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REVIEW

A Review of Artificial Intelligence Enabled Digital-Twin Technologies in Tribology

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ABSTRACT

Artificial intelligence and digital twin technologies have emerged as transformative tools for engineering systems that require accurate prediction, real-time monitoring, and adaptive decision-making. In tribology, conventional wear mitigation approaches rely heavily on empirical testing, simplified analytical models, and periodic condition-based maintenance strategies. While these methods have supported decades of engineering practice, they struggle to capture the multi-scale, multi-physics nature of friction, wear, and lubrication under dynamically changing operating conditions. Limitations such as delayed fault detection, limited adaptability to unseen regimes, high experimental cost, and an inability to integrate real-time system feedback motivate the need for more intelligent and responsive frameworks. Recent advances in artificial intelligence-enabled digital twins address these challenges by combining physics-based models, real-time sensor data, and data-driven learning algorithms within a continuously updated virtual representation of the physical system. In tribological applications, such frameworks enable near real-time prediction of frictional behavior, wear evolution, lubrication regime transitions, and remaining useful life, while supporting adaptive control and optimized maintenance decisions. This review consolidates the current research literature on artificial intelligence-enabled digital twin applications in tribology and lubricated mechanical systems, with emphasis on sensing technologies, hybrid modeling approaches, data management strategies, and system architectures. Key challenges, including data quality, computational burden, model interpretability, and scalability, are discussed alongside emerging solutions. Through an in-depth synthesis of peer-reviewed studies, this paper highlights how the integration of artificial intelligence and digital twins offers a robust pathway toward more reliable, efficient, and sustainable tribological systems.

1. INTRODUCTION

Tribology occupies a foundational position in the reliability and performance of mechanical systems because friction and wear are primary factors that limit the lifespan of components, raise energy consumption, and demand maintenance [1]. Traditionally, the field has relied on empirical observations, laboratory-based wear tests, and theoretical models to calculate wear volume and friction coefficients [2].

However, the evolution of artificial intelligence (AI) has begun to reshape perspectives on tribological data and model building. AI generally refers to computational techniques that enable machines to perform tasks typically requiring human intelligence, such as pattern recognition, reasoning, and decision-making [3-5]. By applying AI techniques, researchers have uncovered patterns in tribological data that were formerly invisible or exceedingly difficult to assess through purely theoretical approaches [6], [7].

The parallel emergence of digital twin (DT) frameworks extends this capability. A DT is a virtual replica of a physical object or system that is continuously updated using real-time data and a validated underlying model [8,9]. Unlike static digital models, DTs offer iterative and bidirectional data flow, enabling real-time monitoring and predictive simulations. In tribology, where conditions such as lubrication flow, contact temperature, and material wear evolve dynamically, DTs facilitate an adaptive and holistic approach to managing these factors [10].

By combining AI-driven analysis with sensor-based data acquisition, engineers gain the ability to generate near real-time predictions of tribological states and the ability to optimize lubrication schedules and component design. This review explores the convergence of AI and DT frameworks within the specialized context of tribology and lubricated mechanical systems and its implications for engineering design.

2. FUNDAMENTALS OF TRIBOLOGY AND DIGITAL TWINS

The term tribology traces back to the mid-twentieth century but has roots in millennia-old studies of friction and lubrication [11]. Tribological systems are inherently multi-scale and multi-physics, involving mechanical, thermal, chemical, and fluid dynamic phenomena [1]. Classical approaches rely on theoretical frameworks such as the Archard wear equation [12] or the friction models proposed by Bowden and Tabor [13]. These theoretical or empirical formulations enable fundamental understanding but do not easily accommodate the complexity of varying loads, surface topographies, lubricants, or real-time operational conditions. In contrast, DTs are a continuously updated digital representation that depends on data from sensors or other monitoring tools [14].

One of the critical differences between conventional modeling and a DT approach is the frequent or real-time synchronization with the physical asset [15]. For tribological applications, DT architecture typically starts with high-definition modeling of contact surfaces, lubrication channels, and load conditions. The synergy of flexible computational modules (finite element analysis, multi-body dynamics, fluid-structure interaction) with sensor-based data is essential. Sensors measuring vibration, temperature, torque, or acoustic emission feed into an overarching data platform, often enhanced by AI algorithms, to generate real-time forecasts of frictional behavior or wear rates [16].

The fundamental building blocks of an AI-enabled DT for tribology include data acquisition from physical sensors, data analysis through AI, physics-based modeling for validation, and feedback loops for system control and design refinement [17]. When all of these segments combine effectively, the DT does not just observe interactions between two surfaces but can run predictive scenarios, evaluate the effects of parameter changes, and then adapt the physical system accordingly.

3. AI TECHNIQUES AND THEIR RELEVANCE TO TRIBOLOGY

AI has gained renewed attention in recent years through the success of machine learning algorithms, particularly neural networks, support vector machines (SVM), random forests, and emerging architectures such as graph neural networks (GNN) [18]. In tribology, these techniques enable the extraction of patterns and relationships from large and often heterogeneous datasets that are difficult to capture using purely analytical or empirical models [19]. A structured overview of the principal AI techniques applied in tribology-oriented digital twins is provided in Table 1.

Table 1. Artificial intelligence techniques used in AI-enabled digital twins for tribology.

AI technique	Primary tribology task	Key strengths	Key limitations
Support Vector Machines (SVM)	Fault and wear-state classification	Effective with limited data; robust classifiers	Limited scalability; static models
Feedforward / Deep Neural Networks (DNN)	Friction and wear prediction	Captures strong nonlinearities	Low interpretability; data intensive
Convolutional Neural Networks (CNN)	Feature extraction from signals or images	Automated feature learning	Requires large labeled datasets
Recurrent Neural Networks (LSTM)	Wear evolution and RUL prediction	Captures temporal degradation trends	Training complexity; long data histories
Physics-informed neural networks (PINN)	Hybrid friction and lubrication modeling	Improved extrapolation, stability	Higher model and training complexity
Reinforcement learning (RL)	Adaptive lubrication and control	Enables real-time optimization	Safety, convergence, and validation challenges

Support vector machines have been widely adopted for classification tasks in tribological applications, especially in bearing fault diagnosis based on vibration data [20-23]. Their ability to construct robust decision boundaries makes them well suited for identifying discrete wear states or fault classes from high-dimensional feature spaces. SVM-based approaches are frequently employed where labeled datasets are limited, and fault categorization is the primary objective.

