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REVIEW ARTICLE

AI for tribology: Present and future

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Abstract: With remarkable learning capabilities and swift operational speeds, artificial intelligence (AI) can assist researchers in swiftly extracting valuable patterns, trends, and associations from subjective information. Tribological behaviors are characterized by dependence on systems, evolution with time, and multidisciplinary coupling. The friction process involves a variety of phenomena, including mechanics, thermology, electricity, optics, magnetics, and so on. Hence, tribological information possesses the distinct characteristics of being multidisciplinary, multilevel, and multiscale, so that the application of AI in tribology is highly extensive. To delineate the scope, classification, and recent trends of AI implementation in tribology, this review embarks on exploration of the tribology research domain. It comprehensively outlines the utilization of AI in basic theory of tribology, intelligent tribology, component tribology, extreme tribology, bio-tribology, green tribology, and other fields. Finally, considering the emergence of "tribo-informatics" as a novel interdisciplinary field, which combines tribology with informatics, this review elucidates the future directions and research framework of "AI for tribology". In this paper, tribo-system information is divided into 5 categories: input information (I), system intrinsic information (S), output information (O), tribological state information (T_s), and derived state information (D_s). Then, a fusion method among 5 types of tribo-system information and different AI technologies (regression, classification, clustering, and dimension reduction) has been proposed, which enables tribo-informatics methods to solve common problems such as tribological behavior state monitoring, behavior prediction, and system optimization. The purpose of this review is to offer a systematic comprehension of tribo-informatics and to inspire new research ideas of tribo-informatics. Ultimately, it aspires to enhance the efficiency of problem-solving in tribology.

Keywords: artificial intelligence (AI); tribology; machine learning; tribo-informatics; AI for tribology

1 Introduction

Since the 1980s, tribology, as an independent frontier discipline, aims to save resources and prolong the service life of mechanical equipment [1, 2]. Tribology involves the cross-integration of many disciplines such as machinery, mechanics, physics, chemistry, and materials. It needs to consider, adjust, and optimize the design process and method framework based on models, and also needs to enhance the information exchange among different scales, levels, and systems based on data. Tribology is an experiment-based discipline. In the research process, a large number of working condition tests or operation and maintenance data are often designed and carried out based on different engineering and research needs. These massive data have the characteristics of multi-disciplinary, multi-scale, and multi-level [3], and it is difficult to form a complete tribological information unit. This leads to the contradiction between the massive

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tribological test data and the lack of tribological information with application value, which seriously restricts the development of tribo-informatics.

The term "artificial intelligence (AI)" was born in 1956 at a conference at Dartmouth University. In 1980, Carnegie Mellon University pioneered the development of the first expert system known as "XCON". Subsequently, in 2006, Hinton and Salakhutdinov systematically introduced the methodology of deep learning [4]. After decades of technological accumulation, it finally sparked a wave of research on AI globally after AlphaGo defeated the world chess champion in 2016 [5]. In 2021, Bommasani et al. comprehensively summarized the opportunities and challenges of foundation models, marking a significant shift in AI development towards the era of large-scale models [6]. The release of ChatGPT in 2022 signified a major advancement in the field of AI, particularly in its capabilities for processing natural language. On the whole, AI is the science that uses computers to simulate the intelligent behaviors of human including learning, judgment, and decision making. It compiles computer science, biology, logic, psychology, philosophy, and other disciplines targeting wide applications (as shown in Fig. 1). It has made great progress in knowledge representation and reasoning, pattern recognition, image processing, natural language processing, and other aspects [7]. AI plays an important role in human production and life which is applied in multiple research fields including materials science [8], biology [9], and tribology [10, 11]. Massive high-dimensional data is the foundation of the development of AI [12].

Tribology, due to its unique system dependence, multidisciplinary coupling, and time dependence, has produced a large number of multi-dimensional and multi-structural research data, which is the basis of the application of AI in tribology [13–16]. Therefore, the deep integration of AI methods with tribology will inevitably improve the efficiency of knowledge acquisition, integration, analysis, and research in tribology research, and promote the development of

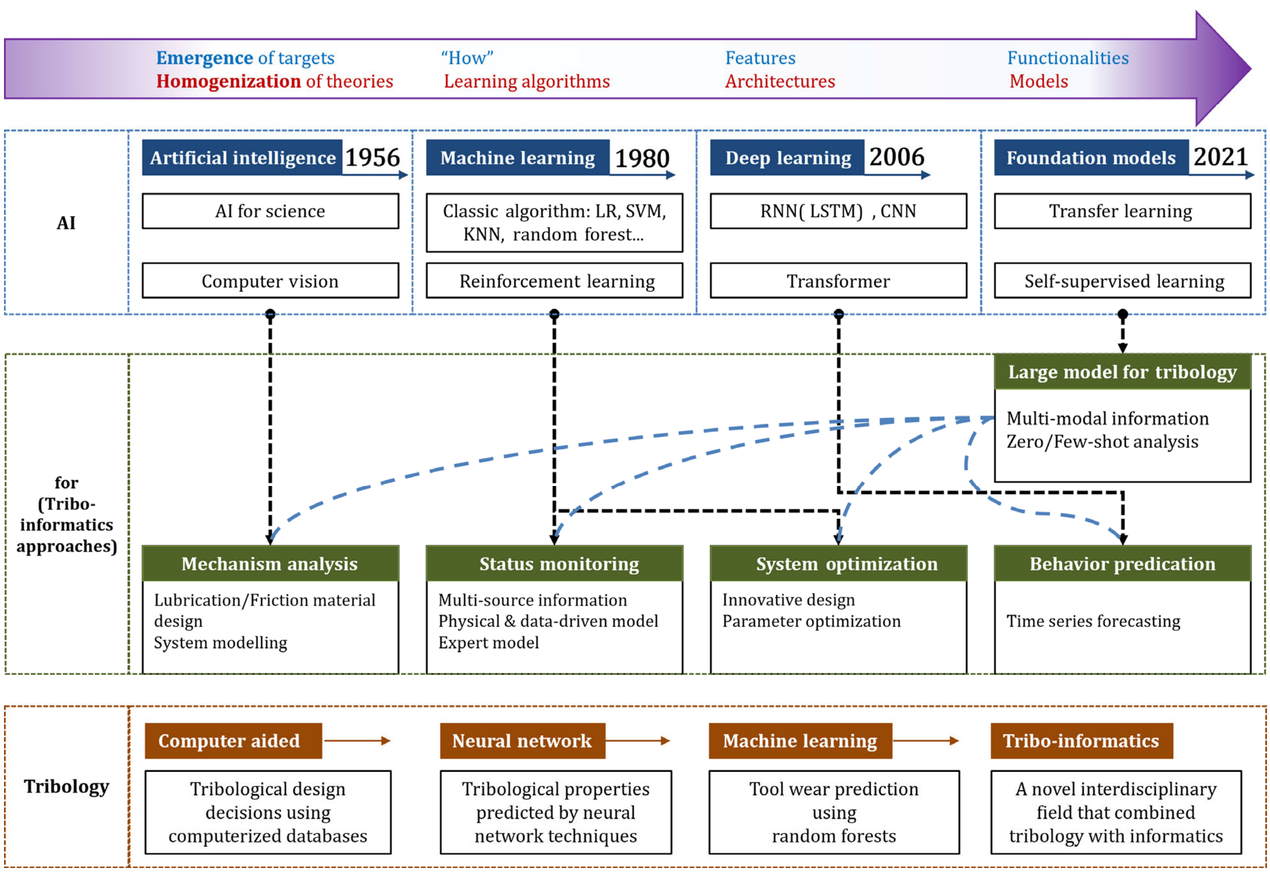

Fig. 1 Development of AI in the field of tribology.

the discipline. For example, the robust capabilities of AI in data and pattern recognition can establish correlations between various signals (e.g., vibration, acoustics, electrical, and sound pressure) and wear, making early detection of mechanical wear feasible. At the same time, AI can simulate and predict tribological behaviors under diverse operational conditions, which is crucial for designing more durable and reliable mechanical systems. As early as 1986, Tallian employed computer-aided approaches in tribological design [17]. In 1997, there was research on using neural networks to predict tribological properties, but it has been tepid [18]. In 2017, Wu et al. utilized random forest algorithms for wear prediction and garnered considerable interest among researchers [19]. This development catalyzed the gradual adoption of AI across various tribology research domains. However, the complexity of these machine learning methods and their varying applicability to the specific research needs in tribology presented challenges. In this context, "tribo-informatics" has been proposed to address the systematic fusion of AI and tribology [10]. This novel direction has immediately garnered significant attention in tribology.

In this article, we mainly focus on the application of AI technology in various research fields of tribology. Tribology problems are divided into six main research areas: basic theory of tribology, intelligent tribology, component tribology, extreme tribology, bio-tribology, and green tribology. The article mainly includes the current research status of the integration of AI and tribology in recent years, the application of AI in different tribological research fields, the product of the integration of AI and tribology (tribo-informatics or triboinformatics), and the development trend and implementation framework of this emerging direction. We hope this article can provide tribology researchers with a systematic understanding and research inspiration on the field of "AI for tribology", and promote the development of the discipline of tribology.

2 Publication status of papers on the application of AI in tribology

The publication status is a visual representation of the development of a research field, which allows for the understanding of the latest research achievements, analysis of research trends, and research hotspots in the field. Therefore, in this review, the search formula "TS = (artificial intelligence or machine learning) AND TS = (tribology or friction or wear or lubrication)" was used. A total of 1,882 papers were retrieved from the web of science core database on June 12, 2023. It should be noted that due to the increasing number of publications, the following analysis results can only reflect the latest research status as of the retrieval date.

Based on the number of papers published (as shown in Fig. 2), there has been a surge in the number of articles related to the application of AI in tribology since 2016. In just five years, the annual publication volume has increased by about 20 times, with 506 papers published in 2022 alone. This coincides with the year when AlphaGo defeated the world chess champion (2016) [20]. There is no doubt that this global event not only sparked a revolution in the computer field, but also brought new ideas and methods to solve problems in many other fields [21]. From the perspective of journal publication volume, the distribution of publications is extremely scattered, and the journal *International Journal of Advanced Manufacturing Technology* with the highest proportion of publications is only 4.89%. And a large proportion of "AI for tribology" articles are published in journals related to manufacturing and sensing technology, with a higher volume of articles published in the manufacturing semester journal. It is easy to understand that tribological systems are an important component of machine systems, and the addition of AI technology helps in online monitoring, fault diagnosis, and optimization design of machining, assembly, and operation processes. The rise of research on the correlation between tribology and sensing technology is an undeniable feature. The integration of information technology makes it easier to classify and summarize various types of information during the operation of tribology systems, and the correlation between various information can be quickly obtained. When the target quantity is perceived through observable measurements, a sensing technology is developed.

