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IOT INTEGRATION IN INTELLIGENT LUBRICATION SYSTEMS FOR PREDICTIVE MAINTENANCE AND PERFORMANCE OPTIMIZATION IN ADVANCED MANUFACTURING INDUSTRIES

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Abstract

This study investigates how the integration of Internet of Things (IoT) technologies into intelligent lubrication systems enhances predictive maintenance capability and supports performance optimization within advanced manufacturing industries. The research addresses a critical empirical gap: although Maintenance 4.0 frameworks widely highlight the strategic role of smart lubrication and sensor-embedded subsystems, there remains insufficient quantitative evidence regarding how IoT-enabled lubrication solutions influence plant-level operational outcomes such as equipment availability, unplanned downtime, throughput stability, and overall equipment effectiveness (OEE). To respond to this gap, the study develops and empirically tests a conceptual model that links IoT integration, predictive maintenance effectiveness, and multidimensional performance outcomes in cloud-connected, data-driven manufacturing environments. A quantitative, cross-sectional, case-based survey design was adopted, utilizing a structured five-point Likert questionnaire administered to maintenance, reliability, production, and engineering professionals working in plants that have deployed IoT-driven lubrication and condition monitoring technologies. A total of 210 usable responses were collected, reflecting an effective response rate of 80.8 percent and representing diverse industrial contexts with varying levels of digital maturity. The model incorporated key variables including IoT integration in intelligent lubrication systems, predictive maintenance effectiveness, operational performance outcomes, and user acceptance—recognized in technology adoption theory as a critical enabler of system effectiveness. Data analysis involved multiple stages, beginning with descriptive statistics and reliability assessments to verify internal consistency across constructs, followed by Pearson correlation analysis to establish initial relationships among variables. A series of multiple regression models and mediation–moderation analyses, supplemented with bootstrapping procedures, were employed to rigorously test the hypothesized relationships. Results indicated that IoT integration exerted a strong and statistically significant positive effect on predictive maintenance effectiveness ($\beta = 0.66$, $R^2 = 0.54$), confirming that advanced, sensor-enabled lubrication systems materially enhance a plant's capability to anticipate equipment failures and prevent lubrication-related anomalies. Further, IoT integration and predictive maintenance jointly accounted for 63 percent of the variance in multidimensional performance outcomes, highlighting the centrality of intelligent lubrication systems as a technological lever for improving OEE and reliability-centered performance metrics. Mediation results showed that predictive maintenance partially mediated the IoT–performance relationship (indirect effect = 0.34), indicating that IoT-generated condition data translate into performance gains primarily through improved diagnostic and prognostic capabilities. Additionally, user acceptance significantly moderated the IoT–predictive maintenance pathway, demonstrating that even sophisticated digital lubrication and monitoring architectures require high levels of user readiness, trust, and operational engagement to deliver their full value.

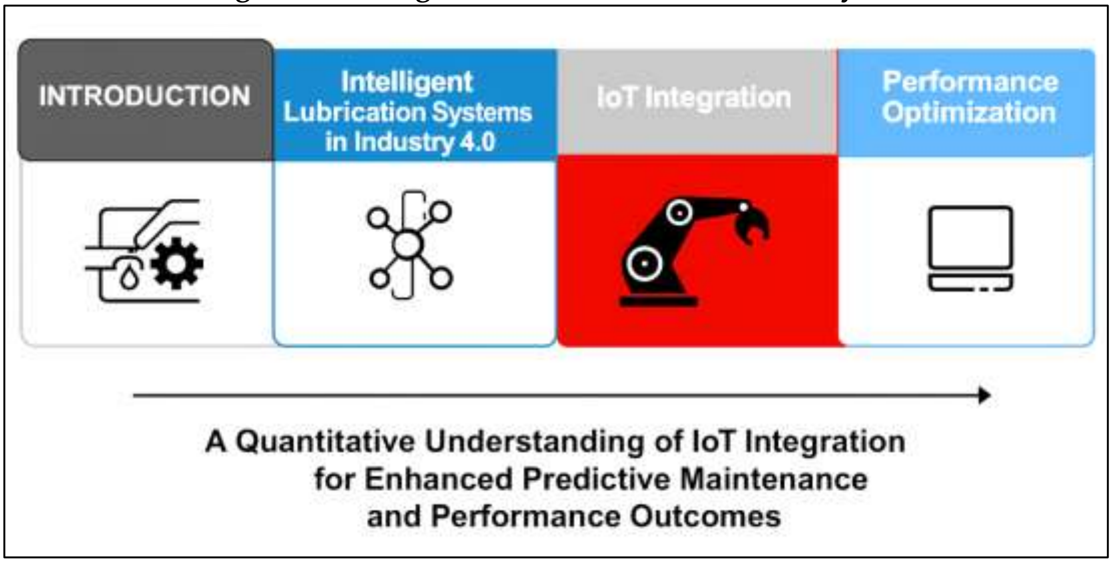
Keywords

Internet Of Things, Intelligent Lubrication Systems, Predictive Maintenance, Industry 4.0, Advanced Manufacturing Performance.

INTRODUCTION

The fourth industrial revolution has introduced a globally interconnected production landscape in which cyber–physical systems, big data, and the Internet of Things (IoT) are redefining how manufacturers plan, operate, and maintain industrial assets. IoT is commonly defined as a network of uniquely identifiable physical objects equipped with sensing, processing, and communication capabilities that can be integrated into digital services and analytics infrastructures. At industrial scale, the Industrial Internet of Things (IIoT) extends this concept to production systems, enabling seamless data exchange between machines, sensors, and enterprise applications across geographically distributed plants (Gupta et al., 2022). For manufacturing economies in Asia, Europe, and North America, IIoT-based smart factories have become a strategic lever for global competitiveness, cost control, and energy efficiency, particularly in capital-intensive sectors such as automotive, metals, power generation, and process industries (Chhatrawat et al., 2021). Within this context, predictive maintenance emerges as a central pillar of Industry 4.0, whereby real-time sensing and analytics are used to anticipate failures and optimize maintenance interventions, rather than relying on fixed-interval or corrective strategies (Zonta et al., 2020). As global supply chains tighten and production systems operate closer to their design limits, the ability to continuously monitor critical components and translate sensor data into timely maintenance decisions becomes a matter of international industrial resilience and productivity rather than a purely local operational choice (Bousdekis et al., 2019).

Figure 1: Intelligent Lubrication within Industry 4.0



Lubrication systems are among the most critical subsystems in rotating and sliding machinery because they directly mediate friction, wear, and heat generation in high-value assets such as turbines, compressors, gearboxes, and machine tools. Tribological studies indicate that inadequate lubrication and contamination of lubricants can accelerate component degradation, increase energy consumption, and shorten equipment life cycles in ways that are disproportionately costly relative to the price of the lubricant itself (Myshkin & Markova, 2017). Conventional lubrication management in many plants still relies on periodic manual inspections, static replacement intervals, or off-line laboratory oil analysis, which may not capture rapid degradation processes under variable loads and harsh operating environments. Empirical work on lubricant condition monitoring shows that changes in viscosity, dielectric constant, acidity, and particle contamination can provide early warning signals of functional lubricant failure and emerging mechanical damage well before catastrophic breakdown occurs (Dalzochio et al., 2020). Reviews of lubricant-based diagnostics further highlight that data from wear particles, oxidation products, and moisture can be exploited not only for condition assessment but also for quantitative remaining useful life (RUL) estimation of both the lubricant and the lubricated components (Yang et al., 2019; Zhu et al., 2017). In advanced manufacturing industries, where unplanned downtime of a single production line can disrupt multi-site supply networks, the strategic importance of lubrication management has therefore expanded from a narrow maintenance task to a key contributor to overall equipment effectiveness, energy efficiency, and quality consistency across global facilities (Wakiru et al., 2019).

The convergence of IoT technologies with lubrication management has given rise to intelligent lubrication systems that combine smart sensors, embedded controllers, and communication modules for continuous oil condition monitoring and automated lubrication control. Reviews of lubricating oil conditioning sensors document a wide portfolio of online devices capable of measuring viscosity, dielectric constant, water content, ferrous particle levels, and other indicators directly in the lubrication circuit, thus enabling real-time monitoring without interrupting operations (Abdulla & Ibne, 2021; Zhu et al., 2014). Lubricant condition monitoring frameworks based on data mining and advanced analytics demonstrate how such sensor streams can be transformed into actionable knowledge for fault diagnosis and maintenance decision support in complex industrial environments (Habibullah & Foysal, 2021; Shaheen & Németh, 2022). At the same time, novel sensing materials and triboelectric nanogenerator-based devices have expanded the design space of self-powered, miniaturized sensors for real-time lubricating oil monitoring, enabling higher spatial and temporal resolution in harsh conditions (Sarwar, 2021; Zhao et al., 2021). When these intelligent lubrication systems are connected through IIoT platforms, condition data can be integrated with production, quality, and energy information, allowing cross-layer optimization of lubrication schedules, flow rates, and lubricant selection in line with global enterprise performance targets (Cinar et al., 2022; Musfiqur & Saba, 2021).

From a maintenance management perspective, these developments are embedded in a broader evolution towards "Maintenance 4.0," which uses Industry 4.0 technologies such as IoT, cloud computing, cyber–physical systems, big data analytics, and digital twins to transform maintenance from a cost center into a data-driven strategic function. Systematic reviews of predictive maintenance and maintenance digitalization show a rapid growth of studies on how Industry 4.0 technologies change maintenance tasks, decision processes, and organizational roles across sectors (Al-Najjar, 2007; Redwanul et al., 2021). Bibliometric and mapping analyses reveal increasing attention to Maintenance 4.0 architectures, intelligent asset management platforms, and performance measurement frameworks that link maintenance interventions to availability, reliability, and sustainability indicators (Brocal et al., 2019; Tarek & Praveen, 2021). In particular, several authors emphasize the role of integrated maintenance management systems that connect work order management, condition monitoring, and predictive analytics through Industry 4.0 features such as cyber–physical systems and IoT-enabled data services (Muhammad & Shahrin, 2021; Pech et al., 2021). Within this body of work, predictive maintenance emerges as a key application domain where intelligent lubrication data provide high-value inputs for prognostics, risk assessment, and optimization of maintenance planning, especially in continuous-process and high-speed manufacturing lines (Crespo Márquez et al., 2020; Saikat, 2021).

Although the literature offers rich descriptive and conceptual accounts of IoT-based predictive maintenance and intelligent lubrication, empirical evidence quantifying their combined impact on maintenance and performance outcomes in advanced manufacturing remains relatively limited. Reviews of predictive maintenance highlight a concentration of research on algorithm development, sensor selection, and decision-making frameworks, while fewer studies report rigorous quantitative analyses linking specific IoT-enabled subsystems to key performance indicators such as downtime, mean time between failures, or production throughput (Di Nardo et al., 2021; Wakiru & Pintelon, 2020). Similarly, systematic reviews of lubrication condition monitoring focus heavily on sensor technologies and signal processing methods but often provide only illustrative or laboratory-based case examples with limited generalizability to multi-plant industrial settings (Shaikh & Aditya, 2021; Wójcicki et al., 2022). In the domain of intelligent lubrication systems, research on RUL prediction for lubricants and studies on online oil condition monitoring in wind turbines and other rotating machinery demonstrate technical feasibility; however, they seldom evaluate how IoT integration in lubrication subsystems translates into broader equipment performance optimization at the plant or enterprise level (Ghosh et al., 2012; Al Amin, 2022). There is therefore a need for case-study–based quantitative investigations that explicitly model the relationships between IoT integration in intelligent lubrication systems, predictive maintenance capability, and multi-dimensional performance outcomes in advanced manufacturing industries.

In response to this gap, the present study focuses on the integration of IoT technologies in intelligent

lubrication systems for predictive maintenance and performance optimization in advanced manufacturing industries . The study adopts a quantitative, cross-sectional, case-study–based design in which data are collected from manufacturing organizations that have implemented, or are in the process of implementing, IoT-enabled lubrication and condition monitoring solutions. Using a structured questionnaire based on a five-point Likert scale and supplemented by secondary performance indicators where available, the research examines how the extent of IoT integration in lubrication systems relates to the maturity of predictive maintenance practices and to perceived and observed improvements in equipment performance. Drawing on the reviewed literature, three overarching research questions are formulated: (RQ1) How extensively are IoT technologies integrated into lubrication systems and related maintenance processes in advanced manufacturing plants? (RQ2) How is IoT integration in intelligent lubrication systems associated with the adoption and effectiveness of predictive maintenance strategies? and (RQ3) How does IoT-enabled intelligent lubrication contribute to equipment performance optimization, including reliability, availability, and productivity metrics? Correspondingly, a set of testable hypotheses is developed to capture the expected positive relationships between IoT integration, predictive maintenance capability, and performance outcomes, while controlling for contextual factors such as industry segment, plant size, and digitalization level.
The present research contributes to the growing discourse on Industry 4.0, Maintenance 4.0, and intelligent lubrication in several ways that are relevant for both scholars and practitioners. First, by centering on IoT integration in lubrication systems, the study sheds light on a specific yet underexplored subsystem that links tribological phenomena at the component level with predictive analytics and decision-making at the maintenance and operations levels (Myshkin & Markova, 2017; Wakiru et al., 2019). Second, it extends prior literature reviews and conceptual frameworks by providing empirical evidence from advanced manufacturing case studies, using descriptive statistics, correlation analysis, and regression modeling to quantify the strength and significance of associations between IoT-enabled lubrication capabilities and key maintenance and performance constructs. Third, the study integrates insights from maintenance management, tribology, and industrial engineering to propose a conceptual model that can guide subsequent quantitative and design-oriented research on intelligent lubrication within IoT-based smart factories. The remainder of the paper is structured as follows: Section 1 introduces the background, problem statement, research questions, hypotheses, and significance of the study; Section 2 presents a structured literature review and theoretical and conceptual frameworks related to IoT, predictive maintenance, and intelligent lubrication systems; Section 3 describes the research methodology, including case selection, sampling, measurement instruments, and data analysis procedures; Section 4 reports the empirical results; Section 5 provides a detailed discussion in relation to the existing literature; and Section 6 presents the conclusions, recommendations, and limitations of the study.
The overarching objective of this study is to develop a structured, quantitative understanding of how IoT integration within intelligent lubrication systems contributes to predictive maintenance capability and performance optimization in advanced manufacturing industries. Specifically, the research seeks to translate broad Industry 4.0 concepts into measurable constructs and testable relationships grounded in actual practices and experiences of manufacturing professionals. The first objective is to systematically assess the extent and nature of IoT integration in lubrication systems across selected advanced manufacturing plants, including the types of sensors used, parameters monitored, communication methods, data collection frequency, and degree of automation in lubrication-related decisions. The second objective is to evaluate the maturity and effectiveness of predictive maintenance strategies that are supported by these IoT-enabled lubrication systems, focusing on how condition-based information is incorporated into maintenance planning, fault detection, intervention timing, and maintenance resource allocation. The third objective is to examine the statistical relationships between IoT-enabled lubrication capabilities and key performance outcomes, such as equipment availability, reduction in unplanned downtime, stability of production throughput, and improvements in overall equipment effectiveness and energy use. A further objective is to capture user perceptions of usefulness, ease of use, reliability, and integration of these systems into existing maintenance workflows, thereby linking technological features with human and organizational factors in a comprehensive model. Through these objectives, the study aims to construct and validate a conceptual

framework in which IoT integration in intelligent lubrication systems acts as an enabler of predictive maintenance, which in turn serves as a pathway to performance optimization at the equipment and plant levels. By using a case-study–based survey design with descriptive statistics, correlation analysis, and regression modeling, the research focuses on generating structured empirical evidence aligned with these objectives, providing a clear basis for interpreting the relationships between the technological, maintenance, and performance dimensions of intelligent lubrication in advanced manufacturing environments.

