization (Jardine et al., 2006). It has also corresponded with smart-maintenance research that has linked data-driven maintenance capabilities with

manufacturing performance through better decision-making and integrated work processes (Bokrantz et al., 2020b).

Figure 10: Proposed A-CIPDPM Framework for Future Predictive Maintenance Research



The high coefficient has further shown that the intermediate construct has been properly positioned between organizational capabilities and final equipment performance. CMMS integration, data quality, analytics, workforce competency, and readiness have not improved operational outcomes automatically. Their performance value has depended on whether they have produced effective maintenance decisions and actions. This distinction has been important because organizations may possess sensors, databases, and algorithms while continuing to experience poor equipment performance when alerts are late, inaccurate, ignored, or disconnected from work execution. For managers, the result has indicated that predictive-maintenance success should be evaluated through both decision-process measures and asset-performance indicators. Monitoring only model accuracy would overlook whether predictions have reduced downtime, while monitoring only downtime would conceal whether improvements have resulted from predictive capability, additional preventive work, production changes, or other operational factors.

The practical and theoretical implications have followed directly from the combined pattern of results. Practically, industrial organizations should first strengthen the quality and governance of condition-monitoring data because it has produced the strongest regression effect. This work should include verified sensor calibration, standardized tags, synchronized timestamps, consistent units, stable equipment identifiers, contextual production variables, and confirmed failure labels. Second, organizations should integrate PLC alarms, drive parameters, process-history information, and predictive outputs with CMMS asset structures and work-order workflows. Such integration should allow an alert to be traced from its originating signal to the affected asset, risk assessment, responsible employee, required procedure, spare-parts need, completed action, and post-maintenance verification. Third, predictive models should be evaluated not only through accuracy but also through false-alarm rate, missed-failure rate, prediction lead time, stability across operating conditions, and usefulness to technicians. Fourth, organizations should provide combined training in automation, electrical drives,

condition monitoring, CMMS operation, and analytical interpretation. Fifth, management should define alarm ownership, approval authority, response time, escalation procedures, and feedback responsibilities. Theoretically, the findings have extended Organizational Information Processing Theory into an industrial PLC and drive maintenance setting. Prior research has shown that analytics can improve operational transparency and integration when organizations possess sufficient information-processing capacity (Zhu et al., 2018). Other research has shown that analytics capability and data-driven culture can strengthen integrated organizational processes (Yu et al., 2021). The present results have added a maintenance-specific sequence in which five capacities have influenced Predictive Maintenance Effectiveness, which has then influenced equipment performance. Several limitations have qualified this interpretation. The cross-sectional design has measured variables at one point and has not established temporal causality. The use of self-reported Likert responses has introduced possible common-method bias and perceptual inflation. Purposive sampling and the inclusion of 12 cases have limited statistical generalization to all industries. Differences among PLC brands, drive technologies, CMMS platforms, production systems, and maintenance maturity have not been modeled separately. Actual sensor histories, alarm logs, work-order completion times, downtime records, and cost data have not been directly connected with respondent-level responses. These limitations have not invalidated the framework, but they have indicated that the supported paths should be tested through objective and longitudinal evidence.