From the word cloud analysis in the research field, it can be seen that "material science multidisciplinary",

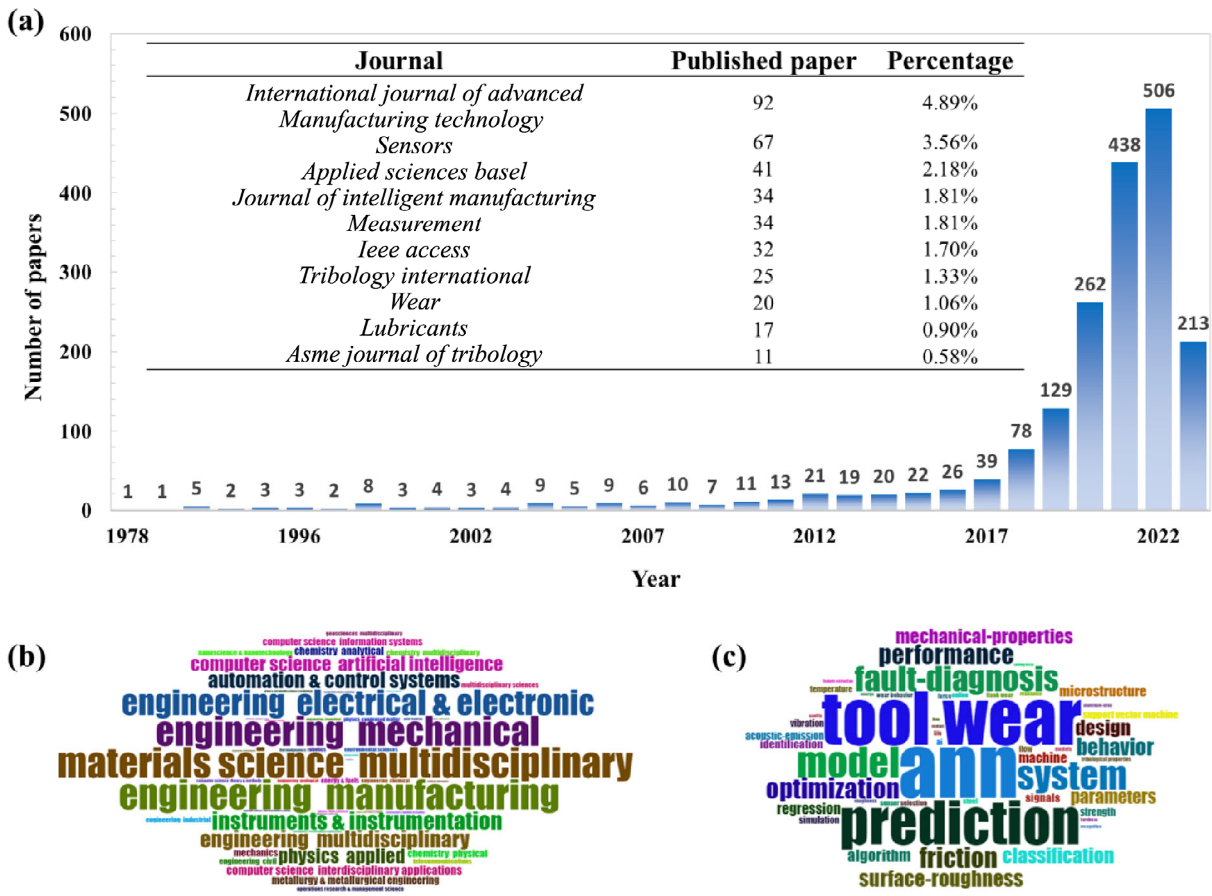

Fig. 2 Paper publication status of "AI for tribology". (a) Number of publications in different years and journals; (b) word cloud analysis in the research field of the papers; and (c) word cloud analysis of research keywords in the papers.

"engineering manufacturing", and "engineering mechanical" are the most frequently occurring fields. The application of AI technology in tribology focuses more on two main directions: material science and mechanical manufacturing. From the word cloud analysis of the keywords as shown in Fig. 2, it can be found that "artificial neural networks (ANN)" are the most frequently used algorithm model in AI technology, and "tool wear" is the most concerned research object in this field. "Prediction" is the most common application purpose in "AI for tribology". The above three aspects will also be detailed in the specific research fields in Section 3.

To display the evolution trend of keywords more intuitively, a bubble chart method was used to analyze the proportion of keywords in a single year and their trend over time (as shown in Fig. 3). From the horizontal comparison of each year, it can be seen that the three keywords "ANN", "tool wear", and "prediction" have always been research hotspots, and with the increase of years, more keywords have emerged, such as "model", "fault-diagnosis", and "prediction". This indicates that AI technology has a broader application scenario in tribology research. From the vertical comparison that increases over time, it can be seen that all keywords have shown an explosive growth since 2016–2017, and the integration of AI technology and tribology research has entered a period of rapid development. In addition, the keywords "model" and "performance" have a relatively large proportion in 2022, which also reflects the increasing emphasis placed by researchers on the development of AI algorithm models and the performance of tribological systems.

Overall, the application of AI technology in tribology research has shown a rapid growth trend [22–24].

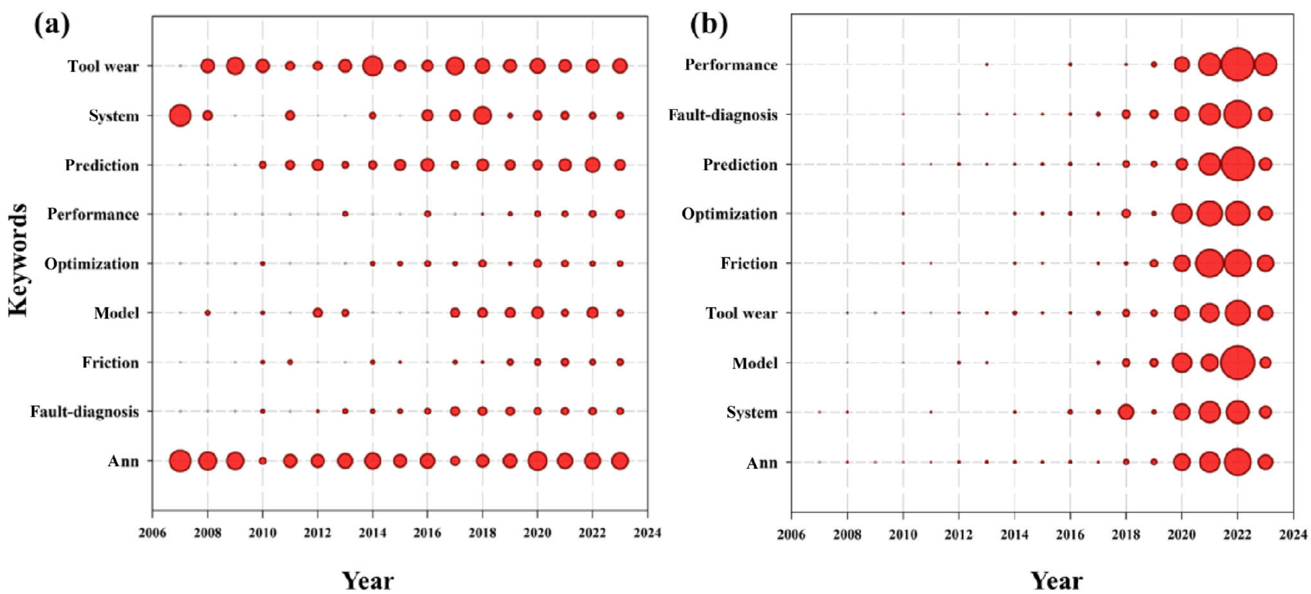

Fig. 3 Bubble chart analysis of keywords. (a) Horizontal comparison in each year and (b) vertical comparison with annual changes.

The research focus is mainly on machine learning methods for wear prediction and optimization of tribological system design [25, 26]. However, the application of AI in tribological research is still not comprehensive. AI technology includes three main concepts: symbolism, connectionism, and behaviorism. Among them, symbolism uses data logic symbols to express human cognition. Connectionism simulates the structure and working mode of the human brain with the idea of bionics, the most prominent of which is neural network. Behaviorism focuses on simulating various human control behaviors [7]. Transferring it to tribological research should enable the identification of tribological behavior (such as wear forms, lubrication states, and failure mode), data-driven monitoring and behavior prediction of tribological systems (such as friction, frictional heat, frictional vibration, frictional electricity), as well as optimization and behavior control of tribological systems. In order to demonstrate stronger systematic and systematic thinking in the application of AI in tribology research and promote comprehensive integration between both parties. The concept of "Tribo-informatics" has been proposed as a new field of research, indicating that the integration of AI and tribology has entered a new stage [10, 11, 27]. AI will no longer simply play the role of a numerical solution tool for traditional tribology problems, but can also inspire the thinking of tribology research.

3 Applications of AI in different tribological research fields

Tribology is a discipline that studies the fundamental theory and application technology of friction, lubrication, and wear between surfaces in relative motion, as well as the interrelationships among them [2]. The research scope of tribology is very extensive, involving many fields including mechanical processing, transportation, ships and oceans, aviation, aerospace, and biomedical devices [1, 28–31], etc. From the perspective of application purposes, tribological systems play an important role in energy transmission, motion transmission, and even information dissemination, and are also the main pathway for resource and energy consumption in production and manufacturing processes. In order to improve the energy-saving, reliable, stable, and intelligent characteristics of the relative motion interface, in recent years, the research scope of tribology has been mainly divided into the following six categories, which are the basic theory of tribology [32, 33], component tribology [34, 35], extreme tribology [36, 37], green tribology [38, 39], bio-tribology [40, 41], and intelligent tribology [32, 42–44]. In addition, a large number of research results have emerged in the field of geotribology [45–51], which studies earthquakes [52, 53], landslides [54–56], and crustal movements. In order to gain a deeper understanding of the application of AI technology in tribological research, this article reviews the scope, degree, and effectiveness of AI technology in these tribological research areas. It is believed that the mutual reference of application methods in different fields will inevitably promote the achievement of their respective research goals, and further improve the efficiency and quality of tribology research.

The publication status typically serves as a useful indicator for analyzing developmental trends, research hotspots, and technological advancements. By examining the distribution of AI applications within various sub-disciplines of tribology, we can gain insights into how different tribological challenges are amenable to AI technologies. From the analysis of literature search results, it can be seen that the application of AI in various fields of tribology research varies greatly. Among them, there are many achievements in the application of intelligent tribology, basic theory of tribology, and component tribology, accounting for nearly 90% of the total (as shown in Fig. 4). However, the application results in other research fields are very scarce, and some are even at the preliminary exploration stage. Next, the application of AI will be divided based on different tribological research scopes and objectives, in order to clarify the tribological problems and objects that different AI methods are suitable for. Research directions of broad development space will also be identified.

3.1 Basic theory of tribology

The basic theory of tribology mainly conducts research on universality, cutting-edge, and other aspects. The application of AI technology in this field is mainly divided into three aspects: the explanation of tribological behavior mechanism, micro- and nano-tribology, and analysis of behavior patterns based on standard tribological experiments (as shown in Fig. 5). It should be noted that the essential role of AI technology is to establish data associations among different categories of information, and it cannot directly provide an explanation of the mechanism. In order to improve the application effect of AI in the basic theory of tribology, the interpretability of AI calculation results can be improved by adding physical models [57–59]. At the same time, regression, classification, clustering, or dimensionality reduction methods can also be used to artificially obtain the mechanism and the meaning of data patterns after data processing [60–65]. Classification or correlation on data can improve the cognitive efficiency of tribology, but there is still a distance to form a universal tribology theory that can be generalized. What is more, the standardization of experimental procedures, data storage, model expression, and other processes in tribology is an important factor that restricts the reusability of data.

