

Review

AI and Robotics in Tribological Experimentation: Robotic Platforms, Artificial Intelligence, and Closed-Loop Evaluation

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Abstract

Tribology, the science of friction, wear, and lubrication, governs the reliability of nearly every mechanical system. Tribological contacts account for approximately 23% of global energy consumption, including 20% used to overcome friction and 3% associated with remanufacturing worn components. Nevertheless, the field has remained constrained by low experimental throughput, operator variability, and a scarcity of standardized, reusable datasets. This review surveys two converging trends positioned to address these limitations: the development of robotic and automated platforms for tribological experimentation, and the growing application of artificial intelligence to tribological analysis. High-throughput tribometer architectures, robotic specimen preparation, and multi-modal in situ sensing are examined as components of an emerging automated tribometry infrastructure. Supervised learning, physics-informed neural networks, and Bayesian optimization are reviewed as AI methods organized by the data regime in which they operate. The convergence of these trends in closed-loop autonomous tribological experimentation is assessed, including system architecture, optimization target specification, current partial implementations, and tribology-specific integration barriers that distinguish this domain from adjacent self-driving laboratory applications. Application domains spanning industrial machinery, biomedical implants, and aerospace and automotive drivetrains are discussed. Key challenges including dataset standardization, model transferability, and hardware-software integration complexity are identified. Prospects for fully autonomous tribological discovery pipelines are outlined, with emphasis on open-access data infrastructure and physics-constrained learning as the enabling conditions for the field.

Keywords: tribology; automated tribometry; machine learning; closed-loop experimentation; self-driving laboratory



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1. Introduction

The economic and operational impacts of friction and wear remain a challenge across modern industrial infrastructure. Historical assessments like the Jost Report have consistently demonstrated that a considerable proportion of global energy is lost to interfacial losses. Updated global estimates indicate that approximately 23% of the total energy consumption of the world originates from tribological contacts, with 20% spent directly on overcoming friction and 3% dedicated to remanufacturing parts damaged by wear [1]. In

transportation, roughly one-third of a passenger car's fuel energy is consumed overcoming friction in the engine, transmission, tires, and brakes [2]. Similarly, manufacturing systems face severe mechanical downtime and component replacement costs [1]. Biomedical interfaces, including artificial joints and prosthetic implants, suffer from wear debris that compromise system longevity and patient health [3]. Despite these issues, tribology remains a problem that the field of robotics has not systemically engaged. Robotic systems are often employed to automate macro-scale tasks, but the autonomous optimization of the fundamental contact mechanics governing these machines and their environments is an open frontier for research. The current state of empirical tribology relies almost entirely on manual tribometry. These tests require an operator to meticulously clean specimens, align components, set experimental parameters, and manually log data over extended test durations that can span dozens of hours for individual material pairs. This reliance on manual intervention creates a sensitivity to human error [4]. In addition, data scarcity remains a considerable issue. Publicly available tribological datasets are limited, usually confined to supplementary materials of individual papers. This lack of centralized data stems from a deeper structural issue rather than individual operator failures. Because tribological system behavior is a system property dependent on transient contact dynamics, minor differences in experimental execution undermine interlaboratory reproducibility [5]. This means that conventional trial and error methodologies cannot be scaled to meet the demands of modern materials discovery. This structural throughput bottleneck is the main motivation to transition toward standard, automated methods that eliminate human error and accelerate data generation. One trend that can help overcome these bottlenecks is the rise of robotic and automated testing platforms. High-throughput experimentation has already fundamentally transformed adjacent scientific disciplines, including accelerated battery research [6], autonomous drug discovery [7], and combinatorial materials synthesis [8]. By delegating physical execution to robotic architecture, researchers can achieve consistency and continuous testing capabilities. The second trend is the rapid adoption of artificial intelligence in tribology, marked by a massive surge in machine learning models for friction and wear prediction since 2018 [9]. These data-driven algorithms can capture the highly nonlinear relationships that govern interfacial contact, outperforming classical empirical equations. The integration of robotic physical platforms with intelligent AI creates an autonomous closed-loop system capable of executing, learning from, and directing tribological experiments without human intervention [9].

Against this background, this review contributes an integrated assessment of the convergence between automated tribological experimentation and artificial intelligence. Unlike prior reviews focused primarily on AI-based friction and wear prediction, this review emphasizes robotic test execution, multimodal in situ sensing, closed-loop experimental design, and tribology-specific implementation barriers. It further evaluates the current maturity of autonomous tribological experimentation and identifies the data, physical modeling, and hardware requirements needed for its broader adoption.

2. Fundamentals of Tribological Testing

2.1. Standard Tribometers

Evaluating material performance requires tribometers, which are devices that simulate specific contact geometries and kinematic conditions. The most common configuration is the pin-on-disk tribometer, where a stationary pin is pressed against a rotating disk to evaluate continuous or sliding wear [10]. For extreme pressure and lubricant evaluations, the four-ball tribometer utilizes three fixed balls clamped together under a liquid lubricant while a fourth ball rotates against them under a specified load [11]. Other common configurations include the block-on-ring tester, which provides a line contact ideal for evaluating

conformal bearings, and reciprocating tribometers that simulate the cyclic motion in piston assemblies [12]. These tests are strictly regulated by standard procedures, such as those established by the American Society of Testing and Materials (ASTM), to ensure a baseline level of consistency across different testing facilities. These four configurations are shown schematically in Figure 1.

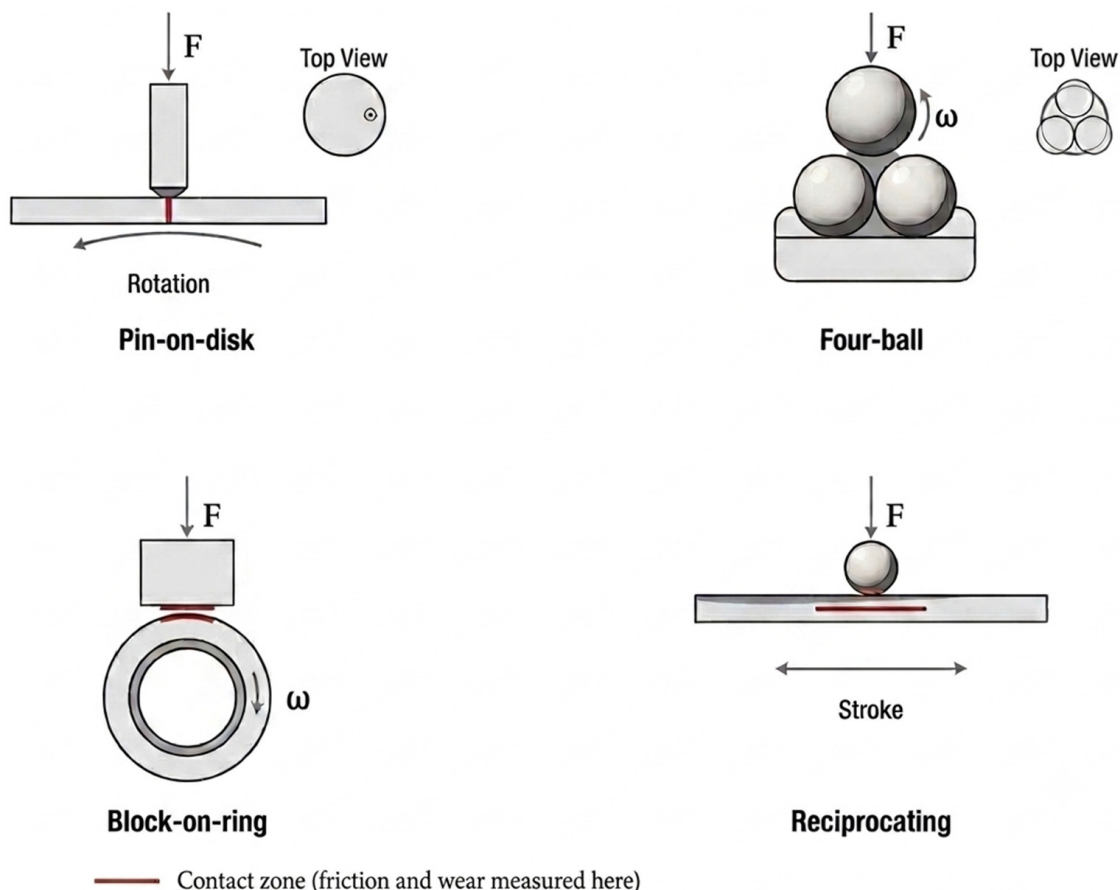


Figure 1. Schematic representations of the four standard tribometer contact configurations described in the text: pin-on-disk, four-ball, block-on-ring, and reciprocating.

2.2. Key Metrics in Tribological Testing

During these experimental runs, researchers monitor physical metrics to characterize tribological performance. The coefficient of friction (CoF), defined as the ratio of the friction force to applied normal force, provides an indication of energy dissipation within the contact region [13]. Material degradation over time is quantified using the specific wear rate, which calculates the volume of material lost per unit of normal load and total sliding distance. In lubricated contacts, the fluid film thickness determines whether the substance operates in boundary, mixed, or full hydrodynamic lubrication regimes [13]. Finally, surface roughness parameters such as the arithmetic average roughness and root-mean-square roughness reveal the microscale changes in surface morphology, allowing researchers to identify active wear mechanisms such as adhesion, abrasion, or surface fatigue [13].

2.3. Sources of Variability

Despite the existence of standardized testing, conventional tribometry suffers from the extreme sensitivity to environmental variables that introduce noise into experimental outcomes. Minor variations in ambient relative humidity and temperature can alter oxide layer formation and lubricant viscosity, leading to different results for identical material pairs

tested in different facilities [14]. Structural misalignments of the tribometer components, micro-vibrations from surrounding laboratory equipment, and subtle differences in initial surface preparation techniques further compound this variability. This context sensitivity is the foundation of the data scarcity issue mentioned earlier. Because a single CoF or wear rate is dependent on the unrecorded metadata of the specific test setup, historical data cannot be easily aggregated or compared. The resulting literature consists of isolated islands of data, making it exceedingly difficult to train machine learning (ML) models without a standardized, automated approach to data capture and storage.

