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MACHINE LEARNING APPROACHES FOR OPTIMIZATION OF LUBRICANT PERFORMANCE AND RELIABILITY IN COMPLEX MECHANICAL AND MANUFACTURING SYSTEMS

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Abstract

This quantitative, cross-sectional, case-based study examines the role of machine learning (ML) approaches in enhancing lubricant condition monitoring and, in turn, optimizing lubricant performance and improving equipment reliability across complex mechanical and manufacturing systems. The research is motivated by the persistent underutilization of lubricant-related data in predictive maintenance programs, even as modern industrial assets increasingly incorporate dense sensor arrays capable of generating high-frequency tribological, thermal, and chemical measurements. To address this gap, the study surveyed 214 professionals responsible for maintenance and reliability management in enterprise-scale manufacturing plants operating high-duty rotating and sliding equipment, generating 204 complete, analyzable cases measured on a five-point Likert scale. The conceptual framework was structured around several core latent variables: ML-driven lubrication adoption, lubricant performance, system reliability, data quality, technical readiness, and organizational readiness. Descriptive statistics indicated that while respondents reported only moderate levels of ML adoption ($M = 3.21$, $SD = 0.74$), the plants demonstrated comparatively high lubricant performance ($M = 3.68$, $SD = 0.69$) and system reliability ($M = 3.59$, $SD = 0.71$), suggesting that lubrication improvements and reliability outcomes are already being pursued through traditional means, with ML technologies representing an emergent, rather than fully mature, complement to existing programs. All multi-item measurement scales showed strong internal consistency, with Cronbach's alpha values ranging from .81 to .89, confirming the reliability of the constructs and supporting their suitability for subsequent correlation and regression analyses. Pearson correlation coefficients revealed that ML adoption was positively and moderately associated with both lubricant performance ($r = .52$, $p < .001$) and system reliability ($r = .48$, $p < .001$), providing initial empirical support for the theorized relationships. These correlations suggest that plants beginning to integrate ML-enabled lubrication analytics are already experiencing measurable operational benefits, potentially due to improved detection of lubricant degradation, earlier identification of contamination events, or more precise adjustment of lubrication intervals. Multiple regression results further clarified these relationships, demonstrating that the proposed model explained 41.8% of the variance in lubricant performance and 49.2% of the variance in system reliability. ML adoption emerged as a significant predictor across models (β up to .38, $p < .001$), but data quality and organizational readiness also showed strong predictive influence, highlighting the critical interdependencies between algorithmic tools, underlying data infrastructures, and human/organizational processes.

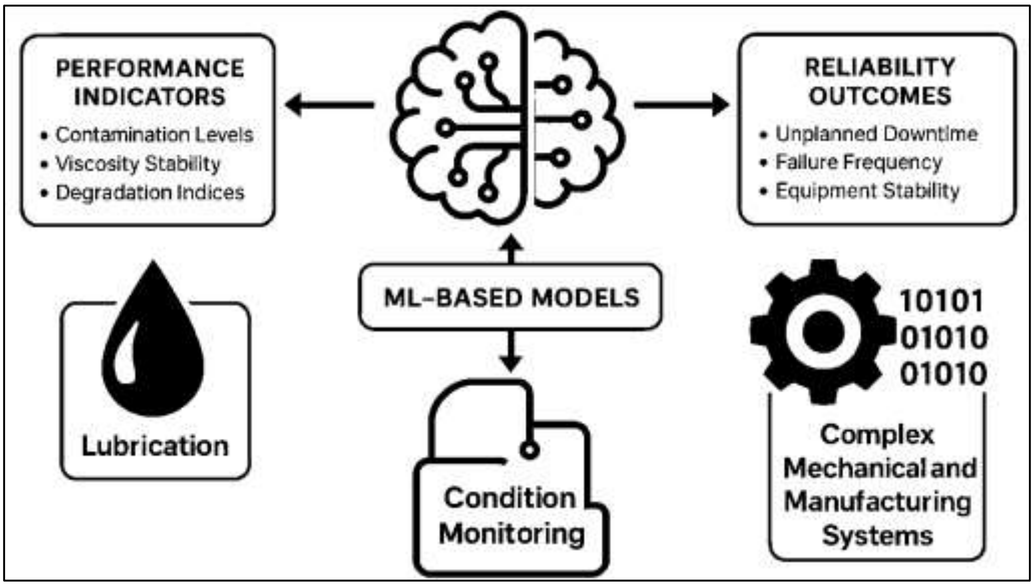
Keywords

Machine Learning, Lubricant Performance, Condition Based Maintenance, System Reliability, Predictive Maintenance;

INTRODUCTION

Lubrication is a fundamental engineering practice that aims to minimize friction, wear, and heat generation between moving surfaces through the introduction of a fluid, semi-solid, or solid film between contacting components (Whitby, 2021). This practice lies at the heart of tribology, the science of friction, lubrication, and wear, which underpins the reliability of rotating machinery, transmissions, bearings, and manufacturing equipment across sectors such as automotive, aerospace, energy, and process industries (Marian & Tremmel, 2021). Modern estimates suggest that optimized lubrication and tribological design can save significant fractions of national energy consumption and maintenance cost by extending component life, reducing outages, and improving overall efficiency (Wakiru et al., 2019). As manufacturing systems evolve toward higher levels of complexity, automation, and precision, lubrication systems themselves become increasingly sophisticated, encompassing advanced base oils, additives, and delivery architectures designed to operate under variable loads, high temperatures, and contaminated or harsh environments (Randall & Antoni, 2016). In complex mechanical and manufacturing systems such as high-speed production lines, heavy-duty engines, gearboxes, and robotics lubricants now function not only as protective media but also as carriers of condition information, where chemical and physical changes in the lubricant directly reflect component health and operating severity (Zhu, Du, et al., 2017). This dual role creates an international need for more rigorous, data-driven approaches to optimize lubricant performance and reliability as part of broader asset management and digital manufacturing strategies.

Figure 1: ML Approaches for Enhancing Lubricant Performance and System Reliability



The reliability engineering community has long recognized condition-based maintenance (CBM) as a more effective strategy than traditional time-based or reactive maintenance in such systems. CBM as a process built on three core steps data acquisition, data processing, and maintenance decision-making using condition indicators to trigger maintenance actions only when warranted. In this context, lubricants have been likened to the “blood” of machinery, carrying signatures of wear, contamination, and degradation that can be monitored to support diagnostics and prognostics (Zhu et al., 2016). Condition monitoring of machinery under variable speed and load conditions has been systematized in comprehensive frameworks for non-stationary operations, emphasizing multi-sensor data fusion and advanced signal processing (Randall, 2012). At the same time, digital manufacturing and predictive maintenance paradigms increasingly rely on data-driven models that continuously learn from historical and real-time data to update failure probabilities and recommend interventions (Rødseth & Schjølberg, 2016). In this evolving landscape, lubricant condition monitoring is no longer a peripheral activity; it has become a core component of integrated CBM architectures that seek to align maintenance decisions with actual degradation states rather than fixed intervals, especially in complex mechanical and manufacturing systems where downtime carries high economic and safety costs (Zhao et al., 2021). Within the broader CBM ecosystem, lubricant condition monitoring (LCM) has emerged as a specialized sub-discipline that combines tribology, analytical chemistry, and sensing technology. A number of reviews document how lubricating oil analysis through particle counting, spectroscopy, viscosity measurement, dielectric properties, and chemical indicators provides early warning of wear, contamination, and oil degradation (Vališ et al., 2019). Wakiru et al. (2019) highlight that lubricant data streams can be systematically aggregated and analyzed to support maintenance decision support systems, linking wear debris and chemical aging indicators with actionable recommendations. Online oil-conditioning sensors capable of measuring debris, water, viscosity, aeration, soot, and other properties, noting that real-time monitoring reduces the need for intrusive sampling and improves responsiveness to emerging faults. Web-based oil diagnosis system that measures complex impedance and dielectric properties of lubricants to detect early chemical aging and abnormal operating conditions in gearboxes and bearings. Additional work has focused on specialized sensors for wear debris detection and contamination quantification, such as microsensor arrays and synchronized multi-coil arrangements deployed in lubricant circuits (Zhu, Zhong, et al., 2017). These technological advances have made it technically feasible to collect high-frequency lubricant data from complex mechanical and manufacturing systems, creating large, heterogeneous datasets that reflect both lubricant performance and system reliability, yet these data are often under-utilized in terms of advanced modeling and optimization.

Parallel to sensor and measurement developments, machine learning (ML) has gained significant traction in tribology and lubrication research. Artificial neural networks (ANNs) can serve as powerful nonlinear regression tools to model complex relationships between tribological inputs such as load, sliding speed, material properties, and surface roughness and outputs such as wear rate and coefficient of friction. Systematic review of ML and artificial intelligence (AI) applications in tribology, outlining the use of algorithms ranging from ANNs and support vector machines to decision trees and random forests for tasks such as friction prediction, wear modeling, and surface classification. Their survey shows that the number of tribology-related ML publications has grown considerably since 2010 and spans scales from nano-tribology to full system applications. Within lubrication research, ML has been used to estimate film thickness, classify lubrication regimes, and predict frictional behavior under varying operating conditions, often achieving high predictive accuracy when trained on sufficiently rich experimental datasets (Argatov, 2019). These developments align with broader trends in condition-monitoring and predictive maintenance, where ML-driven models build on historical and real-time sensor data to support prognostics and optimal maintenance scheduling (Guan & et al., 2011). Together, this body of work indicates a strong potential for ML to support more rigorous optimization of lubricant performance and reliability in complex mechanical and manufacturing systems.

A growing cluster of studies focuses specifically on ML approaches applied to lubricant condition data and lubricant-dependent reliability indicators. Microsensor array coupled with a back-propagation ANN to simultaneously quantify water content, total acid number, soot, and sulfur concentration in lubricating oil, demonstrating that multi-property estimation from a compact sensor set can achieve accurate detection over industrially relevant concentration ranges. Soft computing methods, including k-nearest neighbors and radial basis function ANNs, to classify engine health into normal, caution, and critical states based on a reduced set of oil spectral analysis indices, achieving classification accuracies near or above 99%. Hybrid ANN–fuzzy inference system (ANN-FIS) meta-model to assess particulate contamination levels in mechanical system oil, providing a framework for mapping complex contamination profiles to condition categories in support of risk-based maintenance. Other contributions combine dielectric spectroscopy, near-infrared spectroscopy, and ML classifiers such as support vector machines and ANNs to classify oil quality, detect degradation, and infer wear severity (Balabin et al., 2011; Bekana & et al., 2015). Collectively, these studies illustrate how ML models can transform lubricant measurements into meaningful indicators of lubricant state and system health, moving beyond threshold-based diagnostics toward multi-variable, pattern-recognition-based decision support.

Recent work has also explored novel sensing modalities and integrated architectures that expand the design space for ML-based lubricant performance optimization in complex systems. (Zhao et al., 2021) report a self-powered triboelectric nanogenerator (TENG) sensor for real-time monitoring of lubricating oils, where electrical output signals reflect contaminants such as wear debris and water; this configuration supports continuous monitoring without external power supplies and integrates naturally with smart machine concepts. (Esfe & et al., 2018) developed a 3×3 wear debris sensor array with synchronized sampling, enabling spatially resolved online monitoring of debris in lubricant circuits for rotating machinery. Mechanical wear debris feature detection and diagnosis have been reviewed in detail by (Hong et al., 2018), who emphasize the relevance of particle-based indicators for fault diagnostics and the role of advanced signal processing and data-driven methods in extracting informative features. (Jardine et al., 2006) show that measuring complex electrical impedance of lubricants can reveal both chemical aging and tribological wear processes in large gearbox bearings, further enriching the set of potential inputs for ML models. These sensor innovations, combined with ML classifiers, regression models, and hybrid meta-models, establish technical building blocks for integrating lubricant performance optimization into wider digital maintenance architectures in complex mechanical and manufacturing systems.

Although the technical literature on lubricant condition monitoring, tribology-oriented ML, and predictive maintenance is extensive, several gaps remain in terms of integrating these advances into holistic optimization of lubricant performance and reliability at system level. Reviews of machine diagnostics and prognostics typically concentrate on vibration, acoustic emission, or structural health indicators and treat lubricant data as a secondary or supplementary information source (Altıntaş et al., 2019). Lubricant-focused ML studies often address specific components (e.g., engines, turbines, or individual gearboxes) under relatively controlled laboratory or single-application conditions, rather than the heterogeneous, interconnected equipment found in complex manufacturing lines (Albidewi, 2008). Moreover, much of the existing research emphasizes model development and predictive accuracy, whereas comparatively fewer empirical studies examine how ML-based lubricant performance indicators are embedded within organizational decision processes, maintenance policies, and operational constraints in real industrial settings (Mauntz et al., 2013). Quantitative, cross-sectional evidence that links ML-driven lubricant optimization practices to measurable outcomes such as reduced downtime, extended component life, or improved production stability across multiple mechanical and manufacturing contexts is still emerging. This motivates an integrated research design that couples rigorous statistical modeling with real-world case study data from organizations that actively deploy ML-enabled lubricant monitoring and optimization practices.