3.1.1 *Mechanism explanation of tribological behavior*

The mechanism explanation of AI-assisted tribological

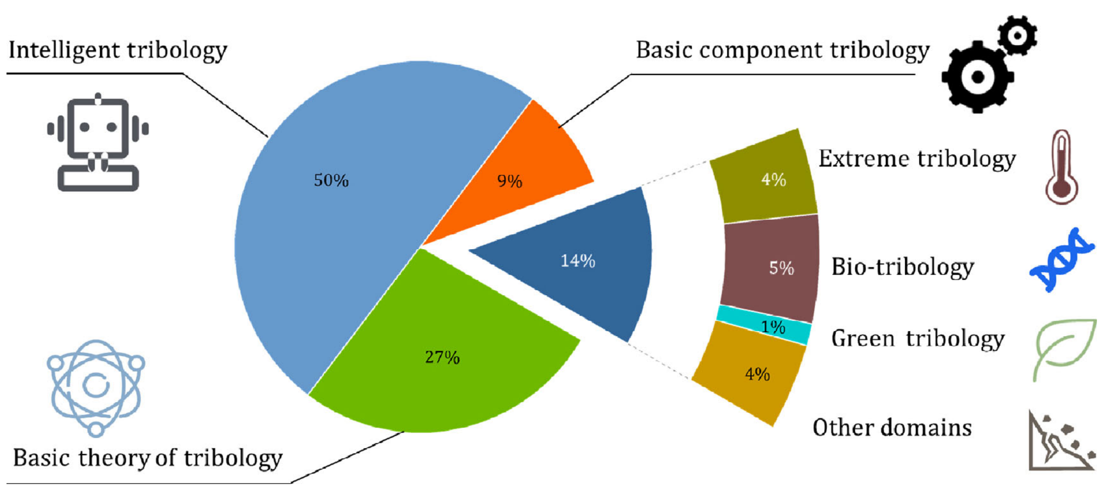

Fig. 4 Proportion of AI technology in various research fields of tribology.

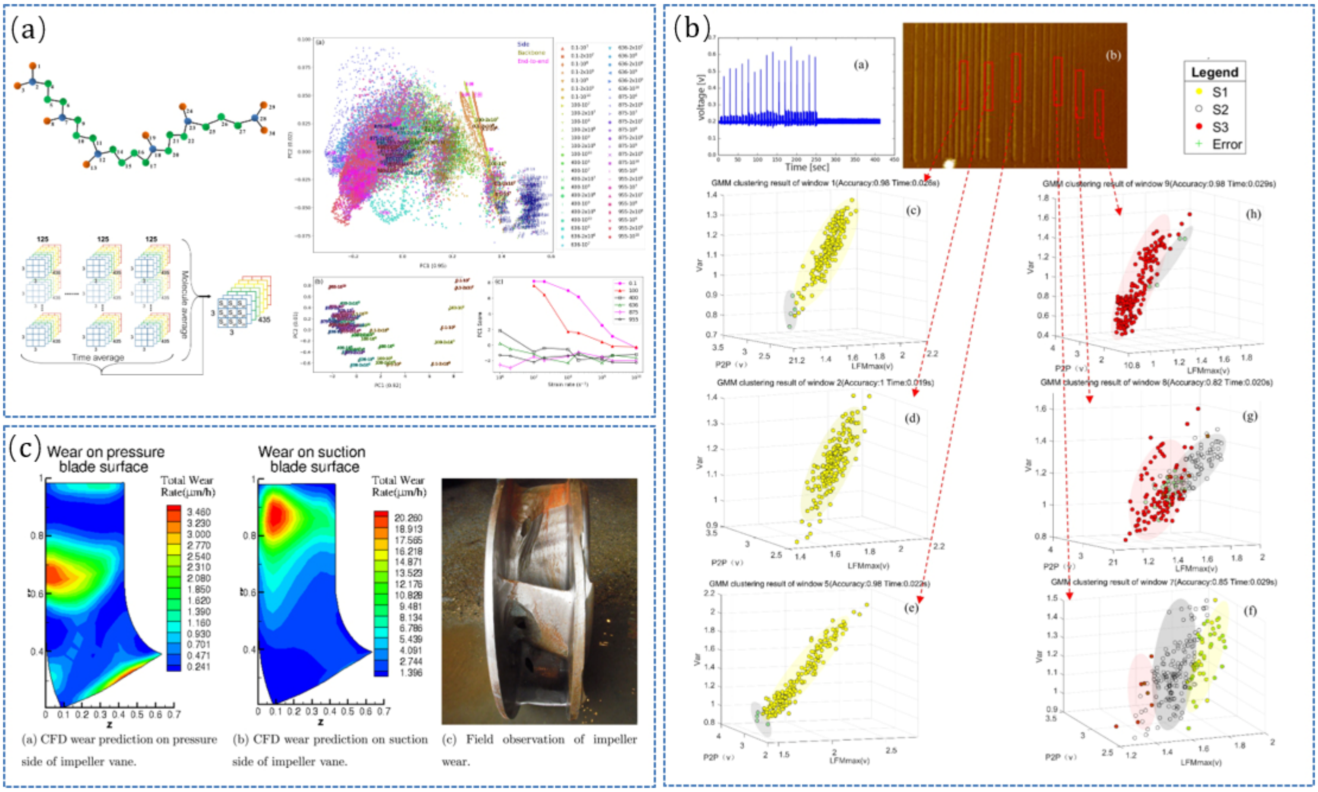

Fig. 5 Applications of AI in basic theory of tribology. (a) Investigation of liquid rheological behaviors under elastohydrodynamic lubrication through integrated machine learning and simulation techniques [66]. Reproduced with permission from Ref. [66], © The Author(s) 2021. (b) Real-time diagnosis of tip wear during tip-based nanomachining via an unsupervised machine learning technique, using an atomic force microscope (AFM) and employing a Gaussian mixture model (GMM) for in-process pattern recognition with process-generated data [67]. Reproduced with permission from Ref. [67], © Elsevier Ltd. 2022. (c) Introduction of a machine learning algorithm, WearGP, designed to refine predictions of 3D local wear by training on and testing against data derived from steady-state computational fluid dynamics (CFD) simulations [68]. Reproduced with permission from Ref. [68], © Elsevier B.V. 2019.

behavior generally involves first processing high-dimensional data generated during simulation or experimental processes through AI technology, separating the correlations of the main variables, and finally analyzing the mechanism of a certain tribological phenomenon [69]. For example, Kadupitiya and Jadhao [66] used machine learning methods to process high-dimensional simulation data generated in non-equilibrium molecular dynamics simulations, and ultimately obtained the correlation between rheological properties and molecular arrangement evolution in elastohydro dynamic lubrication, revealing the mechanism of viscosity decreasing with rates under low pressure of lubricants. Zhao et al. [70] combined the machine learning method with density functional theory, and characterized by structure factor and interlayer charge density, realizing accurate prediction of sliding energy barrier of polarized two-dimensional materials. Hossain et al. [71] studied the friction and wear behavior of mill steel using pin disk experiments, and introduced machine learning methods to analyze the effects of lubrication, reciprocating motion, and low speed on friction reduction and wear resistance. Sieberg et al. [72] used artificial neural network to analyze the images of scanning electron microscope (SEM), and obtained classification methods for different wear mechanisms. In the analysis of the mechanisms underlying tribological behavior, AI technology can be utilized to establish correlations between tribological phenomena and their influencing factors, thereby uncovering the primary causes of these phenomena. Consequently, clustering and classification methods within AI are particularly useful in the mechanism explanation of tribological behavior.

3.1.2 Micro- and nano-tribology

With the development of AFM, transmission electron microscopy (TEM) and other high-precision testing technologies, the research of tribology has entered the micro nano scale [73, 74]. Micro- and nano-tribology is currently at the forefront of tribology research, which not only reveals the fundamental principles of tribological behavior at the atomic scale, but also gives rise to new directions in applied research such as superlubricity and ultra-low friction [75, 76]. The application of AI technology in micro- and nano- tribology mainly has two aspects: one is to predict the friction and wear properties of nanocomposites [77–80] or 2D materials [81] using machine learning methods. The other is to process the test results of precision instruments such as AFM to analyze the friction and wear properties of nanomaterials [82, 83]. Najjar et al. [84] proposed an improved machine-learning model to predict the microstructure, mechanical properties, and wear of Cu–Al_2O_3 nanocomposites with different Al_2O_3 contents. Cheng et al. [67] used an unsupervised Gaussian mixture model (GMM) to analyze the friction and wear data collected by AFM, and realized real-time online automatic diagnosis of tool wear in nano manufacturing. Hasan et al. [85] developed five machine-learning regression models to predict the effect of graphene addition on the friction and wear properties of self-lubricating aluminum matrix composites, and found that the mass percentage of graphene and load conditions will have a greater impact on the friction and wear properties of composites. In the field of micro- and nano-tribology, AI is predominantly employed to predict the tribological properties of micro- and nano-scale surfaces. The training datasets for these AI models may originate from microscopic simulation data or experimental data gathered using high-precision instruments. Micro- and nano-tribology represents the cutting edge of current tribological research. AI technology can pre-analyze the selection of superlubricity materials, structural design, and operational principles, thereby accelerating the progress of related research.

3.1.3 Tribological behavior analysis based on standard experiments

The tribological standard test refers to the test conducted based on product-based and standardized friction and wear testing machines and referring to standardized processes [86–90]. In fact, this part is the main source of data for friction informatics, which has repeatability and accumulation, and is often used to analyze the universal laws of tribological behavior [91–94]. The tribological behavior includes the following aspects: (1) the processing of surface texture and its influence on wear resistance [95–99]; (2) wear image analysis and wear state recognition [100–107]; (3) the correlation between tribological derived signals (such as acoustics, vibration, acoustic emission, and thermodynamics) and the state of friction and wear [108–110]; (4) the influence of the preparation process of friction pair materials on friction and wear behavior [111–117]; and (5) the influence of input conditions on friction and wear performance of tribological systems [118–122]. Overall, it mainly includes three aspects: the relationship between state variables during the operation of tribological systems [123–125]; the evolution law of the tribological system behavior [126–130]; and the correlation law between the friction and wear performance and the system input and intrinsic variables [131–134]. Tran et al. [68] proposed a machine learning method called WearGP to approximate 3D local wear prediction, and used CFD simulation data for training, which could ultimately improve the calculation efficiency by 10^5–10^6 orders of magnitude. The foundation of “tribo-informatics” is a comprehensive tribology database, with standardized tribological test data being a crucial component. AI technology can establish relationships between various signals, such as experimental setup parameters, images, audio, temperature, and vibration. This facilitates the prediction of experimental trends and monitoring of specimen conditions, serving as a vital aid in high-throughput testing scenarios.