3. Robotic and Automated Platforms for Tribological Experimentation

3.1. High-Throughput Tribometer Architectures

To achieve high throughput, researchers have diverse engineering architectures that move beyond single-station testing. Parallel testing platforms utilize multi specimen holders or carousel-based configurations that allow a single motorized drive system to actuate multiple contact interfaces simultaneously or sequentially without manual intervention [15]. Designs of this nature scale up data generation rates by permitting concurrent evaluations of diverse material pairings of lubricant compositions under identical environmental conditions. In parallel, with multi-specimen hardware, combinatorial tribometry relies on gradient composition specimens or library-based screening techniques [16]. Instead of testing discrete uniform samples, automated systems can scan across a single substrate that features a continuously varying property, such as a localized chemical gradient or a stepped surface roughness profile. This approach enables the mapping of vast composition spaces in a fraction of the time required for traditional methods [16]. Commercial high-throughput tribometers have begun to emerge, often featuring multi-station modules that adapt to pin-on-disk or reciprocating motions while utilizing centralized software to monitor all the stations concurrently. This paradigm is exemplified by commercial platforms like the Bruker UMT TriboLab and the Rtec MFT-5000, which rely on proprietary, unified software dashboards to collect real-time multi-channel friction data simultaneously without cross-talk [17]. In the literature, researchers seeking to analyze complex biological geometries developed the TriBot platform [18]. This system integrates a six-axis FANUC robotic arm, which enables a pin probe to trace the precise trajectories across non-planar surfaces like articular cartilage. The six degrees of freedom allow the robot to maintain a orthogonal positioning relative to the curved tissue surface, which would be impossible with traditional single axis tribometers [18]. Integrating automated multi-probe hardware with stepper motor arrays has allowed academic researchers to transition fully away from slow, single-specimen screening methodologies. For example, researchers developed a specialized automated high-throughput tribometer designed specifically to map out massive combinatorial libraries deposited on a single substrate [19]. This academic system systematically actuates an array of probes across continuous structural or compositional gradients without requiring manual human adjustment between individual testing points [19]. Similarly, high-precision academic setups combine multi-dimensional stepper motor positioning stages with sensitive force sensors to automate localized mechanical scanning. By linking software-controlled motors directly to the positioning apparatus, these systems coordinate lateral and tangential translation across a sample to evaluate variable surface parameters in real time [20]. The integration of continuous spatial stepping with automated collection allows researchers to map vast composition zones or topography profiles in a fraction of the time needed for traditional methods [21]. The principal high-throughput architectures discussed above are compared in Table 1, which groups them by development origin and contrasts the actuation mechanism, target substrate, and specific throughput advantage of each.

Table 1. Representative high-throughput tribometer architectures and platforms, summarizing their development origin, actuation and motion mechanism, sample or substrate type, and primary high-throughput benefit.

Architecture/ Platform	Development Origin	Actuation & Motion Mechanism	Sample/Substrate Type	Primary High-Throughput Benefit
Parallel Multi-Specimen/ Carousel Systems	Academic/ General	Single motorized drive actuating multiple contacts simultaneously or sequentially	Multiple discrete samples or varying lubricant compositions	Eliminates manual intervention; evaluates diverse pairings under identical environmental conditions.
Combinatorial High-Throughput Tribometers	Academic/ General	Automated multi-probe scanning arrays	Single substrate with continuously varying properties (chemical gradients or stepped roughness)	Maps vast composition spaces in a fraction of the time required for traditional methods.
Bruker UMT TriboLab & Rtec MFT-5000	Commercial	Multi-station modules adapting to pin-on-disk or reciprocating motions	Discrete multi-specimen arrays or localized coatings	Proprietary, unified software dashboards collect real-time multi-channel data simultaneously without cross-talk.
TriBot Platform	Academic	Six-axis FANUC robotic arm providing six degrees of freedom	Non-planar, curved biological surfaces (e.g., articular cartilage)	Maintains a strictly orthogonal probe positioning relative to complex, curved tissue geometries.
Automated Stepper Motor Array Rigs	Academic	Multi-dimensional stepper motor positioning stages with sensitive force sensors	Massive combinatorial libraries and variable surface topography profiles	Coordinates automated lateral and tangential translation for real-time spatial mapping without human adjustments.

3.2. Robotic Specimen Preparation and Handling

The time sink of preparing samples before the actual test has driven the development of specialized automated handling lines. Recent research has demonstrated the ability to integrate automated material handling modules that manage the entire pre-test workflow [4]. These systems utilize multi-axis robotic arms equipped with vacuum or mechanical grippers to execute grinding and polishing routines. Beyond substrate polishing, the deposition of protective coatings and liquid lubricants must also be mechanized. Automated spray and dip coating systems utilize multi-axis robotic arms to apply thin films with highly reproducible thicknesses, minimizing edge effects and structural defects [22]. For liquid lubricants, automated micro-fluidic pipetting modules and controlled volume dispensers ensure that the exact microliter volume of fluid is delivered to the contact zone, preventing variations in hydrodynamic film formation that occur with manual fluid application [23]. To achieve high testing efficiency, automated sample and tool management systems handle the pre-test tool transitions without human intervention. For example, advanced high-throughput tribometer architectures utilize an integrated robotic arm equipped with a specialized mechanical gripper to retrieve spherical probe heads from a storage hopper [24]. The robotic handling system transfers these fresh probes directly into the specialized loading fixtures of the friction head [24]. This automated workflow eliminates manual mounting variations and ensures that each sequential material evaluation begins with an

uncontaminated contact interface. This step requires precise spatial calibration to prevent scratching or contaminating the pristine surfaces before the test begins. Furthermore, cleaning and drying protocols must be embedded within the automated workflow. Integrating these automated fluidic and drying stages into the pre-test workflow guarantees that every specimen achieves an identical state of surface cleanliness prior to mechanical evaluation. Despite these advancements, a significant gap remains in the published literature, as most reported systems focus almost exclusively on the automated testing phase while still relying on manual intervention for specimen preparation, cleaning, and loading. True end-to-end automation will require the seamless integration of these preparation modules with the primary testing architecture.

3.3. *In Situ and Operando Sensing*

The value of a tribometer is improved using integrated sensors. In situ and operando monitoring techniques provide real-time information about transient phenomena that are lost during characterization after the test. Acoustic emission sensors are widely integrated to achieve real-time wear mechanism identification [25–27]. High-frequency elastic waves reveal microfractures, abrasive plowing events and the moment of surface coating crack initiation [27]. To complement acoustic data, electrical contact resistance monitoring tracks the integrity of lubricant film or the onset of scuffing by measuring voltage drop across the sliding surface, where a sudden drop in resistance indicates the collapse of the separating film and the onset of direct metallic contact [28–31]. Infrared thermography provides spatially resolved thermal mapping of the contact region, allowing researchers to identify flash temperature concentrations and track the progressive thermal loading that precedes catastrophic surface failure [32–37]. Because frictional heating is closely coupled to lubrication regime transitions [38], thermal data acquired during testing provides an independent channel for detecting regime shifts that may not appear clearly in friction force signals alone. Raman spectroscopy has been increasingly integrated into tribometer stages to monitor tribofilm chemistry in real time [39]. These techniques allow researchers to track the formation and decomposition of boundary lubricant films [39,40], without interrupting the test to extract samples [41]. This operando chemical resolution is particularly valuable for understanding the mechanochemical activation pathways that govern additive performance under load. Beyond standard uniaxial load cells, multi-axis force and torque sensors enable full three-dimensional characterization of contact loading, capturing lateral and out of plane force components that conventional tribometers discard [42]. This richer force signature improves the fidelity of surrogate models trained on the resulting data [42]. Vision-based monitoring and in situ optical profilometry represent the final layer of the sensing stack. High-resolution cameras positioned above the wear track provide continuous optical records of scar evolution, enabling automated image segmentation algorithms to quantify wear volume incrementally rather than only at test termination [43]. Coupled white light interferometry or confocal profilometry modules mounted coaxially with the tribometer can acquire surface height maps at programmed intervals without removing the specimen from the fixture [44–46]. The integration of multiple sensing modalities introduces mechanical and metrological challenges that must be addressed before the resulting data can be used for machine learning. Sensor placement and fixture alignment influence the measured response, while transducer misalignment can introduce cross-axis forces and systematic errors [31,42]. Each sensing channel therefore requires calibration under conditions representative of the experiment. ECR calibration depends on the contact configuration, lubricant properties, load, speed, and temperature [28], whereas infrared measurements require calibration for emissivity, optical configuration, and background

radiation [33]. Baseline measurements should also be collected before each test to quantify drift and instrumentation noise.

Signal quality is particularly important for acoustic-emission measurements because the amplitudes generated during friction can be low and may overlap with vibration, electrical interference, and mechanical noise from the tribometer. Amplification, band-pass filtering, and appropriate sampling are therefore required before feature extraction [26,27]. A low signal-to-noise ratio can cause machine-learning models to learn instrument- or background-specific features rather than wear-related characteristics, reducing their accuracy when transferred to another test or tribometer. Multimodal acquisition introduces an additional synchronization challenge because AE may be sampled at MHz rates, whereas ECR, infrared, and optical measurements may operate at substantially lower rates [26,30,33]. A common hardware-trigger signal should therefore be recorded by each acquisition system and combined with a shared time reference. The streams can then be aligned using timestamps and mapped to common analysis windows. High-frequency channels should be summarized within each window using physically meaningful features, while lower-frequency channels should be interpolated only when their temporal resolution supports it. This approach preserves the timing of friction spikes, AE bursts, thermal changes, and wear events for reliable multimodal machine-learning analysis. The principal in situ and operando sensing modalities discussed above are summarized in Table 2.

Table 2. Representative in situ and operando sensing techniques for automated tribometry, summarizing the physical quantity that each technique measures, the tribological phenomenon it reveals, its characteristic data-acquisition rate, and supporting references.