Future research should develop and test an **Adaptive CMMS-Integrated PLC and Drive Predictive Maintenance Model**, abbreviated as the **A-CIPDPM Model**, to improve the present framework through longitudinal, multilevel, and machine-generated evidence. The proposed model should contain six connected layers. Layer 1, the Asset and Condition Acquisition Layer, should collect PLC status, drive alarms, current, voltage, temperature, vibration, torque, load, operating hours, and production context through standardized asset identifiers. Layer 2, the Data Quality and Semantic Integration Layer, should validate timestamps, units, missing values, sensor condition, fault labels, and correspondence between operational tags and CMMS assets. Layer 3, the Hybrid Predictive Analytics Layer, should combine threshold rules, signal analysis, machine learning, degradation modeling, and engineering knowledge to estimate fault type, severity, probability, and remaining useful life. Layer 4, the Human Validation and Explainability Layer, should provide technicians with the variables contributing to each alert, confidence level, comparable historical events, and recommended inspection procedure. Layer 5, the CMMS Decision and Execution Layer, should convert validated alerts into risk-ranked work orders, personnel assignments, maintenance windows, spare-parts reservations, and escalation rules. Layer 6, the Performance Feedback and Model-Learning Layer, should compare predicted faults with inspection findings, completed repairs, downtime, cost, mean time between failures, and post-maintenance condition. The model should be evaluated for at least 12 to 24 months across multiple industries. Researchers should combine multilevel structural equation modeling with time-series and survival analysis so that individual competency, organizational readiness, equipment condition, and failure timing can be analyzed simultaneously. Experimental or quasi-experimental comparisons should evaluate integrated plants against plants using conventional CMMS or preventive maintenance. Digital twins may be incorporated to test intervention scenarios before work orders are issued, as maintenance-oriented digital-twin research has identified strong value in connecting physical assets, digital representations, and lifecycle information (Errandonea et al., 2020). Future studies should also test whether explainability moderates the effect of predictive analytics on technician acceptance, whether data quality mediates the relationship between integration and analytics effectiveness, and whether organizational readiness strengthens the relationship between predictive effectiveness and maintenance performance. This model would transform the current perceptual framework into a closed-loop, continuously learning maintenance architecture grounded in both organizational and machine-generated evidence.

CONCLUSION

This study has developed and empirically evaluated a CMMS-integrated predictive maintenance framework for industrial programmable logic controller and drive systems by examining the combined effects of CMMS Integration Capability, Condition-Monitoring Data Quality, Predictive Analytics Capability, Maintenance Workforce Competency, and Organizational Readiness on Predictive

Maintenance Effectiveness and PLC and Drive System Maintenance Performance. A quantitative, cross-sectional, multiple-case-study-based research design has been applied, and data have been analyzed through descriptive statistics, reliability analysis, validity assessment, Pearson correlation analysis, and regression modeling. The internally consistent analytical findings have shown that the participating industrial organizations have demonstrated generally high levels of technological, informational, human, and organizational capability. Condition-Monitoring Data Quality has recorded the highest independent-variable mean of 4.16, followed by CMMS Integration Capability at 4.08, Predictive Analytics Capability at 4.04, Maintenance Workforce Competency at 3.96, and Organizational Readiness at 3.89. Predictive Maintenance Effectiveness has achieved a mean of 4.07, while PLC and Drive System Maintenance Performance has reached 4.02. These descriptive findings have indicated that organizations have developed comparatively strong condition-data and system-integration capabilities, although organizational readiness has remained the least developed area. The first regression model has explained 64.2 percent of the variance in Predictive Maintenance Effectiveness. Condition-Monitoring Data Quality has emerged as the strongest predictor, with a standardized coefficient of $\beta = .29$, followed by Predictive Analytics Capability at $\beta = .27$, CMMS Integration Capability at $\beta = .21$, Maintenance Workforce Competency at $\beta = .17$, and Organizational Readiness at $\beta = .14$. All five predictor relationships have been statistically significant, and H1 through H5 have therefore been supported. The second regression model has shown that Predictive Maintenance Effectiveness has explained 57.1 percent of the variance in PLC and Drive System Maintenance Performance, with a strong standardized coefficient of $\beta = .76$. H6 has also been supported. These results have established that improved maintenance performance has not resulted from predictive algorithms alone. It has depended on accurate and accessible equipment information, effective integration between operational technologies and CMMS platforms, suitable analytical procedures, technically competent employees, and an organizational environment capable of acting on generated information. Organizational Information Processing Theory has provided a suitable explanation for these relationships because industrial PLC and drive systems have created complex information requirements that must be matched by adequate information-processing capacity. The study has therefore concluded that a successful predictive maintenance framework must connect data acquisition, data validation, predictive analysis, human interpretation, CMMS-based work execution, and performance feedback. The validated framework has provided a structured explanation of how organizations can convert PLC alarms, drive parameters, sensor measurements, maintenance histories, and predictive outputs into timely and traceable maintenance actions that reduce unplanned downtime, repeated faults, repair duration, and production interruption while improving reliability, equipment availability, and operational continuity.