Deep neural networks, including feedforward and convolutional architectures, have demonstrated strong performance in supervised regression tasks related to tribology, such as mapping friction coefficients or wear rates to operating parameters including normal load, sliding speed, surface hardness, and lubricant properties [24-26]. By learning highly nonlinear input–output relationships, these models enable predictive capability across a wide range of operating conditions. Convolutional neural networks have also been applied to tribological signal representations and surface images, where automated feature extraction improves robustness relative to manually engineered descriptors.

Although less commonly applied, reinforcement learning has shown promise for optimizing control actions in real-time lubrication strategies [27-29]. Within a digital twin framework, reinforcement learning agents can interact with a virtual representation of the tribological system to learn control policies that minimize friction, wear, or energy consumption under variable operating conditions. These approaches extend AI use beyond prediction toward autonomous decision-making.

While individual AI techniques have demonstrated substantial capability, tribological systems pose unique challenges. Friction and wear processes are strongly governed by contact mechanics, lubrication theory, thermal transport, and material behavior. Purely data-driven models may struggle to generalize beyond the operating regimes represented in their training datasets, particularly in safety-critical or high-load applications. This limitation has motivated the development of hybrid modeling approaches that integrate machine learning with physics-based formulations.

The synergy between artificial intelligence and digital twins arises from the complementary strengths of data-driven learning and physics-based modeling. Hybrid digital twins integrate sensor-derived data streams with validated computational solvers, enabling AI models to estimate parameters or states that are difficult to measure directly while ensuring consistency with tribological principles [30-37]. In such frameworks, physics-based models constrain the solution space of the AI model, while data-driven components provide adaptability and responsiveness under evolving operating conditions.

Figure 1 illustrates this hybrid modeling concept within a tribology-oriented digital twin. Raw sensor data, including vibration, acoustic emission, temperature, and lubricant condition signals, are processed and transformed into features that feed both AI-based models and physics-based simulations. Data-driven models perform regression, classification, and sequence-based prediction tasks, such as estimating friction coefficients, wear rates, or remaining useful life. In parallel, physics-based models capture contact mechanics, elastohydrodynamic lubrication behavior, thermal effects, and wear laws. These two modeling pathways converge within a hybrid integration layer, where physical constraints, model correction strategies, or physics-informed learning approaches ensure that predictions remain consistent with governing tribological principles. The resulting state estimates support maintenance decisions, lubrication adjustment, and adaptive control, while feedback loops continuously update both AI and physics components.

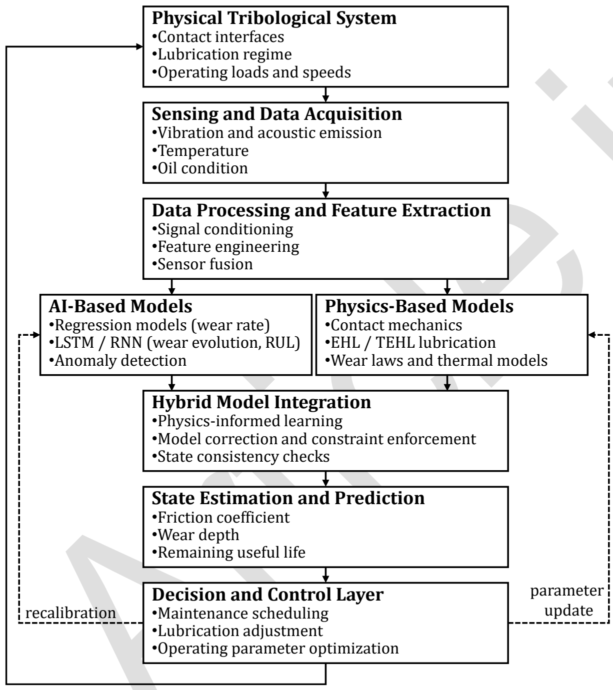

Fig. 1. Flowchart illustrating the integration of data-driven artificial intelligence models and physics-based tribological models within a hybrid digital twin framework.

Recent advances in physics-informed neural networks further formalize this integration by embedding governing equations and physical constraints directly into the training process. By enforcing consistency with lubrication theory or wear formulations during optimization, these models improve extrapolation stability and reduce the risk of physically implausible predictions. This approach is particularly valuable in tribology, where limited experimental data and complex multi-physics interactions can otherwise degrade model reliability.

Wear prediction via AI models often focuses on time-to-failure estimation. Recurrent neural networks, especially long short-term memory variants, are suitable for sequencing tasks and capturing the temporal evolution of surface degradation. Inputs may include historical vibration or oil debris sequences, while outputs estimate wear depth or failure intervals. These predictions can then be passed to the digital twin for scenario evaluation or proactive maintenance scheduling. SVM-based classifiers combined with dimensionality reduction techniques such as principal component analysis are frequently used to identify discrete wear stages in rotating machinery. By subdividing degradation processes into progressive classes, maintenance strategies can be refined and aligned with actual system conditions.

Collectively, the AI techniques summarized in Table 1 form the analytical core of AI-enabled digital twins for tribology. Their integration with physics-based simulations within hybrid modeling frameworks, as depicted in Figure 1, enables consistent state estimation, wear progression tracking, lubrication regime identification, and adaptive decision support. This hybrid paradigm underpins the predictive and responsive capabilities that distinguish digital twin–based tribological systems from traditional empirical or purely theoretical approaches.

4. DIGITAL TWIN ARCHITECTURE FOR TRIBOLOGICAL SYSTEMS

4.1. AI enabled digital twin architecture

Digital twins for tribology operate by integrating sensor data, physics-based models, and artificial intelligence into a unified representation of friction, wear, and lubrication behaviors. Although implementations vary by application, such as bearings, gears, piston-liner systems, hydraulic pumps, or wind turbine gearboxes, most tribology-focused digital twins follow a common four-layer architecture, as shown in

Figure 2. Establishing this architecture provides a consistent conceptual framework for interpreting the diverse methods and case studies reviewed throughout this paper.