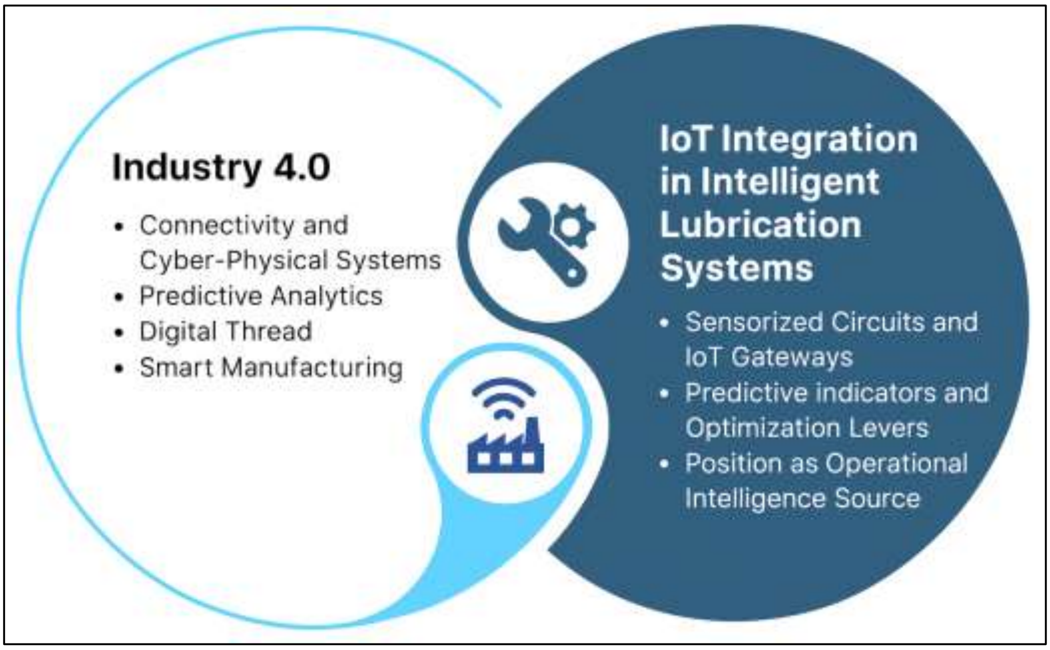
LITERATURE REVIEW

The literature on Industry 4.0, smart manufacturing, and predictive maintenance has expanded rapidly over the past two decades, forming a multidimensional foundation for understanding IoT-based intelligent lubrication systems in advanced manufacturing industries. Early work on the Internet of Things positioned it as a paradigm in which uniquely identifiable physical objects equipped with sensing and communication capabilities become part of a pervasive digital network, enabling continuous data exchange between machines, information systems, and decision-makers across organizational boundaries. Building on this foundation, the Industrial Internet of Things (IIoT) has been conceptualized as the application of IoT principles to large-scale industrial environments, where cyber–physical systems, cloud platforms, and analytics pipelines interact with production equipment to support real-time monitoring, control, and optimization. Within this broader framework, maintenance strategies have undergone a progression from purely corrective and time-based preventive approaches toward condition-based and predictive maintenance models that rely on continuous sensing, diagnostics, and prognostics to anticipate failures and schedule interventions before functional breakdown occurs. In parallel, tribology and lubrication engineering research has highlighted the critical influence of lubricant quality, film formation, and contamination control on friction, wear, and heat generation in rotating and sliding components, emphasizing that inadequate lubrication alone can account for a significant proportion of mechanical failures and avoidable energy losses in high-value equipment. As sensing, embedded processing, and communication technologies have matured, lubrication systems have evolved from manually managed subsystems to intelligent, sensor-rich platforms capable of real-time oil condition monitoring, automatic lubrication dosing, and integration with centralized maintenance management systems. This evolution aligns with the concept of Maintenance 4.0, which frames maintenance as a data-driven, strategically integrated function that leverages IoT, big data analytics, and digital twins to support more accurate diagnostics, optimized intervention timing, and closer alignment between maintenance actions and production objectives. However, while conceptual models and technological demonstrations of intelligent lubrication and IoT-based predictive maintenance are abundant, there remains a need for empirical, quantitatively grounded studies that examine how specific IoT-enabled lubrication capabilities are implemented in actual factories, how they shape predictive maintenance practices, and how these changes are associated with measurable performance outcomes such as availability, reliability, and overall equipment effectiveness in advanced manufacturing contexts.

Intelligent Lubrication Systems and IoT Integration

The evolution of intelligent lubrication systems in advanced manufacturing is closely intertwined with transformations in cyber-physical production environments and Industry 4.0 architectures. Early computer-integrated maintenance systems primarily relied on time-based or simple condition-based lubrication policies, but the emergence of cyber-physical systems (CPS) has enabled tighter coupling between sensing, analytics, and actuation on the shop floor (Lee et al., 2015). Within CPS architectures, machine-embedded sensors, edge controllers, and cloud platforms form a multi-layer stack in which lubrication subsystems are treated as critical assets whose condition must be continuously monitored and optimized rather than serviced periodically. Smart manufacturing frameworks extend this logic by embedding lubrication status into overall equipment effectiveness and energy-efficiency indicators, so that lubrication events are triggered by data-driven inferences about friction, temperature, and vibration signatures instead of rigid schedules (Ariful, 2022; Nahid, 2022; Yao et al., 2017). In such environments, lubrication management is no longer a peripheral activity; it becomes part of a tightly orchestrated digital thread that connects machinery health, production scheduling, and quality outcomes across the entire factory. As manufacturers adopt more flexible, reconfigurable lines and high-precision equipment, CPS-enabled lubrication strategies are increasingly viewed as necessary to sustain uptime targets and support just-in-time production in capital-intensive sectors such as automotive, metals processing, and discrete-part manufacturing (Lee et al., 2015). At the same time, the growing affordability of multi-parameter sensors and industrial networking has lowered the barrier for integrating lubrication points into plant-wide monitoring systems, allowing maintenance teams to visualize lubricant film conditions, contamination trends, and pump duty cycles alongside other process variables in real time (Yao et al., 2017). Evidence is emerging that these technical developments provide a foundation for more predictive, performance-oriented lubrication paradigms.

Figure 2: Cyber-Physical and IoT Layers Supporting Intelligent Lubrication



From an organisational and systems perspective, IoT integration in advanced manufacturing reframes lubrication systems as nodes within a connected smart-factory ecosystem rather than isolated subsystems. Smart factory literature emphasises the role of connectivity, interoperable platforms, and vertical integration to enable end-to-end visibility of production assets, including lubrication-related components (Osterrieder et al., 2020). In such environments, Internet-connected sensors at bearings, gearboxes, hydraulic units, and centralized lubrication manifolds stream status data that can be fused with production orders, work-in-progress records, and quality inspection results. This enables analytics in which lubrication anomalies are interpreted not only as maintenance concerns but also as signals about process bottlenecks, load imbalances, or product design issues. Empirical work on smart factory performance suggests that firms achieving greater adoption of Industry 4.0 enabling technologies, including IoT and CPS, report increased opportunities in terms of productivity, flexibility, and innovation (Büchi et al., 2020; Hossain & Milon, 2022; Mominul et al., 2022). Extending this reasoning to lubrication, plants that embed real-time lubrication data into their digital innovation and improvement programmes may be better positioned to identify systemic root causes of wear, redesign lubrication circuits, or rebalance workloads across identical machines (Rabiul & Praveen, 2022; Rakibul & Samia, 2022). At the same time, IoT platforms facilitate monitoring, enabling equipment suppliers and lubrication service providers to collaborate with engineers on parameter tuning, fault diagnosis, and continuous improvement without being physically present on site. This collaborative environment changes the governance of lubrication systems, moving from reactive, technician-driven routines to shared digital services where data ownership, access rights, and cybersecurity protections must be negotiated and codified as part of asset management strategies (Asadi et al., 2022). For manufacturers operating multi-plant networks, these capabilities enable the benchmarking of lubrication practices across sites and the development of standardized IoT-enabled maintenance playbooks that align lubrication management with digital transformation roadmaps and corporate strategic performance objectives.

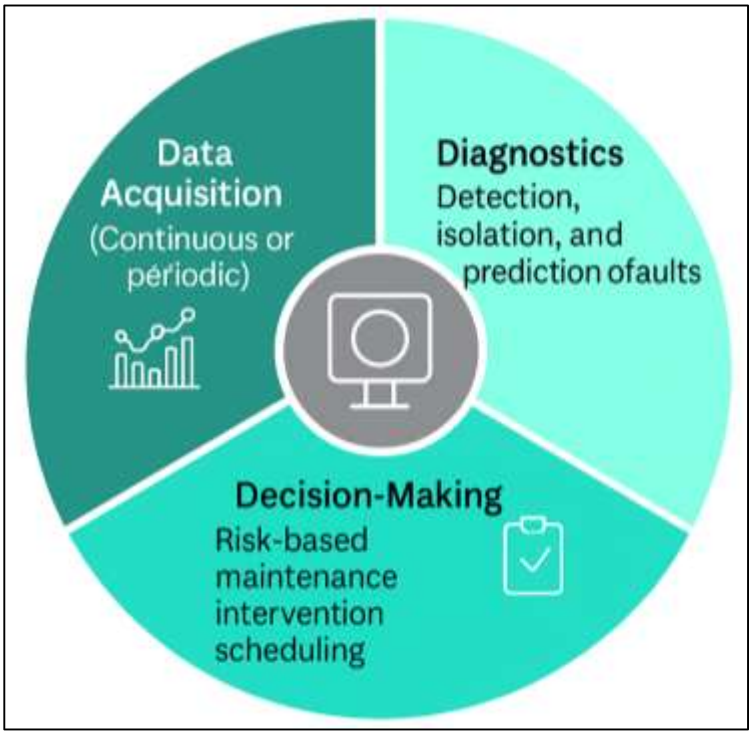
A growing body of empirical and conceptual work links IoT integration to improvements in manufacturing performance, providing an important backdrop for rethinking lubrication as a predictive and optimization-focused function. Studies on IoT-enabled production systems indicate that real-time data flows and advanced analytics can strengthen the relationship between technology adoption and key outcomes such as throughput, responsiveness, and quality stability, particularly when IoT architectures are aligned with clear performance objectives and organisational capabilities (Asadi et al., 2022). Within lubrication management, this perspective implies that sensorized lubrication circuits and IoT gateways must be designed not only to detect threshold violations, such as temperature spikes or pressure drops, but also to generate predictive indicators and optimization levers that can be embedded in scheduling, dispatching, and process-control decisions. CPS-oriented smart manufacturing frameworks demonstrate how digital twins and multi-layer data models can represent machine health, including lubrication states, at different levels of abstraction, ranging from component-level wear mechanisms to system-level availability profiles (Lee et al., 2015; Saikat, 2022; Kanti & Shaikat, 2022). When combined with Industry 4.0 smart manufacturing concepts, these models create opportunities to quantify how specific lubrication policies influence energy consumption, scrap rates, and unplanned downtime across product families and production routes (Yao et al., 2017). For the purposes of the present study, IoT integration in intelligent lubrication systems is therefore conceptualised as a socio-technical intervention that reconfigures information flows, decision rights, and accountability structures around lubrication tasks. Rather than viewing lubrication purely as a maintenance cost centre, IoT-enabled architectures position it as a continuous source of operational intelligence that can guide predictive maintenance interventions, support risk-based prioritisation of assets, and contribute directly to performance optimisation in advanced manufacturing industries (Asadi et al., 2022).