3.2 Intelligent tribology

In a sense, intelligent tribology is the greatest manifestation of the application of AI methods in tribology research, and it is also the research field most influenced by AI in tribology research. Intelligent tribology mainly aims at evaluating the operational reliability and predicting the lifespan of tribological systems in key engineering fields such as transportation equipment, energy equipment, and mechanical processing [135–139]. With the development of technology, intelligent tribology has developed the branch of intelligent lubrication/friction material design. Therefore, intelligent tribology can be mainly divided into two aspects: status monitoring, fault diagnosis and life prediction of tribo-systems, and intelligent lubrication/friction material design (as shown in Fig. 6). This section mainly introduces the

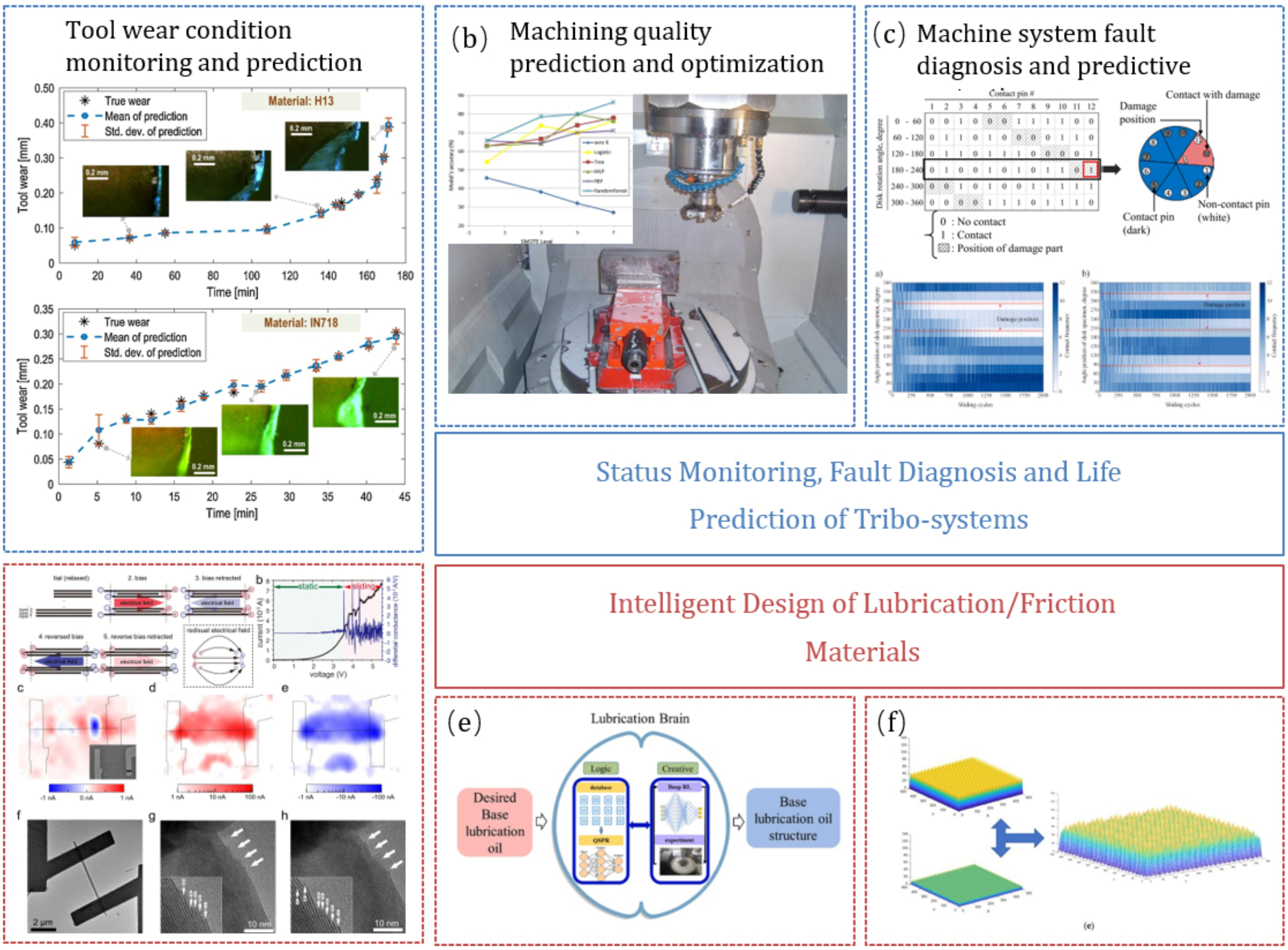

Fig. 6 Applications of AI in intelligent tribology. (a) A hybrid machine learning approach combining structured process parameters with unstructured power profiles and tool wear imagery for prognostics of tool condition [140]. Reproduced with permission from Ref. [140], © Elsevier Ltd. 2019. (b) Enhanced predictive performance using random forest algorithms in conjunction with the synthetic minority over-sampling technique (SMOTE) to balance datasets, tailored for industrial applications where flatness levels are discretized [141]. Reproduced with permission from Ref. [141], © The Author(s) 2020. (c) An innovative damage mitigation strategy employing AI-based control mechanisms (e.g., genetic algorithms) in tandem with contact position control systems (e.g., morphing surfaces) to extend the lifespan of sliding surfaces through stable friction management [142]. Reproduced with permission from Ref. [142], © Elsevier Ltd. 2023. (d) Insights from experimental and numerical analyses revealing a unique nano-electro-mechanical- opto system inherent in individual multiwall tungsten disulfide nanotubes, facilitating an unprecedented form of in-plane van der Waals ferroelectricity derived from a synergistic interaction of superlubricity and piezoelectricity [143]. Reproduced with permission from Ref. [143], © The Author(s) 2022. (e) The "lubrication brain", utilizing generative adversarial networks (GANs) in conjunction with reinforcement learning to autonomously engineer novel lubricant molecules with specified attributes [144]. Reproduced with permission from Ref. [144], © Elsevier Ltd. 2023. (f) A focus on manipulating surface wettability via designed hierarchical structures, optimized and predicted using well-trained ANNs [145]. Reproduced with permission from Ref. [145], © The Author(s) 2020.

current application status of AI in intelligent tribology from these two aspects. The application of AI technology in intelligent tribology is more reflected in the use of machine learning methods, while the application of other artificial intelligence technologies (such as natural language processing, computer vision, and expert system, etc.) is still lacking exploration, and the overall degree of intelligence still needs to be systematically deepened.

3.2.1 *Status monitoring, fault diagnosis, and life prediction of tribo-systems*

This part is the largest proportion in intelligent tribology and the most effective application of AI in tribology. It is also the birthplace of the concept of "tribo-informatics". Its application objects mainly include tribological systems with the main purpose of machining and forming, such as turning [146–150], milling [151–160], drilling [161–163], grinding [164–166], and friction stir welding (FSW) [167–169]. These systems usually have characteristics such as rapid wear, rapid forming, and obvious process signal characteristics, which is also the main reason for the effective application of AI methods [170–174]. In addition, the fault identification, predictive maintenance, and residual life monitoring of these machine systems are also the main focuses of intelligent tribology [175–180]. In the machining system, the most critical wear components are various types of tools, such as turning tools, milling cutters, drill bits, and grinding wheels. This section is classified according to the research purpose, which is mainly divided into three aspects: tool wear condition monitoring, machining quality prediction and optimization, and machine system fault diagnosis and predictive protection (as shown in Fig. 7). It should be noted that friction stir welding, as a welding technique, mainly focuses on welding quality and less on wear issues. Therefore, it is only discussed in the prediction and optimization of processing quality. The primary principle of monitoring tribological system states involves using AI to establish links between target signals that are difficult to monitor directly and other easily observable signals. This requires researchers to have a preliminary qualitative understanding of the correlation between signals. Fault diagnosis in tribological systems often involves retracing abnormal states. By employing interpolation and regression methods, researchers can clarify the evolution of signals over time, identifying the timing, location, and type of faults. Lifetime prediction is one of the most straightforward applications of AI technology. It utilizes time series forecasting with specific feature parameters and estimates the remaining life based on a predefined failure threshold, making it a widely used method in engineering.

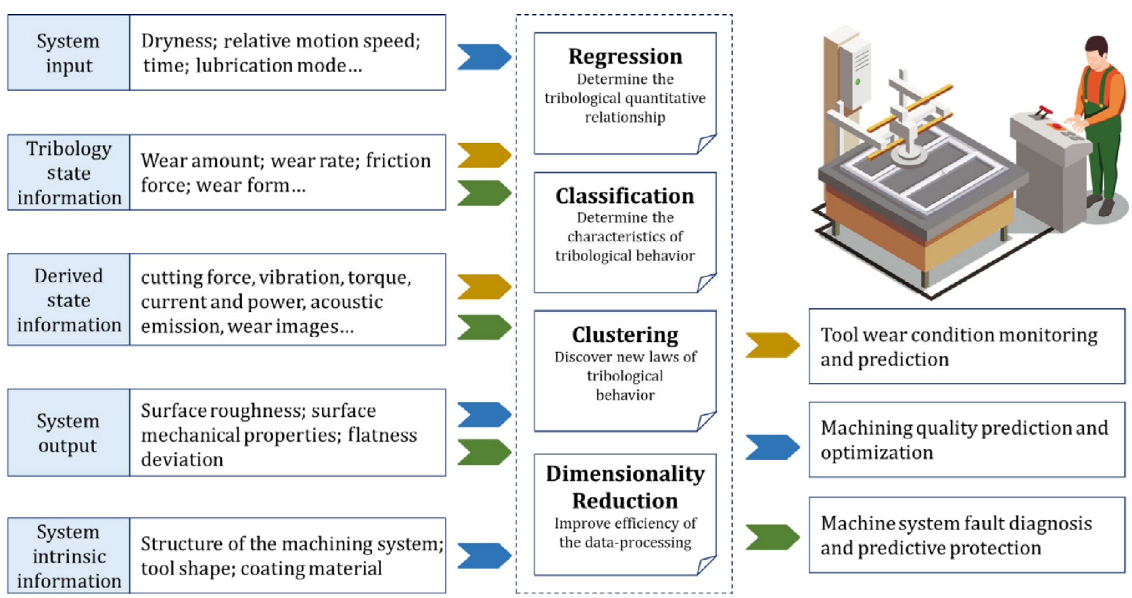

Fig. 7 Information flow within the process of status monitoring, fault diagnosis, and life prediction of tribo-systems.

(1) Tool wear condition monitoring and prediction

Tool wear is the most important cost factor in metal cutting, which affects machining quality, machine tool life, and even safety issues [181–188]. Therefore, it is very important to monitor the tool wear status in real time and predict the appropriate tool change time. During the operation of tools, a large amount of data is generated. If the correlation between these signals can be obtained, the status of non-observable measurements (usually wear) can be obtained by monitoring observable measurements [189–199]. Similarly, when the system inputs (such as dryness, temperature, and lubrication mode) and tool wear or cutting force establish a time series data association, then the remaining life of the tool can be predicted [200–206]. In general, signals such as cutting force, vibration, torque, current and power, acoustic emission, wear images, temperature, and sound are all observable measurements [207–212]. In engineering, these quantities can be used to monitor the current wear status, such as wear amount, wear rate, and wear form, in order to determine whether it is in a normal wear state or a wear failure state, and whether abnormal phenomena such as vibration and shaking have occurred [213–216].

Various machine learning methods have been applied to the monitoring of tool wear status. The method of selecting the appropriate algorithm to establish data correlations is one of the hot topics of research. [19, 217–226]. Sandeep and Natarajan [227] used the optimal linear associative memory (OLAM) neural network to establish the data association between cutting parameters, spindle motor load, and tool wear status in the turning process, and the correct rate reached 93.8%. Lei et al. [228] combined intrinsic timescale decomposition (ITD) technique with kernel extreme learning machine (KELM) technique to predict three stages of milling tool wear using multiple sensor signals. Rafezi and Hassani [229] used a backpropagation artificial neural network model to classify the wear status of drill bits used in surface mining and predict their faults. Azizi et al. [166] studied three kernel-based supervised learning algorithms and monitored the medium wear rate during the grinding process using solid percentage, mill speed, and grinding time as input factors. Lee et al. [165] used deep learning methods to establish a data correlation between the frequency domain signals of sound during machining and the wear status of grinding wheels, thereby monitor the tool status during grinding. With regard to the development of tool wear condition monitoring, there are generally two directions: more categories of information acquisition and more accurate algorithm models [140, 230–239].