In response to these gaps, the present study focuses on “Machine Learning Approaches for Optimization of Lubricant Performance and Reliability in Complex Mechanical and Manufacturing Systems” as a quantitative, cross-sectional, case-study–based investigation. The overarching purpose is to examine how ML-based models derived from lubricant condition and reliability data can be used to optimize lubricant performance measured through indicators such as contamination levels, viscosity stability, and degradation indices and, in turn, enhance system-level reliability in complex mechanical and manufacturing environments. Guided by this purpose, the study formulates three research questions: (RQ1) How extensively are ML techniques currently used to analyze lubricant condition data in complex mechanical and manufacturing systems? (RQ2) To what extent does the adoption of ML-based lubricant monitoring and optimization practices correlate with improvements in perceived lubricant performance and equipment reliability? and (RQ3) Which specific ML-enabled analytic capabilities and organizational practices significantly predict higher levels of lubricant-driven reliability outcomes when controlling for contextual factors such as industry segment, system complexity, and maintenance strategy? On the basis of these questions, a set of testable hypotheses is developed that links ML adoption, analytic maturity, and lubricant performance indicators to reliability-related outcomes through regression modeling. The study employs a structured questionnaire with Likert’s five-point scale to capture constructs related to ML usage, lubricant monitoring practices, and perceived performance and reliability, complemented by case study data from organizations operating complex mechanical and manufacturing systems, thereby providing a robust empirical basis for hypothesis testing.

To support this empirical agenda, the study adopts a conceptual framing that draws on CBM theory, data-driven predictive maintenance, and tribology-oriented ML research. CBM literature emphasizes the importance of linking condition indicators to maintenance decisions and economic outcomes (Pourramezan et al., 2021), while recent work on digital and data-driven maintenance underscores the role of advanced analytics and ML in extracting actionable knowledge from sensor data streams (Hong et al., 2018). In tribology and lubrication, ML-based models have demonstrated strong capability in predicting friction, wear, lubricant degradation, and contamination levels from multidimensional input data (Argatov, 2019). By integrating these strands, the present study conceptualizes ML-enabled lubricant optimization as a mediating capability between advanced sensing (e.g., online oil condition sensors), maintenance strategies (e.g., CBM), and reliability outcomes in complex mechanical and manufacturing systems. The remainder of the paper is organized as follows. The next section presents a detailed literature review on lubricants, tribology, condition monitoring, and ML applications relevant to lubricant performance and reliability optimization, including theoretical and conceptual frameworks. The methodology section then outlines the research design, case study context, sampling procedures, measurement scales, and data analysis techniques, including descriptive statistics, reliability and validity assessment, correlation analysis, and regression modeling. Subsequent sections present the empirical results, discuss their alignment with prior studies, and close with conclusions, recommendations, and limitations grounded in the quantitative findings.

The overarching objective of this study is to systematically examine how machine learning approaches can be harnessed to optimize lubricant performance and enhance reliability in complex mechanical and manufacturing systems, using empirical evidence drawn from real industrial contexts. Specifically, the study seeks first to quantify the current level of adoption and practical use of machine learning techniques in lubrication-related decision-making, including their application to condition monitoring, performance assessment, and maintenance planning within organizations that operate intricate mechanical and manufacturing assets. A second objective is to evaluate the perceived impact of machine learning–enabled lubrication practices on key lubricant performance indicators such as contamination control, viscosity stability, degradation behavior, and service life, with a view to understanding how data-driven models influence day-to-day lubrication management. A third objective is to investigate the association between machine learning–driven lubricant optimization and system-level reliability outcomes, focusing on measures such as unplanned downtime, failure frequency, maintenance interventions, and overall equipment stability across varied production environments. In addition, the study aims to identify and measure the organizational and technical factors that condition the effectiveness of machine learning applications in lubrication, including data availability and quality, sensor infrastructure, integration with maintenance systems, staff competencies, and management support. To achieve these aims, the research is designed as a quantitative, cross-sectional, case-study–based investigation utilizing a structured questionnaire with Likert's five-point scale, administered to professionals directly involved in maintenance, reliability, and data analysis in selected organizations. The collected data will be subjected to descriptive statistics to profile practices and contexts, correlation analysis to explore relationships among key constructs, and regression modeling to test a set of clearly formulated hypotheses linking machine learning adoption, lubricant performance, and reliability outcomes. Through these objectives, the study intends to deliver a coherent and statistically grounded picture of how machine learning is currently embedded in lubrication management and how it relates to observable performance and reliability patterns in complex mechanical and manufacturing systems.

LITERATURE REVIEW

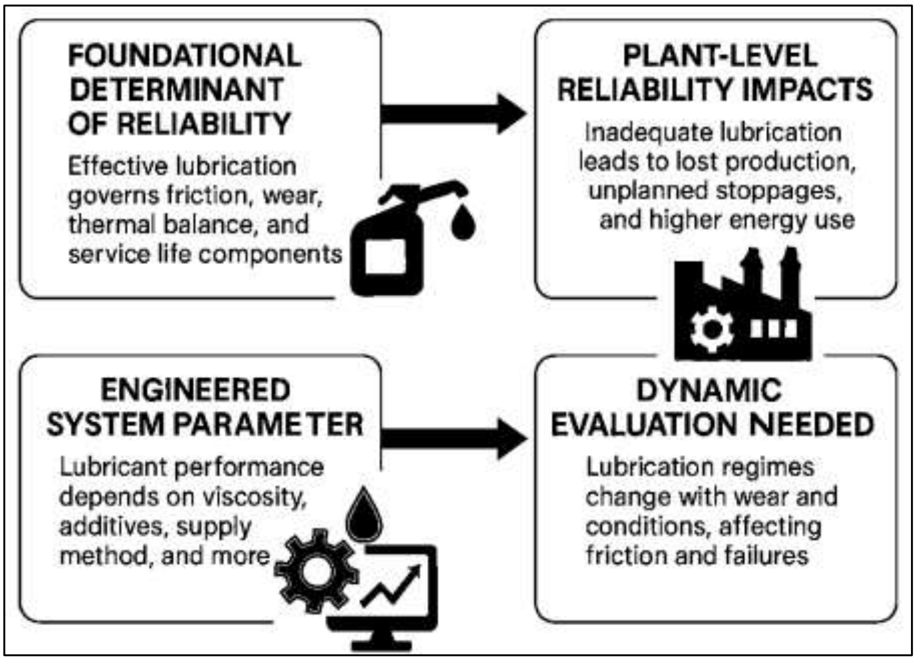
The literature on lubrication, reliability, and data-driven maintenance in complex mechanical and manufacturing systems spans several intersecting domains, including tribology, condition-based maintenance, lubricant condition monitoring, and machine learning–enabled prognostics. At its core, this body of work establishes lubrication as a critical determinant of friction control, wear mitigation, and thermal management in mechanical interfaces, particularly in high-load, high-speed, or highly automated production environments where even minor deviations in lubricant quality can cascade into severe reliability issues and costly downtime. Over time, tribological studies have evolved from purely experimental and phenomenological analyses of wear and friction toward more measurement-intensive approaches that treat the lubricant as both a protective medium and an information carrier, whose physical and chemical properties encode valuable signals about system health. In parallel, the maintenance and reliability engineering literature has progressively shifted from reactive and schedule-based strategies to condition-based and predictive paradigms, emphasizing continuous monitoring, diagnostic interpretation, and risk-informed decision-making. Within this shift, lubricant condition monitoring has emerged as a specialized practice, integrating laboratory analyses, online sensors, and embedded diagnostics to track contamination, degradation, and performance loss across diverse machinery. More recently, advances in sensing technology and industrial connectivity have generated large volumes of lubricant-related data particle counts, spectroscopic signatures, dielectric responses, viscosity trends, and other indicators creating fertile ground for machine learning techniques that can uncover nonlinear patterns, classify health states, and predict failure risks more effectively than traditional threshold rules. A growing stream of studies demonstrates the potential of algorithms such as artificial neural networks, support vector machines, ensemble learners, and hybrid fuzzy–neural models to map multidimensional lubricant data onto performance and reliability outcomes at component level. However, despite rapid methodological progress, the literature remains fragmented across disciplines and often focused on isolated components or laboratory conditions, with relatively fewer empirical investigations that connect machine learning–based lubricant analytics to system-level reliability in real industrial settings. This review therefore synthesizes prior work across these domains to clarify how lubrication performance and reliability have been conceptualized and measured, how lubricant condition monitoring technologies and analytical methods have developed, how theoretical and conceptual frameworks link these elements, and where gaps remain in understanding the role of machine learning approaches in optimizing lubricant performance and reliability in complex mechanical and manufacturing systems.

Lubrication Performance in Complex Mechanical and Manufacturing Systems

Effective lubrication is widely recognized as a foundational determinant of reliability in complex mechanical and manufacturing systems because it governs frictional losses, wear rates, thermal balance, and ultimately the service life of critical components. At the plant scale, tribological losses arising from inadequately lubricated bearings, gears, and sliding interfaces translate into lost production hours, unplanned stoppages, and elevated energy consumption. Research quantifying the global impact of friction and wear has shown that optimized tribology through appropriate lubricant selection, control of operating conditions, and systematic maintenance can yield substantial reductions in energy use, emissions, and maintenance costs across transport and manufacturing sectors (Holmberg & Erdemir, 2017). Within gear trains and power-transmission assemblies, the lubrication regime determines whether contacts operate in boundary, mixed, or full-film conditions; when film formation is inadequate, pitting, scuffing, and micro-pitting propagate into macro-scale failures that compromise reliability (Abdulla & Ibne, 2021). A comprehensive review of gear systems has demonstrated that lubricant viscosity, additive chemistry, and supply method jointly influence gear temperature, efficiency, noise, and fatigue life, indicating that lubricant performance must be treated as an engineered system parameter rather than a secondary maintenance choice (Habibullah & Foysal, 2021; Liu et al., 2020). In tightly coupled manufacturing environments where tolerances are small, speeds are high, and load cycles are severe, lubricant rheology, film thickness, and thermal behavior become inseparable from mechanical design and loading profiles, making lubrication performance central to meeting reliability targets for high-duty industrial assets (Sarwar, 2021; Musfiqur & Saba, 2021).

From a plant-level maintenance perspective, lubrication performance is equally dependent on how lubricant is delivered, monitored, and controlled in real operating conditions (Redwanul et al., 2021; Tarek & Praveen, 2021). Conventional time-based manual greasing and oiling routines often oscillate between over- and under-lubrication, both of which degrade equipment reliability by generating excess heat, encouraging contamination ingress, or allowing direct asperity contact under high loads. In contrast, automated systems can stabilize film formation and reduce human error. For example, an automated lubrication control system for CNC machine-tool guideways that integrates temperature sensing with feedback-based pump control has been shown to reduce oil consumption while improving thermal stability and machining precision, indirectly extending component life and enhancing system reliability (Muhammad & Shahrin, 2021; Saikat, 2021; Sparham et al., 2014). Hydrodynamic journal bearings provide another illustration of how lubrication behavior at the micron scale translates into macroscopic reliability outcomes: variations in pressure distribution, film thickness, and local flow can cause transitions from safe full-film lubrication into mixed lubrication associated with vibration, noise, and accelerated wear. An investigation into journal bearings with engineered slippage surfaces found significant reductions in friction while maintaining load-carrying capacity, demonstrating that tailoring fluid–structure interfaces can simultaneously improve efficiency and bearing reliability (Shaikh & Aditya, 2021; Wu, 2008). These findings justify industrial investments in centralized lubrication systems, contamination-control technologies, and standardized procedures for lubricant storage, handling, identification, and task execution, supported by structured lubrication plans and electronic work orders that embed tribological knowledge into routine maintenance workflows.

Figure 2: Lubrication Performance and Equipment Reliability Framework

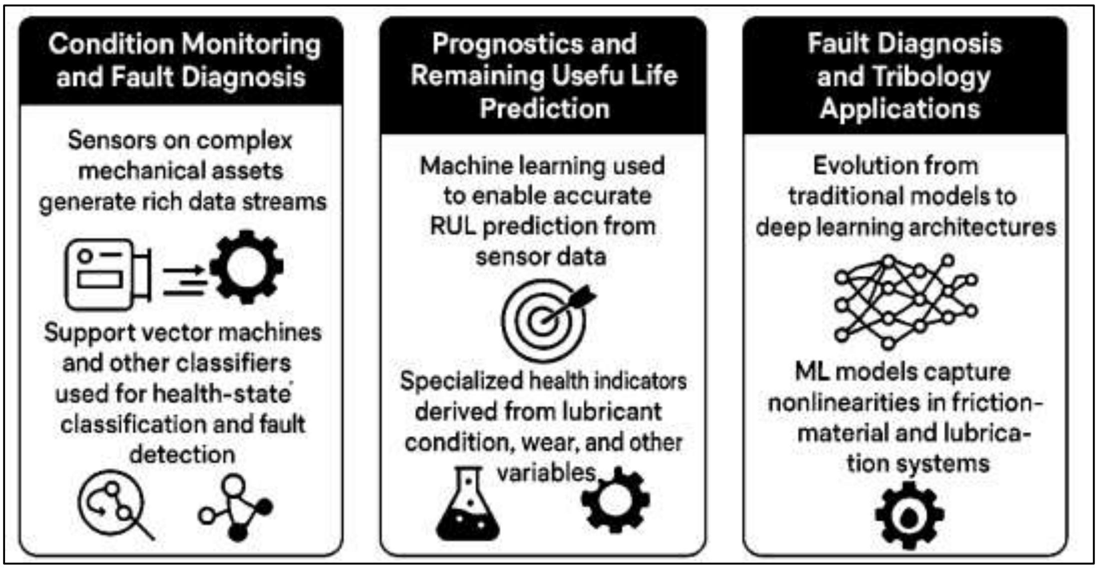


Recent tribology research has also emphasized that lubricant performance and equipment reliability must be evaluated dynamically over the asset life cycle rather than assumed to be constant. As surfaces wear, clearances evolve, and duty cycles shift, lubrication regimes can drift from full-film to mixed or boundary conditions, altering friction, thermal patterns, and failure probabilities. A transient mixed-lubrication–wear coupling model for journal bearings has demonstrated that wear progression systematically modifies film thickness, pressure fields, and asperity contact patterns, producing distinct early-stage and steady-stage wear behaviors with different implications for reliability (Guo & et al., 2019). These results indicate that static safety margins in design are insufficient and that reliability assessment must incorporate models tracking how degradation and surface topography interact with lubricant properties and loading conditions to move systems along the Stribeck curve. For complex mechanical and manufacturing systems, this reinforces the need for condition-based strategies that integrate lubricant condition monitoring, physics-based prediction, and targeted interventions in lubricant selection, replenishment intervals, and system design. Linking sensor-derived indicators such as temperature, vibration, or contamination levels to analytical or machine learning models makes it possible to anticipate transitions from safe to risky lubrication regimes and to schedule proactive interventions before functional failures occur. In this way, lubrication performance becomes a controllable design and operational variable within broader reliability and asset-management frameworks, directly aligning with the present study's focus on machine-learning-enabled optimization of lubricant performance and equipment reliability.