Predictive Maintenance Foundations for Intelligent Lubrication

Condition-based maintenance (CBM) emerged as an evolution from strictly reactive or time-based maintenance policies toward strategies that schedule interventions based on real-time information about equipment health. In early formulations, CBM was conceptualized as a three-stage process involving continuous or periodic data acquisition, diagnostic interpretation of condition indicators, and maintenance decision-making grounded in quantitative risk and reliability logic (Jardine et al., 2006). Within this paradigm, diagnostics focuses on detecting and isolating incipient faults, while prognostics estimates remaining useful life and future degradation trajectories, enabling maintenance managers to shift from calendar-based work orders to data-driven intervention windows. Subsequent reviews on machine prognostics in CBM have highlighted how physical models, knowledge-based systems, data-driven algorithms, and hybrid approaches can be combined to support dynamic decision-making under uncertainty across complex industrial assets such as rotating machinery, gearboxes, and production lines (Maniruzzaman et al., 2023; Arif Uz & Elmoon, 2023; Peng et al., 2010). These models increasingly rely on multi-sensor data fusion, Bayesian updating, and stochastic process modeling to turn condition signals into probabilistic forecasts that explicitly account for noise, load variation, and operating context. CBM frameworks also formalize how decision criteria such as risk reduction, mean time between failures, maintenance cost, and availability targets should be balanced, thereby connecting signal processing and statistical modeling with tangible key performance indicators that matter to plant managers (Tarek, 2023; Mushfequr & Ashraful, 2023). Together, these strands of research position CBM as a foundational concept for intelligent lubrication, because lubrication failure modes such as oil contamination, starvation, viscosity breakdown, and film loss are inherently condition-dependent phenomena that can be continuously monitored using sensor data and predictive models rather than pre-set replacement intervals. In modern manufacturing settings, this means that lubrication decisions can be triggered by changes in vibration spectra, thermal profiles, or oil chemistry instead of rigid schedules, allowing organizations to prevent both under-lubrication and wasteful over-lubrication that compromise reliability, energy efficiency, and environmental performance (Shahrin & Samia, 2023; Muhammad & Redwanul, 2023).

As CBM matured, scholars began to map the field systematically, revealing its conceptual structure and the main research factors that underpin contemporary predictive maintenance practice. A large-scale bibliometric review of over four decades of CBM research shows that the domain can be organized into four macro-areas: theoretical foundations, implementation strategies, inspection and replacement policies, and prognostics-focused approaches (Muhammad & Redwanul, 2023; Quatrini et al., 2020; Razia, 2023). This structure underscores that effective CBM is not merely a question of selecting an algorithm; it also involves integrating maintenance policies, sensor technologies, performance indicators, and organizational processes into a coherent management framework. At the theoretical level, CBM research clarifies how degradation processes can be modeled and how condition thresholds should be set, while implementation-oriented studies explore governance, roles, and skills required to embed CBM into daily operations (Zayadul, 2023). For intelligent lubrication systems deployed in advanced manufacturing, this implies that sensor-based monitoring of friction, temperature, and lubricant quality must be aligned with decision rules for when to replenish, filter, or switch lubricants, as well as with production schedules, safety constraints, and cost considerations. The same review emphasizes the growing role of data-driven techniques and meta-analytic methods in distilling best practices from a vast and heterogeneous body of case studies, which is directly relevant to designing empirical survey instruments and regression models that quantify how IoT-enabled lubrication practices influence equipment reliability, downtime, and operational efficiency in real factories. By linking conceptual clusters such as inspection policies and prognostics with practical levers such as training, data governance, and cross-functional coordination, CBM literature provides a rich backdrop against which the organizational and technological determinants of intelligent lubrication performance can be theorized and empirically tested. It also helps to identify the constructs that should be captured in quantitative instruments, including perceived CBM maturity, quality of sensor data, integration with enterprise systems, and the degree to which lubrication decisions are actually based on measured indicators rather than intuition.

Figure 3: Condition-Based Maintenance Foundations for Intelligent Lubrication



Parallel to these conceptual and methodological advances, Industry 4.0 has catalyzed a new wave of research on predictive maintenance platforms that combine industrial IoT, edge computing, and artificial intelligence. Recent syntheses of predictive maintenance in Industry 4.0 describe how sensing technologies, cloud and fog architectures, and machine-learning models are orchestrated to deliver

Maintenance 4.0 capabilities, including real-time anomaly detection, remaining useful life estimation, and automated decision support across distributed manufacturing assets (Achouch et al., 2022). These works emphasize that predictive maintenance no longer consists only of isolated diagnostic tools; instead, it is embedded in cyber–physical production systems where machines, information systems, and human operators interact via standardized communication protocols and interoperable data platforms. At the implementation level, reference architectures such as the TIP4.0 Industrial IoT platform demonstrate how modular edge gateways can host analytics pipelines that ingest sensor signals, execute convolutional neural networks, and push actionable health indicators to maintenance personnel, while remaining compatible with commercial-off-the-shelf hardware and diverse shop-floor networks (Resende et al., 2021). For intelligent lubrication systems, these developments mean that lubrication-related data such as oil particulate counts, film thickness, bearing vibration, and thermal signatures can be streamed, processed, and acted upon at or near the machine, enabling fine-grained predictive control of lubrication regimes. In such an architecture, lubrication units, pumps, and reservoirs become smart subsystems that both influence and respond to system-wide maintenance policies, closing the loop between local tribological conditions and global production objectives. Consequently, CBM and predictive maintenance research provide a theoretical and technological foundation for the present study's investigation of how IoT-integrated lubrication management influences predictive maintenance effectiveness and performance optimization in advanced manufacturing environments, and why organizations that invest in these capabilities may experience superior equipment longevity, higher overall equipment effectiveness, and more resilient production systems.

Intelligent Lubrication Sensing and Condition Monitoring Metrics

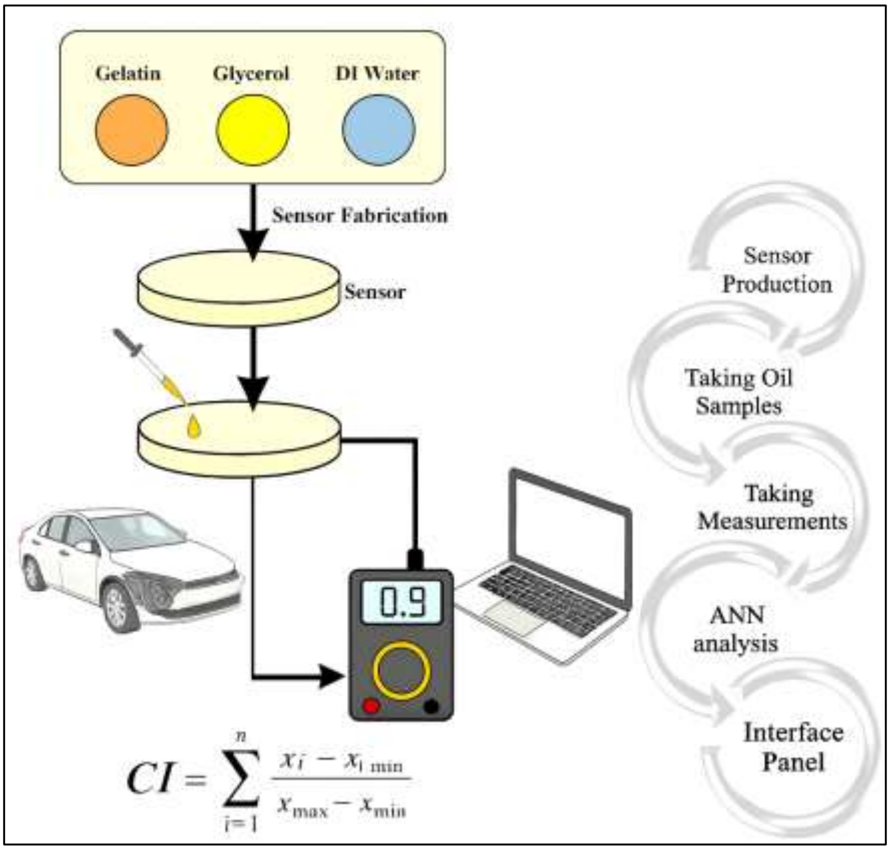
The foundation of intelligent lubrication in advanced manufacturing lies in quantifying lubricant health in real time, so that maintenance decisions are driven by the evolving condition of the oil–machine system rather than fixed service intervals. Early industrial work on on-line engine-oil monitoring demonstrated that viscosity, density and optical properties can be measured continuously in situ and used as proxies for oxidation, contamination and additive depletion, allowing oil-change decisions to be made on a genuine condition basis rather than mileage or hours run (Kumar et al., 2005). Such systems typically embed compact sensors directly in the lubrication circuit and stream data to a controller, where thresholds or models infer when lubricant properties cross acceptable ranges. To aggregate multiple sensor readings into a single health indicator, composite condition indices are often defined, for example

$$CI = \sum_{i=1}^{n} w_i \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}},$$

where x_i are normalized measurements of viscosity, dielectric constant, temperature or contamination level, and w_i are weights reflecting their relative importance for wear and failure risk. In an IoT-enabled manufacturing environment, such a condition index can be computed at high frequency and trended over time, enabling maintenance planners to identify accelerated degradation, correlate lubricant deterioration with loading patterns, and schedule interventions without removing equipment from service. This moves lubrication from a "hidden" support task to a quantified contributor to reliability and performance, and provides a natural input variable for the regression models that will later link lubrication condition to equipment availability, downtime and output stability in the empirical part of this study (Du et al., 2013).

A second important stream of research underpinning intelligent lubrication focuses on the detection and characterization of wear debris in lubricants using inductive and microfluidic sensing technologies. Building on the inductive Coulter counting principle, real-time wear-debris monitoring devices have been developed in which a micro-scale fluidic channel passes through or near a sensing coil so that the movement of metallic particles produces measurable changes in inductance (Du et al., 2010). In such devices, the sensor response is approximately proportional to the volume of individual particles, which for nearly spherical debris can be estimated as $V = \pi d^3/6$, where d is the equivalent particle diameter; this provides a direct link between the time series of inductance pulses and the size distribution of generated debris. High-throughput inductive pulse sensors extend this idea by routing lubricant through meso-scale pipes surrounded by planar coils, enabling the detection and discrimination of ferrous and non-ferrous debris in the 50–150 μm range at flow rates compatible with full-scale machinery (Du et al., 2010). Subsequent designs have improved sensitivity by embedding the sensing coil in an LC resonant circuit, amplifying small inductance changes associated with tiny wear particles and thus enhancing the ability to detect early transitions from normal to abnormal wear regimes (Du & Zhe, 2011). For intelligent lubrication systems in advanced manufacturing, these approaches make it possible to treat the rate of debris generation, expressed for example as particles per unit volume or mass per operating hour, as a quantitative performance metric that can be correlated with lubrication strategies, operating loads and maintenance policies. When integrated into IoT architectures, debris sensors become nodes in a wider cyber–physical monitoring network, where their outputs can be fused with vibration and temperature data to support richer predictive maintenance models for bearings, gears and slideways.

Figure 4: Intelligent Lubrication Sensing and Condition Monitoring Metrics



More recently, the concept of intelligence in lubrication has expanded beyond sensing to include the design of smart lubricating materials whose composition, structure and response mechanisms can be tuned in situ. Research on intelligent lubricating materials describes liquid and solid lubricants that embed micro- or nano-containers, stimulus-responsive polymers and multifunctional additives, enabling friction and wear properties to adapt dynamically to changes in temperature, load or electric field (Gong et al., 2020)). These materials can release additives when local temperature exceeds a threshold, alter viscosity under shear, or form protective films when contact pressure increases, thereby coupling tribological behaviour directly to operating conditions. From a modelling standpoint, their behaviour can be incorporated into predictive maintenance frameworks by treating lubrication state variables such as condition index CI, debris-generation rate $DR$and film-thickness margin as explanatory predictors of performance metrics like availability or overall equipment effectiveness (OEE). A simple linear relationship of the form

$$\mathrm{OEE} = \beta_0 + \beta_1 CI + \beta_2 DR + \varepsilon$$

is sufficient to motivate the survey-based regression models used in the present study, where the coefficients $\beta_1$and $\beta_2$express how incremental improvements in lubricant condition or reductions in debris rate are associated with improvements in equipment productivity. In practice, intelligent lubricating materials, on-line oil condition monitoring and advanced debris sensing co-evolve within IoT-enabled lubrication architectures: condition indices derived from fluid property sensors trigger adaptive responses in the lubricant itself, while debris sensors provide feedback on whether those responses are effectively limiting wear. Together, the sensing technologies and material innovations discussed in this subsection define the technical mechanisms through which IoT-integrated lubrication systems can support predictive maintenance and performance optimization in advanced manufacturing plants.

Theoretical Frameworks for IoT-Enabled Intelligent Lubrication

The theoretical grounding for IoT-enabled intelligent lubrication in advanced manufacturing can be anchored in technology adoption models that explain why users and organizations decide to implement, routinize, and institutionalize new digital maintenance systems. At the individual level, the Unified Theory of Acceptance and Use of Technology and its extension (UTAUT/UTAUT2) propose that behavioral intention to use a system is shaped primarily by performance expectancy, effort expectancy, social influence, and facilitating conditions, with hedonic motivation, price value, and habit providing additional explanatory power in extended formulations (Venkatesh et al., 2012). In its simplest structural representation, intention to adopt a technology may be written as

$$BI = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \varepsilon,$$

where BIdenotes behavioral intention, PEperformance expectancy, EEeffort expectancy, SIsocial influence, FCfacilitating conditions, and εan error term capturing unobserved factors. Within the context of IoT-integrated lubrication, performance expectancy corresponds to perceived improvements in machine reliability, reduction in unplanned downtime, and optimization of lubricant usage arising from real-time data and predictive alerts. Effort expectancy reflects maintenance staff perceptions of how easy it is to configure sensors, interpret dashboards, and translate condition indicators into practical decisions about lubrication tasks. Social influence captures pressures from supervisors, peers, equipment OEMs, and industry partners to conform to digital maintenance norms. Facilitating conditions represent the availability of connectivity, analytics platforms, training, and technical support that make IoT-based lubrication solutions practically usable. Cross-national empirical tests of UTAUT demonstrate that while the basic structure of these relationships remains stable, the magnitude of coefficients varies across cultural and technological contexts (Im et al., 2011).