Sensing Technique	Measured Quantity	Tribological Phenomenon Revealed	Acquisition Rate Regime	Refs.
Acoustic emission (AE)	High-frequency elastic waves from the contact	Microfractures, abrasive plowing events, and surface-coating crack initiation	kHz (high frequency)	[25–27]
Electrical contact resistance (ECR)	Voltage drop across the sliding interface	Lubricant-film integrity and scuffing onset; a sudden drop signals film collapse and direct metallic contact	Instrument-dependent	[28–31]
Infrared thermography	Spatially resolved surface temperature field	Flash-temperature concentrations and progressive thermal loading preceding failure	Hz (frame rate)	[33–37]
Raman spectroscopy	Tribofilm chemical composition	Formation and decomposition of boundary films and mechanochemical additive activation, without interrupting the test	Sub-Hz to Hz (per spectrum)	[39–41]
Multi-axis force/torque sensing	Three-dimensional contact force and moment components	Lateral and out-of-plane loading that uniaxial cells discard, improving surrogate-model fidelity	Instrument-dependent	[42]
Vision-based monitoring and in situ optical profilometry	Wear-scar images and surface height maps	Incremental wear-volume and scar evolution, and interval topography maps acquired without removing the specimen	Sub-Hz (interval scans)	[43–46]

3.4. Data Infrastructure and Standardization in Automated Platforms

The automation of tribological testing generates data at a rate that manual methods cannot match, but the value of this increased throughput is contingent on the quality and consistency of the data formats produced. Current automated tribometer platforms output experimental records in a wide range of proprietary formats, with metadata conventions that vary between instrument manufacturers and individual research groups. Load, velocity, friction force, and wear depth signals are frequently stored in formats that are not directly interoperable, requiring manual reformatting before any cross-platform comparison or aggregation is possible. This lack of standardization is a systemic problem rather than an isolated issue. Without a common metadata schema that mandates the recording of specimen material, surface preparation method, contact geometry, environmental conditions, and instrument configuration alongside the primary measurement channels, datasets from different facilities cannot be meaningfully combined. The resulting literature remains a collection of isolated experimental records rather than a cumulative, queryable knowledge base. The FAIR data principles, which require that research data be findable, accessible, interoperable, and reusable, provide a practical framework for addressing this fragmentation [47]. Adopting FAIR-compliant reporting conventions for automated tribological platforms would substantially increase the utility of generated datasets for downstream machine learning applications and closed-loop system development, both of which are discussed in the sections that follow.

4. Artificial Intelligence Methods in Tribological Analysis

The application of artificial intelligence to tribological analysis has expanded since 2018, driven by the convergence of increased computational accessibility, the proliferation of open-source machine learning libraries, and a growing recognition within the tribology community that classical empirical models cannot capture the nonlinear, multivariable nature of interfacial contact behavior [48]. The volume of published work applying supervised learning, neural networks, and optimization algorithms to friction and wear problems has grown considerably, spanning lubricant formulation, surface texture classification, and remaining useful life prediction. The methods discussed in this section can be organized by the data regime in which they operate. Supervised and ensemble learning methods require large labeled datasets and excel at regression and classification tasks when sufficient experimental records are available [49,50]. Physics-informed neural networks are suited to the opposite regime, where governing equations are known but experimental data is sparse, embedding physical constraints directly into the learning architecture to regularize model behavior [51,52]. Bayesian optimization and active learning methods occupy a third category, designed for sequential data acquisition where each experiment is expensive and the objective is to extract maximum information from the fewest possible tests [53]. This third category is of particular relevance to the field of tribology. Bayesian optimization is not merely a prediction method but an experimental design method, and its compatibility with robotic actuation systems makes it the most natural bridge between the automated platforms described in Section 3 and the closed-loop experimentation architectures discussed in Section 5. These method families and the results reported for each are summarized in Table 3.

Table 3. Artificial-intelligence methods for tribological analysis, organized by the data regime in which they operate, with representative applications and the results reported by the reviewed studies.

Method Family	Data Regime	Application/Target	Reported Result or Status (as Stated in the Reviewed Studies)	Ref(s).
Supervised and ensemble learning (random forest, XGBoost, support vector regression)	Large labeled datasets	Steady-state CoF and specific wear-rate regression from tabular feature sets	Regression demonstrated with interpretable feature-importance rankings; learned mapping is system-specific and transfers poorly without retraining	[54–57]
Convolutional/recurrent networks (CNN-LSTM, CNN-BiLSTM)	Large labeled datasets	Remaining useful life from run-to-failure vibration data (bearings)	Degradation signatures identified; assumes the laboratory degradation trajectory approximates the in-service failure mode	[58,59]
Supervised learning on friction-torque and leakage features	Small, single-laboratory datasets	Rotary-seal degradation from friction-torque signals	Demonstrated on custom rigs; smaller, less-standardized datasets have limited deeper architectures	[60]
Physics-informed neural networks (Reynolds-constrained)	Sparse data, known governing equations	EHL pressure and film-thickness fields	Average pressure errors of 1.81% and 0.34% across two transient-cavitation cases, validated against a reference simulation	[61]
Physics-informed neural networks (thermal, frictional contact)	Sparse data, known governing equations	Interface temperature fields at frictional contacts	Cross-scale temperature-field reconstruction in wet-friction components: 0.49 °C mean absolute error, with 34.6% RMSE and 43.7% MAPE reductions relative to a standalone SA-PINN	[62]
Physics-informed neural networks (thermal, general formulation)	Sparse data, known governing equations	Temperature-field inference from sparse measurements	Under 5% error on prototype heat-transfer problems; methodological template for spatially resolved thermal prediction at frictional contacts	[63]
Bayesian optimization (expected improvement)	Sequential, expensive experiments	Surface-texture geometry for CFRPEEK/17-4 PH under seawater lubrication	12.86% reduction in CoF with an LSTM-Bayesian hyperparameter-tuning framework	[64]
Bayesian optimization (DoE-coupled)	Sequential, expensive experiments	Nanoparticle lubricant-additive concentration	42% reduction in CoF for a CuO nanolubricant at an optimized 0.04 wt%	[65]
Bayesian optimization	Sequential, expensive experiments	Alloy composition screening (thermal expansion, phase stability)	38% of target-meeting alloys identified while sampling only 7% of a 1986-alloy composition space	[66]
Genetic algorithm/multi-criteria (NSGA-II, TOPSIS)	Sequential, expensive experiments	Multi-objective CoF and specific wear-rate minimization (Pareto front)	Tradeoff demonstrated; multi-objective Bayesian optimization on this specific tradeoff remains unestablished in the tribology literature	[67–69]

4.1. Supervised and Ensemble Learning for Friction and Wear Prediction

Supervised machine learning methods have seen the broadest adoption in tribological analysis, largely because the regression and classification tasks they perform map directly

onto the prediction problems that tribologists have historically approached through empirical correlation. Given a labeled dataset of experimental records, these methods learn functional mapping from input conditions to output tribological responses without requiring an explicit physical model of the contact [54–57]. Coefficient of friction and specific wear rate regression represent the most common application targets. Random forest regressors and gradient boosting methods, including XGBoost [55,56] and LightGBM [56] implementations, have been applied to predict steady-state CoF and volumetric wear rate from tabular input feature sets. These ensemble methods are well suited to tribological datasets, which tend to be small, heterogeneous, and structured rather than high-dimensional. They produce feature importance rankings that provide interpretable insight into which input variables most strongly govern contact behavior. Support vector regression has similarly been applied to CoF prediction in lubricated contacts, particularly in cases where dataset sizes are too small to support deeper architectures without overfitting [70,71]. Input feature sets in these models typically span three categories [72–74]. Material property features include hardness, elastic modulus, surface energy, and thermal conductivity of the contacting pair. Surface roughness parameters, including R_a , R_q , R_{sk} , and R_{ku} , characterize the initial topographic state of the specimen [75]. Operating condition features encode the applied load, sliding velocity, temperature, and lubricant type or viscosity grade. The selection and normalization of these features have a substantial effect on model performance, and inconsistent reporting conventions across the tribology literature mean that feature engineering remains a manual and labor-intensive step in most published workflows [76]. Remaining useful life prediction represents a higher-stakes application of supervised learning in tribology, particularly for bearing systems in rotating machinery. Convolutional and recurrent neural networks, including CNN-LSTM and CNN-BiLSTM hybrid architectures, trained on run-to-failure vibration datasets have demonstrated the ability to identify the characteristic signatures of progressive degradation and estimate remaining useful life from these time series [58,59]. A related line of work addresses degradation prediction in rotary seals using friction torque signals as the primary input, generally relying on support vector machine and hybrid optimization-based architectures such as particle swarm optimization coupled SVM [60]. Unlike bearing systems, which benefit from public run to failure benchmarks such as PRONOSTIA [77] and CWRU [78], seal degradation studies typically rely on custom, single laboratory test rigs, so the comparatively smaller and less standardized datasets available for seal systems have likely limited the adoption of deep convolutional or recurrent architectures in this subdomain. Across both lines of work, models are trained on run-to-failure datasets generated under controlled laboratory conditions, with the implicit assumption that the degradation trajectory observed in the laboratory approximates the in-service failure mode [79]. Surface texture classification from scanning electron microscopy and optical microscopy images represents a parallel application domain. Convolutional neural networks trained on labeled wear scar image libraries can distinguish adhesive, abrasive, fatigue, and tribochemical mechanisms. Published classifications have been shown to agree closely with expert visual assessment on held-out test images [80]. This capability is particularly relevant to automated tribometry pipelines where post-test imaging is performed robotically because it offers a path toward reducing the degree of human review needed for wear mechanism assignment from micrographs. A fundamental limitation across all these methods is poor cross-system generalizability. A tribological contact system is defined by its material pair, contact geometry, lubrication condition, and operating regime. A model trained on one system fails to predict performance on a new system without explicit retraining. This reflects an intrinsic domain shift rather than a deficit in model capacity or hyperparameter tuning. It reflects the fact that tribological behavior is a system property rather than a material property [81], meaning that

the learned mapping is specific to the conditions under which training data was generated. This transferability problem is one of the central unresolved challenges in data-driven tribology, and it is discussed further in Section 6.