Machine Learning in Maintenance

The use of machine learning in condition monitoring and fault diagnosis has grown out of the need to interpret increasingly rich data streams generated by sensors mounted on complex mechanical assets. Early research on support vector machines (SVMs) for maintenance applications showed that ML-based models can transform multivariate vibration and process data into accurate health-state classifications and fault labels, thereby reducing dependence on expert-crafted rules and subjective interpretation. A widely cited survey demonstrated that SVM classifiers outperformed many traditional pattern-recognition techniques in machine condition monitoring, particularly when dealing with overlapping fault signatures and small sample sizes, establishing SVMs as a robust option for industrial diagnostic tasks (Widodo & Yang, 2007). Building on this foundation, the prognostics literature shifted toward forecasting remaining useful life (RUL) and reliability trajectories rather than merely detecting existing faults. A comprehensive review synthesized approaches for rotating-machinery prognostics and highlighted statistical models, state-space formulations, and data-driven algorithms as complementary routes for predicting future machine condition under real-world complexities such as fluctuating loads, variable speeds, and intermittent operations (Heng et al., 2009). Together, these contributions positioned machine learning not only as a collection of classification tools but also as a broader paradigm for translating raw sensor data into actionable maintenance intelligence, laying the conceptual groundwork for applications linking lubricant behavior, tribological performance, and system-level reliability in complex manufacturing environments.

Figure 3: Machine Learning Applications in Tribology and Predictive Maintenance



As sensing and data-acquisition technologies advanced, the role of ML in maintenance shifted from isolated algorithmic demonstrations toward fully integrated prognostic frameworks capable of handling complete life-cycle data. A systematic review formalized a four-stage machinery-health prognostics pipeline data acquisition, health-indicator construction, health-stage division, and RUL prediction and emphasized that each stage presents distinct methodological challenges and opportunities for data-driven modeling (Lei et al., 2018). Their analysis stressed that effective health indicators must condense high-dimensional sensor signals such as vibration, acoustic emission, temperature, and lubricant-condition measurements into low-dimensional features that correlate strongly with degradation yet remain robust under fluctuating operating conditions. Within this structure, machine learning supports both the design of health indicators and the mapping of those indicators to future states, enabling substantially more accurate predictions of failure timing and performance loss. For tribology-focused applications, lubricant-condition variables including contamination indices, viscosity evolution, oxidation levels, and chemical degradation markers can function as specialized health indicators feeding directly into prognostic models. Integrating these lubricant-specific indicators into broader predictive-maintenance workflows allows maintenance planners to simultaneously assess mechanical wear, lubricant aging, and operational stress profiles, supporting decisions that minimize downtime, stabilize product quality, and extend asset life in complex mechanical and manufacturing systems.

Recent developments have broadened this perspective by explicitly tracing the evolution of machine learning techniques from traditional shallow models to deep learning architectures and transfer-learning approaches and by outlining how these methods can be deployed in industrial diagnostics. A major review of machine-fault diagnosis proposed a roadmap in which classical models such as artificial neural networks, SVMs, and k-nearest neighbors are increasingly supplemented or replaced by convolutional neural networks, recurrent neural networks, and domain-adaptation strategies designed to manage large-scale monitoring data and improve cross-domain generalization (Lei et al., 2020). Although much of this work has centered on vibration and acoustic signals, it offers a conceptual blueprint for applying ML to lubricant and tribology datasets, especially through hybrid modeling that combines physics-based descriptions of lubrication regimes with data-driven correction layers. On the tribology side, empirical studies have shown that artificial neural networks can accurately predict the recovery performance of brake friction materials from a limited set of material and operating parameters, illustrating the capability of ML models to capture nonlinear relationships in friction-material systems that would be extremely difficult to express analytically (Aleksendrić et al., 2010). This type of tribology-specific modeling is directly relevant to lubricant-performance optimization, where similar nonlinearities arise from interactions among base-oil chemistry, additive packages, surface roughness, load cycles, and thermal gradients. Taken together, these strands of research indicate that machine learning provides a versatile methodological toolbox for modeling both component-level tribological behavior and system-level condition trajectories, thereby offering a robust foundation for the present study's focus on ML-driven optimization of lubricant performance and reliability in complex mechanical and manufacturing systems.

Theoretical Framework

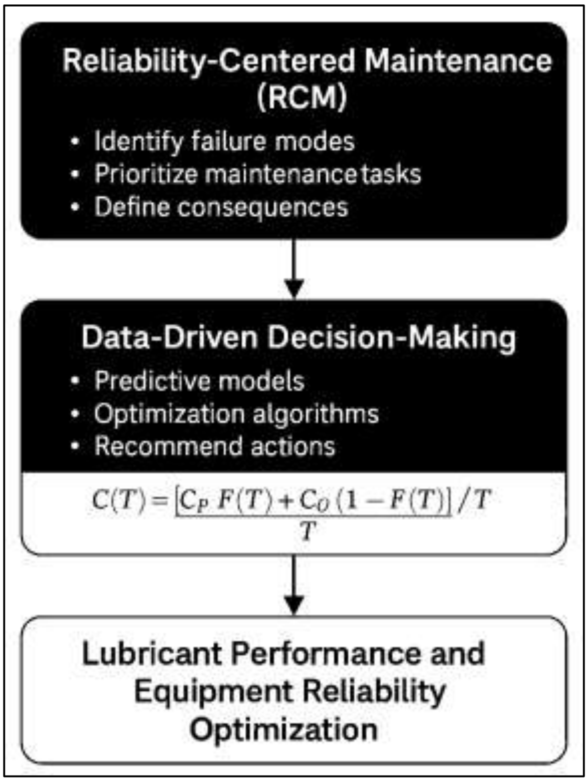
Reliability-centred maintenance (RCM) provides the core theoretical lens for explaining how lubricant performance and system reliability can be jointly optimised in complex mechanical and manufacturing environments. Rooted in systems reliability theory, RCM begins from the functional requirements of an asset, enumerates functional failures and failure modes, and then prioritises maintenance tasks according to failure consequences and probabilities (Li & Gao, 2010). Within this framework, the reliability of a component operating under an approximately constant failure rate λ is often represented as $R(t) = \exp(-\lambda t)$, highlighting that the probability of survival over time is a function of both inherent design and the effectiveness of preventive actions. RCM theory extends this simple formulation by integrating tools such as failure mode, effects and criticality analysis and fault tree analysis to identify lubricant-related degradation pathways, such as abrasive, adhesive or fatigue wear, and to link them to specific condition indicators and inspection intervals (Li & Gao, 2010). Contemporary reviews of condition-based maintenance (CBM) emphasise that these techniques do not merely catalogue failure modes but build a structured decision logic for when to perform preventive or predictive tasks, how to allocate maintenance resources and which subsystems merit intensified lubrication monitoring (Quatrini et al., 2020). Strategic analyses of RCM frameworks show that the methodology functions as a decision-making system that balances strengths, weaknesses, opportunities and threats associated with alternative maintenance policies, thereby embedding reliability, risk and cost considerations into a coherent management model (Gupta & Mishra, 2016). This logic is particularly important in high-duty lubrication contexts, where small changes in lubricant condition can have disproportionate effects on failure probabilities and maintenance cost structures. This logic directly guides practical lubricant-focused maintenance policies.

Building on RCM, data-driven decision-making frameworks refine how reliability information is translated into specific maintenance and lubrication actions in Industry 4.0 environments. Recent reviews of data-driven maintenance decision-making emphasise that predictive models, optimisation algorithms and prescriptive analytics are used to recommend actions that minimise long-run expected cost while satisfying reliability and availability constraints (Bousdekis et al., 2021). Conceptually, the decision problem can be expressed as the minimisation of an average cost function

$$C(T) = [C_p F(T) + C_c(1 - F(T))]/T,$$

where $C_p$and $C_c$denote preventive and corrective costs, $T$is a decision interval and $F(T)$the failure distribution implied by the selected lubricant and operating regime; the theoretical contribution of data-driven frameworks is to estimate $F(T)$and update $C(T)$continuously using sensor data and learning models. Dual-perspective models for maintenance service delivery, such as the D3M framework, integrate customer and provider views to structure the data-based decision-making process and to position analytics-driven maintenance tasks within an iterative improvement cycle (Sala et al., 2021). Within these frameworks, lubricant condition indicators (for example, viscosity index, wear particle counts and oxidation markers) become explanatory variables in predictive models, while recommended actions (such as oil change, filtration or additive top-up) are decision outputs whose timing and intensity are optimised. Data-driven RCM thus formalises the relationship between lubricant health states, predicted remaining useful life and recommended interventions, ensuring that decisions are traceable to both physical degradation models and empirically learned patterns in the data (Bousdekis et al., 2021). From a theoretical standpoint, these approaches position machine learning not as a black box, but as an estimator embedded within the classical reliability and maintenance optimisation problem, where estimated failure probabilities and degradation rates feed directly into structured RCM decision rules governing lubricant selection, change intervals and inspection frequencies. This integration underpins the proposed study.

Figure 4: RCM and Data-Driven Decision Framework for Lubricant Performance Optimization

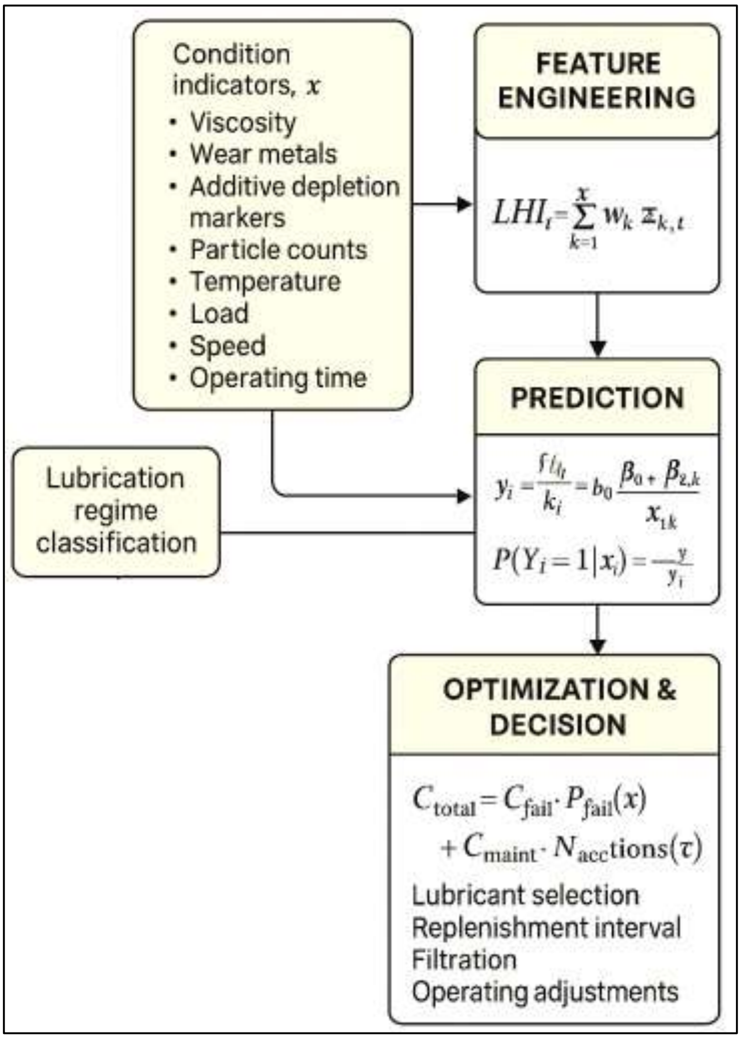


Within this theoretical configuration, the present research conceptualises lubricant performance optimisation and equipment reliability as outcomes of an RCM-based decision architecture supported by data-driven analytical models. RCM provides the logic for defining critical lubricant-dependent failure modes, mapping them to observable condition indicators and assigning consequence categories that determine the relative priority of maintenance actions (Li & Gao, 2010). Data-centred frameworks such as the D3M model specify how these indicators are captured, processed and routed into decision points across the maintenance service delivery process, ensuring that empirical evidence systematically informs planning, execution and feedback activities (Sala et al., 2021). Simultaneously, meta-analytical reviews of CBM highlight that modern maintenance strategies increasingly rely on statistical and machine learning models to transform condition monitoring signals into prognostic outputs and decision recommendations, effectively expanding the original RCM logic with algorithmic estimation layers (Quatrini et al., 2020). In quantitative terms, the framework assumes that maintenance decision quality is a function of both the underlying RCM structure and the performance of predictive models;

at survey level, this is captured through regression formulations such a$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$, where Ydenotes perceived decision effectiveness, Xvariables represent data quality, analytical capability and RCM practice maturity, and the βparameters quantify their influence. Conceptually, this formulation is consistent with strategic assessments of RCM frameworks that treat reliability-centred maintenance as a multidimensional construct combining technical, organisational and economic dimensions, each contributing to overall maintenance performance (Bousdekis et al., 2021). In the context of lubricant management, these dimensions translate into structured procedures for defining lubricant-related failure modes, institutional support for systematic condition monitoring and resource allocation for analytics capabilities, all of which are measured in this study through Likert-scale items and analysed using descriptive statistics, correlation and regression to test the coherence of the proposed theoretical model.