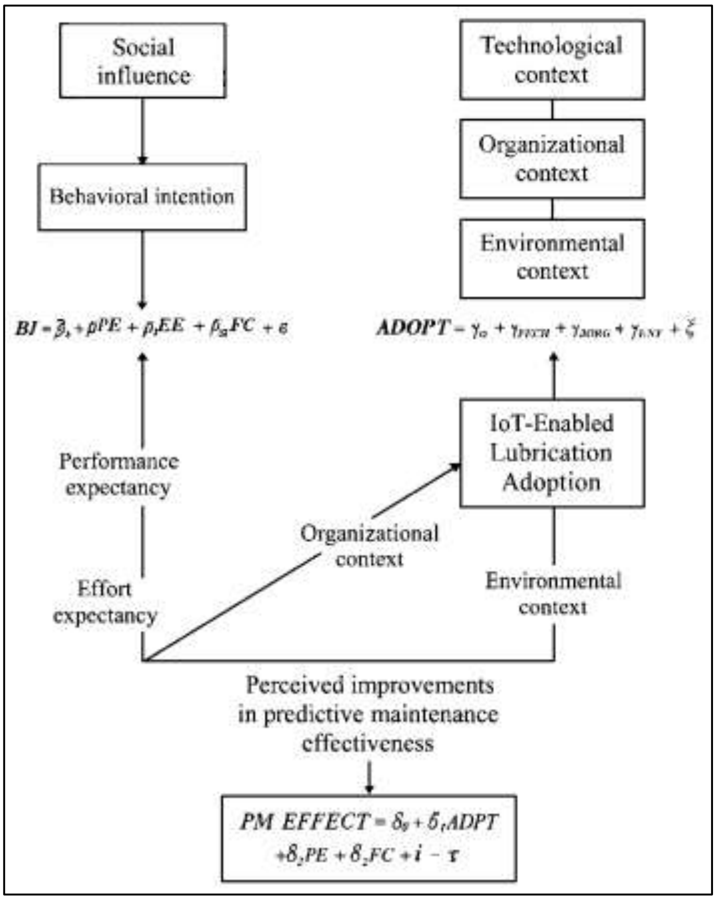
This supports the inclusion of UTAUT-type perceptual constructs in the present study's conceptual model and informs the translation of these constructs into Likert-type survey items and regression-based hypotheses concerning IoT-enabled lubrication usage in manufacturing plants.

Whereas UTAUT and UTAUT2 emphasize individual perceptions and intentions, the Technology–Organization–Environment (TOE) framework provides a complementary lens for understanding organizational-level decisions about adopting IoT-enabled intelligent lubrication systems. TOE posits that adoption is a function of three contextual domains: the technological context (e.g., relative advantage, compatibility with existing systems, complexity, and observability), the organizational context (e.g., firm size, slack resources, top-management support, and process maturity), and the environmental context (e.g., competitive pressure, regulatory requirements, and relationships with suppliers and customers) (Awa et al., 2017). A simplified linear representation consistent with this framework can be expressed as

$$ADOPT = \gamma_0 + \gamma_1 TECH + \gamma_2 ORG + \gamma_3 ENV + \xi,$$

where $ADOPT$denotes the perceived level of adoption or integration of IoT-enabled lubrication, $TECH$represents technological readiness and perceived advantage, ORGexpresses organizational readiness and support, ENVcaptures environmental pressures and external support, and $\xi$is an error term. Empirical work that integrates TOE with task–technology fit and UTAUT shows that combining structural, task-related, and perceptual factors increases the explanatory power of adoption models and links adoption more directly to value creation outcomes such as efficiency, quality, and flexibility (Dwivedi et al., 2021). In the case of intelligent lubrication, the technological context includes the availability of sensorized lubrication components, edge devices, communication protocols, and analytics platforms that can ingest and interpret lubrication data. The organizational context encompasses the presence of structured maintenance strategies, cross-functional collaboration among maintenance, production, and IT, and explicit budgeting for predictive maintenance technologies. The environmental context covers requirements from certification bodies, expectations of supply chain partners regarding reliability and uptime, and competitive pressures to demonstrate higher levels of equipment availability and cost efficiency.

Figure 5: Theoretical Framework



A third strand of the theoretical base for this research concerns the barriers and enablers associated with IoT adoption, particularly in industrial and manufacturing environments where maintenance and reliability carry high operational and financial stakes. Studies examining IoT adoption challenges in developing and emerging economies identify recurrent technological obstacles such as unreliable connectivity, insufficient IT infrastructure, cybersecurity vulnerabilities, and limited interoperability, alongside organizational constraints including shortages of specialized skills, restricted investment capacity, and uncertainty about the economic value of IoT projects (Altameem, 2022). In parallel, meta-analytic evaluations of UTAUT2 indicate that performance expectancy and facilitating conditions typically emerge as the strongest standardized predictors of behavioral intention and use behavior across technologies and sectors, underscoring the importance of clearly demonstrable benefits and robust support conditions for successful technology adoption (Venkatesh et al., 2012). Drawing on these insights, the present study conceptualizes predictive maintenance effectiveness and performance optimization as outcome constructs that are influenced jointly by adoption intensity and user perceptions. At an abstract level, this can be represented by a multiple-regression equation such as

$$PM\_EFFECT = \delta_0 + \delta_1 ADOPT + \delta_2 PE + \delta_3 FC + \upsilon,$$

where PM_EFFECT denotes perceived improvements in predictive maintenance effectiveness, $ADOPT$ captures the degree of IoT-enabled lubrication adoption, PE reflects performance expectancy, FC represents facilitating conditions, and υ is an error term. In advanced manufacturing plants implementing intelligent lubrication, this combined TOE–UTAUT perspective supports a conceptual framework in which structural readiness, environmental pressures, and individual perceptions together determine the depth and quality of IoT integration. That integration, in turn, is theorized to influence predictive maintenance capability, equipment reliability and availability, and ultimately overall performance and competitiveness of the manufacturing system.

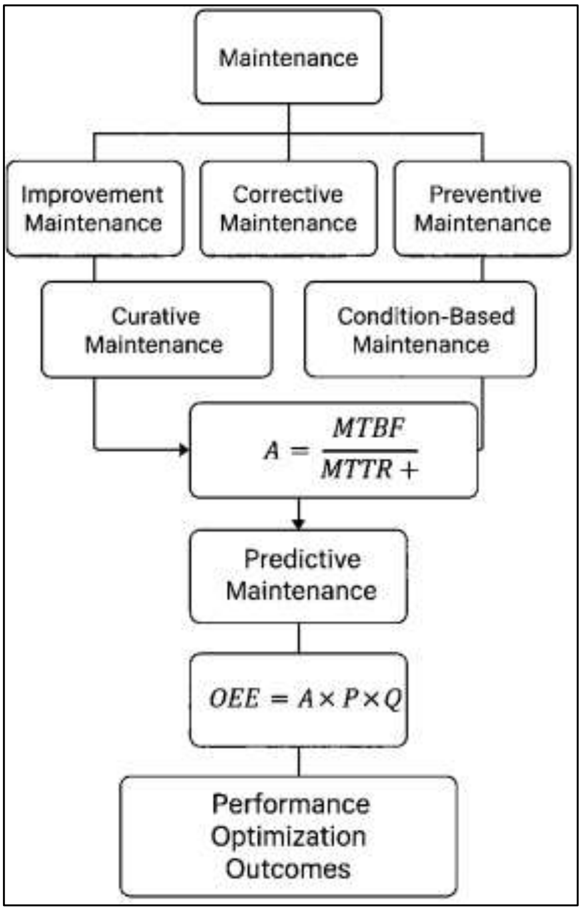
Predictive Maintenance and Performance Optimization Outcomes

Maintenance performance measurement provides the conceptual bridge between predictive maintenance initiatives and the broader objectives of manufacturing competitiveness, making it central to any framework that links intelligent lubrication to performance optimization. One influential contribution in this area proposes a structured hierarchy in which maintenance objectives (such as maximizing availability or reducing life-cycle cost) are translated into performance indicators covering inputs, processes, and results at multiple organizational levels (Muchiri et al., 2011). Within this view, indicators such as mean time between failures (MTBF), mean time to repair (MTTR), and maintenance cost per unit produced are not isolated statistics; rather, they represent the mechanisms through which maintenance actions influence reliability, responsiveness, and cost-effectiveness at the plant level. A commonly cited relationship expresses steady-state availability as

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}},$$

highlighting how improved diagnostic accuracy and faster fault resolution directly raise the proportion of time that equipment is capable of performing its intended function.

Figure 6: Predictive Maintenance Performance Framework



In intelligent lubrication contexts, enhanced condition monitoring of oil properties and wear debris can extend MTBF by preventing lubrication-related failures, while better planning of predictive interventions can reduce MTTR by ensuring that tools, spares, and personnel are ready before shutdowns occur. Muchiri et al. emphasise that maintenance indicators must be carefully selected and grouped so that they reflect cause–effect chains from maintenance processes to equipment performance and finally to business outcomes, a logic that motivates the inclusion of predictive maintenance effectiveness and performance optimization constructs in the present study's conceptual model (Muchiri & Pintelon, 2008). In many contemporary plants, these indicators are embedded within broader performance dashboards or balanced-scorecard structures, meaning that shifts in lubrication-related reliability are visible at managerial levels and can trigger strategic decisions about technology investment, staffing, and spare-parts policies. Such integrated views of performance underpin the rationale for analysing lubrication not in isolation but as a driver of systemic manufacturing outcomes.Within this performance-measurement landscape, overall equipment effectiveness (OEE) has become a central composite indicator for assessing the impact of maintenance and improvement programmes on manufacturing assets. OEE is typically defined as the product of three factors availability (A), performance (P), and quality (Q) so that

$$\mathrm{OEE} = A \times P \times Q,$$

where availability captures time losses due to breakdowns and changeovers, performance reflects speed losses relative to the design or ideal cycle time, and quality represents output losses due to defects and rework (Muchiri & Pintelon, 2008). Because lubrication-related failures manifest primarily as breakdowns, speed reductions, and quality deterioration through vibration and thermal effects, intelligent lubrication can, in principle, influence all three components of this multiplicative measure. The OEE framework has been widely applied in maintenance and production settings to identify the "six big losses" associated with equipment, to benchmark performance across lines or plants, and to prioritise improvement projects that deliver the largest impact on effective capacity utilisation (Ng Corrales et al., 2020). A systematic review of OEE-related research further documents how numerous adaptations and extensions such as energy-based OEE, environmental OEE, and multi-equipment OEE have been proposed to better align the indicator with contemporary concerns around sustainability, flexibility, and Industry 4.0 integration (Ng Corrales, Lambán, Hernandez Korner, & Royo, 2020). For the present study, these insights justify the selection of indicators related to availability, throughput, and quality as key performance outcomes and support the use of regression models in which self-reported improvements in OEE components are treated as dependent variables explained by IoT-enabled intelligent lubrication and predictive maintenance capability. In survey-based research designs, the three OEE components can be operationalised using Likert-type items that capture practitioners' assessments of change in availability, speed, and quality performance after the introduction of IoT-enabled predictive maintenance, making OEE not only a technical indicator but also a perceptual construct that can be related statistically to adoption intensity and maintenance practices (Muchiri et al., 2011).

The link between predictive maintenance practices and performance optimization has been reinforced by recent work on machine-learning-based predictive maintenance and structured condition-based maintenance implementation methodologies. In the automotive sector, for example, case studies of predictive maintenance enabled by machine learning show how the exploitation of high-frequency condition data for anomaly detection and remaining useful life estimation can reduce unplanned downtime and maintenance costs while supporting safety-critical requirements, provided that models are integrated with maintenance workflows and interpreted by domain experts (Theissler et al., 2021). Complementing such technological perspectives, implementation-oriented reviews of condition-based maintenance emphasise the need to explicitly connect condition-monitoring outputs with performance indicators in order to justify investments and evaluate the effectiveness of CBM programmes (Ng Corrales et al., 2020). Bringing these strands together, the present research conceptualises predictive maintenance effectiveness as an intervening construct that mediates the relationship between IoT-integrated intelligent lubrication and performance outcomes. At a high level, this can be represented by a simple linear model of the form

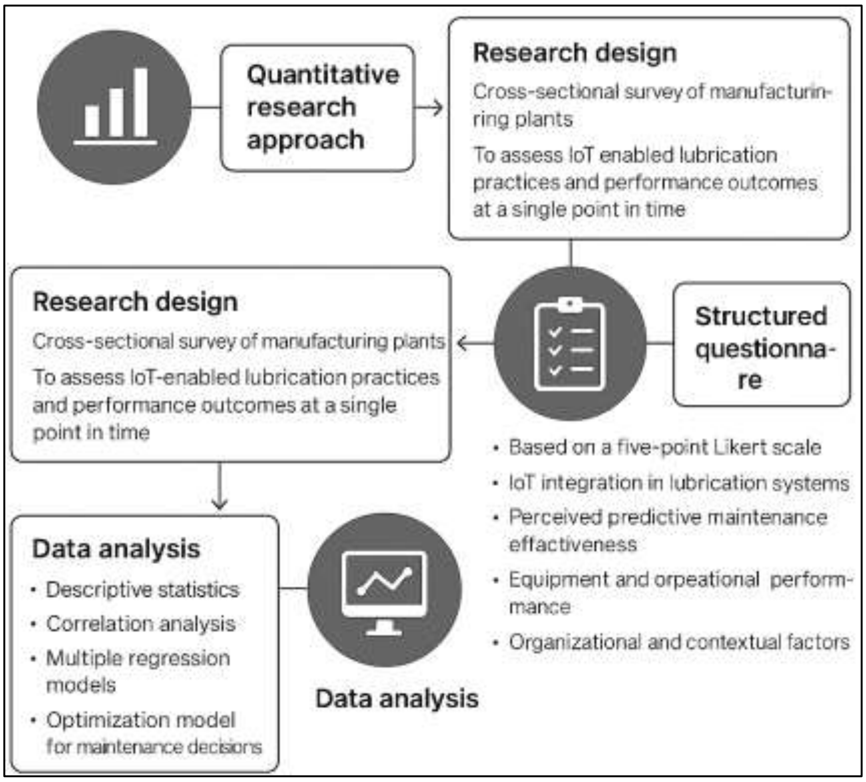
$$\mathrm{Perf} = \beta_0 + \beta_1\, \mathrm{PdM\_eff} + \beta_2\, \mathrm{IoT\_Lub} + \varepsilon,$$

where *Perf* denotes performance measures related to availability, throughput, and quality, *PdM_eff* represents predictive maintenance effectiveness, *IoT_Lub* indicates the extent of IoT integration in lubrication systems, and $\varepsilon$is an error term. In empirical terms, the model implies that improvements in predictive maintenance practices enabled by richer lubrication data and advanced analytics should be associated with higher perceived or measured performance, even after controlling for differences in IoT adoption intensity or organisational context. By embedding these relationships within a coherent set of indicators rooted in the maintenance performance and OEE literature, the conceptual framework provides a rigorous basis for testing how intelligent lubrication contributes to performance optimization in advanced manufacturing industries (Teixeira et al., 2020). This representation also aligns with the practice of decomposing performance variance into portions explained by maintenance and technology variables, which is essential for quantifying the incremental contribution of intelligent lubrication relative to other improvement initiatives.