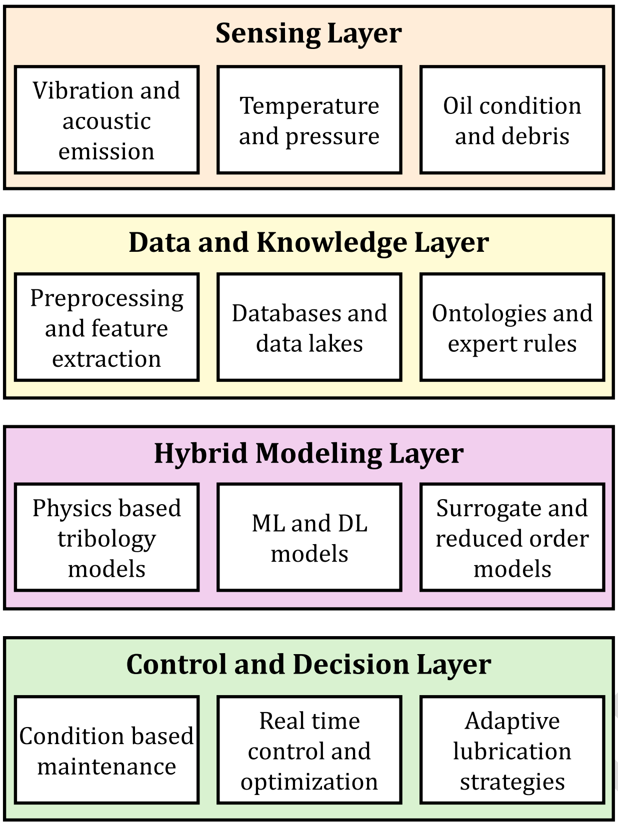

Fig. 2. Four layer digital twin architecture.

The sensing layer captures raw measurements from the physical system through vibration sensors, acoustic emission transducers, thermocouples, infrared detectors, oil-condition sensors, and torque or pressure sensors. The goal is to observe tribological states that evolve over time, including film thickness changes, thermal fluctuations, surface damage initiation, and lubrication regime transitions.

Sensor signals are transmitted to a data infrastructure where they undergo preprocessing, feature extraction, fusion, and storage. Time-series databases, signal-processing pipelines, and semantic data models organize the information required for state estimation. Domain knowledge such as lubrication regimes, material properties, contact mechanics, and wear laws are also embedded here to contextualize raw data and guide model behavior.

The digital twin's analytical core integrates physics-based models with data-driven AI algorithms. Finite-element analysis, multi-body dynamics, elastohydrodynamic lubrication solvers, or molecular dynamics simulations provide mechanistic insight, while machine learning methods such as neural networks, support vector machines, LSTM sequence models, or physics-informed neural networks infer or predict system states from data. The twin continuously updates its internal representation of friction, wear depth, load distribution, or lubrication conditions through bidirectional synchronization with the physical asset.

The highest layer uses the hybrid model's predictions to support real-time decision-making. This may include adjusting lubricant flow rates, modifying viscosity grade selection, altering cooling strategies, changing machine operating parameters, or scheduling maintenance interventions based on remaining useful life estimates. In advanced implementations, reinforcement-learning-based policies or rule-based controllers autonomously optimize friction, temperature, or wear rate during operation. Together, these four layers form a generalizable architecture for tribology-oriented digital twins. Subsequent sections of this review refer back to this framework when discussing sensing technologies, AI models, data integration strategies, and case studies in rotating machinery, engines, hydraulics, and wind turbine gearboxes.

4.2. Sensor technologies for tribological digital twins

For an AI-enabled digital twin to function effectively, it must rely on thorough and detailed data acquisition. Condition monitoring relies heavily on sensor technologies that measure relevant tribological parameters such as temperature, vibration, acoustic emissions, oil quality, and other metrics [38-40]. These sensing modalities provide indirect but sensitive insight into frictional interactions, surface degradation, and lubrication regime evolution. A consolidated overview of the principal sensor types, measured parameters, and associated tribological phenomena is provided in Table 2, which situates individual sensing approaches within their typical application contexts.

Vibrational sensors, typically piezoelectric accelerometers [41], are among the most widely used sensing technologies in tribological monitoring. They can detect imbalances or misalignments in rotating machinery, as friction or wear phenomena often manifest in characteristic waveform changes [42]. As reflected in Table 2, vibration sensing is particularly prevalent in bearings and gearboxes, where signal features extracted from acceleration measurements form a primary input for AI-based fault diagnosis and wear classification.

Acoustic emission sensors offer high sensitivity to crack initiation and surface fracturing, capturing early signs of wear [43]. By detecting high-frequency elastic waves generated during asperity interactions or micro-fracture events, AE sensing enables early-stage damage detection in rolling element bearings, piston–liner systems, and other heavily loaded contacts. Within AI-enabled digital twin frameworks, AE data are often processed using deep learning or sequence-based models to track wear evolution and predict remaining useful life.

Infrared sensors and thermocouples detect temperature variations that relate to friction-generated heat [44]. Temperature measurements play a critical role in interpreting lubrication regime transitions, as lubricant viscosity and film thickness are strongly temperature dependent. Temperature sensing is commonly applied in engines, turbines, and hydraulic systems, where thermal behavior provides contextual information for AI-driven friction and wear predictions.

Lubricant condition sensors measure various parameters including viscosity, contamination, and water content, crucial for lubrication regimes [45,46]. In tribological digital twins for hydraulic systems and internal combustion engines, oil condition data are increasingly fused with mechanical and thermal measurements to improve state estimation accuracy and enable condition-based maintenance decisions. The inclusion of lubricant-related sensing expands the digital twin's scope beyond purely mechanical observables.

The Internet of Things (IoT) paradigm, where IoT reflects the network of interconnected devices, ties these sensor nodes together, allowing real-time data streaming to a central repository or cloud-based platform [47]. This data pipeline underpins the digital twin by supplying continuous, context-rich input for AI algorithms and enabling bidirectional feedback between the physical system and its virtual counterpart.