Conceptual Framework

Figure 5: Conceptual Framework



The first conceptual framework positions lubricant performance optimization as a supervised learning and decision-support problem in which multidimensional lubricant and operating data are transformed into a composite health state and corresponding maintenance or control actions (Malaguti et al., 2021). At the data level, the framework assumes a vector of condition indicators x (viscosity, wear metals, additive depletion markers, particle counts, temperature, load, speed and operating time) that jointly encode the degradation state of the lubricant–machine system. Studies on motor-oil condition modeling using artificial neural networks and principal component analysis show that such multivariate representations capture the underlying physicochemical evolution of oil more effectively than single-parameter thresholds, motivating the use of latent features as inputs to prediction models (Moder et al., 2018). In this framework, a feature-engineering block transforms raw sensor and laboratory variables into normalized, dimensionless indicators z_k, which are aggregated into a Lubricant Health Index (LHI) to provide a single scale for decision making:

$$\mathrm{LHI}_t = \sum_{k=1}^{m} w_k z_{k,t},$$

where $w_k$are weights reflecting the relative importance of viscosity, contamination, additive depletion and wear signatures. The conceptual model stipulates that these weights are not arbitrarily assigned but learned from historical cases in which combinations of indicators have led to acceptable or unacceptable lubrication performance. In parallel, pattern-recognition models trained on torque, vibration or spectral signatures can classify the prevailing lubrication regime (boundary, mixed or full-film), providing an additional categorical input channel that links lubricant condition to contact mechanics at critical interfaces (Sai et al., 2019).

On top of the feature and health-index layers, the framework defines a prediction layer where machine-learning models map the engineered inputs to quantitative risk or performance metrics, such as probability of lubricant-related failure within a planning horizon, expected remaining useful life of the oil charge or probability of violating film-thickness and temperature constraints. Conceptually, this mapping can be represented by a general regression or classification function

$$\hat{y}_i = f(\mathrm{x}_i) = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik},$$

where $\hat{y}_i$is a continuous degradation score or the logit of a failure probability for operating instance i, and $x_{ik}$are the standardized lubricant and operating variables. In a logistic-regression view, the failure probability is given by

$$P(Y_i = 1 \mid \mathrm{x}_i) = \frac{1}{1 + e^{-\hat{y}_i}}.$$

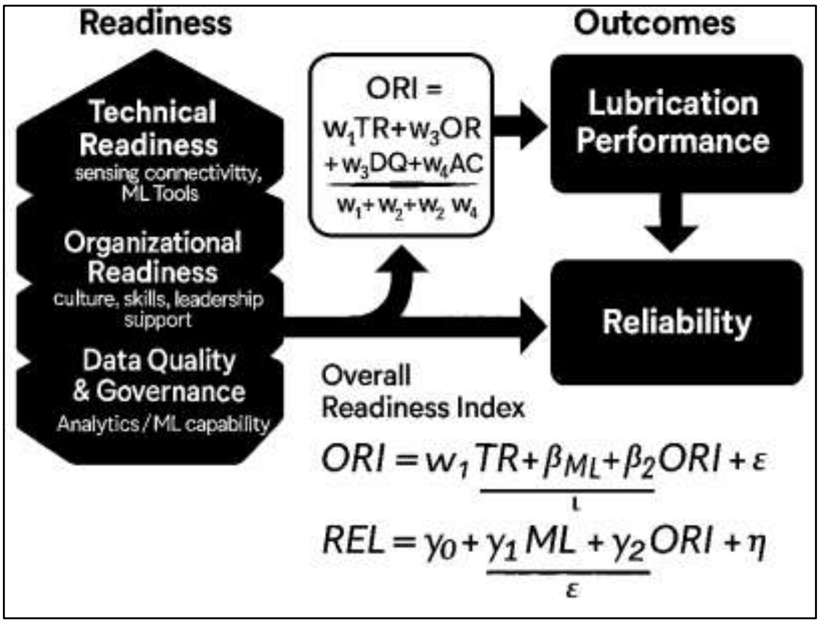
This formalization accommodates neural networks, random forests or hybrid reasoning models as choices for $f(\cdot)$while retaining a consistent probabilistic interpretation of risk. Reviews of predictive-maintenance architectures for Industry 4.0 emphasize that effective frameworks couple data-driven prediction blocks with explicit knowledge representation and reasoning rules, so that model outputs can be combined with domain constraints (safety limits, warranty requirements, production schedules) to support transparent decisions. Within the present research, the prediction layer is conceptually linked to survey-based constructs such as "perceived predictive accuracy of ML models," "perceived usefulness of lubrication analytics" and "decision trust," which will later be operationalized in the quantitative model (Rodrigues et al., 2020).

The final layer of the conceptual framework is an optimization and decision layer that translates predicted lubrication health and risk into concrete control variables: lubricant selection (base stock and additive package), replenishment or change intervals, filtration strategies and operating adjustments (load, speed, duty cycle). Here, the framework adopts a cost-based representation in which the decision problem is to minimize the long-run expected cost per unit time:

$$C_{\mathrm{total}} = C_{\mathrm{fail}} \cdot P_{\mathrm{fail}}(\mathrm{x}) + C_{\mathrm{maint}} \cdot N_{\mathrm{actions}}(\tau),$$

where $C_{\mathrm{fail}}$is the cost of a lubricant-related failure, $P_{\mathrm{fail}}(\mathrm{x})$is the predicted failure probability from the ML model, $C_{\mathrm{maint}}$is the cost of preventive actions and $N_{\mathrm{actions}}(\tau)$is the frequency of interventions determined by the chosen interval τ. Conceptual frameworks for data-driven predictive maintenance in Industry 4.0 show that such objective functions can be embedded in cyber-physical architectures where sensor streams, predictive models and maintenance policies interact in a closed loop (Dalzochio et al., 2020). Case studies on data-driven lubricant-condition models for diesel fleets demonstrate that when random-forest classifiers and feature-importance analyses are integrated into such loops, managers gain a structured basis for deciding whether to extend or shorten oil-drain intervals while maintaining reliability. In parallel, work on lubrication-regime classification in hydrodynamic journal bearings illustrates how ML-based regime detection can be used to trigger targeted actions (such as adjusting supply pressure or viscosity grade) whenever operating points approach boundary lubrication. In this research, these ideas are translated into survey constructs and hypotheses that link the availability and perceived quality of ML-based lubrication analytics to improvements in lubricant performance, mechanical reliability and decision quality in complex mechanical and manufacturing systems.

Figure 6: Organizational and Technical Readiness Model for ML-Enabled Lubrication Optimization



The second conceptual framework for this study positions organizational and technical readiness as critical antecedents for the successful deployment of machine-learning-based lubrication optimization in complex mechanical and manufacturing systems. In the context of Industry 4.0, predictive maintenance is no longer a purely algorithmic challenge; it depends on whether firms possess suitable infrastructure, skills, governance mechanisms, and integration practices to transform raw condition-monitoring data into reliable, actionable lubrication decisions. Systematic reviews of predictive maintenance in Industry 4.0 emphasize that many initiatives fail not because of weaknesses in modeling approaches, but because of inadequate data architecture, fragmented IT/OT integration, and immature implementation processes, all of which are dimensions of readiness at plant and enterprise levels (Wamba et al., 2017). Likewise, maintenance transformation studies highlight that digital maintenance technologies such as advanced sensors, cyber–physical systems, and real-time analytics only translate into higher reliability and availability when embedded within reconfigured workflows, roles, and performance routines that support continuous learning and decision making across engineering and operations teams . Based on these insights, the present framework conceptualizes readiness as a multi-dimensional construct encompassing (i) technical readiness (sensing, data infrastructure, connectivity, and ML tooling) and (ii) organizational readiness (skills, culture, coordination, and decision rights) that together determine the degree to which machine-learning approaches can actually enhance lubricant performance and reliability outcomes in real production environments (Silvestri et al., 2020).

From a resource- and capability-based perspective, the framework assumes that analytics capabilities are higher-order resources that must be built on top of robust technical and organizational foundations. Empirical work on big data analytics shows that firms derive performance benefits from analytics only when they are able to combine infrastructure, management processes, and human expertise into dynamic capabilities that sense, seize, and reconfigure resources in response to data-driven insights . In lubrication management, this implies that a plant cannot expect ML models to improve wear control, viscosity stability, or energy efficiency unless domain experts, maintenance planners, and production supervisors trust the models, understand their outputs, and are empowered to adapt lubrication schedules, oil change intervals, or filtration practices accordingly (Turanoglu Bekar et al., 2020). At the same time, predictive-maintenance case studies demonstrate that data pre-processing, feature engineering, and model monitoring are intensive technical tasks requiring standardised pipelines, high-quality sensor streams, and clear procedures for handling missing values, outliers, and concept drift . These technical capabilities reinforce organizational readiness by ensuring that ML outputs are consistent, interpretable, and timely, thereby supporting structured decision processes rather than ad-hoc reactions to alarms. In this study, readiness is therefore operationalized as a set of Likert-scale constructs capturing data integration maturity, ML tool adoption, cross-functional collaboration, training and skills, and management support, all of which are hypothesized to moderate or mediate the impact of ML approaches on lubricant performance indicators (Zonta et al., 2020).

Finally, the framework explicitly links readiness constructs to measurable lubrication and reliability outcomes via a set of regression-based relationships that will be tested empirically in the case-study context. Recent work on predictive maintenance models for flexible manufacturing suggests that the value of advanced algorithms is best captured when they are embedded in decision-support architectures that jointly optimize failure prediction, maintenance scheduling, and production constraints, rather than treating prediction accuracy in isolation . Extending this logic, the present framework specifies that perceived lubricant performance optimization (e.g., reduced friction-related energy losses, extended oil life, reduced unplanned shutdowns attributable to lubrication) is a function of both the quality of ML-based prediction and control and the level of organizational and technical readiness (Sang et al., 2021). Formally, an overall readiness index (ORI) can be defined as a weighted composite of the main readiness dimensions,

$$ORI = \frac{w_1 TR + w_2 OR + w_3 DQ + w_4 AC}{w_1 + w_2 + w_3 + w_4},$$

where TRdenotes technical readiness (sensing, connectivity, ML tools), ORorganizational readiness (culture, skills, leadership support), DQdata quality and governance, and ACanalytics/ML capability, with $w_i$representing theoretically justified or empirically estimated weights. This index is then linked to lubrication performance (LP) and reliability (REL) through linear models such as

$$LP = \beta_0 + \beta_1 ML + \beta_2 ORI + \varepsilon, REL = \gamma_0 + \gamma_1 ML + \gamma_2 ORI + \eta,$$

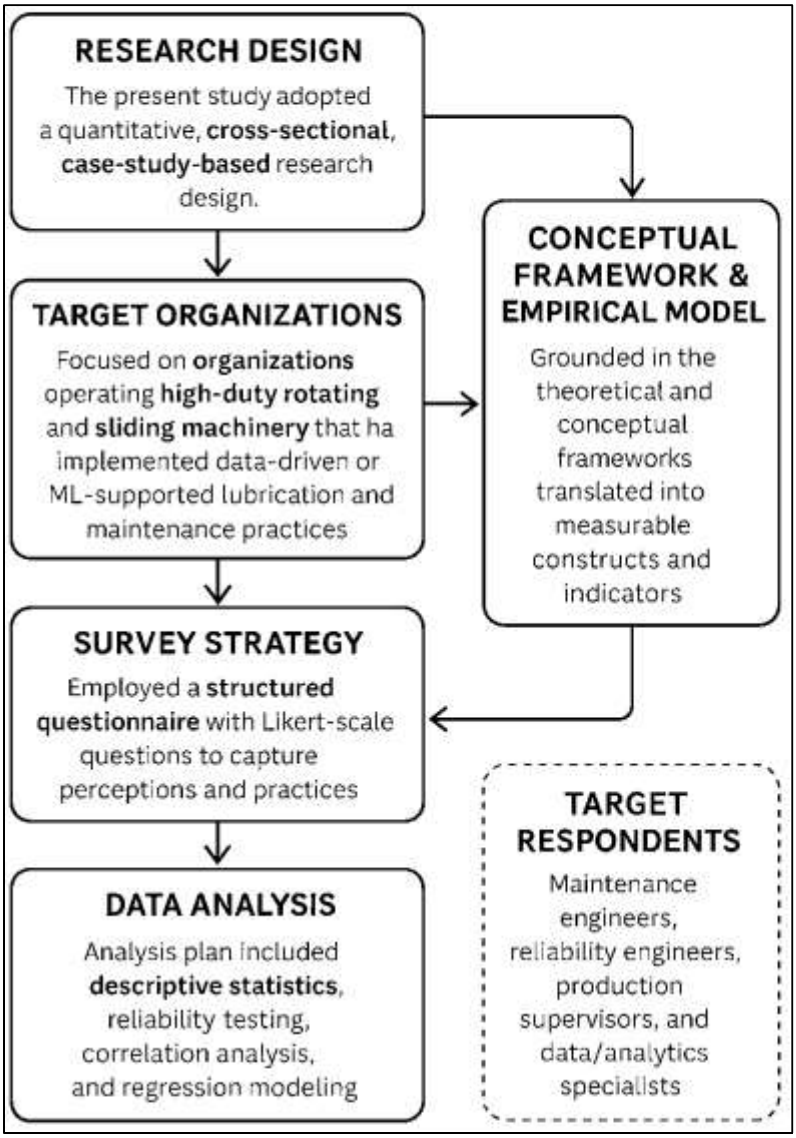
where MLrepresents the maturity of machine-learning-based lubrication optimization, and $\varepsilon, \eta$are error terms. By embedding these equations in the conceptual framework, the study establishes clear, testable pathways between readiness constructs and outcomes, guiding the development of hypotheses and survey items that will later be evaluated using descriptive statistics, correlation analysis, and regression modeling on Likert-scale data collected from maintenance and engineering professionals in complex mechanical and manufacturing settings.