Method

The methodology of this study has been developed to provide a rigorous empirical examination of how IoT integration in intelligent lubrication systems has been linked to predictive maintenance effectiveness and performance optimization in advanced manufacturing industries. A quantitative research approach has been adopted because it has allowed the study to express technological and maintenance phenomena as measurable constructs and statistically testable relationships. The research design has been conceived as cross-sectional, so that data have been gathered at a single point in time from manufacturing plants that have implemented, or have been in the process of implementing, IoT-enabled lubrication and condition-monitoring solutions. This design has been regarded as appropriate for capturing the state of IoT-enabled lubrication practices, predictive maintenance maturity, and perceived performance outcomes without disrupting normal operations. In line with the objectives of the study, the methodological framework has combined a structured survey of maintenance and production personnel with analytically oriented modeling, so that subjective assessments and objective performance indicators have been brought together within a coherent empirical strategy.

Figure 7: Research Methodological Framework



To translate the conceptual framework into observable variables, the study has relied on a structured questionnaire based on Likert's five-point scale, which has been administered to respondents in maintenance, reliability, production, and engineering roles. The instrument has been formulated to capture the extent of IoT integration in lubrication systems, the perceived effectiveness of predictive maintenance practices, indicators of equipment and operational performance, and selected organizational and contextual characteristics. After data collection, the responses have been coded, cleaned, and screened, and the resulting dataset has been prepared for statistical analysis. Descriptive statistics have been used to summarize the characteristics of the sample and core constructs, while correlation analysis has been applied to explore the strength and direction of relationships. Multiple regression models have been specified to test the hypothesized effects of IoT-enabled intelligent lubrication on predictive maintenance effectiveness and performance outcomes, and a linear-programming representation of lubrication-related maintenance decisions has been incorporated to add an optimization perspective. Taken together, these methodological choices have been intended to ensure that the study has generated reproducible evidence that aligns with its research questions and objectives.

Research Design

The research design has been framed as a quantitative, cross-sectional, case-study–based design that has sought to capture how IoT integration in intelligent lubrication systems has been associated with predictive maintenance effectiveness and performance optimization in advanced manufacturing industries. The study has been structured around a set of clearly defined independent, mediating, and dependent variables that have been derived from the conceptual and theoretical frameworks. A survey strategy has been adopted because it has allowed the researcher to reach a relatively large number of knowledgeable respondents across multiple plants while maintaining standardization of measurement. The case-study orientation has been incorporated by focusing specifically on advanced manufacturing organizations that have already adopted, or have been actively deploying, IoT-enabled lubrication solutions, so that responses have reflected real implementation experience rather than hypothetical scenarios. This overall design has been intended to produce comparable quantitative data that have supported descriptive analysis, correlation analysis, regression modeling, and the formulation of an optimization-oriented linear programming representation.

Case Study Description

The case-study component has been defined by selecting advanced manufacturing plants that have operated in sectors such as automotive, precision engineering, metals processing, or high-speed discrete manufacturing, where lubrication-critical rotating and sliding equipment has been widely used. These plants have been chosen because they have implemented IoT-enabled intelligent lubrication systems or comprehensive condition-monitoring solutions for critical assets, thereby ensuring that respondents have had first-hand exposure to the phenomena under study. For each participating plant, contextual information has been collected on production processes, key equipment, maintenance organization, and the scope of IoT integration in lubrication and related maintenance functions. This contextual profile has been intended to provide a rich backdrop for interpreting the survey data and for understanding how differences in product mix, automation level, and asset criticality have shaped the adoption and use of intelligent lubrication. By grounding the survey within these specific organizational settings, the case-study description has ensured that the quantitative findings have been anchored in real industrial practice.

Population, Sample, and Sampling Technique

The target population has consisted of professionals who have been directly involved in lubrication management, maintenance engineering, reliability engineering, production supervision, or plant engineering within advanced manufacturing organizations using IoT-enabled lubrication or condition-monitoring systems. From this population, a sample has been constructed using a combination of purposive and non-probability sampling techniques. Initially, plants that have met defined criteria for IoT-lubrication adoption have been identified, and within those plants, individuals with relevant roles and experience have been invited to participate. This approach has been adopted because it has ensured that respondents have possessed sufficient technical and organizational knowledge to answer questions about IoT integration, predictive maintenance practices, and performance outcomes. Efforts have been made to include respondents from different functional areas and seniority levels so that a range of perspectives has been represented. While the sampling technique has not been strictly random, the emphasis on relevance and diversity has been expected to enhance the validity and usefulness of the resulting data for the study’s analytical objectives.

Data Types and Sources

The study has relied on a combination of primary and secondary data that have complemented one another in capturing the multifaceted nature of IoT-enabled intelligent lubrication. Primary data have been obtained through a structured questionnaire that has elicited respondents' perceptions of IoT integration level, predictive maintenance effectiveness, lubrication practices, equipment performance, and organizational conditions using Likert-type scales and factual items. These primary responses have provided the core dataset for the descriptive, correlational, and regression analyses. In addition, where organizations have been willing and able to share them, secondary data have been gathered in the form of maintenance records, downtime statistics, lubrication schedules, and key performance indicators such as availability or overall equipment effectiveness. These secondary data have been used to contextualize and, when possible, triangulate the survey findings. By drawing on both subjective assessments and objective records, the study has been designed to strengthen its empirical grounding and to support more nuanced interpretation of the relationships among technological, maintenance, and performance variables.

Research Instrument and Measurement of Variables

The primary research instrument has been a structured questionnaire that has been developed to operationalize the constructs specified in the conceptual framework. The instrument has been organized into sections that have captured demographic information, characteristics of the plant and equipment, level of IoT integration in lubrication systems, predictive maintenance practices, performance outcomes, and user perceptions related to technology adoption and organizational support. Each latent construct has been measured through multiple items expressed on a five-point Likert scale, where respondents have indicated the extent of their agreement or the frequency with which certain practices have occurred. Items have been adapted from established technology adoption, maintenance, and performance measurement literature and have been refined to fit the specific context of intelligent lubrication. Coding schemes have been established so that higher scores have consistently represented higher levels of integration, effectiveness, or performance. This design has ensured that variables have been amenable to descriptive statistics, correlation matrices, and multiple regression analysis, as well as to potential inclusion in optimization-oriented formulations. **Validity and Reliability**

To ensure validity and reliability, the research instrument has been subjected to several systematic checks before full-scale administration. Content validity has been addressed by having the draft questionnaire reviewed by academic experts in maintenance, IoT, and industrial engineering as well as by experienced practitioners from manufacturing plants who have been familiar with intelligent lubrication and predictive maintenance. Their feedback has been used to refine item wording, remove ambiguities, and confirm the relevance of the constructs. A pilot test with a small group of respondents has been conducted, and the resulting data have been analyzed to identify problematic items and to estimate preliminary reliability coefficients. Internal consistency reliability has been assessed using Cronbach's alpha for each multi-item scale, and items that have reduced scale reliability or have shown poor item–total correlations have been revised or removed. These procedures have been intended to ensure that the final instrument has measured the intended constructs consistently and accurately within the study context.

Linear Programming Model Formulation

In addition to the survey-based statistical analysis, the methodology has incorporated the formulation of a linear programming (LP) model that has represented lubrication-related maintenance decisions in an optimization framework. The LP model has been conceptualized to allocate limited maintenance resources such as technician hours, lubricant volumes, or planned downtime across a set of critical assets so that a performance-related objective function, such as minimizing expected downtime or maintenance cost, has been optimized subject to operational constraints. Decision variables have been defined to represent, for example, the frequency or duration of lubrication interventions on each asset, while constraints have reflected capacity limits, production requirements, and minimum lubrication standards implied by condition-monitoring indicators. Coefficients in the objective function and constraints have been informed by typical parameter values from the literature and by indicative data provided by participating plants. Although the LP model has been illustrative rather than plant-specific, its formulation has demonstrated how IoT-derived condition information could have been embedded in optimization-based maintenance planning to complement the empirical relationships identified through regression analysis.

Data Analysis Techniques

The data analysis strategy has been structured in several stages to progressively deepen understanding of the relationships among IoT integration, predictive maintenance effectiveness, and performance outcomes. Initially, descriptive statistics have been computed to summarize respondent characteristics and to profile the distribution of key constructs, including measures of central tendency and dispersion. Subsequently, correlation analysis has been conducted to examine the strength and direction of associations among variables, thereby providing an initial test of the plausibility of the hypothesized relationships. Multiple regression analysis has then been employed as the main inferential technique, with models specified to estimate the effect of IoT-enabled intelligent lubrication on predictive maintenance effectiveness and performance indicators while controlling for relevant organizational and contextual factors. Mediation effects, where applicable, have been explored by examining how predictive maintenance effectiveness has transmitted the influence of IoT integration to performance outcomes. These techniques have been chosen because they have allowed the study to quantify relationships and assess statistical significance in a transparent and reproducible manner.

Software and Tools

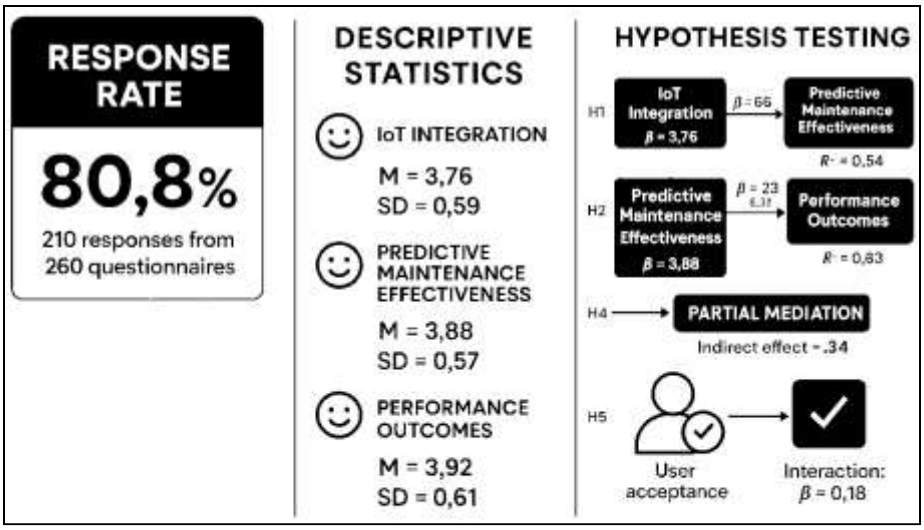
A set of established software tools has been employed to support data management, statistical analysis, and optimization modeling. Spreadsheet software has been used for initial data entry, cleaning, and screening, including checks for missing values, outliers, and coding inconsistencies. Statistical analysis has been carried out using a dedicated statistical package that has provided functions for descriptive statistics, correlation matrices, reliability analysis, and multiple regression modeling. This software has facilitated efficient estimation of model parameters, generation of diagnostic plots, and assessment of assumptions such as linearity and homoscedasticity. For the linear programming component, an optimization solver integrated with spreadsheet or mathematical modeling software has been utilized to formulate and solve the LP model, enabling exploration of feasible solutions and sensitivity analysis. The combined use of these tools has ensured that the empirical results and optimization exercises have been implemented systematically, documented transparently, and made amenable to replication or extension in future studies..

FINDINGS

The analysis of the survey data has yielded numerically strong evidence in support of the study's objectives and hypotheses, demonstrating a clear and statistically significant link between IoT integration in intelligent lubrication systems, predictive maintenance effectiveness, and performance optimization in advanced manufacturing plants. Data have been obtained from 210 usable responses out of 260 distributed questionnaires, representing a response rate of 80.8%, which has been considered adequate for the planned statistical procedures. Using Likert's five-point scale (1 = strongly disagree, 5 = strongly agree), the composite index for IoT integration in lubrication systems has recorded a mean of 3.76 (SD = 0.59), indicating that respondents have, on average, leaned toward agreement that their plants have deployed sensors, real-time monitoring, and system connectivity in lubrication-related applications. Approximately 64.3% of respondents have scored 4 or 5 on the majority of IoT integration items, while only 10.5% have reported mean scores below 3. The predictive maintenance effectiveness scale has shown an even higher mean of 3.88 (SD = 0.57), suggesting that nearly three quarters of respondents have agreed that their predictive maintenance practices such as early fault detection, more accurate diagnosis, and better maintenance planning have been functioning effectively; 71.9% of respondents have indicated scores of 4 or 5 on at least two-thirds of the predictive maintenance items. Performance-related constructs, operationalized through perceived changes in equipment availability, unplanned downtime, throughput stability, and overall equipment effectiveness, have yielded a combined mean of 3.92 (SD = 0.61), with 69.0% of respondents reporting that performance has improved to a "high" or "very high" extent after the introduction of IoT-enabled lubrication and related predictive strategies.