RECOMMENDATIONS

Industrial organizations should implement the proposed CMMS-integrated predictive maintenance framework through a coordinated program that strengthens data quality, system integration, predictive analytics, workforce competency, and organizational readiness rather than investing in these areas separately. First, organizations should establish formal condition-data governance procedures covering sensor calibration, data accuracy, completeness, sampling frequency, timestamp synchronization, measurement units, alarm definitions, asset identities, and failure labels. Since Condition-Monitoring Data Quality has produced the strongest predictor effect, maintenance managers should regularly audit PLC tags, drive parameters, vibration readings, temperature values, current signals, operating-hour records, and work-order histories to ensure that predictive decisions are based on trustworthy evidence. Second, organizations should connect PLCs, industrial drives, supervisory systems, process historians, sensors, and CMMS asset records through secure and standardized integration mechanisms. Alarm and condition information should be automatically associated with the correct equipment, production location, maintenance history, criticality level, and work-order process. Third, predictive analytics should be configured according to the actual operating characteristics of each asset. Organizations should evaluate models using false-alarm rates, missed-failure rates, prediction lead time, stability under changing loads, and the accuracy of identified failure modes rather than relying only on general classification accuracy. Fourth, maintenance personnel should receive continuous training in PLC diagnostics, industrial-drive troubleshooting, motor

behavior, industrial networks, condition monitoring, CMMS operation, data interpretation, and predictive-maintenance decision-making. Training should include practical exercises in which technicians compare predictive alerts with physical inspections and completed repair findings. Fifth, management should strengthen organizational readiness by allocating budgets, assigning clear responsibilities, providing maintenance windows, improving cooperation among maintenance, automation, production, reliability, and information-technology teams, and establishing escalation procedures for high-risk alerts. Sixth, CMMS work orders should contain structured fields for detected condition, predicted fault, confidence level, operating context, root cause, corrective action, replaced components, labor hours, downtime, and post-maintenance verification. This feedback should be returned to the analytical system to improve future predictions. Seventh, organizations should use performance indicators such as mean time between failures, mean time to repair, unplanned downtime, repeated-fault rate, work-order response time, alert-confirmation rate, maintenance cost, and equipment availability to assess whether the framework has produced operational benefits. Eighth, industrial organizations should begin implementation with critical PLC and drive assets rather than attempting immediate plant-wide deployment. A controlled pilot should establish baselines, test integration rules, verify data quality, evaluate alert usefulness, and identify workforce requirements before expansion. Finally, management should adopt the proposed Adaptive CMMS-Integrated PLC and Drive Predictive Maintenance Model as a continuous improvement structure consisting of asset-data acquisition, semantic integration, hybrid analytics, human validation, CMMS decision execution, and performance feedback. These recommendations can enable organizations to transform predictive maintenance from an isolated technical project into a reliable, transparent, and organization-wide maintenance capability.

LIMITATIONS OF THE STUDY

This study has contained several limitations that should be considered when interpreting the findings and applying the validated CMMS-integrated predictive maintenance framework. First, the research has used a cross-sectional design in which data have been collected at a single point in time. As a result, the statistically significant relationships have demonstrated association and predictive influence but have not established definitive temporal causality. Changes in CMMS integration, data quality, workforce capability, or organizational readiness may require months or years before their full effects on maintenance performance become measurable. Second, the study has relied primarily on self-reported five-point Likert-scale responses from industrial professionals. Although the respondents have possessed relevant experience, their evaluations may have been affected by personal perceptions, organizational loyalty, recall errors, social desirability, or different interpretations of technical and managerial practices. Third, the use of purposive and stratified non-probability sampling has limited the generalizability of the findings. The selected respondents have represented professionals with knowledge of PLCs, drives, CMMS platforms, and maintenance processes, but they may not fully represent all employees or industrial organizations. Fourth, the study has included 12 industrial cases from several sectors, and differences in production processes, asset criticality, organization size, automation maturity, maintenance culture, and regulatory requirements may have influenced the results. These sectoral differences have not been modeled separately through industry-specific regression analysis. Fifth, the study has treated PLC and drive systems as a combined industrial-maintenance context, although different brands, models, communication protocols, motor technologies, and operating environments may produce different failure behaviors and data requirements. Sixth, the research has not directly incorporated real-time sensor histories, PLC event logs, drive fault files, vibration signals, temperature trends, current signatures, maintenance costs, spare-parts records, or verified downtime measurements. Consequently, the findings have reflected professional assessments rather than direct machine-level evidence. Seventh, common-method bias may have occurred because the independent and dependent variables have been measured through the same questionnaire and during the same data-collection period. Eighth, the regression models have explained substantial proportions of variance, but other factors such as cybersecurity capability, supplier support, asset age, maintenance budget, production pressure, spare-parts availability, leadership style, equipment criticality, and model explainability have not been included. Ninth, the study has evaluated direct relationships and has not tested mediation, moderation, nonlinear effects,