(2) Machining quality prediction and optimization

Friction plays different roles in different fields of mechanical processing. In machining processes such as turning, milling, drilling, and grinding, friction and wear are important variables in determining the quality of the machining process and can also reflect the healthy state of machine operation [240–245]. In the process of friction stir welding, various parameters of friction (such as friction and relative motion speed) are the input variables of the processing process, which directly determine the quality of the welding [246–248]. Regardless of the processing method, the processing quality is the output quantity that engineers are most concerned about.

For the tool processing process, the system inputs usually include cutting speed, feed rate, cutting depth, cutting time, composition, and concentration of cutting fluid [141, 249, 250]. The state variables mainly include cutting force, cutting zone temperature, and other process signals, and the output variables concerned mainly include surface roughness, surface mechanical properties, and flatness deviation [141, 251–253]. It should be noted that the relationship between input and output is often influenced by the intrinsic information of the system (such as the structure of the machining system, tool shape, and coating material) and does not need to consider the time dimension. When using state variables to predict processing quality, the prediction is often based on time series prediction, as the state variables are time dependent. Singh et al. [254] used polynomial regression process (PR), support vector regression (SVR) and Gaussian process regression (GPR) to predict cutting power and cutting pressure through cutting speed, cutting depth, and feed rate, and then predict product processing quality. Mandal et al. [255] used Naïve-based classifiers to classify tool wear into initial stage (IS), progressive stage (PS), and exponential stage (ES), and analyzed the relationship between tool wear and surface finish. Dubey et al. [256] used machine learning models such as linear regression (LR), random forest (RF), and support vector machine (SVM) to analyze the effects of cutting speed, depth, feed rate, and cutting fluid composition characteristics on the machined surface roughness, and proposed a method to predict the surface roughness by analyzing the particle size in the cutting fluid.

For the machining process of friction stir welding, the most important concern is the welding quality, which is also the output of this machining process [257–259]. There are many characterization parameters for welding quality, including internal and external weld characteristics, tensile strength, elongation, impact strength, microhardness, grain size, fatigue strength, corrosion resistance, and residual stress [260–263]. As a relatively special tribology system, the input of friction stir welding system is the parameter settings of friction motion, such as tool speed, translation speed, shoulder diameter, tilt angle, axial load, coating material, and substrate geometry [264–269]. Similarly, in the process of friction stir welding, there are also some convenient monitoring variables, such as spindle torque, lateral force, lateral force, cutting force, and temperature signals [248]. Yadav and Khurana [270] combined multi-objective optimization technology with a genetic algorithm to establish the relationship between process variables and welding quality, and proposed a process design method for target machining quality, with a prediction accuracy higher than 97%. Thapliyal and Mishra [271] used a deep learning-based neural network model to analyze the influence of process parameters on mechanical properties, and pointed out that tool characteristics are the most critical factor affecting welding quality. Mishra and Dasgupta [272] used the classification algorithm based on supervised learning, including decision tree, logical classification, random forest, and Adaboost to realize the prediction of different fracture positions of friction stir welding products, thus realizing the data association between processing technology and crack positions. More interestingly, Du et al. [273] used various machine learning algorithms to analyze the variables that led to the decline in welding quality, and found that the maximum shear stress was the most important variable in the welding failure mechanism, followed by flow stress. These findings help prevent the decline in welding quality.

(3) Machine system fault diagnosis and predictive protection

Fault identification and preventive maintenance of machine systems is an important branch of intelligent tribology, which mainly includes the monitoring and prediction of machine system performance degradation caused by friction and wear [142, 274–278]. This field typically extracts physical quantities that are easily observable during machine operation, such as vibration, sound, and temperature, followed by feature extraction and fault recognition. Its main purpose is to promptly detect faults *in situ* and implement preventive measures [279–281]. For example, Schlagenhauf and Burghardt [282] used machine learning algorithms to automatically monitor the image of the ball screw transmission process and predict its faults. Wang et al. [283] proposed a reliability judgment method based on active learning Kriging model and Monte Carlo simulation, which can analyze the working reliability of machine systems based on vibration signals.

The above three aspects fully reflect the purpose of AI application in tribology, including tribological system status monitoring, behavior prediction, and system optimization. By using AI technology to obtain the information existing in the tribology system itself and the data association between the information generated in the tribology process, different application purposes can be achieved. Therefore, in order to better apply AI technology in tribology, it is necessary to clarify which types of information exist in the tribology system and which data each type of information mainly consists of, namely "information expression of tribology systems". This concept will be mainly discussed in Section 4.1.

3.2.2 *Intelligent design of lubrication/friction materials*

The intelligent design method for lubrication/friction materials is of great significance for the rapid design of specific components, structures, and functional materials [145, 284–289]. It often efficiently predicts the performance of target products through deep integration of simulation methods and machine learning algorithms. From the perspective of the information composition of tribological systems, the main purpose of this research direction is to study the correlation between the intrinsic information of the system and its output based on the target function of the tribological system [143, 290–294]. By designing the composition and ratio of lubricating grease, optimal friction reduction and wear resistance can be achieved [295]. Customized performance of friction pairs is achieved by designing the size and morphology characteristics of composite materials [296]. Zhou et al. [144] combined generative adversarial neural networks with reinforcement learning to automatically generate new lubricating oil molecules with the required performance, known as the "lubricating brain". Zeng et al. [297] proposed a design method for high-temperature lubricating greases based on backpropagation neural networks. The intelligent and rapid design of friction/lubrication materials is one of the hot research directions in the future of tribology, and is also an important means to reduce the design cost of tribology systems and improve system performance. Intelligent design of lubrication/friction materials is a result of the deep integration of AI technology with simulation and experimental design methods. AI regression techniques, based on existing experimental or simulation results, can establish correlations between input parameters and material properties, reducing the time and economic waste associated with trial-and-error designs.

3.3 Component tribology

The basic components of tribology are the components that contain the Urelement of tribology system and undertake the key tribological functions of mechanical system, mainly including bearings, gears, tires, fasteners, and seals. Among them, bearings are one of the most complex and widely used basic components in tribology, and AI technology is also the most widely used in bearing research [298, 299]. Therefore, this section divides the basic components of tribology into two categories for analysis: bearings and other components.

3.3.1 Bearings

There are many classifications of bearings, such as sliding bearings, rolling bearings, deep groove ball bearings, angular contact bearings, and thrust bearings, according to their structure. According to material classification, there are also metal bearings, non-metallic bearings, and porous metal bearings. The application of AI technology in bearing condition monitoring, performance prediction, design optimization, and other aspects is very extensive, mainly including: (1) predicting bearing lubrication status [300–303], friction coefficient [304], and wear rate [305]; (2) identifying the wear mechanism of bearings [306] and optimize their design [307–310]; and (3) monitoring the service status of bearings using multiple signals [311–316]. For example, Mokhtari et al. [317] extracted effective features in the time and frequency domains of acoustic emission signals, and used continuous wavelet transform and support vector machine to classify the dry friction, mixed friction, and fluid friction states of sliding bearings. Badawi et al. [307] applied artificial neural networks and fuzzy logic techniques to predict the performance of sliding bearings, based on performance characteristics such as bearing capacity, attitude angle, and maximum film pressure ratio under different aspect ratios.

3.3.2 Other components

The application of AI in the research of other tribological components is relatively scattered, such as hydraulic transmission systems [318], automotive tires [319–321], pistons [322], bottom pivots [323], ball screws [324], and cam [325]. However, it can also be roughly divided into two aspects: friction and lubrication status monitoring, and friction and wear performance prediction. There is less involvement in component design optimization.

3.4 Extreme tribology

With the emergence of extreme service environments such as deep sea, polar regions, deep space, and deep ground, tribological systems are also facing extreme operating conditions such as high speed, heavy load, high/low temperature, and special environments such as strong radiation and high vacuum. These working conditions often result in severe friction and wear phenomena, accompanied by the generation of various strong derivative signals, which increases the difficulty of friction and wear testing, online monitoring, and fault diagnosis. On the other hand, the introduction of AI technology will also bring new and more effective solutions to this field. The role of AI technology in extreme tribology is massive. However, the reliability of the data depends on its quantity and authenticity. Obtaining realistic tribology information is a major challenge in this field. If AI technology is utilized, extreme tribology can establish a correlation between simulated environmental data and real working conditions. This breakthrough will help to bridge the gap between theoretical and practical data.

3.4.1 *Heavy load, high speed, and high temperature*

High temperature, high speed, and heavy load are the most intuitive extreme operating conditions, usually occurring during the service process of large high-end mechanical equipment [326]. Due to the influence of extreme working conditions, rapid wear is often the most important feature, and the obvious trend of data changes also makes the prediction results of machine learning more accurate. For example, vibration data can be used to monitor the uneven wear phenomenon between high-speed trains and rails [327, 328]. Other directions, such as tool wear monitoring and control parameter selection in high-speed processing [249, 329, 330], optimization of high-temperature alloy preparation process parameters [331], and composition optimization of pearlite steel used for heavy-duty tracks [332], are not fundamentally different from the introduction in intelligent tribology. However, from the volume of publications and the depth of AI integration, it can be seen that there is still great room for development in the application of AI in extreme working conditions tribology. AI technology is well-suited for addressing rapid wear caused by extreme operating conditions. On the one hand, researchers can initially study tribological properties under lower speeds, loads, and temperatures, and establish the relationship between performance and operating conditions. This allows for studying extreme conditions at a lower cost. On the other hand, under extreme conditions, due to the specific nature of testing technologies, the obtained physical quantities may be limited. AI can assist in researching these issues by establishing correlations between measurable parameters and target parameters.

3.4.2 *Special environmental conditions*

Special environmental conditions mainly occur during the service process of space spacecraft, such as high vacuum, atomic oxygen, and strong radiation [333, 334]. These service conditions often make it extremely difficult to obtain *in-situ* working data and require extremely high requirements for tribological components. Therefore, if AI technology can achieve the correlation between ground test data and space service data, or achieve *in-situ* real-time monitoring of space service performance, it will be of great significance for improving the stability and reliability of spacecraft work. However, there are currently few reports on related research.

3.5 Bio-tribology

Bio-tribology is a research field that studies tribological issues related to organisms [40], mainly focusing on three aspects: (1) functional maintenance of biological friction pairs (such as skin, teeth, and joints) [335, 336]; (2) the tribological behavior of biological implants (such as artificial bones and heart stents) [337]; and (3) the tribological adaptability characteristics of wearable or medical devices to the human body surfaces (such as tactile feedback and human motion signal sensors) [338]. In fact, the application of AI in these fields is quite unsystematic, mainly focusing on predicting tooth wear, human touch/motion perception, and regulating the friction/lubrication performance of implants in the body. Bio-tribology is a highly interdisciplinary field that poses complex challenges. Due to the unique nature of its subjects, bio-tribology necessitates a certain integration with biology. "Tribo-informatics", while primarily addressing engineering tribology issues, can also establish connections with bioinformatics data, thereby enhancing the efficiency of research in bio-tribology. Current research focuses on individual aspects, using advanced data analysis techniques to understand friction and wear performance under multiple factors. The future research focus is on how to achieve the correlation between biological information and tribological information and achieve real-time collection and monitoring of biological signals.