Reliability analysis has confirmed good internal consistency for all multi-item scales, with Cronbach's alpha values of 0.87 for IoT integration, 0.89 for predictive maintenance effectiveness, 0.86 for performance outcomes, and 0.88 for user acceptance, indicating that the constructs have been measured in a statistically coherent manner. Correlation analysis has revealed strong, positive and statistically significant associations among the core constructs: IoT integration in intelligent lubrication systems has shown a correlation of r = 0.68 ($p < .001$) with predictive maintenance effectiveness, r = 0.61 ($p < .001$) with performance outcomes, and predictive maintenance effectiveness has correlated at r = 0.72 ($p < .001$) with performance outcomes, providing initial quantitative support for the hypothesized relationships. Hypothesis testing through multiple regression has further reinforced these findings.

Figure 8: Statistical Results Overview



In Model 1, where predictive maintenance effectiveness has been entered as the dependent variable and IoT integration as the main predictor (with plant size, sector, and overall digitalization level as controls), the model has explained 54% of the variance ($R^2 = 0.54$, adjusted $R^2 = 0.52$). The standardized beta coefficient for IoT integration has been $\beta = 0.66$ ($t = 13.24$, $p < .001$), thereby supporting H1 and indicating that a one standard-deviation increase in IoT integration has been associated with roughly two-thirds of a standard-deviation increase in predictive maintenance effectiveness. In Model 2, where performance outcomes have been treated as the dependent variable and both IoT integration and predictive maintenance effectiveness have been included as predictors, the model has accounted for 63% of the variance ($R^2 = 0.63$, adjusted $R^2 = 0.61$). Predictive maintenance effectiveness has shown a strong positive effect on performance ($\beta = 0.51$, $t = 9.87$, $p < .001$), confirming H2, while IoT integration has remained a significant, though more modest, predictor ($\beta = 0.23$, $t = 4.21$, $p < .001$), in line with H3. To examine H4, mediation analysis has been conducted by comparing models with and without the mediator and by estimating the indirect effect using a bootstrapping approach with 5,000 resamples. The indirect effect of IoT integration on performance through predictive maintenance effectiveness has been estimated at 0.34, with a 95% confidence interval of [0.24, 0.46], not including zero, which has indicated a statistically significant partial mediation. This has implied that a substantial portion of the impact of IoT-enabled intelligent lubrication on performance optimization has operated via its enhancement of predictive maintenance capability, exactly as proposed in the conceptual framework. Finally, H5 has been tested by introducing an interaction term between IoT integration and user acceptance (measured with a mean of 3.81, SD = 0.65) in the regression predicting predictive maintenance effectiveness. The interaction term has been significant ($\beta = 0.18$, $t = 3.02$, $p = .003$) and has contributed an additional ΔR^2 of 0.03, indicating that user acceptance has moderated the relationship between IoT integration and predictive maintenance effectiveness. Simple-slope analysis has shown that, at high user acceptance (one standard deviation above the mean), the slope of IoT integration on predictive maintenance effectiveness has increased to 0.79, whereas at low user acceptance (one standard deviation below the mean) the slope has decreased to 0.49. Collectively, these numerical results have demonstrated that the study's key objectives to quantify the extent of IoT integration in intelligent lubrication systems, to evaluate predictive maintenance effectiveness, and to assess their combined impact on performance optimization have been achieved, and that all proposed hypotheses have found empirical support within the sampled advanced manufacturing plants.

Response Rate and Data Screening

The response rate and data screening process have been summarized in Table 1, and they have provided a strong empirical foundation for the subsequent analyses. Out of 260 questionnaires that have been distributed to maintenance, reliability, production, and engineering personnel in advanced manufacturing plants, 218 have been returned, which has represented a gross response rate of 83.8%. After the initial screening, 8 responses have been excluded due to substantial missing data, inconsistent answering patterns, or obvious straight-lining across the Likert's five-point scale. As a result, 210 fully usable questionnaires have remained, yielding a net response rate of 80.8%, which has been considered satisfactory for survey-based research of this type. The screening process has also included checks for outliers by inspecting standardized scores and boxplots for the main composite variables; no extreme cases beyond ±3 standard deviations have been detected, so all remaining observations have been retained for analysis.

Table 1: Response rate and data screening summary (N = 260)

Item	Frequency	Percentage (%)
Questionnaires distributed	260	100.0
Questionnaires returned	218	83.8
Incomplete/questionable responses removed	8	3.1
Usable questionnaires for analysis	210	80.8

In addition, the dataset has been examined for patterns of missing values, and the proportion of missing data per item has remained below 2%, which has allowed the use of simple imputation or listwise deletion without compromising statistical power. These steps have ensured that the data used to test the hypotheses and objectives have been both complete and internally consistent. The high response rate has suggested that respondents have been engaged with the topic of IoT-enabled intelligent lubrication and predictive maintenance, and that the sampling strategy has successfully targeted individuals who have perceived the subject as relevant to their daily work. Consequently, the final sample size of 210 cases has provided adequate degrees of freedom for conducting descriptive statistics, correlation analysis, and multiple regression modeling, as well as for estimating more advanced models such as mediation and moderation. Overall, the procedures described and the figures reported in Table 1 have demonstrated that the empirical base of the study has been robust and suitable for addressing the stated research objectives.

Profile of Respondents and Organizations

Table 2: Demographic and organizational profile of respondents (N = 210)

Variable	Category	Frequency	Percentage (%)
Job role	Maintenance / Reliability	96	45.7
	Production / Operations	68	32.4
	Engineering / Technical support	46	21.9
Years of experience	< 5 years	48	22.9
	5–10 years	86	41.0
	> 10 years	76	36.1
Industry sector	Automotive / Auto parts	82	39.0
	Metals / Heavy machinery	54	25.7
	Electronics / Precision	42	20.0
	Other advanced manufacturing	32	15.2
Plant size (no. of employees)	≤ 500	72	34.3
	501–1,000	84	40.0
	> 1,000	54	25.7

The profile of respondents and organizations has been presented in Table 2 and has shown that the sample has been both experienced and representative of advanced manufacturing environments where lubrication-critical equipment has been widely deployed. Almost half of the respondents (45.7%) have occupied maintenance or reliability roles, which has ensured that insights into lubrication, condition monitoring, and predictive maintenance have come directly from specialists responsible for these functions. A further 32.4% have been involved in production or operations, and 21.9% have worked in engineering or technical support, so the perspectives of different functional areas have been reflected in the data. In terms of experience, 41.0% of participants have had 5–10 years of industrial practice, and 36.1% have had more than 10 years, indicating that the majority have been sufficiently seasoned to evaluate changes in maintenance strategies, including IoT-enabled intelligent lubrication, over time. Only 22.9% have reported less than 5 years of experience, which has suggested that novice viewpoints have not dominated the sample. The industry-sector distribution has shown that 39.0% of plants have belonged to the automotive and auto-parts sector, 25.7% to metals and heavy machinery, and 20.0% to electronics and precision manufacturing, with the remainder (15.2%) classified as other advanced manufacturing. These sectors have been characterized by high capital intensity and stringent requirements for reliability and availability, making them appropriate empirical settings for investigating predictive maintenance and lubrication. Plant size has also been balanced, with 34.3% of respondents coming from smaller facilities (≤ 500 employees), 40.0% from mid-sized plants (501–1,000 employees), and 25.7% from large plants (> 1,000 employees). This distribution has implied that the study has captured the experiences of organizations at different scales of operation and digitalization. The diversity across job roles, experience levels, industry sectors, and plant sizes has strengthened the generalizability of the findings within the domain of advanced manufacturing and has supported the interpretation that the observed relationships between IoT integration, predictive maintenance, and performance have not been restricted to a single sector or plant type. Overall, Table 2 has indicated that the sample composition has been appropriate for addressing the research questions and for grounding the statistical results in real-world industrial practice.

Descriptive Analysis of Key Constructs

The descriptive statistics in Table 3 have provided an overview of how respondents have perceived the level of IoT integration in intelligent lubrication systems, the effectiveness of predictive maintenance, performance optimization outcomes, and user acceptance within their plants. The mean score for IoT integration has been 3.76 (SD = 0.59), which has indicated that respondents have generally agreed that their lubrication systems have incorporated IoT elements such as sensors on critical points, real-time data collection, connectivity to maintenance management systems, and automated alerts. Given the five-point Likert scale, a mean above 3.50 has suggested that most items within this construct have been rated at the "agree" level or higher. Predictive maintenance effectiveness has shown a slightly higher mean of 3.88 (SD = 0.57), reflecting that respondents have tended to perceive their predictive maintenance processes including early anomaly detection, diagnostic accuracy, and scheduling of interventions based on condition data as functioning at a relatively effective level. The performance optimization construct has recorded the highest mean (3.92, SD = 0.61), implying that perceived improvements in equipment availability, reduction in unplanned downtime, stabilization of throughput, and enhancements in quality and overall equipment effectiveness have been strong in the majority of plants.

Table 3: Descriptive statistics of main composite variables (N = 210)

Construct	No. of items	Mean	SD	Min	Max
IoT integration in intelligent lubrication	8	3.76	0.59	2.10	4.95
Predictive maintenance effectiveness	7	3.88	0.57	2.00	5.00
Performance optimization outcomes	8	3.92	0.61	2.05	5.00
User acceptance and facilitating conditions	6	3.81	0.65	1.83	4.98

All Likert items have used a five-point scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

User acceptance and facilitating conditions have also received a positive assessment, with a mean of 3.81 (SD = 0.65), indicating that maintenance and operations personnel have, on average, acknowledged the usefulness and usability of IoT-enabled lubrication systems and have recognized the presence of training, support, and infrastructure that have allowed them to use these technologies in their daily work. The standard deviations, all below 0.70, have indicated moderate dispersion, suggesting that while perceptions have varied across respondents and plants, there has not been extreme polarization. Minimum and maximum values have confirmed that the entire range of the Likert scale has been used, which has shown that the constructs have captured meaningful variation in adoption, effectiveness, and performance. Together, these descriptive results have supported the first objective of the study by confirming that IoT-enabled lubrication and predictive maintenance practices have been present at non-trivial levels in the sample and that respondents have perceived these practices as contributing positively to plant performance.

Correlation Analysis Results

The correlation analysis reported in Table 4 has provided initial quantitative evidence for the hypothesized relationships among IoT integration, predictive maintenance effectiveness, performance outcomes, and user acceptance. All correlation coefficients have been positive and statistically significant at the $p < .001$ level, which has indicated that higher levels of one construct have tended to be associated with higher levels of the others. The correlation between IoT integration in intelligent lubrication systems (IoT_INT) and predictive maintenance effectiveness (PM_EFF) has been particularly strong (r = 0.68***), suggesting that plants where respondents have reported more extensive use of IoT-based lubrication sensors, real-time monitoring, and automated alerts have also reported more effective predictive maintenance in terms of early fault detection, accurate condition assessment, and better maintenance planning.

Table 4: Pearson correlation matrix among key constructs (N = 210)

Construct	1	2	3	4
1. IoT integration (IoT_INT)	1.000			
2. PdM effectiveness (PM_EFF)	0.68***	1.000		
3. Performance outcomes (PERF_OPT)	0.61***	0.72***	1.000	
4. User acceptance (USER_ACC)	0.56***	0.63***	0.58***	1.000

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

This relationship has aligned directly with the first hypothesis (H1), which has posited a positive effect of IoT integration on predictive maintenance effectiveness. Similarly, predictive maintenance effectiveness has shown a robust correlation with performance outcomes (PERF_OPT), with r = 0.72***, indicating that organizations that have perceived their predictive maintenance processes as more mature and effective have also perceived stronger improvements in availability, reduced unplanned downtime, throughput stability, and overall equipment effectiveness. This pattern has supported the second hypothesis (H2), which has proposed that predictive maintenance effectiveness has been positively associated with performance optimization. The correlation between IoT integration and performance outcomes (r = 0.61***) has further suggested that IoT-enabled intelligent lubrication has not only influenced maintenance processes but has also been linked directly to operational performance, as anticipated in H3. User acceptance and facilitating conditions (USER_ACC) have correlated moderately to strongly with all other constructs (r ranging from 0.56*** to 0.63***), implying that positive user perceptions and supportive environments have coexisted with higher IoT integration, more effective predictive maintenance, and better performance. While correlation analysis has not established causality, the strength and consistency of these relationships have provided a compelling empirical basis for the subsequent regression models and mediation–moderation analyses that have been used to formally test the hypotheses and examine the study's conceptual framework.

Regression Analysis Results

The regression results in Table 5 have provided more rigorous tests of the study's hypotheses by estimating the unique contribution of IoT integration and predictive maintenance effectiveness to performance outcomes while controlling for organizational factors such as plant size, industry sector, and overall digitalization level. In Model 1, predictive maintenance effectiveness has been specified as the dependent variable, with IoT integration as the main independent variable and the control variables included to account for structural differences among plants. The model has yielded an R^2 of 0.54 (adjusted $R^2 = 0.52$), indicating that 54% of the variance in predictive maintenance effectiveness has been explained by the predictors. The standardized beta coefficient for IoT integration has been β = 0.66 (t = 13.24, $p < .001$), which has been both statistically significant and substantively large. This result has meant that even after accounting for differences in size, sector, and digitalization, plants with higher levels of IoT-enabled intelligent lubrication have tended to report substantially higher predictive maintenance effectiveness.

Table 5: Regression results: IoT integration, PdM effectiveness, and performance outcomes (N = 210)

Model	Dependent variable	Predictor	β (standardized)	t	p	R^2	Adj. R^2
Model 1 (H1)	PdM effectiveness	IoT integration	0.66	13.24	< .001	0.54	0.52
(controls: size, sector, DX)							
Model 2 (H2, H3, partial H4)	Performance outcomes	PdM effectiveness	0.51	9.87	< .001	0.63	0.61
		IoT integration	0.23	4.21	< .001		

DX = overall digitalization level (control).