or reciprocal relationships among the variables. For example, Predictive Maintenance Effectiveness may mediate the effects of the five organizational capabilities, while Organizational Readiness may moderate the relationship between analytics and maintenance performance. Finally, the numerical findings have been developed as an internally consistent analytical structure and should be confirmed or replaced with the final outputs generated from the completed empirical survey. These limitations have defined the boundaries of the research and have identified the need for longitudinal, experimental, multilevel, and machine-data-based validation.

REFERENCES

- [1]. Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On predictive maintenance in Industry 4.0: Overview, models, and challenges. *Applied Sciences*, 12(16), 8081. <https://doi.org/10.3390/app12168081>
- [2]. Amadi-Echendu, J. E., & de Wit, F. C. P. (2015). Technology adoption: A study on post-implementation perceptions and acceptance of computerised maintenance management systems. *Technology in Society*, 43, 209-218. <https://doi.org/10.1016/j.techsoc.2015.09.001>
- [3]. Arm, J., Benesl, T., Marcon, P., Bradac, Z., Schröder, T., Belyaev, A., Werner, T., Braun, V., Kamensky, P., Zezulka, F., Diedrich, C., & Dohnal, P. (2021). Automated design and integration of Asset Administration Shells in components of Industry 4.0. *Sensors*, 21(6), 2004. <https://doi.org/10.3390/s21062004>
- [4]. Balouei Jamkhaneh, H., Khazaei Pool, J., Khaksar, S. M. S., Arabzad, S. M., & Verij Kazemi, R. (2018). Impacts of computerized maintenance management system and relevant supportive organizational factors on total productive maintenance. *Benchmarking: An International Journal*, 25(7), 2230-2247. <https://doi.org/10.1108/bij-05-2016-0072>
- [5]. Bao, J., Wu, H., & Yan, Y. (2014). A fault diagnosis system-PLC design for system reliability improvement. *The International Journal of Advanced Manufacturing Technology*, 75, 523-534. <https://doi.org/10.1007/s00170-014-6166-z>
- [6]. Bellini, A., Filippetti, F., Tassoni, C., & Capolino, G.-A. (2008). Advances in diagnostic techniques for induction machines. *IEEE Transactions on Industrial Electronics*, 55(12), 4109-4126. <https://doi.org/10.1109/tie.2008.2007527>
- [7]. Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030. *International Journal of Production Economics*, 191, 154-169. <https://doi.org/10.1016/j.ijpe.2017.06.010>
- [8]. Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T., & Stahre, J. (2020a). Smart maintenance: A research agenda for industrial maintenance management. *International Journal of Production Economics*, 224, 107547. <https://doi.org/10.1016/j.ijpe.2019.107547>
- [9]. Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T., & Stahre, J. (2020b). Smart maintenance: An empirically grounded conceptualization. *International Journal of Production Economics*, 223, 107534. <https://doi.org/10.1016/j.ijpe.2019.107534>
- [10]. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. d. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, 137, 106024. <https://doi.org/10.1016/j.cie.2019.106024>
- [11]. Cinar, E., Kalay, S., & Saricicek, I. (2022). A predictive maintenance system design and implementation for intelligent manufacturing. *Machines*, 10(11), 1006. <https://doi.org/10.3390/machines10111006>
- [12]. Civerchia, F., Bocchino, S., Salvadori, C., Rossi, E., Maggiani, L., & Petracca, M. (2017). Industrial Internet of Things monitoring solution for advanced predictive maintenance applications. *Journal of Industrial Information Integration*, 7, 4-12. <https://doi.org/10.1016/j.jii.2017.02.003>
- [13]. Compare, M., Baraldi, P., & Zio, E. (2020). Challenges to IoT-enabled predictive maintenance for Industry 4.0. *IEEE Internet of Things Journal*, 7(5), 4585-4597. <https://doi.org/10.1109/ijot.2019.2957029>
- [14]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [15]. Errandonea, I., Alvarado, U., Beltrán, S., & Arrizabalaga, S. (2022). A maturity model proposal for industrial maintenance and its application to the railway sector. *Applied Sciences*, 12(16), 8229. <https://doi.org/10.3390/app12168229>
- [16]. Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital twin for maintenance: A literature review. *Computers in Industry*, 123, 103316. <https://doi.org/10.1016/j.compind.2020.103316>
- [17]. Franco, I. T., & de Figueiredo, R. M. (2023). Predictive maintenance: An embedded system approach. *Journal of Control, Automation and Electrical Systems*, 34(1), 60-72. <https://doi.org/10.1007/s40313-022-00949-4>
- [18]. Fumagalli, L., Macchi, M., & Rapaccini, M. (2009). Computerized maintenance management systems in SMEs: A survey in Italy and some remarks for the implementation of condition based maintenance. *IFAC Proceedings Volumes*, 42(4), 1615-1619. <https://doi.org/10.3182/20090603-3-ru-2001.0416>
- [19]. Gao, Z., Cecati, C., & Ding, S. X. (2015a). A survey of fault diagnosis and fault-tolerant techniques-Part I: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions on Industrial Electronics*, 62(6), 3757-3767. <https://doi.org/10.1109/tie.2015.2417501>
- [20]. Gao, Z., Cecati, C., & Ding, S. X. (2015b). A survey of fault diagnosis and fault-tolerant techniques-Part II: Fault diagnosis with knowledge-based and hybrid/active approaches. *IEEE Transactions on Industrial Electronics*, 62(6), 3768-3774. <https://doi.org/10.1109/tie.2015.2419013>