4.2. Unsupervised and Anomaly Detection Methods

While supervised methods dominate the published literature on machine learning in tribology, a smaller but meaningful body of work has applied unsupervised and anomaly detection techniques to problems where labeled training data is unavailable or where the objective is discovery rather than prediction [9]. These methods operate on the structure of the data itself, identifying clusters, outliers, and latent patterns without requiring a predefined output target. Wear mechanism clustering represents the most established unsupervised application in tribology. Acoustic emission signals and friction force traces recorded during sliding contact contain characteristic statistical signatures that correspond to distinct physical wear mechanisms [82]. Unsupervised clustering methods have been applied to statistical features extracted from acoustic emission signals, including root mean square amplitude and kurtosis, to identify transitions in lubrication regime and wear behavior without manual labeling [83]. The practical value of this approach is that it can identify mechanistic transitions during a test, such as the shift from mild oxidative wear to severe adhesive wear, at a temporal resolution that post-test characterization cannot achieve. Dimensionality reduction techniques including t-distributed stochastic neighbor embedding and variational autoencoders have been applied to high-dimensional tribological time series to extract compact latent representations that preserve physically meaningful structure [26,84]. These representations improve the interpretability of large experimental datasets and serve as useful preprocessing steps before clustering or supervised classification. Anomaly detection methods, including isolation forests, one-class support vector machines, and autoencoder reconstruction error thresholding, have been applied to real-time friction and electrostatic charge signals to flag abrupt deviations from an established statistical baseline, marking transitions such as the onset of oxidative wear [85]. Autoencoder reconstruction error thresholding has demonstrated the ability to flag the onset of wear well before visible damage occurs, detecting anomalous behavior hundreds of cycles earlier than isolation forest and other outlier detection methods applied to the same data [85]. The relative scarcity of published unsupervised tribology work compared to supervised methods reflects the persistent data availability asymmetry in the field. Unsupervised methods become more powerful as dataset size increases, and the limited volume of standardized, aggregated tribological data has constrained their development. As automated platforms generate larger and more consistent experimental archives, this balance is likely to shift.

4.3. Physics-Informed Neural Networks for Tribological Modeling

Most tribological research relies on small, noisy experimental datasets that are highly sensitive to uncontrolled variables. These data characteristics conflict directly with the high data requirements of purely data-driven neural networks [76]. Deep networks trained without physical constraints require large labeled datasets to generalize reliably, and they produce predictions that can violate known physical laws when extrapolating beyond the training distribution [86]. Physics-informed neural networks address this issue directly by embedding known governing equations as soft constraints within the loss function, forcing the learned solution to remain consistent with established contact mechanics and transport physics even in regions where experimental data is sparse. The motivation for applying PINNs specifically to tribology is strong because the field possesses a well-developed set of governing equations that describe the most important contact phenomena. The

Reynolds equation governs pressure distribution and film thickness in elastohydrodynamic lubrication, the Archard wear equation relates volumetric material loss to contact load and sliding distance, and the Greenwood-Williamson model describes asperity contact mechanics at rough surfaces. These governing relations and their role as physics constraints are summarized in Table 4.

Table 4. Governing equations from contact mechanics, wear, and lubrication theory that can be embedded as physics constraints in physics-informed neural networks for tribology, including their applicable conditions, limitations, and existing tribological examples.

Governing Relation	Physical Quantity Governed	Role as a Physics Constraint in a PINN	Applicable Conditions	Limitations	Existing Tribological Examples
Reynolds equation	Pressure distribution and film thickness in elastohydrodynamic lubrication	Residual term penalizes network outputs that violate lubrication film-pressure physics; used in EHL film-thickness PINNs	Narrow lubricated contacts governed by hydrodynamic flow, including sliding or squeezing motion and transient cavitation	In the implementation reported in [61], direct friction, contact mechanics, and pressure-dependent surface deformation are neglected and would require additional coupled models.	PINN prediction of pressure development and transient cavitation in dynamically changing sealing contacts [61]
Archard wear equation	Volumetric material loss as a function of contact load and sliding distance	Constrains predicted wear to the established load and sliding-distance dependence	Sliding or abrasive-wear conditions in which wear approximately scales with normal load and sliding distance	Does not fully represent changing wear mechanisms, evolving contact area, local contact pressure, running-in effects, or abrasive-particle behavior	Archard-constrained PINN prediction of volumetric wear loss for HVOF-sprayed WC-10Co-4Cr coatings under ASTM G65-type abrasive-wear conditions, achieving a cross-validated R^2 of 0.985 [87]
Greenwood–Williamson model	Asperity contact mechanics at rough surfaces	Constrains contact-area and pressure predictions to rough-surface asperity theory	Elastic contact between nominally flat rough surfaces represented by statistically distributed spherical asperities	Assumes a common asperity radius and mechanically independent asperities; neighboring-asperity interactions and curved contacts can violate these assumptions; does not directly describe wear evolution	Estimation of real contact area and mean contact pressure for nominally flat rough surfaces, establishing the load–contact-area relationship underlying friction analysis [88]

Each of these equations encodes physical knowledge accumulated over decades of analytical and experimental work. Rather than discarding this knowledge in favor of a purely data-driven mapping, PINNs incorporate it as a regularization term that penalizes network outputs that violate the governing equation residuals during training. In practice,

as described by Raissi, Perdikaris, and Karniadakis, this is implemented by augmenting the standard supervised loss, typically mean squared error against experimental measurements, with additional loss terms that evaluate the residual of the governing partial differential equation at a set of collocation points sampled across the domain [52]. Figure 2 illustrates this loss decomposition.

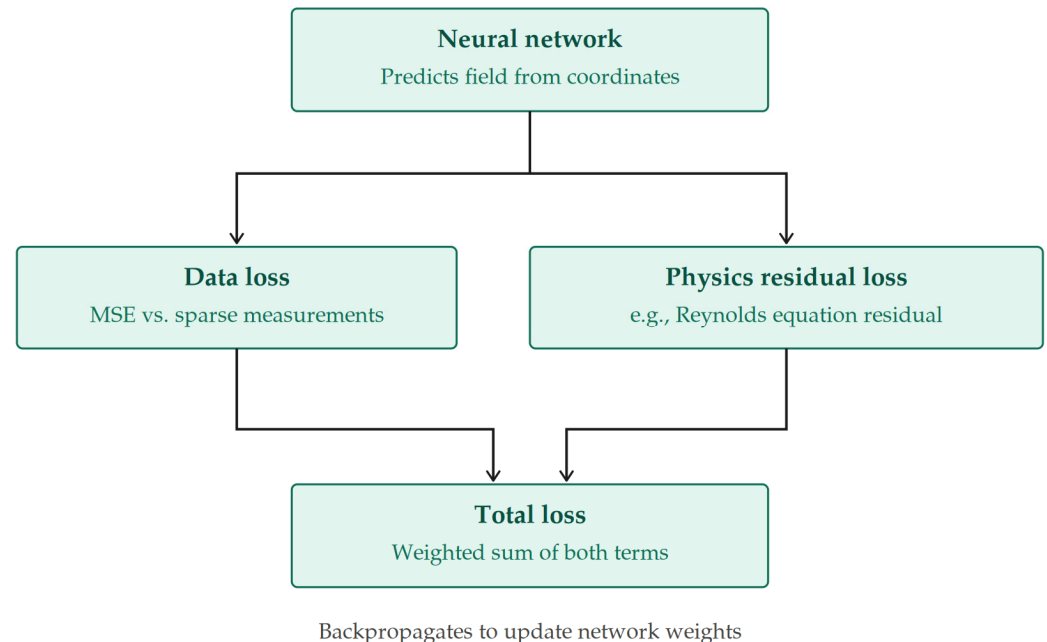


Figure 2. Decomposition of the physics-informed neural network training loss into a data loss against sparse measurements and a physics residual loss evaluated at collocation points, exemplified by the Reynolds equation.

Published applications of PINNs in tribology have concentrated on elastohydrodynamic lubrication film thickness prediction and the thermal modeling of frictional contacts. In EHL applications, PINNs trained on limited film thickness measurements have demonstrated the ability to recover pressure and film thickness distributions consistent with the Reynolds equation across the contact domain, with Brumand-Poor et al. reporting average pressure errors of 1.81% and 0.34% across two transient cavitation test cases, validated against a reference simulation [61]. Thermal PINN formulations have been applied to friction contact interface temperature prediction, with recent work coupling a self-adaptive PINN to a thermal network model to reconstruct temperature fields across scales in wet friction components [62]. More broadly, Cai et al. demonstrated that PINNs can infer temperature fields from sparse measurements with under 5% error for prototype heat transfer problems, providing the methodological template for applying this approach to spatially resolved thermal prediction at frictional contacts [63]. The principal advantage of this architecture over pure data-driven approaches is physically consistent extrapolation. Because the governing equation constrains the solution, PINN predictions outside the training distribution tend to remain physically plausible rather than diverging arbitrarily. This property is particularly valuable in tribology, where testing every relevant combination of load, speed, temperature, and material is experimentally intractable. The primary limitation of PINNs in tribological applications is training instability. The multi-term loss landscape introduces competing gradients that can cause optimization to stall or converge to poor local minima, particularly when the physics residual and data loss terms operate on different numerical scales. The sensitivity of final model performance to the physics constraint weighting coefficient also means that careful hyperparameter tuning is required

for each new contact problem, reducing the plug-and-play accessibility of the method compared to standard supervised approaches [89,90].

4.4. Bayesian Optimization and Active Learning

Rather than a pure optimization algorithm, Bayesian optimization is fundamentally a framework for experimental design. This focus is particularly suited to tribological research. The algorithm uses all prior data to determine the most informative next experiment. In doing so, it balances the exploration of new regions with the exploitation of known top performers [91]. This sequential, decision-theoretic framing makes it fundamentally different from post-hoc regression or classification, and it is this property that makes Bayesian optimization the most natural bridge between the AI methods discussed in this section and the closed-loop robotic experimentation architectures discussed in Section 5. The method operates by maintaining a Gaussian process surrogate model over the tribological response surface of interest. A Gaussian process provides a probabilistic prediction at every point in the input space, returning both a mean estimate and an associated uncertainty [92]. This uncertainty quantification is central to the method because it allows the acquisition function to reason about where additional experiments would be most informative [65]. Common acquisition functions applied in tribological contexts include expected improvement, which was demonstrated by Nie et al. in optimizing surface texture geometry for CFRPEEK/17-4 PH stainless steel friction pairs under seawater lubrication, achieving a 12.86% reduction in coefficient of friction with an LSTM-Bayesian hyperparameter tuning framework [64]. Another standard alternative acquisition function is upper confidence bound, which more aggressively samples uncertain regions to accelerate global exploration of the design space [91]. In lubricant formulation optimization, Bayesian optimization has been applied to identify optimal nanoparticle additive concentrations, with a hybrid design of experiments and Bayesian optimization approach achieving a 42% reduction in coefficient of friction for a CuO-based nanolubricant at an optimized concentration of 0.04 wt% [65]. Bayesian optimization has been applied to alloy composition screening more broadly, with one study identifying up to 38% of alloys meeting target thermal expansion and phase stability criteria while sampling only 7% of a 1986-alloy composition space [66]. Multi-objective optimization of coefficient of friction and specific wear rate, which are frequently in tension across material design spaces, has been demonstrated using genetic algorithm; multi-criteria decision-making approaches such as NSGA-II and TOPSIS [67–69] though multi-objective Bayesian optimization applied specifically to this tradeoff remains unestablished in the published tribology literature.