Given the significance of measurement accuracy in AI data ingestion, sensor calibration and signal processing techniques are essential for ensuring reliable model performance. Further complexities arise from sensor positioning and the hostile operational environments often encountered in industrial tribology applications. Sensor fusion methodologies, in which data from multiple sensor types are combined through advanced signal processing and machine learning, improve AI-driven predictions by providing a multi-dimensional representation of the tribological state. Taken together, the sensing approaches summarized in Table 2 form the foundation of the sensing layer in the tribology-oriented digital twin architecture discussed in the previous sections.

Table 2. Sensor technologies and measured parameters supporting AI-enabled digital twins in tribology.

Sensor type	Measured parameter	Tribological insight	Typical applications
Vibration sensors	Acceleration, frequency response	Imbalance, spalling, surface damage	Bearings, gearboxes
Acoustic emission (AE) sensors	High-frequency elastic waves	Crack initiation, early wear	Bearings, piston–liner systems
Temperature sensors	Bulk or contact temperature	Frictional heating, lubrication regime	Engines, turbines
Oil condition sensors	Viscosity, debris, contamination	Lubricant degradation, wear particles	Hydraulic systems, engines
Torque / force sensors	Load, friction torque	Contact stress, friction changes	Transmissions, test rigs

4.3. Data management and integration

Data management stands as a central challenge in integrating AI and DT solutions for tribology. Data from tribological systems can be heterogeneous, involving structured data (e.g., temperature readings in time series), semi-structured data (e.g., event logs from a distributed control system), and unstructured data (e.g., images from surface microscopy) [48].

Ensuring data quality, which includes dealing with missing values, outliers, and noise, is a key step before AI models can be trained or validated [49]. Moreover, these data considerations extend to how data is stored (for example, in relational databases, NoSQL repositories, or specialized time-series databases) and how it is accessed by AI modules that might be running on-site or in cloud environments [48,50]. Semantic data modeling, where domain-specific ontologies describe how data fields relate to tribological elements, has gained importance to facilitate data sharing and interoperability in complex industrial ecosystems [51].

Equally essential is the guaranteeing of cybersecurity and data integrity, as incorrect sensor readings or malicious alterations can corrupt AI predictions [52-54]. Blockchain-based solutions have been proposed to enhance data immutability, though their adoption in tribology remains a nascent field [55,56]. These data handling and integration strategies support the data and knowledge layer of the digital twin, enabling reliable state estimation and model updating.

5. AI MODEL ARCHITECTURES FOR WEAR AND FRICTION PREDICTION

Friction and wear are emergent phenomena depending on contact materials, lubrication regimes, surface roughness, speed, load, and environmental conditions. Traditional methods for friction modeling rely on simplified assumptions to yield average friction coefficients. AI changes the perspective by deducing relationships from data. Neural network architectures, such as feedforward networks and convolutional neural networks, are effective when large datasets of tribological measurements exist [57]. The networks learn to associate inputs (load, speed, lubricant viscosity) with exact frictional outputs under diverse conditions. However, interpretability remains a significant challenge. Black-box AI models risk overfitting, producing results that might not generalize well.

This shortcoming has prompted research into physics-informed neural networks (PINN), which embed tribological laws into the training process [58]. PINN constraints might, for instance, force the AI model to respect the Reynolds equation for fluid film lubrication or the boundary lubrication constraints from the boundary lubrication regime. While early results suggest improved consistency under extrapolation scenarios, further validation is needed to meet industrial standards.

Wear prediction via AI models usually focuses on time-to-failure estimation. Recurrent neural networks (RNN) [59], especially long short-term memory variants (LSTM) [60], are suitable for sequencing tasks, capturing the evolution of surface degradation over time. The inputs can include historical sequences of vibration or oil debris data, while outputs predict the wear depth or failure intervals. These predictions can then be passed to a DT system for scenario testing or to schedule proactive maintenance. SVM-based classifiers, combined with dimensionality reduction tools such as principal component analysis, are frequently employed to detect stages of wear, especially in rotating machines [23,61,62]. By subdividing wear processes into progressive classes maintenance decisions can be better informed. The AI and hybrid modeling approaches described here operate primarily within the modeling layer of the digital twin, where they complement physics-based solvers.

6. APPLICATIONS OF AI-ENABLED DIGITAL TWINS IN TRIBOLOGY

AI-enabled digital twins have been deployed across a wide spectrum of tribological systems, ranging from rotating machinery and internal combustion engines to hydraulic systems, wind turbines, and tribological material and lubricant design. Although these applications differ substantially in scale, operating environment, and failure mechanisms, they share common functional objectives, including friction and wear prediction, lubrication regime monitoring, remaining useful life estimation, and adaptive decision support.

The application domains considered in this section can be broadly categorized according to their dominant tribological components, data sources, and the functional roles played by artificial intelligence within the digital twin. Table 3 provides a consolidated overview of these domains, highlighting how sensor data, hybrid AI–physics models, and decision-making layers are integrated to address system-specific tribological challenges. The following subsections discuss each application area in detail, illustrating how these shared digital twin functions are instantiated in practice.

Table 3. Application domains of AI-enabled digital twins in tribology.

Domain	Key Tribological Focus	Role of AI-Enabled Digital Twin	Expected Outcomes
Rotating machinery	Bearing and gear wear, lubrication breakdown	Wear evolution tracking, RUL prediction, adaptive lubrication	Reduced unplanned downtime, improved reliability
Internal combustion engines	Piston–liner friction, lubricant degradation	Friction prediction, lubrication regime identification, fault diagnosis	Condition-based maintenance, reduced friction losses
Hydraulic systems	Fluid contamination, pump and valve wear	Anomaly detection, efficiency monitoring, adaptive pressure control	Improved system efficiency, extended component life
Wind turbines	Gearbox and main bearing degradation	Damage progression forecasting, lubrication optimization	Lower maintenance cost, increased availability
Materials and lubricants	Surface coatings, additives, lubricant formulations	Design-space exploration, virtual testing and optimization	Accelerated material and lubricant development

6.1. Rotating machinery

Rotating machinery such as bearings, gearboxes, turbines, and motors typically includes lubricated surfaces that operate under varying loads and speeds. As such, the reliability of such machinery is often compromised by tribological failures. AI-enabled DT frameworks are pivotal in addressing these challenges through improved monitoring, control, and long-term health management.