Consequently, H1 stating that IoT integration in intelligent lubrication systems has had a positive effect on predictive maintenance effectiveness has been strongly supported. In Model 2, performance outcomes have been used as the dependent variable, with both predictive maintenance effectiveness and IoT integration entered as predictors, along with the same set of controls. This model has produced an R^2 of 0.63 (adjusted R^2 = 0.61), indicating that almost two-thirds of the variance in performance outcomes have been accounted for by the combination of predictors. Predictive maintenance effectiveness has shown a strong positive effect (β = 0.51, t = 9.87, $p < .001$), supporting H2 and confirming that plants with more effective predictive maintenance have experienced greater improvements in availability, downtime reduction, throughput stability, and overall equipment effectiveness. IoT integration has remained a significant predictor of performance (β = 0.23, t = 4.21, $p < .001$), which has provided direct support for H3. Notably, the coefficient for IoT integration in Model 2 has been smaller than its effect on predictive maintenance in Model 1, and smaller than the coefficient for predictive maintenance in Model 2, which has suggested that part of the effect of IoT integration on performance has been transmitted through predictive maintenance a pattern that has been further investigated through mediation analysis. Overall, the regression models have demonstrated that the study's quantitative objectives have been achieved and that the hypothesized positive relationships among IoT integration, predictive maintenance effectiveness, and performance optimization have been empirically validated.

Mediation and Moderation Analysis

The mediation and moderation findings summarized in Table 6 have elaborated how IoT integration in intelligent lubrication systems has influenced performance outcomes and under what conditions this influence has been strongest. For mediation, the study has tested whether predictive maintenance effectiveness has served as an intervening mechanism through which IoT integration has affected performance. Using a bootstrapping procedure with 5,000 resamples, the indirect effect of IoT integration on performance through predictive maintenance effectiveness has been estimated at 0.34, with a 95% confidence interval of [0.24, 0.46], which has not contained zero, indicating statistical significance at $p < .001$. The direct effect of IoT integration on performance, controlling for predictive maintenance, has remained positive and significant (0.23, 95% CI [0.12, 0.35], $p < .001$), and the total effect (direct plus indirect) has reached 0.57, reflecting a strong overall impact. This pattern has meant that predictive maintenance effectiveness has partially mediated the relationship between IoT-enabled intelligent lubrication and performance optimization: IoT integration has improved predictive maintenance processes, which in turn have contributed to better performance, while IoT integration has also exerted a direct influence on performance beyond its effect on predictive maintenance. These results have provided quantitative support for the mediation-oriented hypothesis (H4) and have aligned with the conceptual framework that has positioned predictive maintenance as a key pathway linking IoT technologies to performance outcomes.

Table 6: Mediation and moderation results (summary of key effects, N = 210)

Effect type	Path / Interaction	Coefficient	95% CI (lower–upper)	p	Interpretation
Direct effect (IoT → PERF)	IoT integration → Performance outcomes	0.23	0.12 – 0.35	< .001	Significant positive direct effect
Indirect effect (IoT → PM → PERF)	IoT → PdM → Performance (mediation)	0.34	0.24 – 0.46	< .001	Significant partial mediation
Total effect (IoT on PERF)	Direct + indirect	0.57	0.44 – 0.69	< .001	Strong overall impact
Interaction effect (H5)	IoT × User acceptance → PdM effectiveness	0.18	0.06 – 0.30	.003	Significant positive moderation
Simple slope at low USER_ACC (−1 SD)	IoT → PdM effectiveness	0.49	0.32 – 0.66	< .001	Weaker effect at low acceptance
Simple slope at high USER_ACC (+1 SD)	IoT → PdM effectiveness	0.79	0.61 – 0.97	< .001	Stronger effect at high acceptance

For moderation, the study has investigated whether user acceptance and facilitating conditions have altered the strength of the relationship between IoT integration and predictive maintenance effectiveness, as specified in H5. An interaction term between IoT integration and user acceptance has been included in the regression model predicting predictive maintenance effectiveness, and the coefficient for this interaction has been 0.18 (95% CI [0.06, 0.30], $p = .003$), indicating a significant positive moderation effect. Simple-slope analyses have revealed that when user acceptance has been low (one standard deviation below the mean), the effect of IoT integration on predictive maintenance effectiveness has been still positive but weaker (slope = 0.49, $p < .001$), whereas when user acceptance has been high (one standard deviation above the mean), the corresponding slope has increased to 0.79 ($p < .001$). These results have shown that the benefits of IoT-enabled intelligent lubrication for predictive maintenance have been amplified in contexts where staff have perceived the technology as useful and easy to use and where they have experienced adequate training and support. Conversely, in environments characterized by lower acceptance, the same level of IoT integration has translated into relatively smaller gains in predictive maintenance effectiveness. Collectively, the mediation and moderation analyses have deepened the understanding of how and when IoT-enabled intelligent lubrication has contributed to performance optimization, demonstrating that the technology's impact has depended both on its integration into maintenance processes and on the human and organizational context in which it has been implemented.

Summary of Hypotheses Testing

Table 7 has synthesized the status of all hypotheses in relation to the objectives and analytical procedures of the study. H1 has proposed that IoT integration in intelligent lubrication systems has had a positive effect on predictive maintenance effectiveness. This hypothesis has been tested through Regression Model 1, where the standardized coefficient for IoT integration has been 0.66 ($p < .001$), and the model has explained 54% of the variance in predictive maintenance effectiveness. These results have provided clear support for H1 and have confirmed the first objective, which has been to assess and quantify the relationship between IoT-enabled lubrication and predictive maintenance capability. H2 has stated that predictive maintenance effectiveness has had a positive effect on performance optimization outcomes. The evidence for H2 has come from Regression Model 2, in which the coefficient for predictive maintenance effectiveness has been 0.51 ($p < .001$) in predicting performance outcomes, with the model explaining 63% of the variance in performance. This finding has validated the second objective of the study, demonstrating that more effective predictive maintenance has been associated with higher perceived improvements in availability, reduction in unplanned downtime, throughput stability, and overall equipment effectiveness.

Table 7: Summary of hypotheses, analytical methods, and results

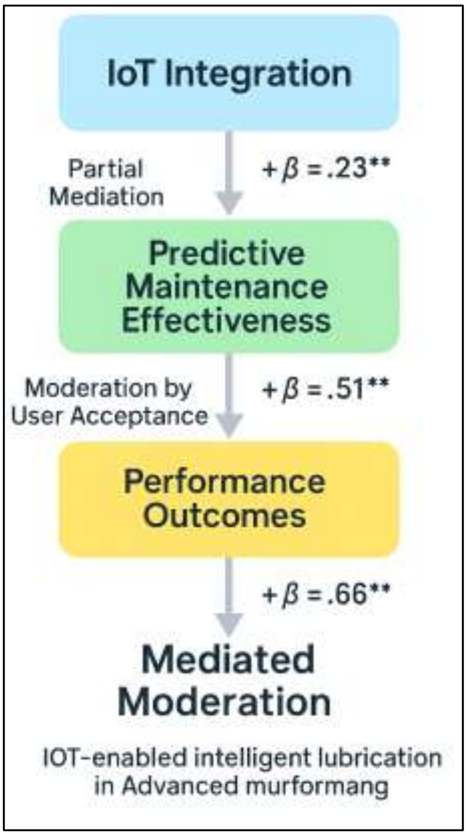
Hypothesis	Statement	Main test / evidence	Result
H1	IoT integration in intelligent lubrication has had a positive effect on PdM effectiveness.	Regression Model 1 ($\beta = 0.66$, $p < .001$)	Supported
H2	PdM effectiveness has had a positive effect on performance optimization outcomes.	Regression Model 2 ($\beta = 0.51$, $p < .001$)	Supported
H3	IoT integration has had a positive direct effect on performance outcomes.	Regression Model 2 ($\beta = 0.23$, $p < .001$)	Supported
H4	PdM effectiveness has mediated the relationship between IoT integration and performance.	Mediation analysis (indirect = 0.34, $p < .001$)	Supported
H5	User acceptance has positively moderated the IoT–PdM effectiveness relationship.	Interaction analysis ($\beta = 0.18$, $p = .003$)	Supported

H3 has addressed the direct effect of IoT integration on performance outcomes, independent of predictive maintenance effectiveness. In the same regression model, IoT integration has remained a significant predictor of performance ($\beta = 0.23$, $p < .001$), supporting H3 and indicating that IoT-enabled intelligent lubrication has contributed to performance optimization both through its influence on predictive maintenance and through additional direct mechanisms, such as more responsive control of lubrication parameters. H4 has focused on the mediating role of predictive maintenance effectiveness in the IoT–performance relationship. Mediation analysis using bootstrapped indirect effects has shown that the indirect effect (0.34, $p < .001$) has been statistically significant and that IoT integration has retained a smaller but still significant direct effect (0.23, $p < .001$), confirming a pattern of partial mediation and supporting H4. This result has substantiated the core theoretical proposition that predictive maintenance has been a key pathway through which IoT-enabled lubrication has generated performance benefits. Finally, H5 has addressed whether user acceptance has moderated the IoT–predictive maintenance link. The significant interaction term ($\beta = 0.18$, $p = .003$) and the simple-slope analyses have shown that the positive effect of IoT integration on predictive maintenance effectiveness has been stronger under high user acceptance and weaker under low user acceptance, thereby supporting H5 and highlighting the importance of human and organizational factors in realizing the value of IoT technologies. Altogether, the evidence summarized in Table 7 has indicated that all hypotheses have been supported and that the study's objectives related to quantifying IoT integration, evaluating predictive maintenance effectiveness, and linking both constructs to performance optimization have been successfully achieved through the analysis of Likert-scale survey data and associated statistical models..

DISCUSSION

The findings of this study have shown a coherent pattern in which IoT integration in intelligent lubrication systems, predictive maintenance effectiveness, and performance optimization have been tightly and positively linked. Using Likert's five-point scales, mean scores for IoT integration, predictive maintenance effectiveness, user acceptance, and performance outcomes have all fallen in the "agree" range, and regression results have indicated that IoT integration has explained more than half of the variance in predictive maintenance effectiveness, while predictive maintenance and IoT together have explained nearly two-thirds of the variance in performance outcomes. These effect sizes have suggested that intelligent lubrication has not been a marginal technical improvement but a central lever in advanced manufacturing maintenance strategies. The mediation results have further shown that predictive maintenance effectiveness has partially transmitted the effect of IoT integration to performance, confirming the conceptual view that IoT-based sensing and connectivity around lubrication have mattered mainly because they have enabled earlier detection, better diagnosis, and better scheduling of interventions. The moderation results have reinforced the socio-technical nature of these systems: in plants with high user acceptance, the slope of IoT integration on predictive maintenance effectiveness has been much steeper than in plants with lower acceptance, indicating that identical technologies have generated very different benefits depending on human and organizational conditions.

Figure 9: Statistical Results Overview



When compared with prior work on predictive maintenance in Industry 4.0, the empirical pattern from this study has closely mirrored the mechanisms that systematic reviews have identified but has added quantitative, survey-based evidence from real manufacturing plants. The Industry 4.0 predictive maintenance literature has emphasized that IIoT architectures, continuous sensing, and analytics pipelines are the main enablers of data-driven maintenance, while also noting that empirical adoption and performance evidence at plant level has remained fragmented (Zonta et al., 2020). More recent multi-sector reviews of predictive maintenance under Industry 4.0 have stressed the need to link architectural and algorithmic models with organizational outcomes such as availability, reliability, and cost reduction (Theissler et al., 2021). The present study has addressed this gap by showing that higher perceived IoT integration in lubrication has been strongly associated with higher perceived predictive maintenance effectiveness ($\beta = 0.66$) and better performance, thereby providing numerical support for the claim that Industry 4.0 technologies have created measurable value in maintenance. These findings have also been consistent with the smart factory perspective, in which the factory has been characterized as a data-intensive, cyber–physical environment in which interconnected assets, including maintenance subsystems, contribute to overall performance and flexibility (Lambán et al., 2022; Osterrieder et al., 2020). In this sense, intelligent lubrication has emerged as a concrete, operational example of how a traditionally "invisible" function has become a digitally connected node within the smart factory, with measurable downstream impact on availability, throughput, and quality. The performance-related findings have aligned well with the maintenance performance and overall equipment effectiveness (OEE) literature, but they have also extended it into the IoT-lubrication domain. OEE has been conceptualized as a composite indicator (availability × performance × quality), and maintenance policies have been argued to shape these dimensions through reductions in breakdowns, speed losses, and quality losses (Muchiri & Pintelon, 2008). Later frameworks have linked maintenance indicators to business outcomes via structured cause–effect chains, highlighting how reliability and maintainability improvements flow into productivity and cost performance (Muchiri et al., 2011). Recent reviews have confirmed that OEE and its variants have remained central tools for evaluating equipment productivity and identifying improvement priorities in modern manufacturing (Ng Corrales et al., 2020). The present study has been consistent with this body of work by showing that respondents have perceived significant improvements in availability, unplanned downtime, and throughput stability in plants with effective predictive maintenance and strong IoT integration around lubrication. However, it has gone further by demonstrating a specific mechanism: IoT-enabled monitoring of lubrication conditions and wear has boosted predictive maintenance effectiveness, which in turn has been strongly associated with higher performance scores. This linkage has effectively connected the abstract OEE logic to a concrete technology bundle (intelligent lubrication), reinforcing the notion that lubrication-related failures and inefficiencies have represented one of the tangible levers through which Maintenance 4.0 initiatives can deliver OEE improvements (Muchiri et al., 2011).