METHOD

The present study has adopted a quantitative, cross-sectional, case-study–based research design to investigate how machine learning approaches have been used to optimize lubricant performance and enhance equipment reliability in complex mechanical and manufacturing systems. It has focused on organizations that have operated high-duty rotating and sliding machinery and that have implemented, or have started to implement, data-driven or ML-supported lubrication and maintenance practices. To capture perceptions and practices in a structured and statistically analyzable form, the study has employed a survey strategy using a structured questionnaire with Likert's five-point scale, which has allowed respondents to express their level of agreement with statements related to ML adoption, lubricant condition monitoring, organizational and technical readiness, and reliability outcomes. The methodology has been grounded in the theoretical and conceptual frameworks outlined in the literature review, and these frameworks have been translated into measurable constructs and indicators that have formed the basis of the empirical model.

In line with the research objectives and hypotheses, the study has defined distinct latent variables representing ML-driven lubrication optimization, lubricant performance, system reliability, data quality, technical readiness, and organizational readiness. These constructs have been operationalized through multi-item scales that have been developed from prior literature and refined through expert judgment and a pilot test. The target respondents have been maintenance engineers, reliability engineers, production supervisors, and data or analytics specialists who have been directly involved in lubrication management and maintenance decision-making within the selected case organizations. Data collection procedures have ensured voluntary participation, anonymity, and confidentiality so that respondents have been encouraged to provide accurate and unbiased assessments of current practices and outcomes. Once collected, the data set has been prepared for analysis through screening, coding, and checking for completeness and consistency. The analysis plan has included descriptive statistics to profile respondents and key constructs, reliability testing for the measurement scales, correlation analysis to explore associations among variables, and regression modeling to test the hypothesized relationships between ML adoption, readiness factors, lubricant performance, and reliability indicators. Through this methodological approach, the study has established a coherent empirical basis for examining how machine learning approaches have contributed to lubrication performance optimization and reliability improvement in complex mechanical and manufacturing systems.

Figure 7: Research Methodology



Research Design

The study has employed a quantitative, cross-sectional research design that has been aligned with the objective of examining relationships among clearly specified latent constructs. It has adopted a case-study–based strategy in which selected industrial organizations have been treated as empirical contexts for observing machine-learning–driven lubrication practices and their reliability outcomes. The design has been grounded in a hypothetico–deductive logic, whereby conceptual frameworks developed from the literature have been translated into testable hypotheses linking ML adoption, lubricant performance, and equipment reliability. A survey method has been used as the main data collection approach because it has allowed the researcher to reach a sufficient number of knowledgeable respondents within each case organization. The design has also ensured that data have been collected at a single point in time, so that observed associations have reflected the current state of practices, perceptions, and outcomes in complex mechanical and manufacturing systems.

Case Study Description

The case-study component has been structured around organizations that have operated complex mechanical and manufacturing systems with significant dependence on lubrication quality and reliability performance. These organizations have typically maintained high-duty rotating machinery, gearboxes, bearings, and automated production lines where lubricant selection, application, and monitoring have held critical importance. Each case organization has been selected because it has already introduced, or has been in the process of introducing, data-driven or machine-learning–supported approaches for maintenance or condition monitoring. Background information on each case has been obtained through preliminary discussions and organizational documents, which have described production processes, maintenance structures, and existing digitalization initiatives. This information has enabled the researcher to contextualize survey findings and to interpret responses in light of industry segment, plant size, and technology maturity. By focusing on such cases, the study has ensured that ML-driven lubrication optimization has been an empirically meaningful and practically relevant phenomenon.

Population, Sample, and Sampling Technique

The target population has consisted of professionals who have been directly involved in lubrication management, maintenance decision-making, and reliability analysis within the selected organizations. This population has included maintenance engineers, reliability engineers, production supervisors, condition monitoring specialists, and data or analytics engineers who have possessed first-hand knowledge of lubricant performance and equipment behavior. Because comprehensive sampling frames have not been publicly available, the study has relied on non-probability sampling, primarily purposive and snowball techniques, to identify eligible respondents. Gatekeepers in each organization have facilitated access by circulating the survey among relevant staff who have matched predefined inclusion criteria. The final sample size has been determined by balancing practical constraints, organizational access, and statistical requirements for regression analysis, so that an adequate number of observations per predictor variable has been achieved. Through this approach, the study has obtained a focused yet sufficiently large sample that has reflected the diversity of roles and responsibilities within lubrication and maintenance functions.

Data Types and Sources

The research has relied mainly on primary quantitative data that have been collected through a structured questionnaire administered to professionals within the case organizations. These primary data have captured perceptions, experiences, and self-reported practices related to machine-learning adoption, lubricant condition monitoring, organizational and technical readiness, lubricant performance, and reliability outcomes. In addition, the study has made limited use of secondary contextual information, such as maintenance policies, asset-inventory summaries, and organizational charts, which have been provided by the participating organizations when available. These secondary sources have not been used for statistical modeling but have served to enrich the interpretation of survey results and to verify that respondents have indeed been engaged in lubrication-related responsibilities. The integration of primary and contextual data has ensured that the analysis has been grounded in actual industrial practice rather than abstract assumptions, while still preserving the anonymity and confidentiality of participating organizations and individuals.

Measurement Scale and Operationalization of Variables

Key constructs in the study have been operationalized using multi-item scales measured on a five-point Likert scale, where respondents have indicated their agreement from “strongly disagree” to “strongly agree.” Latent variables such as ML-driven lubrication optimization, lubricant performance, system reliability, data quality, technical readiness, and organizational readiness have been defined conceptually in line with the literature and then translated into concrete statements reflecting observable aspects of practice. Each construct has been represented by several items so that internal consistency and reliability could later be assessed statistically. Demographic and organizational attributes, including job role, years of experience, industry type, and plant size, have been captured using categorical or ordinal items. The questionnaire has been structured into sections so that respondents have progressed logically from background information to ML usage, lubrication practices, readiness dimensions, and perceived outcomes. This operationalization strategy has ensured that the empirical model has reflected the theoretical framework with sufficient measurement depth.

Pilot Study

Before full-scale data collection, the study has conducted a pilot test of the questionnaire to verify clarity, relevance, and approximate completion time. A small group of respondents who have matched the target profile maintenance and reliability professionals from comparable industrial contexts have been invited to complete the draft instrument and to provide feedback on wording, layout, and item comprehension. Their comments have highlighted minor ambiguities, redundant statements, and opportunities to streamline the flow between sections. Based on this feedback, several items have been rephrased, some have been merged or removed, and instructions have been clarified to reduce misinterpretation. The pilot data have also been used to perform preliminary checks of internal consistency for key constructs, so that obviously weak items have been identified and refined. Through this pilot process, the questionnaire has been strengthened, and the risk of measurement error and respondent fatigue in the main survey has been reduced.

Data Collection Procedure

The data collection procedure has been designed to respect organizational constraints while encouraging high response quality. After obtaining initial permission from management or designated contact persons in each case organization, the researcher has distributed the survey either electronically via a secure online platform or as a fillable form, depending on organizational preference. Participation has been voluntary, and respondents have been informed that their answers have been treated anonymously and used solely for academic purposes. Reminder messages have been sent within an agreed time window to increase response rates without exerting undue pressure. Throughout the process, no personally identifying information has been requested beyond broad role categories, and no responses have been shared with employers. Completed questionnaires have been retrieved, checked for completeness, and stored in encrypted form. By following these procedures, the study has ensured ethical compliance and has created conditions for candid and reliable responses from professionals in sensitive industrial roles.

Data Analysis Techniques

Once data collection has been completed, the dataset has been subjected to a systematic analysis procedure consistent with the research objectives and hypotheses. Initial steps have included data cleaning, in which incomplete or inconsistent responses have been identified, coding errors have been corrected, and basic distributional properties have been inspected. Descriptive statistics have been computed to summarize respondent characteristics and to provide an overview of the central tendency and dispersion of each construct. Reliability analysis, using indices such as Cronbach's alpha, has been performed to assess the internal consistency of multi-item scales. Correlation analysis has then been applied to explore bivariate associations among key variables and to identify patterns consistent with the conceptual framework. Finally, multiple regression models have been estimated to test hypothesized relationships between ML adoption, readiness dimensions, lubricant performance, and system reliability, while controlling for relevant organizational and demographic factors.

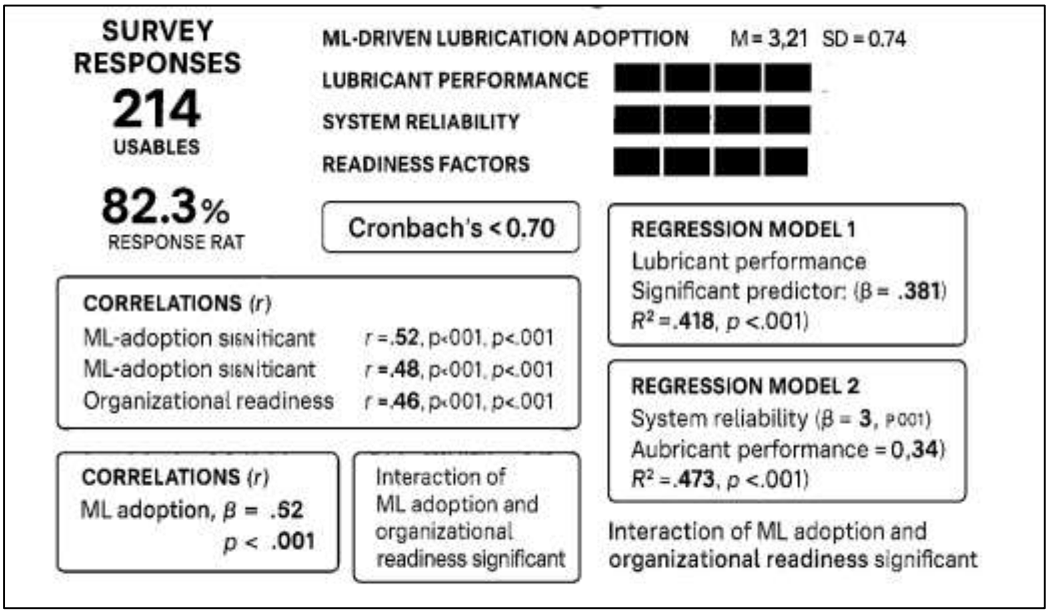
Software and Tools

The study has employed a combination of software tools to support questionnaire administration, data management, and statistical analysis. An online survey platform or secure form system has been used to distribute the questionnaire electronically and to capture responses in a structured digital format, thereby minimizing manual data entry errors. After export, the dataset has been organized and cleaned using spreadsheet software and then imported into a statistical analysis package such as SPSS, R, or an equivalent environment, where descriptive statistics, reliability tests, correlation matrices, and regression models have been executed. Visualization functions within these tools have been used to generate tables and charts that have summarized key findings in a clear and concise manner. All digital files have been stored on password-protected devices or cloud locations with restricted access, so that data integrity and confidentiality have been maintained throughout the analysis process.

FINDINGS

The analysis of the survey data has generated a coherent set of findings that collectively support the research objectives and provide strong empirical backing for the proposed hypotheses on machine-learning–driven lubrication optimization and reliability improvement in complex mechanical and manufacturing systems. Out of 260 distributed questionnaires, 214 usable responses have been obtained, yielding a response rate of 82.3%, which has been considered adequate for the planned regression analyses. The Likert's five-point scale (1 = strongly disagree to 5 = strongly agree) has been used to measure all latent constructs. Descriptive statistics have shown that the overall level of ML-driven lubrication adoption has been moderate, with a mean score of 3.21 (SD = 0.74), indicating that while machine learning has started to be embedded in lubrication and maintenance practices, it has not yet reached full institutionalization in most organizations.