One widely referenced case study involves the application of a DT to a gear train in a wind turbine [63]. In this scenario, sensors measure vibration, torque, speed, oil temperature, and other parameters. Meanwhile, a specialized AI model predicts gear tooth wear progression. This real-time wear data is then fed into a finite element solver that simulates gear tooth deformation under dynamic loads [63]. Through iterative updates, the DT suggests whether lubrication parameters should be modified. For instance, it could suggest switching to a higher viscosity oil during peak load periods or injecting additional lubricants for cooling [63].

For bearing systems, one promising integration pathway involves an AI enabled DT for a high-speed spindle that is continuously updated by multi source condition monitoring data. Building on recent digital twin frameworks for rolling bearings and spindle assemblies, which combine physics-based dynamics with data driven models for fault evolution and remaining useful life prediction, such a system would ingest signals from vibration and acoustic emission sensors mounted near the bearing seats [64-66].

In this configuration, broadband acoustic emission is exploited to detect the earliest signs of spalling, since short high amplitude bursts have been shown to correlate with crack initiation and spall growth on rolling elements and races [66,67]. An LSTM based recurrent model, trained in sequences of acoustic emission features and operating conditions, interprets these bursts and estimates the current spall size as well as its propagation trajectory over future load cycles, extending earlier work where deep recurrent architectures were used to track wear and damage trends over time. The DT couples this data driven estimate of defect geometry to a multi body dynamics solver of the spindle bearing assembly, allowing the simulation to resolve how the evolving surface defect redistributes contact forces and kinematics across rolling elements and races under realistic speed and load histories [68,69].

In parallel, thermo-elastohydrodynamic lubrication models or learned surrogates link the changing load distribution to film thickness and temperature, so that the DT can evaluate whether the prevailing lubrication regime is at risk of breakdown and whether adjustments to lubricant supply are warranted [70,71]. The synergy between measured data and model-based predictions then enables the control layer to adapt lubrication flow rates or cooling strategies in real time, for example by temporarily increasing flow, altering distribution between bearings, or selecting higher viscosity grades under extreme loading, in order to delay the transition to severe damage and mitigate the risk of catastrophic failure. In principle, this kind of predictive and adaptive DT can reduce unplanned downtime by scheduling interventions before the spindle reaches a critical damage state.

6.2. Internal combustion engines and powertrains

Internal combustion engines (ICE) operate with complex lubrication systems to minimize friction between sliding components such as piston rings, cylinder walls, cam shafts, and valve trains [72-75]. The lubrication regime can vary from boundary to hydrodynamic, influenced by engine speed, load, and oil temperature. Traditional prognostic approaches rely on approximate friction models or lab-based wear tests, leading to maintenance schedules that may not match real-world usage.

An AI-enabled DT addresses this gap by fusing telematics data from on-board diagnostics with real-time engine operating conditions and tribological sensor readings, such as oil viscosity, particulate concentration, and metallic debris content [76]. Recent studies have demonstrated that hybrid digital twins for diesel engines can couple physics-based thermodynamic models with machine-learning components to diagnose and predict faults from operational sensor data [77]. Data-driven models using ensemble methods such as Random Forest and XGBoost applied to multi-sensor datasets from marine diesel engines have achieved early detection of piston-ring-related degradation, enabling condition-based replacement scheduling well before conventional indicators signal a problem [78].

Acoustic-emission-based monitoring of piston-ring wear in internal-combustion engines, together with AE-assisted identification of hydrodynamic, mixed, and boundary lubrication regimes in journal bearings, further highlights the value of tribological sensing as an input to such twins [79,80]. In parallel, tribology-focused digital twins and hybrid methodologies have been developed to simulate lubricant transport, mixed-lubrication behavior, and lubrication regimes in engine-relevant contacts, allowing virtual exploration of lubrication strategies and their impact on friction, wear, and oil consumption [80-82].

While these outcomes are promising, ICE systems introduce complexities such as chemical degradation of lubricants and the presence of combustion byproducts, which require advanced data fusion. Additional gating factors include the high temperature environment within an engine and the difficulties in placing sensors where they can capture relevant signals without being damaged [72,83]. Advances in micro-electro-mechanical systems (MEMS)-based sensors offer pathways to robust and miniaturized data acquisition solutions, augmenting the reach of AI-enabled DT in ICE tribology [84].

6.3. Hydraulic systems and fluid power applications

Industrial hydraulic systems provide the primary power transmission in mobile construction machinery, in aerospace actuation systems, and in many classes of robotic manipulators [85]. In excavators and other construction equipment, programmable hydraulic control architectures are central to driving booms, arms, and implements. In aircraft, flight-control and landing-gear functions have traditionally relied on centralized hydraulic power and actuators, with newer electro-hydrostatic architectures still inheriting many of the same fluid-power constraints. In advanced legged robots and manipulators, hydraulically actuated joints are widely used because of their high power density and bandwidth [85].

In all of these applications, the hydraulic fluid acts simultaneously as working medium and lubricant, so fluid viscosity, lubrication regime, and especially oil cleanliness are critical tribological factors, with contamination alone estimated to account for roughly 70 percent of hydraulic system failures and being identified as a dominant wear mechanism in pumps, valves, and motors [86]. A slight increase in friction or leaks in these systems can drastically impair performance, cause inefficiencies, and potentially lead to catastrophic failures.

AI-enabled DT solutions in hydraulic systems focus on real-time health monitoring, adjusting fluid pressure levels, and early detection of component wear such as in pumps, cylinders, or valves [86]. Practically, a DT for a hydraulic pump can consist of an internal computational model describing fluid flow, cavitation dynamics, and wearing contact surfaces [87]. The physical system is instrumented with pressure transducers, flow meters, temperature sensors, and acoustic emission sensors near the pump bearings. A deep neural network or an ensemble learning method processes these signals to detect anomalies. A parallel fluid-structure interaction solver in the DT simulates how these anomalies could propagate, predicting whether early cavitation damage can escalate into significant wear. The AI-based control system can then adjust fluid pressure or modulate the pump speed in real time. A reported study demonstrated a reduction in unplanned maintenance events when employing such an integrated approach in a large-scale hydraulic press [88].