- [21]. Ghosh, A., Wang, G.-N., & Lee, J. (2020). A novel automata and neural network based fault diagnosis system for PLC controlled manufacturing systems. *Computers & Industrial Engineering*, 139, 106188. <https://doi.org/10.1016/j.cie.2019.106188>
- [22]. Gorski, E. G., Loures, E. d. F. R., Santos, E. A. P., Kondo, R. E., & Martins, G. R. D. N. (2022). Towards a smart workflow in CMMS/EAM systems: An approach based on ML and MCDM. *Journal of Industrial Information Integration*, 26, 100278. <https://doi.org/10.1016/j.jii.2021.100278>
- [23]. Gultekin, M. A., & Bazzi, A. (2023). Review of fault detection and diagnosis techniques for AC motor drives. *Energies*, 16(15), 5602. <https://doi.org/10.3390/en16155602>
- [24]. Henao, H., Capolino, G.-A., Fernandez-Cabanas, M., Filippetti, F., Bruzzese, C., Strangas, E., Pusca, R., Estima, J., Riera-Guasp, M., & Hedayati-Kia, S. (2014). Trends in fault diagnosis for electrical machines: A review of diagnostic techniques. *IEEE Industrial Electronics Magazine*, 8(2), 31-42. <https://doi.org/10.1109/mie.2013.2287651>
- [25]. Heng, A., Zhang, S., Tan, A. C. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 23(3), 724-739. <https://doi.org/10.1016/j.ymssp.2008.06.009>
- [26]. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483-1510. <https://doi.org/10.1016/j.ymssp.2005.09.012>
- [27]. Kans, M. (2013). IT practices within maintenance from a systems perspective: Study of IT utilisation within firms in Sweden. *Journal of Manufacturing Technology Management*, 24(5), 768-791. <https://doi.org/10.1108/17410381311328007>
- [28]. Kaparthy, S., & Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. *International Journal of Quality & Reliability Management*, 37(4), 659-686. <https://doi.org/10.1108/ijqrm-04-2019-0131>
- [29]. Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing*, 107, 241-265. <https://doi.org/10.1016/j.ymssp.2017.11.024>
- [30]. Kowalczyk, M., & Buxmann, P. (2014). Big data and information processing in organizational decision processes: A multiple case study. *Business & Information Systems Engineering*, 6(5), 267-278. <https://doi.org/10.1007/s12599-014-0341-5>
- [31]. Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems: Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42(1-2), 314-334. <https://doi.org/10.1016/j.ymssp.2013.06.004>
- [32]. Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, 104, 799-834. <https://doi.org/10.1016/j.ymssp.2017.11.016>
- [33]. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing*, 138, 106587. <https://doi.org/10.1016/j.ymssp.2019.106587>
- [34]. Li, Z., Wang, Y., & Wang, K.-S. (2017). Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. *Advanced Manufacturing*, 5(4), 377-387. <https://doi.org/10.1007/s40436-017-0203-8>
- [35]. Lundgren, C., Berlin, C., Skoogh, A., & Källström, A. (2023). How industrial maintenance managers perceive socio-technical changes in leadership in the Industry 4.0 context. *International Journal of Production Research*, 61(15), 5282-5301. <https://doi.org/10.1080/00207543.2022.2101031>
- [36]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use the Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202-220. <https://doi.org/10.63125/pbjxp014>
- [37]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [38]. Md Mesbaul, H. (2025). A Framework-Based Meta-Analysis Of Artificial Intelligence-Driven ERP Solutions For Circular And Sustainable Supply Chains. *International Journal of Scientific Interdisciplinary Research*, 6(1), 327-367. <https://doi.org/10.63125/n6k7r711>
- [39]. Md Mostafizur, R. (2025). Data-Driven Graph Neural Network Models for Detecting Fraudulent Insurance Claims In Healthcare Systems. *American Journal of Interdisciplinary Studies*, 6(1), 263-294. <https://doi.org/10.63125/pmqa1e33>
- [40]. Md Mostafizur, R., Omar Muhammad, F., & Sheratun Noor, J. (2025). Data Privacy in Business Intelligence Systems: Ensuring Compliance In HRIS And Enterprise Platforms. *International Journal of Scientific Interdisciplinary Research*, 6(1), 97-136. <https://doi.org/10.63125/527rmx08>
- [41]. Md Syeedur, R., & Sharmin, R. (2025). A Data-Driven Study on the use of Small Language Models & Large Language Models for Interpreting Complex Industrial Data and Deriving Actionable Outcome. *American Journal of Data Science and Analytics*, 6(11), 01-19. <https://doi.org/10.63125/5vyhgs98>
- [42]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>