5. Closed-Loop Autonomous Tribological Evaluation

5.1. The Closed-Loop Paradigm in Materials Experimentation

Closed-loop experimentation repeats sensing, inference, decision-making, and physical actuation continuously without human intervention between cycles. This paradigm has already demonstrated substantial gains in adjacent materials research domains. A collaboration led by the Berlinguette, Hein, and Aspuru-Guzik groups developed Ada, a modular self-driving laboratory that integrates robotic liquid handling, optical and spectroscopic characterization, and a global Bayesian optimization algorithm to autonomously optimize the properties of thin-film materials. This is demonstrated by maximizing hole mobility in organic hole transport materials for perovskite solar cells [93]. In pharmaceutical research, autonomous AI-guided platforms have compressed early-stage development timelines substantially, with Insilico Medicine's generative AI pipeline advancing a TNIK inhibitor for idiopathic pulmonary fibrosis from target identification to preclinical candidate nomination in approximately 18 months, roughly half the conventional timeline [94], with many other

examples present in the literature [95]. Combinatorial thin-film synthesis systems have similarly demonstrated closed-loop composition optimization, with one system completing a full deposition-to-measurement cycle in approximately 3 to 4 h across 18 autonomous cycles to identify an optimal five-element alloy composition [96]. The architectural principles from these domains are directly transferable. Hardware components must be modular and reconfigurable with well-defined interfaces. Data schemas should be standardized so that sensor outputs feed directly into inference pipelines. Finally, a surrogate model paired with an acquisition function translates current knowledge into concrete experimental recommendations. Tribology-specific barriers that do not exist in solution-phase chemistry or thin-film deposition constrain this adoption, and they are examined in detail in the sections that follow. Figure 3 summarizes this four-layer architecture, distinguishing links already demonstrated in the literature reviewed here from links that remain partial or unrealized specifically within tribology.

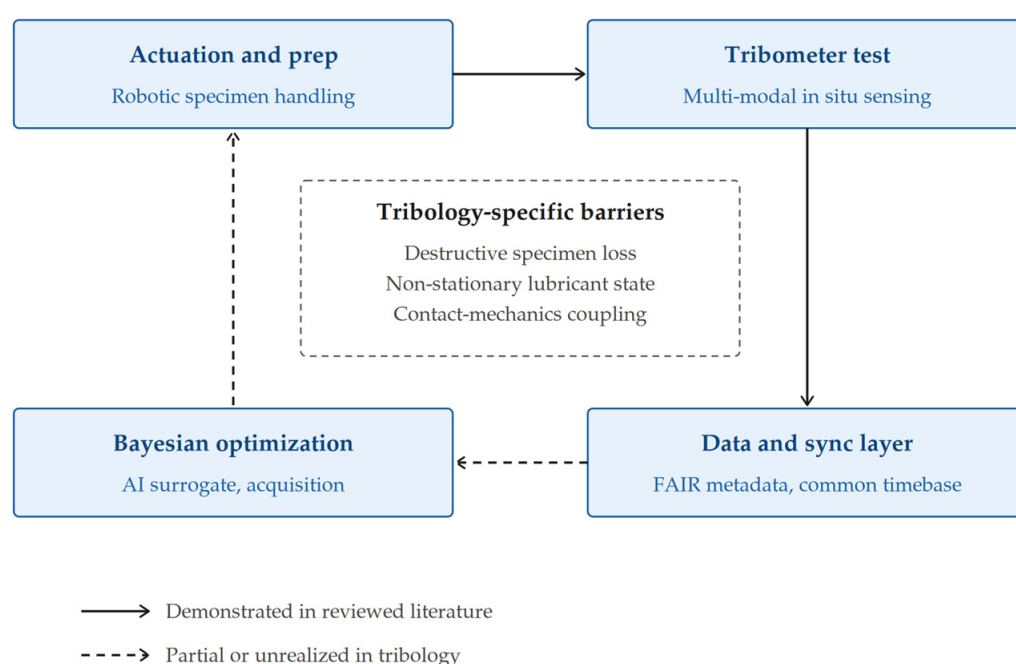


Figure 3. The closed-loop autonomous tribological experimentation cycle across four functional layers, with solid arrows marking links demonstrated in the reviewed literature and dashed arrows marking links that remain partial or unrealized in tribology.

5.2. Optimization Targets in Closed-Loop Tribometry

A closed-loop tribological system requires an explicit optimization target before automated decision-making can proceed. While adjacent fields have also struggled with objective specification, particularly in multi-objective settings where handcrafted figures of merit are difficult to design without prior knowledge [97,98], tribology’s performance proxies are less correlated with the underlying performance construct than in most chemistry applications, making the target-specification problem more acute rather than novel. In tribology, the choice of target is non-trivial because tribological performance is multidimensional, context-dependent, and measured through proxies that do not always correlate with one another. Selecting the wrong target, or leaving it underspecified, produces a closed-loop system that optimizes efficiently toward the wrong outcome. Several candidate optimization targets can be identified, each implying a distinct decision space and acquisition function structure. Minimizing test time to a predefined failure threshold is appropriate for accelerated life testing applications, where the objective is to characterize material durability efficiently. In this case, the decision space consists of stress condition

combinations such as load and velocity that accelerate damage accumulation, and the acquisition function must balance the risk of inducing a different failure mode against the need for speed, since accelerated tribological test conditions can shift the dominant wear mechanism away from that observed under service conditions [99]. Mapping the Stribeck curve with a minimum number of experimental points is a natural target for active learning applied to lubrication regime characterization, since the curve's boundary, mixed, and hydrodynamic regimes are separated by transition regions where an acquisition function could prioritize uncertainty reduction. This specific application has not yet been demonstrated in the published tribology literature and existing Stribeck curve modeling efforts instead rely on dense and exhaustively sampled experimental datasets [100]. Multi-objective formulations, which simultaneously minimize CoF and specific wear rate, require Pareto front estimation rather than scalar optimization. Acquisition functions such as expected hypervolume improvement are useful to this setting [101,102].

5.3. Current State of Closed Loop Tribological Systems

An assessment of the published literature reveals that fully autonomous closed-loop tribological systems, in which robotic actuation, in situ sensing, real-time AI inference, and Bayesian experimental design operate together in an uninterrupted cycle without human intervention, do not yet exist in a mature, reported form. Such an integrated architecture represents a research frontier rather than a consolidated technology. The literature contains a set of partial implementations, each realizing part of the closed-loop cycle. Automated test sequencing without AI decision-making represents the most widely reported partial implementation. Several commercial and custom high-throughput tribometer platforms, such as AMT's multi-station HTP series and purpose-built academic systems, automate the physical execution of predefined test matrices without any adaptive modification of the experimental protocol based on incoming data [103]. These systems eliminate manual intervention during testing but retain a fixed, human-specified experimental design. The result is high-throughput data generation without intelligent experimental steering [24,104,105]. AI-guided lubricant and material screening without robotic actuation represents a complementary partial implementation. Several groups have applied Bayesian optimization and active learning frameworks to tribological design spaces, recommending optimal next experimental conditions from surrogate models trained on existing datasets [64,65,106]. These systems perform the inference and decision layers correctly but rely on human experimenters to physically execute the recommended conditions, introducing the latency and variability that full automation is intended to eliminate. Sensor-triggered test termination without optimization represents the most operationally mature partial capability. Acoustic emission thresholding and friction coefficient deviation monitoring have been implemented in commercial tribometer control software to automatically halt tests upon detection of catastrophic wear events [107,108]. This constitutes a reactive closed-loop at the fast timescale described in Section 4.2 but does not include any surrogate model updating or acquisition function query. The gap between these partial implementations and a fully integrated closed-loop system is primarily one of system integration rather than fundamental scientific capability. The sensing hardware, robotic handling platforms, and AI methods described in Sections 2 and 3 each exist at sufficient maturity to serve as components of a complete system. What is absent from the literature is a reported architecture that connects all four layers with validated interfaces and the demonstration of autonomous multi-iteration experimental campaigns in a tribological context. This integration gap defines the immediate research opportunity in the field.

5.4. Integration Challenges and Near-Term Roadmap

Several barriers to full closed-loop integration are specific to tribology and do not appear in the self-driving laboratory literature from adjacent materials research fields. The first barrier is the destructive and irreversible nature of wear. In solution-phase chemistry or optical characterization, a sample can be re-measured under different conditions without consequence [109]. In tribology, each specimen has a finite wear life, and every test cycle consumes an irreplaceable portion of it. This means that the surrogate model cannot query the same point in the design space twice to reduce measurement uncertainty, and that poor experimental decisions carry a real material cost that has no analog in non-destructive testing paradigms. The second barrier is the non-stationary character of tribological system state during a test. Lubricant rheology evolves continuously as temperature rises, shear degradation accumulates, and additive chemistry depletes at the contact interface. This means that the system the surrogate model was trained on at the beginning of a test is physically different from the system being measured at the end of it. Battery cycling analogs also face coupled, path-dependent degradation mechanisms that remain an active research challenge, but decades of standardized testing protocols and large public cycling datasets have produced degradation path predictions accurate to under 1% error in some studies [110]. This is a level of predictive infrastructure that does not yet exist for the coupled thermal, chemical, and mechanical evolution of a lubricated tribological contact. The third barrier is contact mechanics coupling. Changing the applied load to probe a new operating condition simultaneously changes the Hertzian contact area and mean contact pressure, meaning that load and contact stress cannot be varied independently. This coupling complicates the surrogate model input space in ways that lubricant formulation or coating composition spaces do not, because in those cases, each input dimension can be varied without mechanically perturbing the others. The three barriers mentioned above are summarized below in Table 5.

Table 5. Tribology-specific barriers to closed-loop integration and their status under the proposed lubricant-screening approach.