AI-based models trained on oil spectrometric or spectroscopic measurements of wear metals, contaminants, and additive elements have been used to predict lubricating-oil remaining useful life and detect degradation or contamination states in both mechanical transmissions and transformer insulation oils. Integration of these chemical insights into the DT ensures a comprehensive tribological health assessment, bridging mechanical and chemical aspects, which historically were handled in separate analyses.

6.4. Wind turbine and large-scale applications

Wind turbine gearboxes exemplify large-scale tribological systems that grapple with variable wind loads, unpredictable environmental conditions, and high reliability requirements [89]. Though the fundamental tribological principles remain the same, the scale of wind turbines implies that even small frictional inefficiencies can translate into significant energy losses. Gearbox failures can be extremely expensive to repair, often requiring cranes and specialized equipment to access turbine nacelles located high above ground.

This scenario underscores the importance of predictive maintenance powered by AI-enabled DT [89]. In a practical case, a large onshore wind farm installed a DT-based monitoring platform across multiple turbines [90]. Each gearbox was equipped with vibration, temperature, and oil quality sensors, feeding data into a neural network model that categorized gearbox health into normal, warning, or fault states. Once a warning signal was triggered, the DT launched a finite element simulation of gear contact mechanics to estimate damage progression. The system then recommended an adaptive lubrication schedule, ensuring the correct balance of oil feed rate and temperature reduction through an auxiliary cooling system. This synergy of data-driven detection and physically grounded simulation significantly lowered unscheduled downtimes and was validated by periodic on-site inspections [90].

Large-scale tribological systems impose additional computational workloads for the DT due to extensive contact surfaces and complex load distributions. Strategies to address this scaling issue include model order reduction, distributed computing, and hierarchical AI models [91]. By dissecting a gearbox into multiple sub-models, each focusing on a specific set of gears, bearings, or couplings, the DT can run in near real-time. AI's role here is to orchestrate sub-model outcomes, compile them into an overall wear forecast, and carry out control decisions that balance the intricacies of the entire system.

6.5. Material selection, surface engineering, and lubricant formation

Another domain in which AI-enabled DTs show potential is in guiding material selection, surface engineering, and lubricant formulation. Typically, these decisions are made using trial-and-error, data from laboratory tribometers, and prior engineering experience. Yet, as industries push for lighter materials, lower friction coefficients, and sustainable lubricants, a more systematic approach is required. By harnessing data repositories of existing tribological tests, AI can identify promising candidate materials, coatings, or lubricant additives that deliver superior wear resistance or friction reduction under specified conditions. Once these candidates are proposed, a DT can simulate the entire mechanical system's response to the new material or lubricant.

For example, a specialized study used a generative adversarial network (GAN) to hypothesize new molecular structures for lubricant additives targeting minimal boundary friction [92]. These structures, once identified, were tested in a virtual tribometer environment that incorporated multi-scale simulations: molecular dynamics for surface-additive interactions, fluid dynamics for film thickness distribution, and contact mechanics for stress distribution. The synergy between AI-based discovery and DT-based validation curtailed the number of experimental trials needed to validate a novel additive.

Similar processes have been used for selecting protective coatings, with the DT iteratively refining the recommended thickness or deposition parameters based on feedback from accelerated wear tests [93].

7. REAL-TIME CONTROL AND OPTIMIZATION FOR SELF-ADAPTIVE LUBRICATION

An emerging frontier in tribology involves the development of self-adaptive lubrication systems capable of responding dynamically to changes in load, speed, temperature, and environmental conditions. Unlike conventional lubrication strategies that rely on fixed schedules or pre-set operating assumptions, AI-enabled digital twins enable continuous evaluation of tribological state variables and real-time adjustment of control parameters.

Within this framework, the digital twin functions not only as a predictive model but also as an active decision-support engine. By integrating sensor data with hybrid AI–physics models, the system continuously estimates frictional behavior, lubrication regime transitions, wear progression, and thermal conditions. These state estimates inform control strategies that modify lubricant flow rates, viscosity selection, cooling intensity, or operating parameters to maintain optimal tribological performance.

For example, in boundary lubrication conditions where asperity contact dominates, the system may increase the injection of lubricants containing friction modifiers or anti-wear additives. Under high-speed hydrodynamic conditions, it may adjust pump pressure or modify viscosity to maintain stable fluid film thickness [94]. Over time, feedback from sensor data allows the control algorithm to refine its response policies, reducing frictional losses while mitigating wear accumulation.

Reinforcement learning approaches have gained attention as a means of optimizing such adaptive control policies. By formulating lubrication management as a sequential decision problem, reinforcement learning agents can learn control strategies that balance multiple objectives, including friction reduction, wear minimization, energy efficiency, and environmental considerations [95]. Within a digital twin environment, these policies can be trained and validated before deployment in physical systems, reducing operational risk and improving robustness.

The integration of real-time control within digital twin architectures enables continuous synchronization between prediction and action. The digital twin simulates prospective system responses under alternative lubrication or operating scenarios, evaluates performance metrics, and recommends control adjustments. These recommendations are implemented in the physical system, and the resulting measurements are fed back into the model for recalibration. This closed-loop structure enhances stability and supports long-term optimization of tribological performance.

Experimental implementations illustrate the feasibility of this approach. In automotive transmission systems equipped with electronically controlled clutches, digital twins have been used to predict frictional losses under varying driving scenarios and recommend modifications to slip control timing or fluid pressure [96]. The physical system follows these recommendations autonomously, yielding measurable improvements in energy efficiency during urban driving cycles.

Despite these advances, real-time adaptive lubrication remains technically demanding.