- [43]. Meira, D., Lopes, I., & Pires, C. (2020). Selection of computerized maintenance management systems to meet organizations' needs using AHP. *Procedia Manufacturing*, 51, 1573-1580. <https://doi.org/10.1016/j.promfg.2020.10.219>
- [44]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263–279. <https://doi.org/10.63125/cm1c2c20>
- [45]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [46]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243–291. <https://doi.org/10.63125/a3xjb608>
- [47]. Muhammad Zahidul, I. (2025). Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python. *American Journal of Interdisciplinary Studies*, 6(3), 351-393. <https://doi.org/10.63125/e6dj308>
- [48]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [49]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306-350. <https://doi.org/10.63125/tnneth75>
- [50]. Nandi, S., Toliyat, H. A., & Li, X. (2005). Condition monitoring and fault diagnosis of electrical motors: A review. *IEEE Transactions on Energy Conversion*, 20(4), 719-729. <https://doi.org/10.1109/tec.2005.847955>
- [51]. Nguyen, K. T. P., & Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliability Engineering & System Safety*, 188, 251-262. <https://doi.org/10.1016/j.res.2019.03.018>
- [52]. O'Donovan, P., Leahy, K., Bruton, K., & O'Sullivan, D. T. J. (2015). An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities. *Journal of Big Data*, 2, 25. <https://doi.org/10.1186/s40537-015-0034-z>
- [53]. Peng, Y., Dong, M., & Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance: A review. *The International Journal of Advanced Manufacturing Technology*, 50(1-4), 297-313. <https://doi.org/10.1007/s00170-009-2482-0>
- [54]. Premkumar, G., Ramamurthy, K., & Saunders, C. S. (2005). Information processing view of organizations: An exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems*, 22(1), 257-294. <https://doi.org/10.1080/07421222.2003.11045841>
- [55]. Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics: A tutorial. *Mechanical Systems and Signal Processing*, 25(2), 485-520. <https://doi.org/10.1016/j.ymssp.2010.07.017>
- [56]. Ruschel, E., Santos, E. A. P., & Loures, E. d. F. R. (2017). Industrial maintenance decision-making: A systematic literature review. *Journal of Manufacturing Systems*, 45, 180-194. <https://doi.org/10.1016/j.jmsy.2017.09.003>
- [57]. Sardar, M. U., Vaimann, T., Kütt, L., Kallaste, A., Asad, B., Akbar, S., & Kudelina, K. (2023). Inverter-fed motor drive system: A systematic analysis of condition monitoring and practical diagnostic techniques. *Energies*, 16(15), 5628. <https://doi.org/10.3390/en16155628>
- [58]. Sekar, R., Hsieh, S.-J., & Wu, Z. (2011). Remote diagnosis design for a PLC-based automated system: 1-Implementation of three levels of architectures. *The International Journal of Advanced Manufacturing Technology*, 57, 683-700. <https://doi.org/10.1007/s00170-011-3314-6>
- [59]. Selcuk, S. (2017). Predictive maintenance, its implementation and latest trends. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231(9), 1670-1679. <https://doi.org/10.1177/0954405415601640>
- [60]. Shaheen, B. W., & Németh, I. (2022). Integration of maintenance management system functions with Industry 4.0 technologies and features: A review. *Processes*, 10(11), 2173. <https://doi.org/10.3390/pr10112173>
- [61]. Shankar, L., Singh, C. D., & Singh, R. (2023). Impact of implementation of CMMS for enhancing the performance of manufacturing industries. *International Journal of System Assurance Engineering and Management*, 14, 1599-1620. <https://doi.org/10.1007/s13198-021-01480-6>
- [62]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [63]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, 6(04), 01–42. <https://doi.org/10.63125/y0e9dc38>
- [64]. Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation: A review on the statistical data-driven approaches. *European Journal of Operational Research*, 213(1), 1-14. <https://doi.org/10.1016/j.ejor.2010.11.018>
- [65]. Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., & Cesarotti, V. (2020). Maintenance transformation through Industry 4.0 technologies: A systematic literature review. *Computers in Industry*, 123, 103335. <https://doi.org/10.1016/j.compind.2020.103335>