3.5.1 *Tribology of human organ*

The application of AI in human tribology is mainly manifested in predicting tooth friction loss [339–341], monitoring human joint fever [342, 343], etc [335, 344]. Anaya-Isaza and Zequera-Diaz [342] proposed a heat change index based on the characteristics of foot fever in diabetes patients, and used the deep convolutional neural network to predict the occurrence of diabetes in advance. Zheng and Liu [339] established radial basis function and multilayer perceptron neural network models to predict the wear of tooth repair materials (TC4 alloy) in artificial saliva.

3.5.2 *Tribology of human wearable devices*

Human condition monitoring and behavior perception are the basis for realizing the natural interaction between human and machines, and also the premise for realizing the concept of the "Metaverse". Human condition perception based on friction is an important part of it [338, 345]. Li et al. [346] combined the fingertip tactile sensor with the machine learning module to form a human-simulated tactile sensing system, which can realize multiple functions such as sliding detection, material classification, and roughness recognition. Bi et al. [347] proposed a new method based on support vector machines to achieve precise tactile display function, which provides a technical foundation for the application of virtual reality.

3.5.3 *Tribology of human body impacts*

Artificial joints, as a key component of human implants, are of great significance for the treatment of arthritis and trauma [337]. The wear prediction and lightweight high-strength design of human hip joint implants are essential in medicine [348–350]. Vinoth and Datta [351] used genetic algorithms and artificial neural networks to characterize the structure of composite materials, in order to obtain artificial hip joint materials with higher Young's modulus and tensile strength. Lantada et al. [145] used artificial neural networks to design the texture of artificial biological interfaces, improving their wetting performance.

3.6 Green tribology

Green tribology is a key direction for achieving healthy, safe, energy-saving, and sustainable development in tribology [352, 353]. It mainly includes areas such as friction emission control, friction noise control, and the application of green lubricants [354, 355]. Mahakur et al. [356] used machine learning methods such as support vector machines to study the wear resistance of biodegradable materials with different jute addition ratios. Bhaumik et al. [357] used genetic algorithms and neural network models to study biodegradable lubricants composed of various plant oils and different nano friction modifiers, analyzing the role of different components in improving lubrication performance. In the field of green tribology, AI technology enhances sustainability by optimizing lubrication processes, selecting eco-friendly materials, and improving energy efficiency. Through data analysis and predictive modeling, AI aids in reducing environmental impact, ensuring efficient resource usage, and minimizing wear and tear in tribo-systems.

3.7 Other domains in tribology

Beyond the six research directions highlighted above, the study of tribology is also extensively distributed across a variety of fields, such as landslides, crustal movements, etc. These areas underscore the profound relevance of tribology to human productive activities and everyday life, and they reflect the expansive scope of tribological research. Similarly, these research domains are also variably interconnected with AI to varying extents. Chou et al. [46] developed an effective AI model that improved the prediction of the peak friction angle of fiber-reinforced soil (FRS), achieving notable accuracy improvements. Ren et al. [52] used machine learning to analyze the behavior of seismogenic plate boundaries and showed that statistical features of velocity signals from individual particles in simulated granular faults could predict the overall stick-slip dynamics.

4 The integration trend of AI and tribology: Tribo-informatics

4.1 Informational expression of tribo-system

4.1.1 *Features of tribo-system information*

Tribo-informatics has originated from the profound integration of AI and tribology, enhancing the efficiency and procedural rigor of tribological research through the establishment of standardized tribological methodologies, the construction of extensive tribology databases, and the employment of information technology for the systematic collection, categorization, storage, retrieval, analysis, and dissemination of tribological data [10]. Over recent years, tribo-informatics approaches have been applied in various domains including monitoring of tribological states, prediction of residual life, and reconstruction of wear morphologies [11, 27, 356]. However, the evolution of tribo-informatics is confronted with certain challenges, which will be critically discussed in this review. (1) Classification and recognition of tribological system information. It is necessary to give the multitude of information types within tribo-systems, determine the pertinent data to integrate with AI algorithms for specific tribological inquiries; (2) diversity in tribological research directions, AI algorithms, and tribo-system information. Identifying an optimal pathway for the fusion of these diverse elements in the resolution of tribological issues is crucial; and (3) establishment of standardization in tribological theories, experiments, and simulations. This is of significant importance for the creation of tribological databases. Additionally, the development of this field is contingent upon the availability of advanced signal sensing technologies and data storage systems.

Tribological behavior is the result of the combined action of mechanical, physical, chemical, electrical, material science, and other disciplines. At the same time, it also has obvious system dependence and time evolution [358], so the tribo-system information covers a wide range, involves many disciplines, and is difficult to collect and process. The information sources of the friction process are extensive, and the data structure forms are various. A single physical information cannot accurately and completely describe the behavior of the tribo-system. To this end, it is necessary to establish a systematic tribo-system informatization model first, which provides a basis for revealing the flow law of tribological information at different scales, different levels, and between different systems. At present, the research of tribo-informatics faces many problems such as information collection, processing, and reuse.

(a) In terms of information collection, tribological information mostly exists in the recessive form in the tribo-system, which brings great difficulties to tribological state monitoring. Using tribo-informatics technology, it is possible to easily find the relationship of observable measurements, which is, explicit quantities (such as acoustic, electrical, vibration, and thermal) and unobservable quantities, which are, recessive quantities (such as wear amount, lubrication state, and surface topography) to improve the integrity of the tribo-system information.

(b) In terms of information processing, tribological information has the characteristics of multidisciplinary coupling and cross-scale correlation, resulting in too much information in tribological information units, and it is difficult for physics-based analysis methods to predict the behavior of tribo-systems accurately and efficiently. The information technology methods based on AI can search for the relationship between tribological information from regression, classification, clustering, dimensionality reduction, and other aspects.

(c) In terms of information reuse, database technology can be used to build a huge tribological information pool after gradually establishing tribological standards and data representation consistency. The tribological test data, simulation data, and literature data are summarized into the tribological database, and the tribological information can be reused.

4.1.2 *Representation of tribo-system*

In order to solve the problems of information collection, processing, and reuse of tribo-systems, according to the three axioms of tribology [358], tribo-system information can be divided into five categories: input information, system intrinsic information, output information, tribological state information, and derived state information (as shown in Fig. 8). The information generated by the working process of any tribo-system should be included in these five types of information. It should be noted that these five types of information are divided according to the four categories of tribological research, namely tribological condition monitoring, behavior prediction, system optimization, and mechanism analysis. The essential purpose of AI technologies is to obtain the data association of several groups of information, and to obtain the correlation between

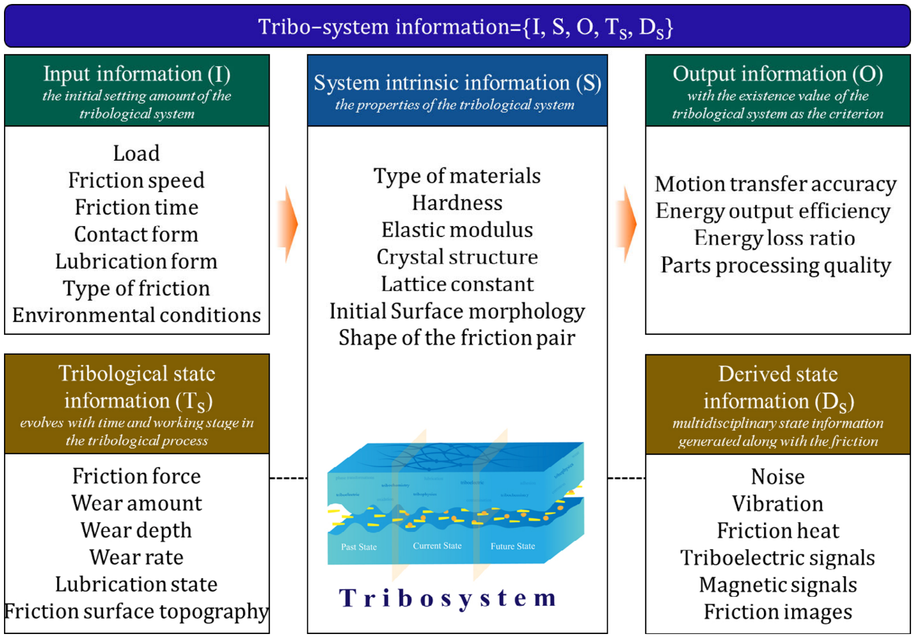

Fig. 8 Information expression of tribo-system.

these five types of information using informatics methods is the focus of tribo-informatics research.

(a) Input information (I), mainly refers to the initial setting amount of the tribo-system. These initial settings should generally include load, friction speed, friction time, contact form (point-to-surface contact and surface-to-surface contact), lubrication form (dry friction, oil lubrication, and grease lubrication), type of friction (sliding friction and rolling friction), and initial setting of environmental conditions (temperature, humidity, vacuum, and radiation intensity). The determination of the input information is related to the identification of the initial state of the work, but not to the evolution of time. Researchers can usually optimize the performance of tribo-systems by adjusting the input information (such as the study of tribo-system optimization) and can also use other methods to offset the negative effects of certain input quantities (such as the study of extreme operating conditions tribology).

(b) System intrinsic information (S), refers to the properties of the tribo-system, mainly including the surface information related to the friction pair itself and the interface information related to the contact of the friction pair. The information includes the friction pair material type, hardness, elastic modulus, crystal structure, lattice constant, initial surface morphology, shape of the friction pair, type, and properties of the lubricant. The existence of certain information is independent of whether friction occurs. However, the evolution of this information is related to the process of friction. For instance, the surface morphology characteristics of a material exist even in the absence of friction, but these characteristics may change when friction occurs. Generally, the eigenvalues of the system generally emphasize the initial value. The inherent parameters of the tribo-system should be confirmed at the beginning of friction.

(c) Output information (O), with the existing value of the tribo-system as the criterion, mainly reflects the function achievement degree of the tribo-system. The functions of the tribo-system mainly include motion transfer, energy transfer, information transfer, and material processing. Therefore, the output information can include motion transfer accuracy, energy output efficiency, energy loss ratio, and parts processing quality. The output information is the primary indicator for judging the working performance and remaining life of the tribo-system. For example, when the amount of wear is used as the life evaluation criterion, it is actually because of the wear that reduces the accuracy of motion transmission, or the proportion of energy loss is too large. Therefore, to determine which information belongs to the system output information, it is most necessary to determine what value of the tribo-system exists.

(d) Tribological state information (T_s), refers to the tribological state quantity that evolves with time and working stage in the tribological process. The information mainly includes friction force, wear amount, wear depth, wear rate, lubrication state, and friction surface topography. The tribological state information has obvious time series characteristics, which is closely related to the input information and system intrinsic information, and greatly affects the output performance and function achievement of the tribo-system. At the same time, this kind of information is also the most concerning quantity in traditional tribological research and is the most important data source in the analysis of tribo-system behavior.