Barrier	Physical Mechanism	Contrast with Adjacent Fields	Status Under Proposed Approach
Destructive, irreversible wear	Each specimen has a finite wear life; every test cycle consumes an irreplaceable portion of it.	Solution-phase chemistry and optical characterization allow for re-measurement of the same sample under different conditions without consequence.	Sidestepped: fixing the material pair avoids repeated destructive sampling across the design space.
Non-stationary system state	Lubricant rheology, shear degradation, and additive depletion evolve continuously during a test, so the system at test start differs physically from the system at test end.	Battery cycling faces analogous coupled degradation, but decades of standardized protocols and large public datasets have produced sub-1% degradation path prediction errors; no comparable infrastructure exists for tribological contacts.	Reduced, but not eliminated: focusing on steady-state friction response rather than transient wear evolution limits exposure to non-stationarity.
Contact mechanics coupling	Changing load simultaneously changes Hertzian contact area and mean contact pressure, so load and contact stress cannot be varied independently.	Lubricant formulation and coating composition spaces allow each input dimension to be varied without mechanically perturbing the others.	Sidestepped: holding load and velocity constant avoids this coupling.

Despite these barriers, a first-generation closed-loop tribological system appears achievable using components that already exist at sufficient maturity, without requiring new fundamental capability development. A plausible starting point couples automated lubricant handling to a standard tribometer under Bayesian optimization, since fixing the material pair and holding load and velocity constant sidesteps the destructive specimen and contact mechanics coupling barriers, while focusing on steady-state friction response rather than transient wear evolution reduces the non-stationarity problem. Lubricant formulation screening is therefore a comparatively feasible near-term target, given the industrial demand for efficient additive optimization and the large, navigable composition spaces that modern lubricant formulation presents.

6. Challenges and Future Prospects

6.1. Dataset Standardization and Open-Access Infrastructure

The fragmentation of tribological data across disconnected institutional repositories, proprietary instrument formats, and individual paper supplementary files is one of the most consequential structural barriers to progress in data-driven tribology. Unlike adjacent fields that have invested in centralized, community-maintained databases, tribology has not yet produced an equivalent infrastructure. The NOMAD repository aggregates first-principles calculation data across materials science [111], the Cambridge Structural Database consolidates crystallographic records from decades of diffraction experiments [112], and the battery community has developed standardized cycling data schemas that allow for cross-institutional model training [113]. Although tribology has not yet established a community-wide repository comparable to those in adjacent fields, several specialized initiatives have addressed aspects of data standardization and reuse. International round-robin studies have demonstrated that differences in test equipment, specimen preparation, operating conditions, and evaluation procedures can produce substantial interlaboratory variability [5]. The tribAIn ontology was developed to formalize shared tribological concepts and support knowledge reuse [114], while the tribo-informatics framework proposed the systematic integration of tribological databases, information technologies, and analytical methods [115]. More recently, Kadi4Mat and the TriboDataFAIR framework demonstrated machine-readable metadata capture and FAIR data packaging for experimental tribology [116,117]. These efforts provide important foundations, but they remain individual frameworks or demonstrations rather than a broadly adopted metadata standard and centralized infrastructure for cross-platform tribological data.

Addressing this requires agreement on a minimum metadata schema that must accompany any deposited tribological dataset, following the precedent set by domain-specific schemas such as the NOMAD MetaInfo in computational materials science [118]. At a minimum, this schema should mandate the recording of contacting material identities and bulk properties, surface preparation method and resulting roughness parameters, contact geometry and nominal Hertzian contact stress, lubricant identity and viscosity grade, environmental temperature and relative humidity, instrument make and model, and the full time-resolved records of friction force, normal load, and wear depth. These minimum fields are summarized in Table 6.

Without this metadata, a friction coefficient value is an isolated number rather than a reusable data point. The FAIR data principles, which require that research outputs be findable, accessible, interoperable, and reusable, provide a practical framework for designing such a repository. A FAIR-compliant tribological database would assign persistent identifiers to individual datasets, expose them through a standardized query interface, and enforce the metadata schema at the point of submission rather than as a post-hoc recommendation.

Table 6. Proposed minimum metadata schema for a FAIR-compliant tribological dataset, with an item-by-item comparison against ASTM G99, G133, G77, and D4172 [119–122], following the fields identified in Section 6.1; without these fields, a reported friction value is an isolated number rather than a reusable data point.

Metadata Field	Recorded Quantity	Comparison with Existing Standards	Why It Is Required for Reuse
Contacting materials	Identities and bulk properties of the contacting pair	G99, G133, G77, and D4172 include material identity and selected properties, although requirements vary by test method.	Fixes the material system so results can be matched across studies
Surface preparation	Preparation method and resulting roughness parameters	G99, G133, G77, and D4172 address surface preparation, roughness, or cleaning, but not uniformly.	Initial surface state governs run-in and wear response
Contact geometry	Geometry and nominal Hertzian contact stress	All four standards specify test-specific geometry and dimensions; G133 also addresses Hertzian stress.	Sets the contact conditions that make CoF and wear values comparable
Lubricant	Identity and viscosity grade	G133, G77, and D4172 identify the lubricant or test fluid, although the reported properties vary.	Determines the lubrication regime of the contact
Environment	Temperature and relative humidity	Environmental conditions are not addressed consistently across the standards.	Ambient conditions alter oxide formation and lubricant viscosity
Instrument	Make and model	The standards address apparatus specifications, alignment, tolerances, or calibration but do not consistently require instrument identity.	Captures apparatus-specific dynamics needed for interlaboratory comparison
Primary measurement channels	Time-resolved friction force, normal load, and wear depth	The standards primarily emphasize final wear measurements and selected friction results rather than time-resolved signals.	The core signals a reusable record must retain rather than a single summary value

6.2. Model Transferability Across Contact Conditions

In tribology, a model that fails to transfer can still be highly accurate. It has learned a valid relationship for one specific contact system. However, it cannot generalize to a new system drawn from a completely different distribution. The second problem does not disappear with more training data or better regularization. As established in Section 4.1, tribological behavior is a system property rather than a material property, meaning that the friction and wear response of a given material is inseparable from the geometry, kinematics, lubrication condition, and thermal environment of the specific contact in which it is measured [81]. The practical consequence is that models trained on data from one tribometer configuration are inherently coupled to that apparatus's specific dynamics, and generalization across different contact geometries, lubrication regimes, or mechanical systems remains a significant and largely unresolved challenge [76]. The contact pressure distribution, the dominant wear mechanism, and the transient thermal response are all sufficiently different that the learned mapping does not transfer. Transfer learning, in which a model trained on one task or dataset is adapted to perform well on a related but

distinct task [123], offers a partial mitigation to this problem, reducing the amount of new data required when moving to an unseen contact system without eliminating the need for some retraining. One path to mitigation is exploiting whatever labeled data exists from the target contact system as efficiently as possible. Domain adaptation methods fine-tune a pre-trained model on a small number of labeled examples from the target system, substantially reducing the data required to reach acceptable performance in a new regime [124]. Meta-learning frameworks push this further, training models explicitly to adapt quickly to new contact conditions from minimal retraining data rather than relying on a single round of fine-tuning [125]. Both strategies have been explored in adjacent condition monitoring and fault diagnosis applications but remain underutilized in tribology specifically [126]. Physics-informed architecture offers a different kind of mitigation that does not depend on acquiring more target-system data. Constraining a model to respect governing equations that hold across contact systems narrows the space of physically implausible failure modes when generalizing to an unseen contact system, though it does not eliminate the transferability problem entirely. The transferability problem ultimately will not be resolved by algorithmic advances alone. It requires the large, diverse, well-characterized datasets discussed in Section 6.1. A model trained on tribological data spanning dozens of contact geometries, material classes, lubrication regimes, and operating conditions has a different generalization capability than one trained on a single laboratory's dataset, as demonstrated by a study combining heterogeneous literature and simulation data to achieve more robust predictions than single-source datasets allow [127]. Building that training corpus is a data infrastructure problem as much as a machine learning problem, and the two challenges are therefore coupled.

This unresolved challenge reflects two separate statistical mechanisms, and the distinction determines which mitigation strategy can succeed [128]. Covariate shift occurs when the distribution of input conditions differs between the source and target tribometer, for example, when one rig explores a wider load range than the other, without any change in the underlying relationship between inputs and tribological response. This mechanism is correctable in principle. Reweighting or aligning the input feature distributions, the approach used by most domain adaptation methods, recovers model performance because the learned mapping remains valid across domains [129]. Concept shift is more important. It occurs when the input-output relationship itself changes, so that the same nominal load, speed, and roughness values produce a different tribological response because the governing contact mechanics differ by geometry. A point contact and a conformal journal bearing under nominally similar load and speed conditions do not share a Hertzian pressure field [130], a lubricant film thickness solution, or a flash temperature distribution [131]. These quantities follow from geometry-specific solutions to the governing contact mechanics and lubrication equations, not from load and speed alone. A model trained under one geometry has therefore learned a mapping tied to a physical relationship that does not hold under a different geometry. This is a distinct and more severe root cause than training on an insufficiently diverse dataset.

This distinction has a direct consequence for how much transfer learning and domain adaptation can help. Standard domain adaptation theory bounds the achievable error on a target domain using three terms. The first is the source error. The second measures the divergence between the source and target input distributions. The third is an irreducible term reflecting how well a single hypothesis can fit both domains at once [132]. Feature alignment methods, such as reweighting, subspace alignment, and adversarial domain-invariant embeddings, act only on the divergence term. This term corresponds to covariate shift. When the failure is concept shift instead, the irreducible term dominates. No single mapping fits both geometries well, and feature alignment cannot reduce this term. The

same bound explains the physical argument above. Fine-tuning and feature alignment can help when the source and target systems share the same governing contact regime and differ mainly in the range of conditions tested, as when both operate in boundary lubrication under the same dominant wear mechanism. These methods are not expected to succeed once the dominant wear mechanism itself changes, as in a shift from adhesive to abrasive wear, because this is a change in which physical model applies, not a change in the parameters of a shared model. Meta-learning methods relax this constraint somewhat. They train explicitly for fast adaptation across a distribution of related tasks [125], learning an initialization that adapts efficiently within a family of related geometries. They still require that the tasks used during meta-training and the target geometry belong to a genuinely related family in the contact mechanics sense, not merely that both are drawn from the tribology literature. A practical consequence follows. Transfer learning or domain adaptation is worth attempting only after a physics-based check, such as comparing Hersey or Sommerfeld numbers across the source and target systems, confirms that both occupy the same lubrication regime. A statistical alignment method applied before this check has no theoretical basis for succeeding.