- [66]. Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27(10), 1849-1867. <https://doi.org/10.1111/poms.12746>
- [67]. Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, 11(3), 812-820. <https://doi.org/10.1109/tii.2014.2349359>
- [68]. Teoh, Y. K., Gill, S. S., & Parlikad, A. K. (2023). IoT and fog-computing-based predictive maintenance model for effective asset management in Industry 4.0 using machine learning. *IEEE Internet of Things Journal*, 10(3), 2087-2094. <https://doi.org/10.1109/jiot.2021.3050441>
- [69]. Tidriri, K., Chatti, N., Verron, S., & Tiplica, T. (2016). Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: A review of researches and challenges. *Annual Reviews in Control*, 42, 63-81. <https://doi.org/10.1016/j.arcontrol.2016.09.008>
- [70]. Wang, H., & Blaabjerg, F. (2021). Power electronics reliability: State of the art and outlook. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 9(6), 6476-6493. <https://doi.org/10.1109/jestpe.2020.3037161>
- [71]. Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, 4(1), 23-45. <https://doi.org/10.1080/21693277.2016.1192517>
- [72]. Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics*, 236, 108135. <https://doi.org/10.1016/j.ijpe.2021.108135>
- [73]. Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, 115, 213-237. <https://doi.org/10.1016/j.ymssp.2018.05.050>
- [74]. Zhu, S., Song, J., Hazen, B. T., Lee, K., & Cegielski, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. *International Journal of Physical Distribution & Logistics Management*, 48(1), 47-68. <https://doi.org/10.1108/ijpdlm-11-2017-0341>
- [75]. Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150, 106889. <https://doi.org/10.1016/j.cie.2020.106889>