Control decisions must be computed within strict latency constraints, particularly in high-speed rotating systems. Sensor reliability, communication bandwidth, and actuator responsiveness directly affect system performance. Moreover, control policies must maintain physical plausibility and safety, reinforcing the importance of hybrid modeling approaches that embed tribological constraints into AI-driven optimization.

As computational resources and sensing technologies continue to evolve, self-adaptive lubrication systems are expected to become increasingly practical across a wider range of industrial applications. By coupling predictive analytics with active control, AI-enabled digital twins extend tribology from passive monitoring toward proactive and continuously optimized system management.

8. CHALLENGES AND LIMITATIONS

Despite the transformative potential of AI-enabled digital twins in tribology, their implementation is constrained by several interdependent technical and operational challenges. These challenges can be understood in terms of fundamental trade-offs among physical fidelity, data adaptability, and computational and operational efficiency. Figure 3 illustrates this triangular trade-off space, within which different modeling approaches occupy distinct regions depending on their emphasis.

A primary limitation concerns data availability and quality. Data-driven AI models require extensive, high-resolution datasets that adequately represent the operating envelope of the tribological system. However, many practical systems operate in harsh or inaccessible environments where sensor placement is limited, or long-term data acquisition is incomplete. Sparse, noisy, or imbalanced datasets can impair model training and reduce predictive reliability, particularly in systems characterized by nonlinear frictional behavior and multi-regime lubrication transitions. In the trade-off space depicted in Figure 3, approaches that emphasize data adaptability may perform well within the training domain but degrade under extrapolation or rare-event conditions if physical constraints are not adequately enforced.

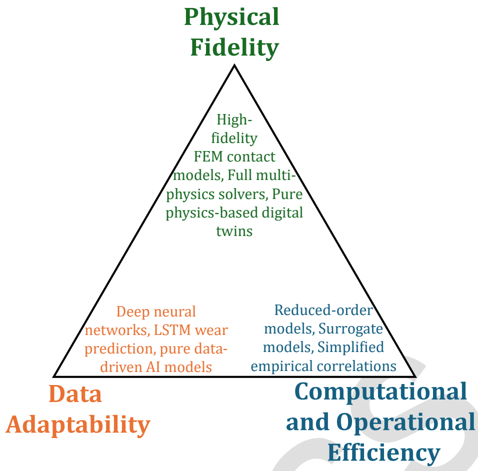

Fig. 3. Conceptual trade-off among physical fidelity, data adaptability, and computational and operational efficiency in AI-enabled digital twins for tribological systems. Hybrid AI–physics models aim to balance these competing objectives.

Closely related is the challenge of generalization. AI models trained on historical data may encounter operating regimes in deployment that exceed the bounds of their training distribution. Extreme loads, unexpected contamination events, or novel material combinations may induce behaviors that purely data-driven models fail to anticipate. This concern underscores the importance of integrating physical constraints and uncertainty quantification mechanisms into digital twin frameworks. Hybrid AI–physics models aim to address this issue by anchoring data-driven inference within governing tribological principles, thereby improving stability and extrapolation robustness.

Computational burden represents another significant constraint, particularly for large-scale or high-fidelity multi-physics simulations. Detailed finite element modeling of gear contact or thermo-elastohydrodynamic lubrication can be computationally intensive, limiting real-time feasibility. Model order reduction, surrogate modeling, and component-based reduced-order modeling approaches have been proposed to mitigate this burden while preserving essential physical behavior [97]. Multi-resolution strategies, in which high-fidelity solvers are selectively applied to critical components and simplified representations approximate secondary subsystems, offer practical pathways to improved efficiency. Within the triangular trade-off framework, these approaches shift models toward greater operational efficiency, though often at the cost of reduced physical granularity.

Interpretability and trust present further barriers to adoption, especially in safety-critical applications. Deep neural networks and other complex AI models may achieve high predictive accuracy while offering limited transparency regarding the features or constraints driving their outputs [98]. In domains such as aerospace, energy production, or heavy industrial systems, decision-makers require explanations before implementing automated lubrication adjustments or maintenance recommendations. Explainable artificial intelligence methods seek to reveal the contribution of input variables or physical constraints to model outputs, thereby enhancing user confidence and supporting regulatory oversight [99]. In the context of the trade-off diagram, interpretability considerations influence the acceptable balance between adaptability and fidelity, as highly flexible models may lack the transparency demanded in regulated environments.

Another limitation stems from the intrinsic complexity of tribological phenomena. Friction and wear processes involve tightly coupled mechanical, thermal, chemical, and surface-evolution mechanisms operating across multiple spatial and temporal scales. Even advanced multi-physics solvers face challenges in fully capturing phenomena such as tribofilm formation, oxidation kinetics, and nanoscale surface transformations [100]. The integration of such processes into a unified digital twin requires careful abstraction and model hierarchy design, reinforcing the need for interdisciplinary collaboration among tribologists, computational scientists, and AI researchers.

Economic feasibility also influences practical deployment. Implementing AI-enabled digital twins requires investment in sensing infrastructure, data management systems, computational resources, and specialized personnel. For smaller organizations or legacy systems, these costs may outweigh short-term benefits. Cloud-based digital twin platforms and digital-twin-as-a-service models have emerged as mechanisms to reduce infrastructure barriers and distribute computational resources more efficiently [101-103]. However, long-term return on investment depends on reliable predictive performance and measurable reductions in downtime, maintenance cost, or energy consumption.

Taken together, these considerations demonstrate that AI-enabled digital twins in tribology operate within a constrained design space defined by competing priorities. Purely physics-based approaches maximize physical fidelity but may be computationally prohibitive. Purely data-driven models emphasize adaptability but may lack interpretability or extrapolation robustness. Simplified or reduced-order models enhance efficiency but may sacrifice detailed mechanistic insight. Hybrid AI–physics digital twins aim to occupy a balanced region within this trade-off space, seeking to maintain sufficient physical consistency, leverage operational data effectively, and remain computationally feasible for real-time deployment. The continued advancement of tribology-oriented digital twins will therefore depend not only on algorithmic innovation but also on carefully navigating these structural trade-offs.

9. FUTURE PROSPECTS

The future of AI-enabled digital twins in tribology appears poised for rapid growth. As illustrated conceptually in Figure 4, development is expected to expand across both system scale and functional capability, ranging from localized monitoring and prediction to autonomous control and sustainability-driven optimization.