6.3. Hardware and Software Integration Complexity

The technical components required for a closed-loop tribological system, robotic actuators, in situ sensor arrays, and machine learning inference pipelines, each exist at sufficient individual maturity to serve as system components, as established throughout this review. The barrier that remains most underappreciated in the literature is not the capability of any individual component but the engineering complexity of integrating them into a functioning system with reliable, low-latency interfaces [133]. Tribometer control software represents the most immediate integration challenge. Commercial tribometer platforms typically offer a limited set of configurable modules and closed, proprietary control software, a constraint significant enough that a substantial share of researchers build custom or self-developed tribometers to meet specific experimental needs [134], consistent with the non-standardized instrument APIs reported as a general barrier across self-driving laboratory efforts [133]. These interfaces were designed for human-supervised test execution rather than machine-readable command and response cycles, and they do not natively support the real-time bidirectional communication that autonomous, closed-loop experimental control requires. Wrapping these interfaces in middleware abstraction layers that present a standardized API to upstream inference and decision software is a necessary engineering step. Standards such as SiLA [135] and frameworks such as UniLabOS [136] have addressed exactly this problem for chemistry and biology laboratory instruments, but none of this middleware infrastructure has yet been adapted or applied to tribometer control specifically, despite being a practical prerequisite for any closed-loop tribological implementation. The Robot Operating System (ROS) provides a potential framework for this abstraction. ROS has been adopted in laboratory automation contexts outside tribology, including robotic chemistry synthesis platforms such as ARChemist, precisely because its publisher-subscriber communication architecture handles heterogeneous hardware interfaces and asynchronous sensor streams naturally [137]. Adoption has remained limited relative to its potential, since installing and maintaining ROS carries a real engineering overhead that has kept many labs from using it despite these advantages. Adapting ROS node architectures to tribometer control and sensor data aggregation would nonetheless substantially reduce the custom integration work required for each new closed-loop tribology implementation, and it would produce reusable software infrastructure that the community could build on incrementally. Sensor synchronization, introduced in Section 3.3 as a data quality requirement, is also a system integration challenge in its own right. Achieving the

timing precision needed for reliable event correlation across channels sampled at rates differing by several orders of magnitude requires dedicated hardware triggering design, not just software timestamp management, making it a system-level reliability concern rather than a peripheral instrumentation detail.

6.4. Toward Fully Autonomous Tribological Discovery

The trajectory established by the robotic platforms, AI methods, and closed-loop architectures reviewed in this paper points a fully autonomous tribological discovery pipeline in which material synthesis, surface preparation, tribological testing, and AI-guided experimental iteration operate as a continuous, unsupervised cycle. No such system exists today, but the enabling components appear sufficiently mature that achieving it may depend more on investment in integration and data infrastructure than on further fundamental capability development. Several convergent developments make this vision possible. Foundation models trained on large, diverse materials datasets have already demonstrated the ability to produce a generalizable prior that can be fine-tuned to specific downstream tasks with limited additional data [138], and an analogous approach applied to tribological datasets could provide a similar generalizable prior over friction and wear behavior. Digital twin integration is a parallel development path. Wear-focused digital twins combining physics-based and data-driven models to continuously update a live wear state from sensor data have already been demonstrated for individual components such as sliding bearings [139], and extending this approach to fielded machinery more broadly would provide a live characterization of in-service tribological state. Coupling digital twins to autonomous laboratory testing systems would close the loop between operational performance data and controlled experimental validation, enabling a model of tribological behavior that improves continuously from both sources simultaneously. Computational capacity is abundant, and algorithmic sophistication has advanced substantially in recent years. Neither factor constrains autonomous tribological discovery. Instead, the primary bottleneck is data. Models capable of generalizing across complex tribological systems require large, diverse, and interoperable sets of labeled experimental records, which remain scarce. Physics-constrained learning architectures remain essential, even as dataset scale increases, since the combinatorial space of contact conditions, material pairs, lubricant chemistries, and operating environments is too large to cover experimentally at any realistic throughput. The combination of large-scale open data and physics-constrained learning is therefore not a contingent research direction but a structural requirement for autonomous tribological discovery to become scientifically credible and industrially actionable.

7. Application Domains and Impact

7.1. Industrial Machinery and Manufacturing

Industrial machinery represents the most economically immediate application domain for robotic and AI-driven tribological methods. Rotating equipment including turbines, compressors, gearboxes, and pumps operates under continuous tribological loading at the bearing and seal interfaces that govern both efficiency and service life. The application of tribology best practices at the national scale has been estimated to yield gross domestic savings of 1.3 to 1.6 percent through reduced downtime, maintenance, and replacement costs [140]. The economic consequences of tribological failure in this context are substantial. Unplanned downtime in large industrial equipment can generate losses well in excess of the cost of the characterization infrastructure required to prevent it, which means that this domain can justify levels of investment in automated monitoring and testing that smaller-scale applications cannot. Bearing and mechanical seal wear monitoring has been the primary entry point for condition monitoring technologies in industrial machinery. Vibration-based

diagnostics and oil debris analysis have been deployed in fielded equipment for decades, generating large operational datasets that represent an underutilized resource for machine learning model training [141–144]. Supervised learning models trained on these historical records have demonstrated the ability to predict remaining useful life and flag anomalous wear signatures with lead times sufficient to permit planned maintenance interventions, including a demonstrated case combining regression and multilayer neural network models to track rolling element bearing degradation across 50 days of vibration measurements on an operational wind turbine gearbox [145]. Laboratory platforms that replicate the specific contact conditions of industrial bearing geometries under controlled conditions can generate the labeled training data that operational monitoring models require, at a throughput and consistency that manual testing cannot provide. This addresses a recognized limitation in which classifiers trained on lab-generated bearing data offer no guarantee of accuracy when applied to bearings of the same type in different operational applications [146]. Cutting tool wear in manufacturing presents a related application. Tool wear governs surface finish quality, dimensional accuracy, and machining energy consumption, and its progression is strongly sensitive to workpiece material, cutting parameters, and coolant delivery. Closed-loop machining systems that monitor acoustic emission and cutting force signatures in real time and adjust feed rate, depth of cut, or coolant flow in response represent an active area of development in manufacturing automation [147,148], with recent work explicitly identifying full closed-loop integration with CNC controllers as a target for future development rather than an established capability. Mapping tool wear against cutting conditions and materials is ideally suited for Bayesian optimization. Automated tribometer testing can rapidly survey these condition spaces in the lab. This process efficiently populates the surrogate models required by in-process monitoring systems. Automated lubricant replenishment is another connection between robotic tribometry and industrial practice. Centralized lubrication systems that deliver metered lubricant volumes to multiple bearing points on a timed schedule are well established in industrial machinery, but they operate on fixed schedules rather than in response to actual contact conditions. Integrating real-time tribological inference, using electrical contact resistance or acoustic emission signals to assess film integrity, with automated replenishment actuation would constitute a genuine closed-loop lubrication system. The laboratory characterization work required to validate the control logic for such a system is precisely the type of high-throughput, condition-spanning tribological testing that the robotic platforms described in Section 3 are designed to perform.

7.2. Biomedical Implants

Biomedical implants are one of the most demanding application domains for tribological characterization, combining the consequence of failure typical of aerospace systems with a biological complexity that has no analog in industrial machinery. Total hip and knee replacements are the most extensively studied implant tribology systems. Cobalt-chromium-molybdenum alloy on ultrahigh-molecular-weight polyethylene remains the most common bearing couple [149], while ceramic-on-ceramic and ceramic-on-polyethylene configurations have been developed as alternatives, each presenting distinct wear and failure mechanisms. Ceramic-on-ceramic bearings exhibit markedly lower wear volumes but carry a meaningful fracture risk not present in metal or polyethylene bearings [150], while ceramic-on-polyethylene configurations reduce debris generation relative to metal-on-polyethylene couples [151]. The clinical consequences of excessive wear extend beyond mechanical failure of the implant itself. Wear debris particles generated at the bearing interface trigger periprosthetic osteolysis, a progressive bone resorption driven by the biological response to particulate contamination, and this remains a leading cause of long-

term implant revision surgery [152]. Because this biological response depends on the size, volume, and composition of the debris, the wear mechanism of a given bearing couple effectively sets its clinical risk. This places a premium on characterizing wear behavior accurately across the full range of conditions an implant will encounter, which is exactly where high-throughput, systematically varied testing becomes valuable. That range is wide, because the biological fluid environment introduces a source of variability with no direct parallel in dry or conventionally lubricated systems. Synovial fluid composition varies between patients, changes with joint disease state, and evolves over the life of the implant as proteins adsorb and degrade at the bearing surface. Protein concentration, albumin to globulin ratio, and inflammatory mediators all influence boundary lubrication film formation and wear rate [153,154], effects that the standardized bovine serum simulants specified in ISO 14242 [155], the primary international standard for hip implant wear testing, do not fully capture [156–158]. This biological variability is the direct analog of the environmental sensitivity problem described in Section 2.3, and it motivates the same response. Characterizing the performance envelope rather than a single nominal result requires high sample number testing under systematically varied fluid conditions, and the statistical power this demands exceeds what manual methods can deliver within a reasonable time and at a reasonable cost. Automated pin-on-disk and hip simulator platforms that vary protein concentration, pH, and fluid volume while precisely holding kinematics and loading parameters can generate the large, well-characterized datasets that both predictive wear models and regulatory submissions require. The regulatory pathway sharpens this into a defined, high-value use case. The FDA and international regulatory bodies rely on ISO 14242 as the accepted methodology for hip implant wear testing in premarket submissions, and manufacturers who deviate from it must separately justify the omission [159,160], so improvements in testing throughput and consistency carry direct regulatory and commercial weight rather than purely scientific value. The AI application most specific to this domain is the prediction of in-vivo wear performance from accelerated in-vitro test data. Laboratory simulator testing applies simplified, standardized kinematic and loading conditions that only approximate the complex, patient-specific motion profiles that implants experience in service. Machine learning models trained on paired in-vitro and retrieved-implant datasets could learn the mapping between these simplified laboratory conditions and actual clinical wear outcomes, narrowing the gap between what a simulator measures and how an implant performs in a patient. This would be an advance over current practice, in which the relationship between simulator results and long-term clinical performance is empirically established rather than mechanistically understood [160,161].