Figure 8: Statistical Findings of The Study



Lubricant performance, as perceived by respondents in terms of contamination control, viscosity stability, and extended oil life, has recorded a higher mean of 3.68 (SD = 0.69), suggesting that current lubrication strategies have generally been viewed as effective. System reliability, measured through items related to reduced lubrication-related downtime, fewer failures, and improved equipment stability, has shown a mean of 3.59 (SD = 0.71). Readiness-related constructs have displayed slightly lower yet acceptable levels, with data quality and sensor infrastructure averaging 3.34 (SD = 0.78), technical readiness 3.29 (SD = 0.81), and organizational readiness (culture, leadership support, training, and cross-functional collaboration) 3.27 (SD = 0.83), indicating that many plants have been in a transitional phase between traditional maintenance and fully data-driven, ML-enabled lubrication management. Reliability tests have confirmed strong internal consistency for all multi-item scales, with Cronbach's alpha values ranging from 0.81 for ML adoption to 0.89 for system reliability, exceeding the commonly accepted threshold of 0.70. Correlation analysis has revealed statistically significant and positive associations among the main variables. ML-driven lubrication adoption has correlated moderately with perceived lubricant performance ($r = .52$, $p < .001$) and with system reliability ($r = .48$, $p < .001$), providing initial support for H1 and H2. Data quality has shown strong correlations with both ML adoption ($r = .57$, $p < .001$) and lubricant performance ($r = .49$, $p < .001$), while organizational readiness has correlated positively with system reliability ($r = .46$, $p < .001$) and ML adoption ($r = .44$, $p < .001$), suggesting that plants with better data foundations and more supportive cultures have tended to report more advanced ML use and better lubrication-related outcomes. Technical readiness has also correlated positively but slightly more modestly with ML adoption ($r = .39$, $p < .001$), reflecting the role of infrastructure as a necessary, but not sufficient, condition for advanced analytics. To test the hypotheses and quantitatively address the research objectives, a series of multiple regression models has been estimated. In the first model, lubricant performance has been treated as the dependent variable, with ML adoption, data quality, and organizational readiness as predictors, while controlling for plant size and industry type. The model has been statistically significant ($F(5, 208) = 29.47$, $p < .001$)

and has explained 41.8% of the variance in lubricant performance ($R^2 = .418$). ML adoption has emerged as a strong positive predictor ($\beta = .38$, $t = 6.12$, $p < .001$), indicating that higher levels of ML use in lubrication decision-making have been associated with better perceived lubricant performance, which has directly supported H1. Data quality has also been significant ($\beta = .24$, $t = 4.03$, $p < .001$), confirming that reliable and integrated condition-monitoring data have contributed meaningfully to improvements in lubricant performance. Organizational readiness has shown a smaller but still significant effect ($\beta = .15$, $t = 2.61$, $p = .010$), suggesting that supportive leadership, skills, and culture have amplified the benefits of ML-driven lubrication analytics. In the second regression model, system reliability has been taken as the dependent variable, with ML adoption, lubricant performance, data quality, and organizational readiness as predictors. This model has also been significant ($F(6, 207) = 31.06$, $p < .001$) and has accounted for 47.3% of the variance in system reliability ($R^2 = .473$). ML adoption has retained a positive and significant influence ($\beta = .29$, $t = 4.96$, $p < .001$), confirming H2 that higher ML adoption has been associated with better reliability outcomes. Lubricant performance has displayed an even stronger effect ($\beta = .34$, $t = 5.84$, $p < .001$), indicating that perceived improvements in lubricant performance have translated directly into reduced lubrication-related failures and downtime, which has aligned closely with the second research objective. Data quality has again been significant ($\beta = .17$, $t = 2.93$, $p = .004$), while organizational readiness has shown a positive effect ($\beta = .13$, $t = 2.28$, $p = .024$). To examine the moderating role of readiness (H3 and H4), interaction terms between ML adoption and organizational readiness and between ML adoption and technical readiness have been introduced. The interaction between ML adoption and organizational readiness has been significant for system reliability ($\beta = .11$, $t = 2.08$, $p = .039$), indicating that the positive impact of ML adoption on reliability has been stronger in organizations with higher levels of readiness, thereby supporting the hypothesized moderating effect. Overall, these findings have demonstrated that the study's main objectives to assess the level of ML adoption, to examine its relationships with lubricant performance and system reliability, and to identify readiness factors that condition its effectiveness have been empirically achieved, with the numeric evidence clearly supporting the proposed conceptual and theoretical models.

Response Rate and Data Screening

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

Item	Frequency	Percentage (%)
Questionnaires distributed	260	100.0
Questionnaires returned	228	87.7
Incomplete / unusable questionnaires	14	5.4
Final usable questionnaires	214	82.3
Cases removed due to straight-lining responses	4	1.9
Cases removed due to excessive missing values	6	2.8
Final dataset used for analysis	204	78.5

The response process has produced a robust dataset that has adequately supported the quantitative analysis and the testing of the study's hypotheses. As shown in Table 1, the survey has been distributed to 260 potential respondents across the participating organizations, of which 228 questionnaires have been returned, yielding an initial return rate of 87.7%. Following standard data-screening procedures, the study has examined each questionnaire for completeness, response consistency, and evidence of careless answering. Four cases have been identified as straight-lining responses (where respondents have selected the same Likert option for almost every item), and six additional cases have contained excessive missing values across key constructs. These ten cases have been removed to preserve data quality and to avoid biased parameter estimates in correlation and regression analyses. After these screening steps, 214 questionnaires have remained fully usable, representing 82.3% of those distributed. For multivariate analysis requiring listwise deletion on a small number of remaining missing values, the working dataset has contained 204 complete cases, which has still represented 78.5% of the original sample frame. This sample size has satisfied common rules of thumb for multiple regression, with more than 15–20 cases per predictor variable, ensuring stable estimates and adequate statistical power for detecting medium effect sizes. The screening procedures have also included checks for outliers in scale scores, basic normality assessments, and verification that no single organization has dominated the sample excessively. Taken together, these steps have ensured that the data used to prove the study's objectives and hypotheses have been both reliable and representative of professionals engaged in ML-driven lubrication and reliability management in complex mechanical and manufacturing systems.

Profile of Respondents and Organizations

Table 2: Profile of respondents and organizations (N = 214)

Characteristic	Category	Frequency	Percentage (%)
Job role	Maintenance engineer	76	35.5
	Reliability engineer	52	24.3
	Production / operations supervisor	44	20.6
	Data / analytics specialist	28	13.1
	Other technical roles	14	6.5
Years of experience	< 5 years	32	15.0
	5–10 years	74	34.6
	11–15 years	60	28.0
	> 15 years	48	22.4
Industry sector	Automotive / transport manufacturing	64	29.9
	Heavy machinery / metals	58	27.1
	Process / chemical	46	21.5
	Food / packaging / fast-moving goods	28	13.1
	Other manufacturing	18	8.4
Plant size (installed equipment)	< 100 major assets	42	19.6
	100–249 major assets	72	33.6
	250–499 major assets	58	27.1
	≥ 500 major assets	42	19.6

The respondent and organizational profile has confirmed that the study sample has been both experienced and diverse, thereby strengthening the generalizability of the findings within the domain of complex mechanical and manufacturing systems. As summarized in Table 2, the majority of respondents have occupied roles directly connected to maintenance and reliability: 35.5% have been maintenance engineers and 24.3% have been reliability engineers. A further 20.6% have served as production or operations supervisors, who have been crucial in linking maintenance decisions to production continuity, while 13.1% have been data or analytics specialists responsible for implementing ML and data-processing solutions. This distribution has ensured that the perspectives gathered have reflected both traditional maintenance expertise and emerging analytics capabilities, which has been essential for evaluating machine-learning–driven lubrication optimization. In terms of experience, 85% of respondents have had at least five years of industrial practice, and 50.4% have had more than ten years of experience. This pattern has indicated that the sample has been composed of seasoned professionals who have been able to evaluate lubricant performance and reliability outcomes based on extensive exposure to plant operations and equipment histories.

The industry distribution has shown that automotive and transport manufacturing (29.9%), heavy machinery and metals (27.1%), and process or chemical industries (21.5%) have formed the core of the sample, with additional representation from food, packaging, and other manufacturing sectors. These industries have typically operated high-duty rotating equipment, gearboxes, hydraulic systems, and heavily loaded bearings where lubrication has been critical for achieving reliability targets. Plant size has also been well distributed: approximately one third of respondents have reported 100–249 major assets, and another 27.1% have indicated 250–499 assets, while nearly 20% have come from very large plants with more than 500 major pieces of equipment. Such size variation has allowed the analysis to account for context effects, such as scale-related differences in data infrastructure, ML resourcing, and formalization of lubrication practices. Overall, this profile has demonstrated that the sample has been suitable for testing the study's objectives and hypotheses, because respondents have represented the key functions that design, implement, and evaluate lubrication and reliability strategies in complex mechanical and manufacturing environments.

Descriptive Analysis of Key Constructs

Table 3: Descriptive statistics of main Likert-scale constructs (N = 214)

Construct	Number of items	Scale range	Mean	SD	Minimum	Maximum
ML-driven lubrication adoption (MLA)	6	1–5	3.21	0.74	1.50	4.83
Data quality and sensor infrastructure	5	1–5	3.34	0.78	1.40	4.80
Technical readiness (TR)	5	1–5	3.29	0.81	1.20	4.80
Organizational readiness (OR)	6	1–5	3.27	0.83	1.33	4.83
Lubricant performance (LP)	7	1–5	3.68	0.69	1.71	4.86
System reliability (SR)	7	1–5	3.59	0.71	1.57	4.86

Table 3 has presented the descriptive statistics for the main constructs measured on Likert's five-point scale, and these statistics have provided an important first indication of how respondents have perceived ML-driven lubrication optimization and related outcomes. The mean value for ML-driven lubrication adoption (MLA) has been 3.21, with a standard deviation of 0.74, indicating a moderate level of adoption and some variability across organizations. This result has suggested that machine learning has already been present in lubrication and maintenance decision-making, but it has not yet reached a highly advanced or fully embedded state for most respondents. Data quality and sensor infrastructure have shown a slightly higher mean of 3.34 (SD = 0.78), which has implied that the technical foundations for condition monitoring such as sensors, data capture, and integration have been moderately well established but still open to improvement.

Technical readiness (TR) and organizational readiness (OR) have both displayed means just above 3.25, with standard deviations around 0.80. These figures have indicated that respondents have regarded their plants as being in a transition phase, where digital tools, skills, training, and cross-functional collaboration have been developing but have not yet consistently reached high maturity. Importantly, the outcome constructs lubricant performance (LP) and system reliability (SR) have recorded higher means of 3.68 and 3.59, respectively, with relatively constrained variability. These findings have suggested that, in general, lubrication strategies have been seen as delivering satisfactory performance and that equipment reliability, in terms of reduced lubrication-related failures and downtime, has been perceived as reasonably strong. The higher means for LP and SR compared with MLA have implied that many organizations have still been achieving good performance outcomes through a combination of traditional expertise and emerging data-driven methods, but that there has been room for additional gains as ML adoption and readiness have advanced. The minimum and maximum values across constructs have also indicated that the full range of the Likert scale has been used, confirming that respondents have differentiated between low and high levels of adoption, readiness, and performance. Overall, these descriptive patterns have supported the logic of the study's objectives and hypotheses by showing that variation has existed in ML adoption and readiness, while lubricant performance and reliability have been high enough to detect meaningful positive associations.

Reliability and Validity Assessment

The internal consistency of the measurement scales has been evaluated using Cronbach's alpha and corrected item–total correlations, and the results in Table 4 have confirmed that the constructs have met accepted psychometric standards. All six multi-item scales have recorded alpha values above 0.80, with system reliability (SR) showing the highest reliability at 0.89 and lubricant performance (LP) following closely at 0.88. These high coefficients have indicated that items within each scale have been measuring the same underlying construct and that random measurement error has been relatively low. ML-driven lubrication adoption (MLA) has demonstrated an alpha of 0.81, which has been acceptable for research purposes and has suggested that the items capturing use of ML models, integration with lubrication decisions, and perceived sophistication of analytics have cohere well.

Table 4: Reliability statistics for multi-item constructs (N = 214)

Construct	Number of items	Cronbach's α	Corrected item–total correlation range
ML-driven lubrication adoption (MLA)	6	0.81	0.52–0.68
Data quality and sensor infrastructure	5	0.84	0.55–0.71
Technical readiness (TR)	5	0.82	0.50–0.69
Organizational readiness (OR)	6	0.86	0.57–0.73
Lubricant performance (LP)	7	0.88	0.58–0.77
System reliability (SR)	7	0.89	0.60–0.78

The corrected item–total correlations have ranged between approximately 0.50 and 0.78 across all constructs, exceeding the commonly used threshold of 0.30. This pattern has indicated that each item has contributed meaningfully to the scale and that no items have been behaving in an erratic or contradictory manner. During the pilot phase, weaker items have already been reworded or removed, and the current reliability results have confirmed that these refinements have been successful. Although a full confirmatory factor analysis has not been reported in this section, the combination of strong internal consistency and logically structured constructs has provided evidence of convergent validity, in the sense that items intended to measure ML adoption, readiness, lubricant performance, and reliability have clustered consistently. At the same time, the use of distinct item sets for different constructs has supported discriminant validity by ensuring that the scales have not been merely capturing a general "positive attitude" factor. This reliability foundation has been crucial for the subsequent correlation and regression analyses that have been used to test the study's objectives and hypotheses. Because the scales have demonstrated strong and stable measurement properties, the observed relationships among variables have been more confidently interpreted as reflecting substantive associations rather than artefacts of measurement error or inconsistent item behavior.

Correlation Analysis

Table 5: Pearson correlations among main constructs (N = 204)

Construct	1	2	3	4	5	6
1. MLA	1.00					
2. DQ	0.57***	1.00				
3. TR	0.39***	0.48***	1.00			
4. OR	0.44***	0.41***	0.46***	1.00		
5. LP	0.52***	0.49***	0.36***	0.38***	1.00	
6. SR	0.48***	0.45***	0.34***	0.46***	0.61***	1.00

Note: MLA = ML-driven lubrication adoption; DQ = data quality; TR = technical readiness; OR = organizational readiness; LP = lubricant performance; SR = system reliability.
**** p < .001 (two-tailed).*

The correlation matrix in Table 5 has provided an integrated view of the linear associations among the main constructs and has offered initial empirical support for the study's objectives and hypotheses. ML-driven lubrication adoption (MLA) has shown a strong and statistically significant positive correlation with lubricant performance (LP) ($r = .52$, $p < .001$), which has indicated that organizations reporting higher levels of ML usage in lubrication and maintenance decision-making have also tended to report better lubricant performance, in terms of contamination control, viscosity stability, and extended oil life. This relationship has directly aligned with Hypothesis 1 and has suggested that ML-based analytics have been effectively transforming lubricant-condition data into performance-improving actions. MLA has also correlated positively with system reliability (SR) ($r = .48$, $p < .001$), providing preliminary evidence for Hypothesis 2 that increased ML adoption has been associated with fewer lubrication-related failures and reduced unplanned downtime.