One promising direction involves the development of adaptive lubrication systems that reconfigure lubricants dynamically, employing fluidic or mechanical actuators controlled by advanced AI [104]. In such systems, digital twins continuously evaluate tribological state variables and modify lubrication parameters in real time. This progression reflects a broader transition from predictive monitoring toward closed-loop control, where friction and wear are actively managed rather than merely estimated.

Sustainability considerations are also expected to shape future research. As climate concerns drive interest in eco-friendly lubricants and reduced resource consumption, tribological performance must be balanced with environmental impact. AI-enabled digital twins can incorporate life-cycle assessment metrics, analyzing not only friction and wear but also carbon footprint and sustainability indicators. Advanced algorithms may explore bio-based lubricants and optimize additive compositions in real time to satisfy performance criteria [105-107]. This integration of environmental metrics into tribological optimization represents a significant expansion of digital twin functionality.

Another prospective area is nanoscale tribology, where friction, adhesion, and wear are governed by atomic-scale interactions. AI-enabled digital twins may integrate atomic force microscopy data, surface microstructure characterization, and molecular dynamics simulations to model frictional processes at nanometer scales. Machine learning approaches have already demonstrated the ability to predict nanoscale friction behavior in two-dimensional materials [108,109]. Although computational costs remain substantial, hybrid strategies combining reduced-order modeling and AI-based approximation may enable practical multiscale digital twins that link nanoscale phenomena to macroscopic system behavior.
Technological advancements in sensing and computation will further enhance digital twin capabilities. Embedded sensor arrays within tribological contact interfaces may provide direct measurements of local friction forces, temperature gradients, and wear patterns in demanding environments. In parallel, a shift toward edge computing architectures is anticipated, allowing data processing and AI inference to occur closer to the physical asset. This transition supports low-latency control decisions in dynamic systems, while advances in 5G and 6G communication networks enable high-bandwidth connectivity among distributed digital twins [110,111].

Training datasets are also expected to evolve. Rather than relying solely on proprietary or siloed industrial data, collaborations among universities, industry partners, and standards organizations may produce open, anonymized tribological datasets encompassing diverse materials and operating conditions. Broader data availability would promote improved generalization and cross-validation of AI models, strengthening the reliability of tribology-focused digital twins.

Figure 4 summarizes these directions within a two-dimensional framework defined by scale and functional capability. Lower-scale developments emphasize detailed monitoring and predictive modeling, while larger-scale implementations pursue adaptive control and sustainability-oriented optimization. The progression toward fleet-scale, environmentally integrated, and partially autonomous digital twin systems reflects the continuing convergence of tribology, artificial intelligence, sensing technology, and systems engineering.

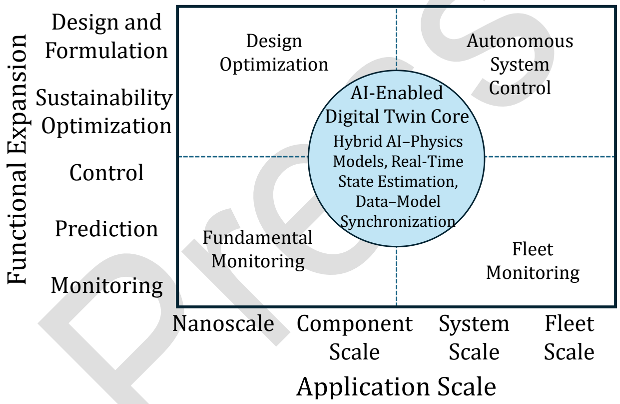

Fig. 4. Conceptual expansion of AI-enabled digital twins in tribology across scale and functional capability, from nanoscale monitoring to fleet-level autonomous and sustainability-oriented optimization.

Collectively, these trends suggest that AI-enabled digital twins will evolve into comprehensive platforms supporting design, operation, maintenance, and sustainability assessment across the lifecycle of tribological systems.

10. CONCLUSION

AI-enabled DT frameworks hold transformative potential for tribology and lubricated mechanical systems. Through a comprehensive review of peer-reviewed studies, this paper has highlighted how the predictive, real-time nature of AI-driven models, combined with physics-based simulations, enhances reliability and efficiency across a range of applications. From bearings and gearboxes to internal combustion engines and hydraulic actuators, the confluence of sensor data, hybrid AI models, and multi-physics solvers demonstrates a clear advantage over traditional empirical or purely theoretical approaches. The iterative, real-time synchronization of physical and digital counterparts is uniquely suited to managing friction, wear, and lubrication.

Key advancements include the use of machine learning architectures such as neural networks, support vector machines, and ensemble methods to interpret large-scale tribological data, facilitating predictive maintenance strategies and real-time control measures. The integration of physics-based constraints via digital twins ensures that these predictions remain consistent with established tribological principles while benefiting from the adaptability of AI. Sensor fusion, advanced data management, and robust model development have already shown impressive results in rotating machinery and large-scale systems like wind turbine gearboxes, offering cost-effective, data-driven alternatives to rigid static models.

Nevertheless, hurdles remain significant. The scarcity and quality of tribological data, high computational requirements for large-scale or multi-physics simulations, interpretability challenges of black-box AI, and the complexities of capturing all relevant physical phenomena pose obstacles. Interdisciplinary collaboration is essential to address these issues effectively.

The future directions for AI-enabled DT in tribology seem rich with promise: from adaptive lubrication orchestrated by AI control loops to green tribology initiatives that integrate eco-friendly lubricants and life-cycle assessment. Emerging technologies, including nanoscale sensors, edge computing, and quantum-based computational methods, may drive new paradigms in friction and wear management.

Overall, the application of AI-enabled DT in tribology is poised to offer sophisticated, real-time solutions to reduce wear, optimize lubrication, and extend the functioning lifespan of mechanical systems. As industries attempt to reconcile efficiency, sustainability, and reliability, these digital strategies intensify the evolution of tribological engineering, ushering in a future where data-driven, adaptive, and integrated solutions become the new standard for advanced mechanical design and operation.

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