(e) Derived state information (D_s), refers to the multidisciplinary state information generated along with the tribological behavior during the working process of the tribo-system, which is determined by the multidisciplinary coupling characteristics of tribology. This information widely distributes in a variety of friction-derived phenomena, and the variety will increase with the deepening of tribological research. At present, the derived state information mainly includes friction images, noise, vibration, friction heat, triboelectric signals, and magnetic signals. This kind of information is often associated with tribological state information, which is explicit or implicit. For example, the image information is closely related to the friction surface morphology, and the vibration information is closely related to the friction force information. Therefore, researchers can enhance their understanding of the working state of a tribo-system by establishing a data association of the two types of state information.

According to the above analysis and information classification, we can obtain the information expression formula of the tribology system, and for any tribology research object, the information can be classified and stored according to Eq. (1):

$$\text{Tribo-system information} = \{I, S, O, T_s, D_s\} \tag{1}$$

After this, it is convenient for researchers to intervene in informatics methods and increase the data association between different categories of information. In a sense, the focus of "tribo-informatics" research is to use informatics methods to establish the correlation of two or more tribological information.

4.1.3 *Example: Triboelectric nanogenerators (TENGs)*

The TENG, as an innovative tribological device, facilitates both energy harvesting and information sensing. It can function as a sensor, an energy harvester, or a power supply unit, and there is a critical need for systemic optimization to enhance its performance. Hence, its applications need a more comprehensive and intuitive utilization of tribo-system information. In this section, TENG will be rediscovered from the perspective of informatics based on the informational expression of tribo-system (as shown in Fig. 9). This example illustrates that the framework of tribo-informatics allows for an in-depth understanding of the informational architecture, functional typologies, and optimization directions of the tribo-systems (e.g., TENGs). More importantly, it delineates the general objectives of tribo-informatics, which include state monitoring, behavior prediction, and system optimization.

Firstly, TENG needs to be analyzed from the functionality of the tribo-system. In terms of system function, the main functions of the TENG tribo-system include sensing and energy supply, so the purpose of its tribological system is energy transfer and information transfer. The main design purpose of the tribological system is the main basis for judging its output information.

Secondly, it is classified from the purpose of tribological research, including condition monitoring, behavior prediction, system optimization, and mechanism analysis. In the research of TENG, its state monitoring mainly includes real-time monitoring of tribological and derived state information such as output current, voltage, friction force, and wear amount. Similarly, its behavior prediction mainly focuses on the evolution of these state quantities over time. As for system optimization, we first learned that the main purpose of TENG is information and energy transfer, so the main measures of its system performance are physical quantities such as information transfer efficiency, information carrying

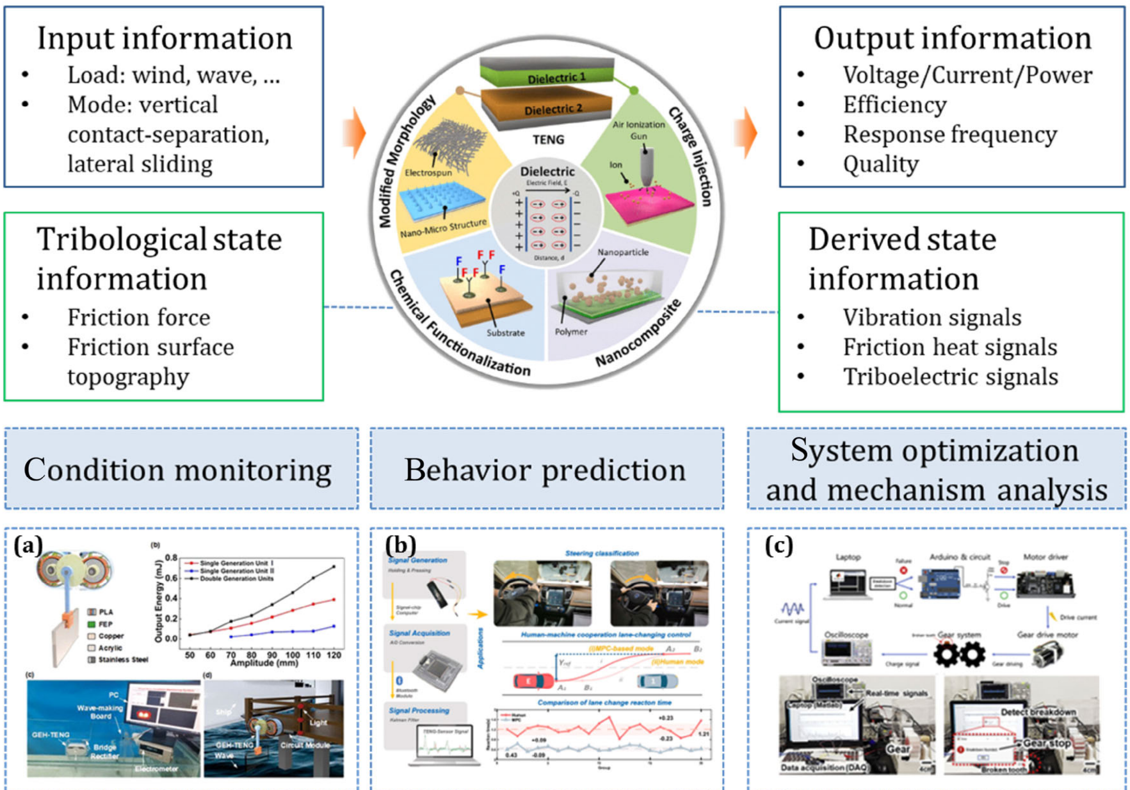

Fig. 9 Informational expression of tribo-system: Taking the TENG as an example [359]. Reproduced with permission from Ref. [359], © American Chemical Society 2023. (a) A TENG designed for adaptable energy harvesting capabilities, suitable for deployment in coastal environments to monitor oceanic wave conditions [360]. Reproduced with permission from Ref. [360], © American Chemical Society, 2021. (b) Integration of a TENG-based sensor within a vehicle's steering mechanism to infer driver intentions [361]. Reproduced with permission from Ref. [361], © Elsevier Ltd. 2023. (c) Development of a self-actuated, real-time gear condition monitoring system utilizing TENG technology, which concurrently harvests energy from gear power transmission [362]. Reproduced with permission from Ref. [362], © Elsevier Ltd. 2020.

capacity, output function, and power conversion efficiency. According to the information expression of the tribological system, in order to achieve system optimization, its input quantities (such as relative motion speed, vibration frequency, ambient temperature, and humidity), system intrinsic information (such as surface contact materials, and surface topography) can be changed. It can be seen from this that the use of the informational expression model of the tribology system can provide researchers with a more comprehensive system optimization direction and improve research efficiency.

4.2 Research process of tribo-informatics

From the classification of research purposes, tribological research can be divided into tribological condition monitoring, tribological behavior prediction [363], tribo-system optimization, and friction/wear/lubrication mechanism analysis. At the same time, informatics methods usually have the purpose of regression, classification, clustering, and dimensionality reduction [11]. Under the background of the birth of tribo-informatics, these types of tribological research with different purposes will have new and more efficient solutions. In this section, from the perspective of tribo-informatics, the way of thinking and the research process to solve these types of tribological problems is reorganized. It should be pointed out that the analysis of friction/wear/lubrication mechanism is often performed by finding data associations of various types of information, and then combining them with physical models for analysis. The research process is diverse, and the informatics method is difficult to achieve the research purpose completely.

4.2.1 Tribo-informatics approach for status monitoring

The core purpose of tribo-informatics research on tribological status monitoring is to achieve the fault diagnosis by fitting tribological state information with five types of tribo-system information through information processing methods (as shown in Fig. 10). A complete status monitoring process can be listed as follows: (a) the first step is to gather information, which mainly includes easy-to-observe state parameters and existing parameters. The easy-to-observe state parameters may be state parameters that are readily available from the derivative signals, outputs, and tribological information and these parameters may be different for each particular tribological study. Existing parameters include system intrinsic information and input information, which are determined when the system is set up, thus there is no need to set up sensors to obtain them; (b) the second step is to process information. Easy-to-observe state parameters as data sets are necessary for this process yet existing parameters are not necessary, which can assist in building a suitable model. A suitable model makes information processing more efficient and research interpretable. In order to fit tribological state information, two informatics processing methods, regression, and dimensionality reduction, are usually used. Regression can help establish the correlation between obtained five types of tribo-system information and tribological state information parameters, and dimensionality reduction can sort the correlation strength. With the correlation strength ranking, specific information can be selected to achieve a better fitting effect and robustness; and (c) the final step is to have a fault diagnosis with the obtained tribological state information through classification.

4.2.2 Tribo-informatics approach for behavior prediction

The core purpose of tribological behavior prediction is to predict the remaining service life with temporal signals and existing parameters (as shown in Fig. 11). The process can be described as "information gathering, pre-processing, information processing, and remaining service life predicting". (a) The first step is to gather information which can mainly be divided into temporal signals and existing parameters. While the existing parameters information is the same as the one in tribological status monitoring research, temporal signals are different from easy-to-observe status parameters. Temporal signals also consist of tribological state information, output, and derivative signals, and the tribological information could be the result of the status monitoring process. The main difference is that temporal signals insist on time-variant characteristics when easy-to-observe status already eliminates these characteristics, for example, by averaging parameters. Temporal signals contain information gathered from historical stages and current stages of various systems under similar circumstances; (b) the second step is to pre-process

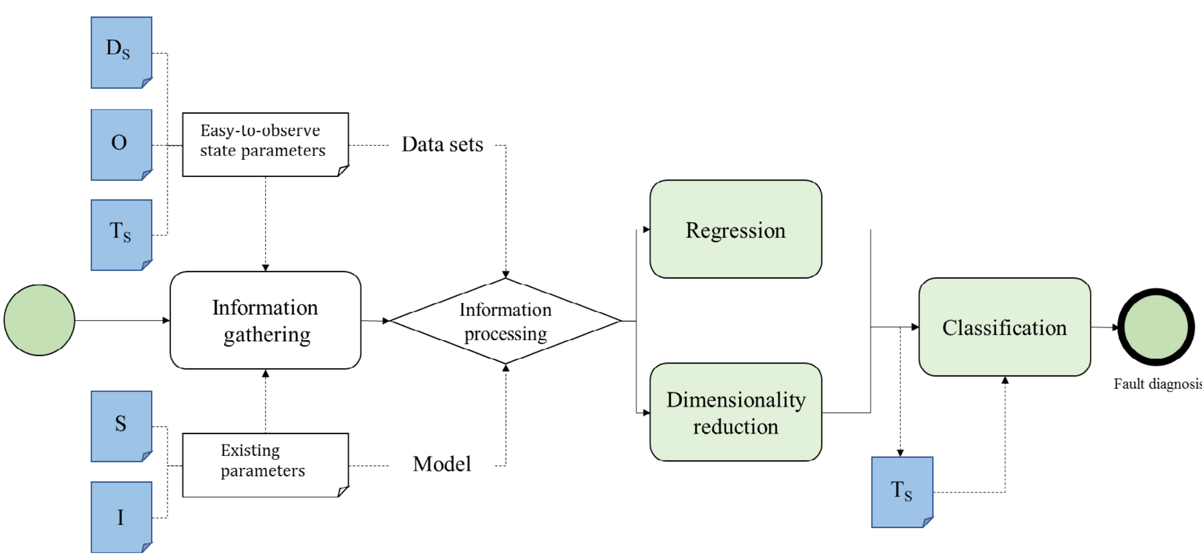

Fig. 10 Tribo-informatics research process for status monitoring.