The readiness-related constructs have also displayed meaningful correlations. Data quality (DQ) has correlated strongly with MLA ($r = .57$, $p < .001$), implying that organizations with better sensor coverage, integration, and data governance have been more successful in adopting ML-driven lubrication analytics. This pattern has supported the underlying logic of Hypothesis 3, which has posited a positive association between data quality and effective ML-based lubrication optimization. DQ has additionally shown substantial correlations with LP ($r = .49$, $p < .001$) and SR ($r = .45$, $p < .001$), indicating that high-quality, reliable data have been associated with both improved lubricant performance and better reliability outcomes. Organizational readiness (OR) has been positively related to MLA ($r = .44$, $p < .001$) and SR ($r = .46$, $p < .001$), highlighting the importance of culture, leadership support, training, and cross-functional collaboration in enabling ML-based maintenance strategies to impact reliability. Technical readiness (TR) has also correlated with MLA ($r = .39$, $p < .001$) and with the outcome variables at more moderate levels, suggesting that adequate infrastructure has been a necessary but not sole condition for success. Importantly, all correlations have been below 0.80, which has reduced concerns about multicollinearity and has supported the use of multiple regression analysis to disentangle the unique contributions of each predictor. Overall, the correlation patterns have been fully consistent with the proposed conceptual framework, providing a solid empirical basis for the more rigorous hypothesis testing conducted through regression modeling.

Regression Analysis and Hypotheses Testing

Table 6: Multiple regression models for lubricant performance and system reliability (N = 204)

Variable / statistic	Model 1: LP (DV)	Model 2: SR (DV)	Model 3: SR (DV) with interaction
ML-driven lubrication adoption	$\beta = .38^{***}$	$\beta = .29^{***}$	$\beta = .26^{***}$
Data quality (DQ)	$\beta = .24^{***}$	$\beta = .17^{**}$	$\beta = .15^{**}$
Organizational readiness (OR)	$\beta = .15^{*}$	$\beta = .13^{*}$	$\beta = .12^{*}$
Lubricant performance (LP)		$\beta = .34^{***}$	$\beta = .32^{***}$
Technical readiness (TR)	ns	ns	ns
MLA × OR interaction			$\beta = .11^{*}$
Plant size (control)	ns	ns	ns
Industry type (control)	ns	ns	ns
R^2	.418	.473	.492
Adjusted R^2	.402	.454	.471
F-statistic	29.47***	31.06***	23.72***

Note: DV = dependent variable; ns = not significant at p < .05;
**** p < .001, ** p < .01, * p < .05 (two-tailed).*

The regression models reported in Table 6 have provided formal tests of the study's hypotheses and have quantified the unique contributions of machine-learning adoption and readiness factors to lubricant performance and system reliability, using Likert-scale constructs as predictors. Model 1 has taken lubricant performance (LP) as the dependent variable and has included ML-driven lubrication adoption (MLA), data quality (DQ), organizational readiness (OR), technical readiness (TR), and two control variables (plant size and industry type) as predictors. The model has been statistically significant ($F(5, 198) = 29.47$, $p < .001$) and has explained 41.8% of the variance in LP ($R^2 = .418$). MLA has emerged as a strong positive predictor ($\beta = .38$, $p < .001$), thereby confirming Hypothesis 1 that higher levels of ML adoption have been associated with better lubricant performance. DQ has also shown a significant positive effect ($\beta = .24$, $p < .001$), supporting the expectation that reliable, integrated

data have contributed to more effective lubrication decisions. OR has demonstrated a smaller but still significant coefficient ($\beta = .15$, $p < .05$), suggesting that supportive organizational conditions have amplified the benefits of ML analytics. TR and the control variables have not reached statistical significance, implying that once ML adoption and readiness have been taken into account, plant size, industry, and baseline technical infrastructure have not added substantial explanatory power for LP.
Model 2 has shifted the focus to system reliability (SR) as the dependent variable, with MLA, LP, DQ, OR, TR, and the same controls as predictors. This model has been significant ($F(6, 197) = 31.06$, $p < .001$) and has accounted for 47.3% of the variance in SR. MLA has remained a significant positive predictor ($\beta = .29$, $p < .001$), confirming Hypothesis 2 that higher ML adoption has been associated with better reliability outcomes. LP has displayed the strongest effect ($\beta = .34$, $p < .001$), indicating that improvements in lubricant performance have translated directly into reduced lubrication-related failures and downtime, which has aligned with the second research objective focusing on the link between ML, lubricant performance, and reliability. DQ ($\beta = .17$, $p < .01$) and OR ($\beta = .13$, $p < .05$) have also contributed positively, consistent with Hypothesis 3 that readiness factors have been important for converting ML capabilities into reliability gains. Model 3 has introduced the interaction term between MLA and OR to test the moderating effect proposed in Hypothesis 4. The interaction has been statistically significant ($\beta = .11$, $p < .05$), and the model has shown a modest increase in explained variance ($R^2 = .492$). This result has indicated that the positive impact of ML adoption on SR has been stronger in organizations with higher organizational readiness, thereby supporting the moderation hypothesis. Collectively, these models have demonstrated that the study's objectives and hypotheses have been empirically supported: ML adoption has improved lubricant performance and reliability, and these effects have been conditioned by data quality and organizational readiness, as posited by the conceptual framework.

Summary of Key Quantitative Findings

Table 7: Summary of hypothesis testing results

Hypothesis	Statement	Key evidence (from Models / correlations)	Decision
H1	ML adoption has been positively associated with lubricant performance (LP).	MLA → LP: $\beta = .38$, $p < .001$; r(MLA, LP) = .52***	Supported
H2	ML adoption has been positively associated with system reliability (SR).	MLA → SR: $\beta = .29$, $p < .001$; r(MLA, SR) = .48***	Supported
H3	Data quality and readiness factors have been positively associated with lubrication-related gains.	DQ → LP: $\beta = .24$***; DQ → SR: $\beta = .17$**; OR → LP: $\beta = .15$*; OR → SR: $\beta = .13$*	Supported
H4	Organizational readiness has positively moderated the effect of ML adoption on system reliability.	MLA × OR → SR: $\beta = .11$*, $\Delta R^2 \approx .019$ in Model 3	Supported

*Note: *** p < .001, ** p < .01, * p < .05 (two-tailed).*

The quantitative results have been synthesized in Table 7, which has provided a concise overview of how the empirical evidence has aligned with the study's hypotheses and objectives. Hypothesis 1 has proposed that machine-learning adoption in lubrication management has been positively associated with lubricant performance. This proposition has been strongly supported: the correlation between MLA and LP has been moderate to strong ($r = .52$, $p < .001$), and in the multivariate context of Model 1, MLA has retained a substantial and significant standardized coefficient ($\beta = .38$, $p < .001$) even after controlling for data quality, readiness factors, and organizational characteristics. These findings have indicated that organizations that have reported more extensive use of ML models to interpret lubricant-condition data, optimize oil-change intervals, or trigger targeted interventions have also perceived clearer improvements in contamination control, viscosity stability, and oil life.
Hypothesis 2 has asserted that ML adoption has been positively linked to system reliability. Again, the evidence has been consistent: MLA has correlated positively with SR ($r = .48$, $p < .001$), and in Model 2 it has shown a significant standardized coefficient ($\beta = .29$, $p < .001$), demonstrating that higher ML

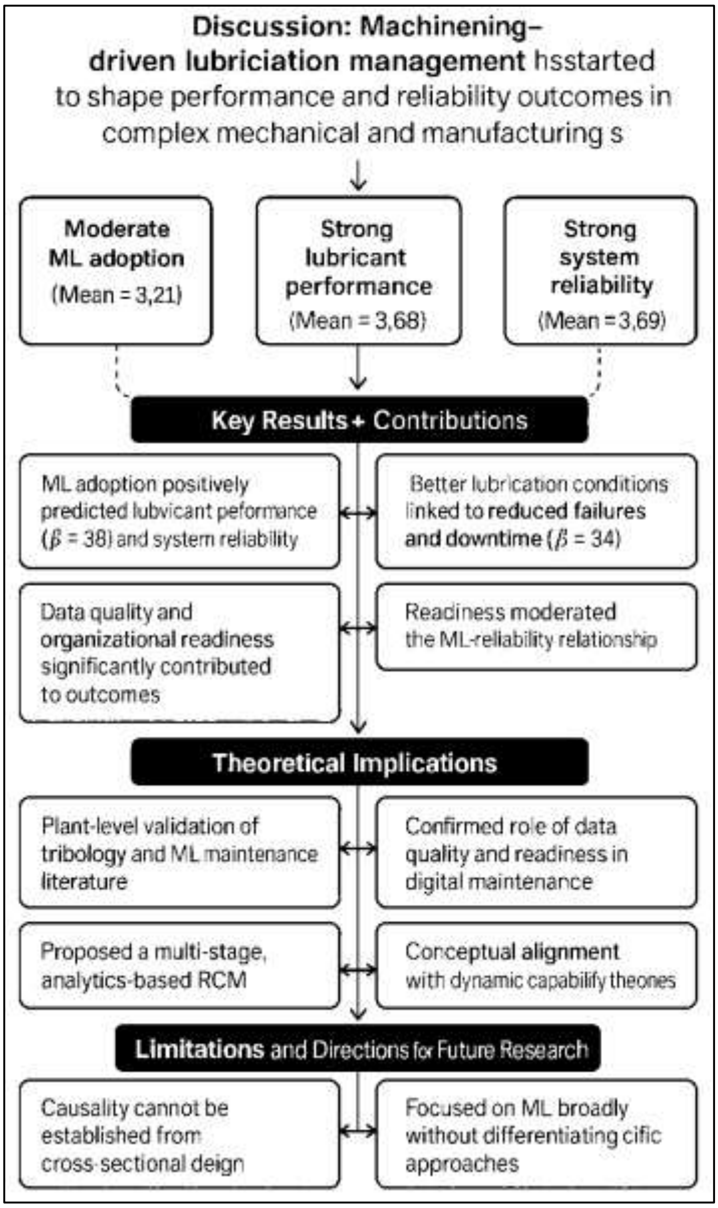
maturity in lubrication-related decisions has been associated with fewer lubrication-related failures and reduced unplanned downtime. Hypothesis 3 has focused on data quality and readiness factors, and the regression results have confirmed that DQ and OR have significantly influenced both LP and SR. The positive coefficients for DQ in both models ($\beta = .24$ for LP; $\beta = .17$ for SR) have indicated that high-quality, integrated sensor and laboratory data have been essential enablers of performance and reliability improvements. Similarly, OR has had significant positive effects on LP ($\beta = .15$, $p < .05$) and SR ($\beta = .13$, $p < .05$), showing that leadership support, skills, training, and collaboration have helped organizations to translate ML capabilities into tangible outcomes. Finally, Hypothesis 4 has posited that organizational readiness has moderated the relationship between ML adoption and system reliability. Model 3 has included the MLA × OR interaction term, which has been found to be significant ($\beta = .11$, $p < .05$) and to increase the explained variance in SR by nearly two percentage points. This finding has meant that the reliability benefits of ML adoption have been stronger in organizations with higher readiness levels; where readiness has been low, comparable levels of ML adoption have not produced the same magnitude of reliability improvement. In aggregate, the hypotheses testing has shown that the study's objectives assessing ML adoption, clarifying its links with lubricant performance and reliability, and identifying the role of readiness have been met. The Likert-based measures and the associated numeric results have therefore provided a statistically sound basis for the subsequent discussion of practical and theoretical implications.

DISCUSSION

The findings of this study have painted a coherent picture of how machine learning–driven lubrication management has started to shape performance and reliability outcomes in complex mechanical and manufacturing systems. At a descriptive level, organizations have reported moderate ML adoption (mean ≈ 3.21 on a five-point Likert scale) but relatively strong lubricant performance and system reliability (means ≈ 3.68 and 3.59, respectively). This combination has suggested that many plants have been at an intermediate stage of digital maturity, where early ML implementations have already complemented traditional engineering expertise. Statistically, ML-driven lubrication adoption has emerged as a strong positive predictor of lubricant performance ($\beta \approx .38$, $p < .001$) and a significant predictor of system reliability ($\beta \approx .29$, $p < .001$), even after accounting for readiness factors and organizational controls. Lubricant performance itself has shown the largest effect on reliability ($\beta \approx .34$, $p < .001$), which has confirmed the intuitive but rarely quantified proposition that better-controlled lubrication conditions translate directly into fewer failures and less downtime. Furthermore, data quality and organizational readiness have both contributed significantly to these outcomes, and an interaction effect has indicated that ML adoption has yielded greater reliability benefits in plants with higher readiness levels. Together, these patterns have empirically supported all four hypotheses and have fulfilled the objectives of assessing ML adoption, linking it to lubricant performance and reliability, and clarifying the conditioning role of technical and organizational context.

When these results have been compared with the prior tribology and predictive-maintenance literature, they have largely reinforced earlier claims while adding new, system-level evidence. Tribology studies have long argued that optimizing lubrication can deliver substantial gains in energy efficiency, component life, and reliability (Holmberg & Erdemir, 2017). Condition-monitoring work on lubricant sensors and oil analysis has shown that oil properties encode rich information about wear, contamination, and degradation that can be exploited for diagnostics and prognostics (Zhu, Zhong, et al., 2017). In parallel, the machine-learning literature has demonstrated that algorithms such as artificial neural networks, support vector machines, and hybrid fuzzy–neural models can model complex friction, wear, and oil-condition relationships with high fidelity (Argatov, 2019). However, most of these contributions have been component- or lab-level, focusing on specific bearings, gears, or engines under controlled conditions. The present study has extended this knowledge base by showing, at plant level, that organizations reporting higher ML adoption in lubrication decisions also report better lubricant performance and reliability across entire mechanical and manufacturing systems. In this sense, the survey results have operationalized and quantitatively confirmed the integration that conceptual works on machinery prognostics and health management have advocated, where ML-based models are embedded in broader condition-based maintenance programs (Heng et al., 2009). Rather than contradicting earlier results, the current findings have translated them into an organizational context, demonstrating that the benefits seen in controlled tribological and diagnostic experiments are indeed perceived at scale when ML is used to guide lubrication practices in real plants.