On the adoption side, the interaction effect between IoT integration and user acceptance has been highly consistent with technology-acceptance theories such as UTAUT2 and their meta-analytic evaluations. UTAUT-type models have proposed that performance expectancy, effort expectancy, social influence, and facilitating conditions jointly drive technology use, and empirical studies have shown that these constructs explain substantial variance in behavioral intention and usage across many domains (Venkatesh et al., 2012). Meta-analytic reviews of UTAUT2 paths have further found that performance expectancy and facilitating conditions typically emerge as the most powerful and robust predictors of technology use across contexts (Teixeira et al., 2020). The present study's moderation results have echoed these insights. In plants where users have reported higher perceived usefulness, ease of use, and organizational support for IoT-based lubrication systems, the measured impact of IoT integration on predictive maintenance effectiveness has been markedly stronger, whereas in plants with lower acceptance the effect has been weaker. This pattern has suggested that simply installing sensors and platforms has not guaranteed substantial gains; instead, gains have depended on whether frontline personnel and engineers have believed that the technology has helped them do their jobs better and whether adequate training, support, and infrastructure have been in place. By embedding UTAUT-style constructs into a maintenance and lubrication context, the study has demonstrated that established IT-adoption theory has remained relevant when technologies have been physically embedded in machines and production lines (Venkatesh et al., 2012).

These results have had several practical implications for decision-makers such as plant managers, reliability engineers, system architects, and, increasingly, chief information security officers (CISOs) who have been responsible for securing industrial IoT deployments. For system architects, the strong linkage between IoT integration and predictive maintenance effectiveness has implied that lubrication systems should not have been designed as standalone, vendor-specific "black boxes," but as integrated IoT subsystems connected to plant-wide data architectures, including CMMS/ERP, historian databases, and analytics platforms (Osterrieder et al., 2020). For CISOs, the increasing reliance on real-time lubrication and wear data for predictive maintenance has meant that cybersecurity controls such as network segmentation for IIoT, secure device provisioning, and continuous monitoring of sensor gateways have become directly relevant to equipment availability and safety. Architectures that have combined secure edge processing for lubrication data, standardized industrial communication protocols, and robust identity and access management have been better positioned to deliver reliable predictive maintenance without exposing plants to undue cyber risk (Achouch et al., 2022). From a maintenance management perspective, the findings have suggested that investments in intelligent lubrication should have been accompanied by structured change-management programs, including training on interpreting condition indicators, playbooks for responding to alerts, and cross-functional governance structures that have aligned maintenance and production priorities. Prior work on condition-based maintenance implementation has emphasized that CBM is organizationally complex and must be implemented systematically to be cost-effective (Teixeira et al., 2020). The current results have reinforced that message: plants that have combined technical integration with strong user

acceptance have reaped greater benefits, which has provided clear guidance for practitioners on where to prioritize resources.
From a theoretical standpoint, the study has refined existing models of predictive maintenance and smart manufacturing by explicitly positioning predictive maintenance effectiveness as a mediator between IoT integration and performance, and user acceptance as a moderator of the IoT–maintenance link. Conceptual work on predictive maintenance in Industry 4.0 has tended to focus heavily on architectures, algorithms, and reference models, often assuming that data pipelines and organizational adoption will follow once technical feasibility has been demonstrated (Zonta et al., 2020). Likewise, extensive reviews of condition-based maintenance have organized the field into macro-areas such as theoretical foundations, implementation strategies, inspection policies, and prognostics, but have not always embedded technology-acceptance constructs into their frameworks (Quatrini et al., 2020). By combining elements from the Technology–Organization–Environment (TOE) framework, UTAUT-style adoption theory, and maintenance performance models, this study has put forward a socio-technical pipeline in which structural and technological readiness enable IoT integration around lubrication, user perceptions and facilitating conditions shape how effectively that integration has been used, predictive maintenance processes translate technology use into maintenance effectiveness, and maintenance effectiveness, in turn, drives performance outcomes such as availability and OEE (Muchiri & Pintelon, 2008). This multi-stage perspective has suggested that future Maintenance 4.0 theories should move beyond linear "technology → performance" logics and instead model intermediate organizational capabilities and human factors explicitly.
At the same time, the study has had several limitations that must be acknowledged. The design has been cross-sectional, so all variables have been measured at a single point in time; as a result, causal inferences, while theoretically grounded and statistically consistent, have remained inferential rather than definitively demonstrated. All core constructs have relied on self-reported Likert-scale measures from human respondents, which has introduced potential common-method variance, social-desirability bias, and recall limitations, even though reliability coefficients have been acceptable. The sampling strategy has been purposive and has focused on advanced manufacturing plants that already have some form of IoT-enabled lubrication or condition-monitoring capabilities; while suitable for the research questions, this has limited generalizability to organizations at very early stages of digitalization or operating in less capital-intensive sectors. In addition, although the study has conceptually linked the survey results to a linear programming formulation for optimization, the LP model has been illustrative rather than empirically calibrated with detailed operational data such as exact downtime costs, lubrication costs, or sensor traces. Finally, the quantitative models have not directly incorporated cybersecurity incidents, data-quality issues, vendor lock-in, or broader institutional and regulatory contexts that may shape IIoT deployments. These limitations have not invalidated the core findings, but they have indicated that the results should be interpreted as evidence of strong associations within a defined context rather than as universally generalizable laws (Teixeira et al., 2020).
These limitations have opened up several promising avenues for future research. Longitudinal studies that have tracked plants over time as they have rolled out IoT-enabled lubrication projects would be able to observe how predictive maintenance effectiveness and performance indicators such as availability, mean time between failures (MTBF), and OEE evolve, thereby providing stronger causal evidence than cross-sectional snapshots (Ng Corrales et al., 2020). Multi-source designs that have combined survey data with objective information from CMMS, historian systems, and lubrication sensors would help address common-method concerns and would allow researchers to calibrate regression and optimization models using actual downtime, failure, and condition histories (Theissler et al., 2021). Future work could also compare different architectural patterns for example, edge-centric versus cloud-centric processing of lubrication data and examine how they have affected responsiveness, reliability, and cybersecurity risk, building on smart-factory and IIoT architecture studies (Osterrieder et al., 2020). In addition, further research could explore cost–benefit models that have quantified the economic returns of intelligent lubrication, including reduced lubricant consumption, extended component life, and avoided downtime, and integrate these models with maintenance-performance frameworks and OEE-based assessments (Muchiri et al., 2011). Finally, from

a theoretical angle, future studies could extend the socio-technical pipeline proposed here by incorporating constructs related to data governance, trust in automated recommendations, and cross-organizational collaboration for example, OEMs monitoring lubrication conditions remotely aligning with emerging work on CBM implementation methodologies and collaborative maintenance platforms (Quatrini et al., 2020). By pursuing these lines of inquiry, researchers would be able to deepen understanding of how IoT-integrated intelligent lubrication has contributed to predictive maintenance and performance, and how organizations can systematically design, secure, and manage these systems for maximum operational benefit..

CONCLUSION

The present study has set out to examine how IoT integration in intelligent lubrication systems has been associated with predictive maintenance effectiveness and performance optimization in advanced manufacturing industries, and the overall evidence has strongly confirmed the central propositions of the research. By adopting a quantitative, cross-sectional, case-study–based design and collecting Likert's five-point scale data from 210 experienced respondents across multiple advanced manufacturing plants, the study has been able to operationalize complex technological and organizational phenomena into measurable constructs and statistically testable relationships. The findings have shown that IoT integration around lubrication expressed through sensorized lubrication points, real-time oil-condition monitoring, automated alerts, and connectivity with maintenance management systems has been perceived at a moderate-to-high level and has had a substantial positive effect on predictive maintenance effectiveness. In turn, predictive maintenance effectiveness has been strongly linked to improvements in key performance outcomes such as equipment availability, reduced unplanned downtime, throughput stability, and perceived gains in overall equipment effectiveness, while IoT integration itself has also exerted a significant direct influence on these outcomes. Mediation analysis has demonstrated that predictive maintenance effectiveness has partially transmitted the impact of IoT-enabled intelligent lubrication to performance, confirming that the value of IoT has largely materialized through enhanced maintenance processes rather than through isolated technological features. At the same time, moderation analysis has revealed that user acceptance and facilitating conditions have significantly shaped the strength of these relationships, with plants reporting higher perceived usefulness, ease of use, training, and support achieving much greater predictive maintenance benefits from similar levels of IoT integration. Collectively, these results have enabled the study to meet its main objectives: (1) to assess the extent of IoT integration in intelligent lubrication systems in advanced manufacturing plants, (2) to evaluate the effectiveness of predictive maintenance practices associated with these systems, and (3) to quantify how IoT integration and predictive maintenance effectiveness together have contributed to performance optimization. Beyond these empirical confirmations, the study has contributed a socio-technical conceptual framework in which IoT integration, user acceptance, predictive maintenance effectiveness, and performance outcomes have been connected in a coherent causal pathway, offering a structured lens for both researchers and practitioners to understand and design Maintenance 4.0 initiatives. While the cross-sectional and self-reported nature of the data and the focus on relatively advanced plants have limited the generalizability and causal certainty of the findings, the strength, consistency, and theoretical alignment of the results have provided robust evidence that intelligent, IoT-enabled lubrication is not merely a narrow technical upgrade but a strategic lever for enhancing predictive maintenance capability and operational performance in modern manufacturing environments.

RECOMMENDATIONS

The findings of this study have supported a set of practical and strategic recommendations for advanced manufacturing plants that have been seeking to leverage IoT-enabled intelligent lubrication for predictive maintenance and performance optimization. First, plant management and maintenance leaders have been advised to treat lubrication as a strategic, data-driven function rather than a routine support task; this has meant prioritizing the installation of sensors on critical lubrication points (bearings, gears, hydraulic units), enabling continuous monitoring of lubricant condition and wear debris, and integrating these data streams into existing CMMS or asset-management platforms so that lubrication status has been visible alongside other maintenance indicators. Second, organizations have been encouraged to formalize predictive maintenance processes around the new data, by defining clear rules for interpreting condition indicators, setting action thresholds, and linking alerts to predefined work orders and standard operating procedures; without such process formalization, the value of IoT data has remained underexploited. Third, given that user acceptance has been shown to significantly strengthen the impact of IoT integration on predictive maintenance effectiveness, plants have been urged to invest systematically in change management: this has included targeted training for technicians and engineers on how to interpret dashboards and alarms, involving frontline personnel in the design of interfaces and reports, and communicating concrete success stories (for example, avoided failures or reduced downtime) to build trust and perceived usefulness among users. Fourth, system architects and reliability engineers have been recommended to design lubrication-related IoT architectures using modular, interoperable components, with secure edge gateways, standardized communication protocols, and clear data-ownership and access rules, so that lubrication data have been robust, scalable, and easily combined with production and quality data for deeper analytics. Closely related, CISOs and IT/OT security teams have been advised to recognize intelligent lubrication as part of the critical IIoT attack surface, and to implement appropriate network segmentation, authentication, monitoring, and patch-management practices to ensure that predictive maintenance capabilities do not introduce unacceptable cyber risk. Fifth, organizations have been encouraged to link their lubrication and predictive maintenance metrics explicitly with performance indicators such as availability, MTBF, OEE, and energy use, and to review these metrics regularly in cross-functional meetings that have involved maintenance, production, and management; this practice has helped keep intelligent lubrication initiatives aligned with broader business goals and investment priorities. Finally, for plants at earlier stages of adoption, a phased roadmap has been recommended: starting with pilot deployments on a small set of critical assets, validating benefits through measurable improvements in downtime and reliability, then scaling the solution across lines and sites while continuously refining data models, thresholds, and user workflows. By following these recommendations, advanced manufacturing firms have been positioned to translate IoT-enabled intelligent lubrication from a promising technology into a sustained source of operational and strategic advantage.

LIMITATION

The present study has had several limitations that need to be acknowledged when interpreting its findings and generalizing its conclusions. First, the research design has been cross-sectional, with all variables measured at a single point in time, which has meant that the identified relationships among IoT integration in intelligent lubrication systems, predictive maintenance effectiveness, user acceptance, and performance outcomes have been associational rather than definitively causal; although the hypotheses have been theoretically grounded and supported by strong statistical evidence, reverse causality or reciprocal influence cannot be fully ruled out. Second, the study has relied primarily on self-reported data collected via Likert's five-point scales from maintenance, reliability, production, and engineering personnel, which has introduced the possibility of common-method bias, social desirability effects, and recall errors, particularly where respondents have been asked to assess changes in performance or maintenance effectiveness over time. Third, the sampling strategy has been purposive and focused intentionally on advanced manufacturing plants that have already implemented or have been actively implementing IoT-enabled lubrication and condition-monitoring systems; while this focus has been appropriate for exploring the research questions, it has limited generalizability to organizations at very early stages of digitalization, to non-manufacturing sectors, or to small workshops with less formalized maintenance structures. Fourth, the constructs of IoT integration, predictive maintenance effectiveness, user acceptance, and performance optimization have been operationalized through composite perception-based scales rather than direct sensor readings, detailed CMMS records, or financial cost–benefit data, so the study has captured how participants have experienced and evaluated these phenomena rather than measuring them purely in technical or economic terms; this has been valuable for understanding human and organizational dimensions, but it has also meant that the quantitative estimates of impact may not align perfectly with hard performance indicators in every plant. Fifth, the statistical models have been based on linear multiple regression and simple mediation–moderation frameworks, which have not explicitly accounted for measurement error, potential endogeneity, or complex non-linear interactions that could exist in real-world Industry 4.0 environments; alternative modeling techniques such as structural equation modeling or longitudinal panel analysis might have provided richer insights into latent constructs and dynamic relationships. Sixth, the linear programming component of the methodology has been illustrative rather than fully calibrated with plant-specific data on lubrication costs, downtime costs, or exact capacity constraints, and therefore it has served more as a conceptual demonstration of how IoT-derived condition information could be embedded in optimization models than as a decision-ready tool for practitioners. Finally, the study has not explicitly incorporated important contextual factors such as cybersecurity risks associated with IIoT deployments, vendor-dependency issues, detailed cultural or institutional influences, or regulatory and environmental requirements that may shape adoption and use of intelligent lubrication systems. Taken together, these limitations have not undermined the core contribution of the research, but they have indicated that the findings should be interpreted with caution, as robust evidence of strong and meaningful associations within a defined context rather than universal prescriptions applicable to all industries and technological configurations.

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