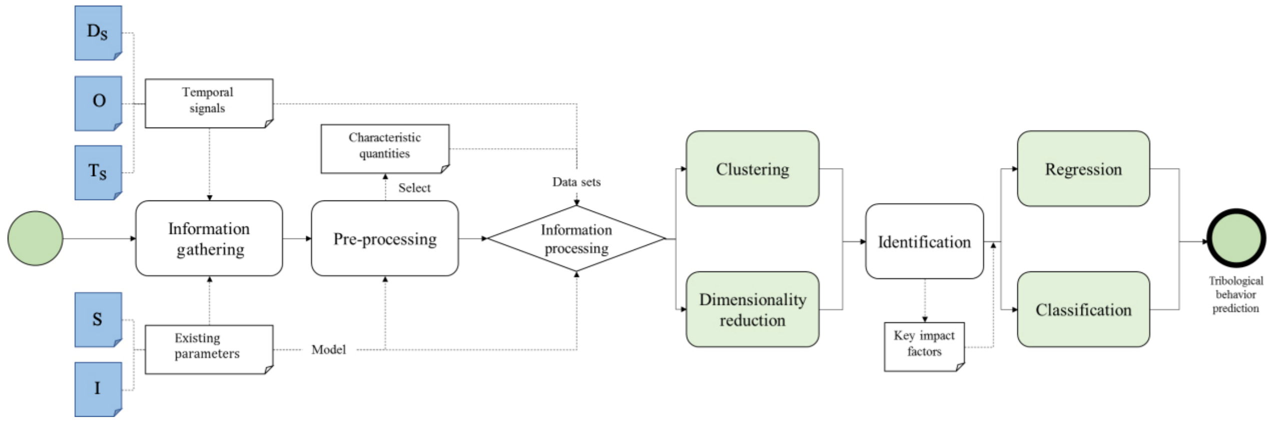

Fig. 11 Tribo-informatics research process for behavior prediction.

the gathered information to quantify a complicated tribology system. In this step, characteristic quantities should be carefully selected with the help of models built by existing parameters. For example, to quantify surface morphology, parameters such as roughness and skewness are preferred; (c) the third step is to process information with data sets from characteristic quantities and models based on existing parameters. Still, models are strongly recommended but not necessary. To identify key impact factors, clustering and dimensionality reduction methods are adopted. Clustering is used to establish the correlation between no-label time-variant characteristics and service life. Dimensionality reduction is used to identify factors that are strongly correlated with service life while weakly correlated with other factors; and (d) in the final step, key impact factors are classified to predict different failure forms and regressed to predict the remaining service life.

4.2.3 *Tribo-informatics approach for system optimization*

The main purpose of system optimization is to achieve the optimization of target performance (as shown in Fig. 12). (a) In the first step, specific targets will be obtained at the beginning of the research. These targets are derived from the deficiencies in practical applications and the pre-research for advanced tribo-systems; (b) in the second step, decision-making needs to distinguish the system optimization during the design stage or the working stage. The degrees of freedom are different at different stages, but all these optimizations can be classified into system intrinsic information characters and input information characters. In the working stage, to have performance-seeking

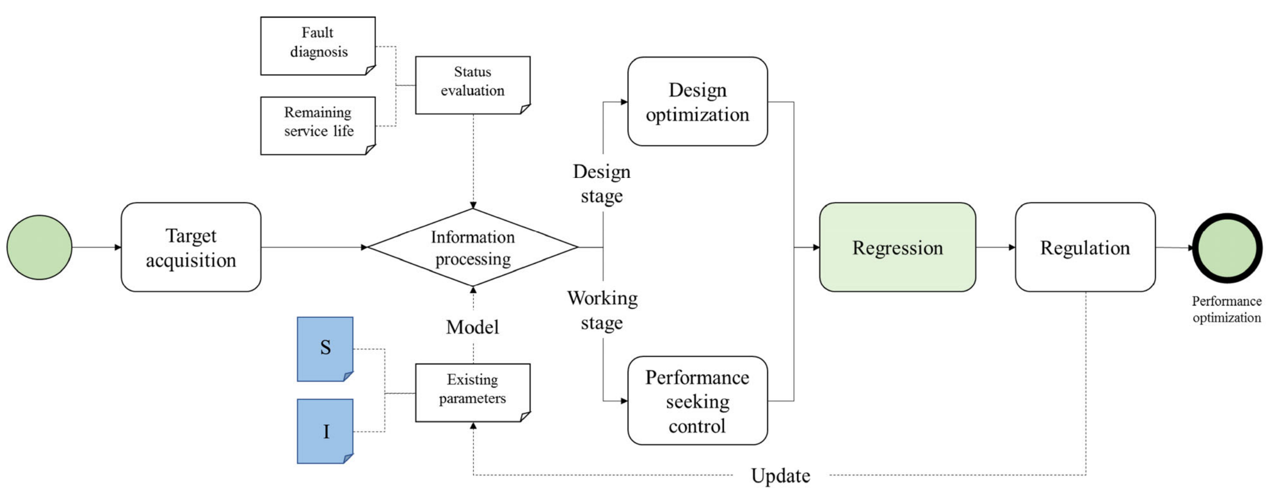

Fig. 12 Tribo-informatics research process for performance optimization.

control, system intrinsic information characters tend to be optimized such as automatic oil replenishment bearing and intelligent surface by adjusting the contact pair and lubricant. The system optimization in the design stage can be more biased towards the adjustment of the input information characters. Some compromises in other systems may significantly improve the state of the tribo-system by changing the friction velocity, friction time, and friction form. These decisions are supported by status evaluation and models. Status monitoring and behavior prediction play vital roles in status evaluation; (c) the third step is to determine the amount of adjustment by regression and update the existing parameters in time; and (d) the first three steps are executed repeatedly until the goal of performance optimization is achieved.

4.3 Future trends of tribo-informatics

Tribo-informatics was born under the background of the rapid development of informatics technology. AI technologies have improved the efficiency of data collection, processing, analysis, and reuse. Under the guidance of tribo-system informatization expression and tribo-informatics research ideas, new driving force will be given to tribological research. The future development trend of "tribo-informatics" is to improve the induction and classification of tribo-system information, and enrich the conceptual connotation, application scenarios, and technical implementation paths of tribo-informatics. To elaborate on the driving role of tribo-informatics in tribology more specifically, the future research directions of tribo-informatics will be carried out from six aspects based on the different research fields of tribology research.

4.3.1 Basic theory of tribology

Basic theoretical research has creative characteristics, while AI technology is essentially about obtaining data correlations between physical quantities, so it cannot directly create theoretical knowledge. However, using AI technology can provide a more intuitive data foundation for mechanism analysis. For example, researchers can firstly establish the correlation between the dynamic contact resistance of the current carrying friction pair and signals such as acoustics, vibration, and acoustic emission, conducting correlation analysis, and then identify the main factors affecting the current carrying friction performance, and reveal mechanism. On the other hand, super-slip/ultra-low wear is the purpose of most tribological studies, which is of great significance for reducing frictional energy consumption and prolonging the life of mechanical systems. Using tribo-informatics-based behavior prediction methods, it is possible to establish the relationship between various inputs such as structures, compositions, environments, or system intrinsic information, and friction/wear performance. In this way, various factors affecting super-slip/ultra-low wear can be found, and high-throughput screening of input/system eigenvalues can be established to realize the design of super-slip/ultra-low wear tribo-systems.

4.3.2 Intelligent tribology

Intelligent tribology is the most typical research direction with the characteristics of "tribo-informatics", and it is also the most widely studied field. It not only enables online monitoring and fault diagnosis of tribological systems, but also enables efficient and intelligent design of friction/lubrication materials. Here is only one possible development idea proposed, intelligent regulation of interfacial friction/lubrication behavior is an important research direction that has developed rapidly in recent years, mainly including online monitoring of coating status, self-healing of damage, and active lubrication regulation. Among them, the online monitoring technology can monitor the coating state in real-time by establishing the relationship between the coating structure variables (such as morphology, cracks, and wear) and the easily observable derived state information. Damage self-healing involves high-throughput screening of many lubricating materials, and active lubrication regulation requires establishing the relationship between lubricant dosage and tribological state. These intelligent detection, regulation, repair, and other purposes can be used to establish data association through tribo-informatics methods to provide a basis for final decision-making.

4.3.3 Component tribology

The fundamental components of tribology are those important parts of machine systems that can exist and be sold separately. The application of AI technology in this field should mainly focus on product optimization design and service performance prediction. For example, using AI technology to optimize the pore structure of bearing cages can improve the passive oil replenishment performance of bearings. At the same time, establishing the relationship between different oil replenishments and friction torque fluctuations can guide the amount of lubricating oil added. Improving product design efficiency and predicting performance degradation patterns are of great significance for the application of AI technology in this field.

4.3.4 *Extreme tribology*

Extreme tribology problems under extreme working conditions often exist in deep space, deep ground, deep sea, polar regions, and other environments. These tribo-systems have high precision requirements, complex structures, and extremely high costs, which makes it difficult to predict performance and life through repeated tests. Tribo-informatics methods can first combine limited data for sample amplification, and then perform data association based on condition monitoring and life prediction methods. This method can effectively avoid the inaccurate prediction caused by the difficulty of direct measurement of some state parameters under extreme working conditions.

4.3.5 *Bio-tribology*

Bio-tribology mainly studies the tribological properties of joints, implants, and wearable devices in living organisms. Among them, there is no significant difference in the study of the tribological performance between joints in living organisms and implants in the human body compared to the tribological research in machine systems. In terms of wearable devices, with the development of the concept of "metaverse", more attention should be paid to the development of tribological devices that can realize environmental awareness and human-computer information interaction, including artificial limbs that can sense contact movement, tactile skin based on tribology, and so on. Among them, achieving data correlation between environmental information, contact point tribology information, and brain signals is the key application focus of AI technology.

4.3.6 *Green tribology*

Green tribology mainly studies various aspects such as friction emission control, friction noise suppression, green lubricants, and the design of extended life friction pairs. The control of friction process derivatives is the research focus of green tribology. AI technology can promote the development of green tribology by establishing a data relationship between the input and derivative quantities of the tribology system, such as noise, debris particles, and lubricant loss.

5 Conclusions

With the integration of artificial intelligence (AI) technology and tribology research, "AI for tribology" has attracted more and more researchers' attention. This article first analyzes the publication status of papers in this direction and clarifies the research hotspots and trends of "AI for tribology". Subsequently, the field of tribology research was divided into basic theory of tribology, intelligent tribology, component tribology, extreme tribology, bio-tribology, and green tribology. Then, the role of AI technology in each research field was reviewed.

AI technology has greatly promoted the development of tribology by establishing data associations between tribological system information. To achieve a deep integration of tribology and informatics, "tribo-informatics" has been proposed as a new discipline direction. In this paper, informational expression for tribology systems are proposed, namely input information (I), system intrinsic information (S), output information (O), tribological state information (T_s), and derived state information (D_s). Then, the technical implementation path of tribo-informatics is introduced in terms of tribological state monitoring, behavior prediction, and system optimization. Finally, the future development trend of AI Technological convergence is prospected based on the tribology research field. It is hoped that this article can increase researchers' understanding of "AI for tribology", "tribo-informatics", and improve the efficiency of tribology research.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article. The author Zhinan ZHANG is the Editorial Board Member of this journal, and the author Shuaihang PAN is the Youth Editorial Board Member of this journal.

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