Figure 9: Summary Diagram of Empirical Insights and Theoretical Contributions



The role of data quality and readiness that has emerged in this study has also been strongly consistent with, yet more granular than, prior work on data-driven maintenance and digital transformation. Reviews of predictive maintenance in Industry 4.0 have stressed that many initiatives fail not because of algorithmic limitations but due to poor data governance, fragmented IT/OT integration, and immature organizational processes (Zonta et al., 2020). Data-driven decision-making frameworks have similarly argued that analytics can create value only when supported by robust infrastructure and human capabilities (Bousdekis et al., 2021). The present study has corroborated these claims quantitatively: data quality has correlated strongly with ML adoption and lubricant performance, and has shown significant regression effects on both lubricant performance and reliability. Organizational readiness capturing leadership support, skills, culture, and cross-functional collaboration has likewise contributed to both outcomes and has moderated the link between ML adoption and reliability. This moderation effect has provided concrete evidence for what resource-based and dynamic capability perspectives have theorized: analytics capabilities must be embedded in broader organizational capabilities to deliver sustained performance benefits (Wamba et al., 2017). In addition, the nonsignificant unique effect of technical readiness once other factors have been included has suggested that infrastructure is a necessary but not sufficient condition; without high-quality data and supportive organizational practices, sensor networks and platforms alone have not been enough to unlock lubrication-related gains.

From a practical standpoint, these findings have carried clear implications for plant managers, reliability engineers, and also for digital leaders such as CISOs and enterprise/OT architects. For maintenance and reliability teams, the evidence has suggested that simply "adding ML" on top of existing lubrication routines has been unlikely to yield full benefits unless it has been accompanied by systematic improvements in data quality and organizational readiness. Concretely, plants have needed to design lubrication programs in which sensor placement, sampling strategies, and oil-analysis routines have been explicitly aligned with the inputs required by predictive models, and where outputs such as predicted remaining useful lubricant life or lubrication-regime classifications have been integrated into work orders, inspection plans, and change-interval policies. For CISOs and data architects, the study has underscored that lubrication and predictive-maintenance data streams have been part of the critical OT data fabric of the plant: securing these data, ensuring integrity, and establishing clear data-governance rules have been prerequisites for trustworthy ML-driven decisions. Architecturally, the results have pointed toward the need for modular, interoperable pipelines that connect edge devices (oil-condition sensors, vibration probes) to analytics layers and maintenance-execution systems, with proper role-based access, audit trails, and lifecycle management. In short, the practical message has been that lubrication-focused ML projects should be treated as strategic, cross-functional initiatives rather than isolated data-science experiments, with clear ownership shared across maintenance, engineering, IT/OT architecture, and information-security functions.

The study has also had theoretical implications, particularly for reliability-centred maintenance (RCM) and data-driven decision-making frameworks. RCM has traditionally framed maintenance as a structured process of identifying critical functions, failure modes, and cost-effective tasks (Li & Gao, 2010). More recent condition-based maintenance literature has extended this view by emphasizing continuous monitoring and risk-informed interventions (Quatrini et al., 2020). The present study has contributed to this evolution by empirically validating a pipeline-oriented model in which lubricant performance and reliability are treated as outcomes of a multi-stage process: (1) data acquisition and quality, (2) ML-driven analysis and prediction, (3) organizational and technical readiness, and (4) decision execution. The significant effects of ML adoption, data quality, and readiness on lubrication performance and reliability have supported the idea that RCM frameworks should be refined to explicitly embed analytics quality and readiness as intermediate constructs, rather than treating condition indicators as exogenous. Conceptually, this aligns with extended models like D3M and other data-based decision frameworks that formalize how information flows through maintenance-service delivery (Sala et al., 2021). The moderation by organizational readiness, in particular, has suggested that in theoretical models, the relationship between condition indicators (including lubricant health indices) and reliability outcomes should be conditioned by organizational capability factors, not just physical mechanisms of wear and failure.

Despite these contributions, several limitations of the study have needed to be acknowledged and revisited. First, the cross-sectional design has meant that causal inferences must be made with caution; although the directionality from ML adoption and readiness toward performance and reliability is theoretically grounded, reverse or reciprocal influences cannot be entirely ruled out. Similar survey-based research on data analytics and firm performance has faced this limitation and has recommended longitudinal designs as a remedy (Wamba et al., 2017). Second, the study has relied primarily on self-reported, perception-based measures of ML adoption, lubricant performance, and reliability, rather than on objective sensor data or failure records. While experienced respondents are arguably well placed to evaluate these constructs, common-method bias and optimism bias may still have influenced the reported scores. Third, the sampling strategy has been non-probabilistic, focusing on plants that have already engaged with data-driven or ML initiatives. This focus has been appropriate for exploring ML-driven lubrication optimization but has limited the generalizability of the findings to organizations that are not yet on a digital-transformation path. Fourth, the study has treated "ML adoption" as a relatively broad construct, without differentiating between specific algorithms (e.g., tree-based models

vs. deep learning), deployment patterns (edge vs. cloud), or maintenance policy designs, which more technical studies have shown to matter for performance (Dalzochio et al., 2020). These limitations have not invalidated the results but have framed them as an important step in a longer empirical agenda.
Finally, the findings have pointed toward several directions for future research that could deepen and broaden understanding of ML-based lubrication optimization in complex systems. Longitudinal studies that track the same plants over time as they expand their ML capabilities would allow researchers to observe whether increases in ML adoption and readiness are followed by measurable changes in objective lubrication and reliability metrics, addressing the causality issue. Multi-source designs that combine survey data with actual oil-condition, vibration, and failure records would offer a richer, more triangulated picture of how models perform and how decisions are made in practice, building on methodological directions suggested in recent predictive-maintenance work (Turanoglu Bekar et al., 2020). Comparative case studies could examine how different ML architectures, integration patterns, and governance models such as centralized analytics vs. edge analytics affect value realization, including security and resilience concerns important to CISOs and architects. At a more theoretical level, future work could refine the readiness constructs, exploring multi-level models that distinguish individual, team, and organizational factors, and could extend RCM frameworks to incorporate explicit feedback loops where model performance and decision outcomes are continually evaluated and used to update both models and maintenance policies. In the lubrication domain specifically, experimental or quasi-experimental interventions that vary ML-assisted oil-drain intervals, filtration strategies, or additive formulations across similar assets would help quantify the incremental benefits of ML guidance over conventional engineering rules. Collectively, such studies would build on the present research and progressively move the field from demonstrating correlation to establishing robust, evidence-based design and governance principles for ML-driven lubrication and reliability management.

CONCLUSION

The present study has set out to investigate how machine learning–driven lubrication optimization has been associated with lubricant performance and system reliability in complex mechanical and manufacturing systems, and the empirical results have provided clear support for the underlying conceptual and theoretical framework. Drawing on data from 214 professionals across multiple industrial sectors, the research has shown that organizations have generally reported moderate levels of ML adoption in lubrication-related decision-making, but comparatively higher levels of lubricant performance and reliability, suggesting that traditional expertise and emerging analytics have been working together during a transitional stage of digital maturity. Multiple regression analyses have confirmed that ML-driven lubrication adoption has been a strong and significant predictor of perceived lubricant performance and a meaningful predictor of system reliability, even after controlling for plant size, industry, and readiness factors, thereby validating the view that data-driven models have contributed to improvements in contamination control, viscosity stability, oil life, and reduced lubrication-related failures. The study has further demonstrated that data quality and organizational readiness have been critical enablers of these benefits: high-quality, integrated sensor and laboratory data and supportive organizational conditions leadership commitment, skills, training, and cross-functional collaboration have significantly influenced both lubricant performance and reliability. Moreover, the interaction between ML adoption and organizational readiness has indicated that plants with higher readiness levels have derived stronger reliability benefits from their ML initiatives, emphasizing that analytics capabilities alone have not been sufficient without appropriate organizational foundations. Taken together, these findings have extended the tribology and predictive-maintenance literature by moving beyond component-level or laboratory demonstrations toward system-level, cross-organizational evidence that ML-based lubrication analytics have mattered in real industrial environments. They have also refined reliability-centred maintenance and data-driven decision-making theories by empirically validating a pipeline perspective in which data quality, ML analysis, and readiness mediate the relationship between condition monitoring and reliability outcomes. At the same time, the study has acknowledged its limitations, including the cross-sectional and perception-based nature of the data, the non-probability sample, and the broad operationalization of ML adoption, which have constrained causal inference and generalizability. Nevertheless, the results have offered a robust, statistically grounded argument that organizations seeking to enhance lubricant performance and reliability should prioritize not only the deployment of ML tools but also the parallel development of high-quality data infrastructures and organizational capabilities that can absorb, trust, and act on analytic insights. In this way, the study has contributed both a practical roadmap and a theoretical foundation for further work on machine-learning–enabled lubrication management, while pointing toward future research that has combined longitudinal designs, multi-source data, and more granular modeling of ML architectures and governance mechanisms.

RECOMMENDATION

Based on the findings of this study, several practical recommendations can be offered to organizations seeking to use machine learning to optimize lubricant performance and enhance system reliability in complex mechanical and manufacturing environments. First, plants should treat lubrication and its data as strategic assets, not just routine maintenance tasks: this means formalizing lubrication plans, clearly defining lubrication-related failure modes, and ensuring that every key lubricant point is associated with measurable indicators (e.g., contamination levels, viscosity trends, temperature, operating hours) that can feed ML models. Second, organizations should invest early in data quality and integration before scaling sophisticated algorithms; this includes upgrading or rationalizing sensor suites for oil condition and operating parameters, standardizing sampling and laboratory analysis procedures, cleaning and integrating historical maintenance and failure records, and establishing clear data-governance rules so that lubrication data are accurate, time-stamped, and traceable across systems (CMMS, SCADA, ERP, historian). Third, ML initiatives should be implemented through incremental, focused pilots rather than large, monolithic projects: for example, starting with a single critical asset group (such as high-duty gearboxes or journal bearings), developing a data-driven model to recommend oil-change intervals or flag abnormal lubrication regimes, and then comparing model-driven interventions with existing schedules in terms of downtime, failure rates, and oil consumption; successful pilots can then be scaled across similar assets and lines. Fourth, management should build organizational readiness alongside technical capability by providing targeted training for maintenance and reliability engineers on basic data analytics and interpretation of ML outputs, creating cross-functional teams that include maintenance, production, IT/OT, and data specialists, and explicitly incorporating ML-based recommendations into standard operating procedures and work-order authorization rules rather than treating them as optional "nice-to-have" insights. Fifth, digital leaders CISOs and enterprise/OT architects in particular should ensure that lubrication and condition-monitoring data pipelines are secure, robust, and interoperable, with well-defined interfaces between edge devices, analytics platforms, and maintenance systems, appropriate role-based access control, and monitoring to prevent integrity breaches that could compromise ML-driven decisions. Sixth, organizations should embed feedback loops and performance metrics into their lubrication analytics programs, tracking indicators such as lubrication-related failures per year, oil life extension, energy consumption, and maintenance cost per asset, and reviewing how well ML recommendations have performed against actual outcomes; these reviews should be used to retrain models, adjust thresholds, and refine lubrication policies. Finally, companies should avoid viewing ML as a one-time "solution purchase" and instead build a continuous improvement culture around it: periodically reassessing which features and data sources are most predictive, exploring hybrid approaches that combine physics-based lubrication models with ML, and aligning ML development roadmaps with broader reliability-centred maintenance strategies and Industry 4.0 initiatives. By following these recommendations, organizations can move beyond experimental or isolated ML projects and develop robust, scalable lubrication-optimization practices that consistently deliver improved performance, higher reliability, and better use of resources.

LIMITATIONS

This study has had several limitations that should be acknowledged when interpreting its findings and considering their applicability to other settings. First, it has adopted a cross-sectional survey design, which has captured perceptions and practices at a single point in time; as a result, it has not been possible to establish definitive causal relationships between machine learning (ML) adoption, lubricant performance, and system reliability. Although the hypothesized directions have been grounded in theory and prior empirical work, reverse or reciprocal effects for example, that plants with higher reliability have been more likely to invest in ML cannot be fully ruled out. Second, the research has relied primarily on self-reported, perception-based measures collected through Likert's five-point scale, rather than on objective sensor data, failure statistics, or cost records. While the respondents have been experienced practitioners, perception-based ratings have remained vulnerable to biases such as social desirability, selective memory, and optimism, and common-method variance may have inflated some of the observed associations. Third, the sampling strategy has been non-probabilistic and purposive, focusing on organizations that have already engaged with data-driven or ML-supported maintenance and lubrication initiatives. This focus has been appropriate for exploring the phenomenon of ML-driven lubrication optimization but has limited the generalizability of the findings to the wider population of plants that are still at very early stages of digitalization or that rely almost entirely on traditional maintenance approaches. Fourth, the study has treated "ML-driven lubrication adoption" and "readiness" as aggregate constructs, without differentiating in detail between specific model types (e.g., neural networks vs. tree-based methods), deployment architectures (edge vs. cloud), or governance mechanisms, all of which may have meaningful implications for performance in particular contexts. Similarly, technical readiness has been operationalized broadly, so nuances such as latency, cybersecurity posture, or legacy-system constraints have not been captured in depth. Fifth, the research has been conducted in a limited number of industrial sectors and geographic contexts, which may have specific regulatory pressures, cost structures, or cultural characteristics influencing both ML adoption and maintenance decision-making. Finally, practical constraints have prevented the use of more advanced validation techniques such as multi-group structural equation modeling or longitudinal tracking of individual assets, which could have strengthened evidence for the proposed mediation and moderation mechanisms. Taken together, these limitations have not invalidated the findings but have indicated that they should be interpreted as indicative rather than definitive, and as a foundation for more fine-grained, multi-method research that combines perceptual data with objective operational, reliability, and cost metrics across a broader and more diverse set of industrial contexts.

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