7.3. Aerospace and Automotive Drivetrain Components

Aerospace and automotive drivetrain applications represent the frontier of tribological demand, combining extreme operating conditions with failure costly and catastrophic consequence. In both sectors, the engineering and economic stakes justify characterization investments that would be disproportionate in less critical applications, making them natural early adopters of the robotic and AI-driven tribological methods reviewed in this paper [162]. In aerospace structures, fretting wear at blade-disk attachment interfaces and spline couplings is one of the most consequential and least tractable tribological problems in service, with mortise and tenon joint failures alone accounting for an estimated 20% of aero-engine failures [163]. Fretting occurs when two clamped surfaces experience small-amplitude oscillatory relative motion under high contact pressure, generating wear debris and initiating fatigue cracks at stress concentrations that can propagate to component fracture under cyclic loading [164]. The contact conditions at these interfaces, sub-millimeter displacement amplitudes, contact pressures in the tens of megapascals, and superimposed

high-cycle fatigue loading, are difficult to replicate and instrument manually [165]. The sensitivity of fretting damage accumulation to subtle variations in surface finish, coating integrity, and contact geometry makes high-throughput characterization under systematically varied conditions essential for reliable life prediction [166]. Robotic fretting tribometers capable of scanning contact pressure and displacement amplitude spaces across coated and uncoated titanium and nickel superalloy specimen libraries would substantially improve the fidelity of fretting fatigue life models used in certification analysis. Such models already inform real risk assessment for military aircraft engine disks through tools such as DARWIN (Design Assessment of Reliability with Inspection), a probabilistic fracture mechanics code that combines finite element contact stress analysis with fleet failure data to quantify fracture probability and guide inspection intervals [167]. The electrification of automotive powertrains has introduced a new class of tribological challenges that existing characterization databases do not adequately cover [168]. Regenerative braking imposes reversed torque transients through the driveline that create contact loading cycles with no precedent in conventional transmission tribology data [168]. Torque vectoring systems in performance electric vehicles generate rapid, large-magnitude load reversals at gear and bearing contacts that accelerate micropitting and surface fatigue at rates that conservative design margins derived from ICE experience do not anticipate [168]. The thermal environment is also distinct since the absence of combustion heat means that drivetrain lubricants operate at lower bulk temperatures than in ICE systems, shifting the lubrication regime balance and altering additive activation chemistry in ways that require new characterization data rather than extrapolation from existing datasets [169,170]. Aeroengine health monitoring systems already acquire vibration and oil debris data through both online in-flight sensors and offline periodic laboratory analysis [171,172], and integrating tribological inference models trained on robotic laboratory data into these monitoring pipelines would improve the specificity of wear mechanism identification from operational signals. In electric vehicle gearboxes, real-time film integrity monitoring using electrical contact resistance, coupled to adaptive lubricant replenishment systems of the type described in Section 3.2, represents a near-term closed-loop application where the safety and efficiency benefits are large enough to justify the integration investment. The laboratory characterization work required to train and validate the inference models underlying both applications is precisely the problem that the automated platforms and AI methods reviewed in this paper are positioned to address. The three application domains are summarized in Table 7.

Table 7. Application domains for robotic and AI-driven tribology, summarizing the dominant tribological problem, the driver that justifies characterization investment, and the specific robotic or AI opportunity in each.

Application Domain	Dominant Tribological Problem	Economic/Consequence Driver	Robotic and AI Opportunity
Industrial machinery and manufacturing	Bearing and mechanical-seal wear; cutting-tool wear	Unplanned downtime cost dwarfs the cost of the characterization infrastructure	High-throughput laboratory data for RUL models; Bayesian-optimization-guided cutting-condition mapping; closed-loop lubricant replenishment
Biomedical implants	Hip and knee bearing-couple wear; periprosthetic osteolysis from wear debris	Revision surgery and mandated regulatory wear testing (ISO 14242)	Automated simulators varying protein concentration, pH, and fluid volume to build regulatory datasets; ML mapping of in-vitro to in-vivo wear
Aerospace and automotive drivetrains	Fretting at blade-disk and spline interfaces; EV micropitting and surface fatigue under torque reversals	Failure consequences ranging from costly to catastrophic; certification requirements	Robotic fretting tribometers scanning pressure and displacement amplitude; ECR film-integrity monitoring with adaptive replenishment in EV gearboxes

7.4. Economic Feasibility and Adoption Barriers

The domain-specific opportunities described above assume that a research group or company can justify the capital and operating cost of the required robotic and sensing infrastructure. This assumption does not hold uniformly across the three domains. A fully custom high-throughput tribometer platform, of the kind summarized in Table 1, combines a robotic handling system, an environmental or fluid-control chamber, and a multichannel in situ sensing suite. The integration labor discussed in Section 6.3 is a recurring cost rather than a one-time expense, since middleware such as SiLA or ROS-based abstraction layers requires ongoing maintenance as instruments and software versions change. Retrofitting a robotic specimen-handling module or an added sensing channel onto an existing commercial tribometer is a lower-cost entry point than building a fully custom platform. This is the more realistic near-term path for laboratories that cannot justify a ground-up build. The return on this investment is also domain-dependent rather than fixed. The gross domestic savings attributable to tribology best practices, cited in Section 7.1 at 1.3 to 1.6 percent [140], is a macroeconomic figure. It does not by itself tell an individual lab or company whether automation pays for itself. That calculation depends on the reduction in downtime or failure rate the automated characterization enables, weighed against the amortized capital and operating cost of the platform over its service life. This calculus is most favorable in the biomedical and aerospace domains discussed in Sections 7.2 and 7.3. The cost of a single field failure, such as a fracture in a ceramic hip bearing or a fretting-initiated fatigue crack at a blade-disk interface, can exceed the entire capital cost of the automated characterization platform. The cost of a regulatory delay tied to an insufficient wear dataset can do the same. A defined regulatory pathway such as ISO 14242 also gives the investment a concrete compliance justification beyond the scientific one. For lower consequence-of-failure applications within industrial machinery, discussed in Section 7.1, the same platform is harder to justify for a single lab's testing volume alone. Equipment accessibility becomes the binding constraint rather than raw cost, since few individual industrial labs need enough continuous tribometer throughput to keep a dedicated robotic platform utilized. A shared-use core facility model, comparable to university shared instrumentation centers or the vendor-operated time-share arrangements common for advanced electron microscopy, would let multiple smaller users amortize the platform cost across their combined testing demand. The practical adoption path this review anticipates is therefore uneven. It is early and self-justifying in domains with high failure consequences or a regulatory driver, and slower elsewhere until access costs fall.

8. Conclusions

Robotic and automated tribometry has advanced substantially from single-station manual testing toward parallelized, sensor-rich platforms capable of generating data at throughput rates that conventional methods cannot approach. High-throughput tribometer architectures, combinatorial specimen libraries, and integrated in situ sensing now exist at sufficient individual maturity to support systematic tribological characterization across wide operating condition spaces. The critical gap that remains is not hardware capability but the absence of standardized data infrastructure. Without common metadata schemas and open-access repositories, the data generated by these platforms cannot be aggregated across institutions into the large, diverse training corpora that downstream AI methods require. Artificial intelligence has established a meaningful presence in tribological analysis, with supervised and ensemble learning methods demonstrating reliable performance on friction and wear prediction within well-characterized contact systems. Physics-informed neural networks represent the most technically promising direction for the field's specific data regime, embedding governing equations from contact mechanics and lubrication the-

ory as constraints that allow physically consistent extrapolation from sparse experimental records. Bayesian optimization occupies a distinct and particularly consequential role, functioning as an experimental design method rather than a prediction method, and providing the algorithmic foundation on which closed-loop tribological systems must be built. The convergence of robotic platforms and AI methods into closed-loop autonomous tribological experimentation represents the central thesis of this review, and an honest assessment of the current literature finds that this convergence remains unrealized in its complete form. Partial implementations exist across each of the four functional layers, automated test sequencing, AI-guided experimental design, and sensor-triggered test termination, but no reported system integrates all four layers into a continuous, self-directing experimental cycle. The tribology-specific barriers of destructive specimen consumption, non-stationary lubricant state, and contact mechanics coupling distinguish this integration problem from the self-driving laboratory achievements in adjacent fields and define the concrete engineering challenges that the next generation of research must address. The minimum viable closed-loop system, coupling Bayesian optimization-guided lubricant formulation screening to automated dispensing and real-time friction monitoring, is achievable within a near-term horizon using components that already exist. The long-term trajectory of the field points toward fully autonomous tribological discovery pipelines in which material synthesis, surface preparation, tribological testing, and AI-guided iteration operate as a continuous unsupervised cycle. Realizing this vision is not primarily constrained by computational capacity or algorithmic sophistication, both of which are abundantly available, but by the volume, diversity, and interoperability of labeled experimental data accessible to the research community. The establishment of FAIR-compliant open tribological data infrastructure, led by community organizations such as STLE and ASTM International, combined with the continued development of physics-constrained learning architectures that generalize across contact systems, constitutes the enabling condition for autonomous tribological discovery to become both scientifically credible and industrially actionable.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Acoustic Emission
AI	Artificial Intelligence
API	Application Programming Interface
ASTM	American Society for Testing and Materials
BiLSTM	Bidirectional Long Short-Term Memory
BO	Bayesian Optimization
CNC	Computer Numerical Control

CNN	Convolutional Neural Network
CoF	Coefficient of Friction
DoE	Design of Experiments
ECR	Electrical Contact Resistance
EHL	Elastohydrodynamic Lubrication
EV	Electric Vehicle
FAIR	Findable, Accessible, Interoperable, Reusable
FDA	Food and Drug Administration
ICE	Internal Combustion Engine
ISO	International Organization for Standardization
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PINN	Physics-Informed Neural Network
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
ROS	Robot Operating System
RUL	Remaining Useful Life
SEM	Scanning Electron Microscopy
STLE	Society of Tribologists and Lubrication Engineers
SVM	Support Vector Machine
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

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