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Advances in Predictive Reliability Assessment and Failure Prevention for Semiconductor Manufacturing Equipment

Enoch Ogunnowo[1], Emmanuel Chukwuma Okeke[2*], Marvin Komi[3], Oluranti Ogundapo[4], Precious Nnamdi Ibe[5]

[1]McNeese State University, Lake Charles, LA, USA
[2]IDEX Corporation, USA
[3]Independent Researcher, Nigeria
[4]Airtel Networks, Nigeria
[5]University of Port Harcourt, Port Harcourt, Nigeria

Abstract

Semiconductor fabrication relies on hundreds of capital-intensive process tools, each containing subsystems (RF generators, vacuum pumps, electrostatic chucks, gas delivery modules, ion sources, and cooling loops) whose degradation can scrap wafers, interrupt cycle time, and erode yield. In recent years, the field of equipment reliability in semiconductor manufacturing moved decisively from fixed-interval preventive maintenance toward data-driven predictive and prescriptive approaches. This paper reviews the principal advances to date. It covers (i) deep learning for fault detection and classification (FDC) that operates on raw, variable-length sensor traces rather than hand-crafted summary statistics; (ii) remaining useful life (RUL) prognostics catalyzed by the public PHM ion mill etch benchmark; (iii) comparative machine-learning studies of failure prediction from production sensor data; (iv) the extension of prediction into prescriptive maintenance that couples time-to-failure models with Bayesian root-cause inference and maintenance planning; (v) enabling data and cloud infrastructure; and (vi) facility, power, and subsystem reliability. Methodologically, the study is an integrative narrative review of 114 sources published to date, comprising 14 core semiconductor prognostics sources and 100 related and semi-related studies screened from a consolidated list of 1,056 records and spanning reliability engineering, energy, offshore asset integrity, industrial safety, cybersecurity, cloud infrastructure, and supply chain research. A five-layer conceptual model linking detection, diagnosis, prognosis, and maintenance decisions is proposed together with four testable propositions. The discussion identifies persistent obstacles, namely class imbalance, label scarcity, maintenance-induced drift, chamber-to-chamber variability, cybersecurity of connected tools, human factors, and spare-parts supply, and the paper sets out implications for practitioners, researchers, and equipment suppliers, states the limitations of the review, and proposes directions for future research.

Keywords: predictive maintenance; prognostics and health management; remaining useful life; fault detection and classification; semiconductor equipment; deep learning; prescriptive maintenance; reliability-centered maintenance; Industry 4.0

INTRODUCTION

A modern 300 mm fab operates several hundred process and metrology tools, many costing tens of millions of dollars, in a sequence that may exceed one thousand steps per wafer. Equipment availability is therefore a first-order economic variable: an unscheduled outage on a bottleneck lithography or etch tool can idle downstream capacity, lengthen cycle time, and force rework or scrap of wafers already in process. The industry has long tracked these effects through the reliability, availability, and maintainability (RAM) metrics defined in the SEMI E10 specification, including mean time between failures (MTBF), mean time to repair (MTTR), and the partitioning of equipment time into productive, standby, engineering, scheduled downtime, and unscheduled downtime states (SEMI, n.d.). Reliability engineering and failure analysis methods developed for complex engineering systems provide the conceptual base on which equipment health assessment rests (Gideon et al., 2019).

Historically, semiconductor equipment maintenance has followed two patterns. Corrective, or run-to-failure, maintenance repairs a tool after a fault occurs, accepting the cost of unplanned downtime. Preventive maintenance (PM) replaces consumables and cleans chambers at fixed wafer counts, RF hours, or calendar intervals, which reduces surprise failures but discards useful component life and introduces post-PM recovery and seasoning periods that themselves consume capacity. Predictive maintenance (PdM) seeks the middle path: it estimates the health of a component from operating data and schedules intervention only when degradation warrants it (Ran et al., 2019; Zhang et al., 2019).

By 2020 several forces had converged to make PdM practical in fabs. Equipment interfaces such as SEMI Interface A (EDA) had raised sensor sampling rates and data accessibility; fabs had accumulated years of trace data and maintenance records; deep learning methods had matured for time-series problems; and public benchmarks had begun to appear. At the same time, the 2020 pandemic restricted on-site field service, tested business continuity and disaster recovery arrangements across industries (Fadero et al., 2020), and exposed the fragility of contractual and logistical arrangements in global supply chains (Uchechi et al., 2020). These pressures heightened interest in remote diagnostics and in maintenance strategies that conserve scarce parts and technician time. This paper reviews the methodological progress of that period and situates it within the wider body of reliability, condition-monitoring, and industrial analytics research published to date.

The paper pursues three objectives: to synthesize the principal methodological advances in predictive reliability assessment for semiconductor equipment to date; to integrate transferable insights from related asset-intensive and data-intensive domains; and to propose a conceptual model linking detection, diagnosis, prognosis, and maintenance decision-making. The remainder of the paper is organized as follows. Section 2 describes the research method. Section 3 presents the results and discussion, comprising the literature synthesis, the conceptual model and its propositions, a discussion of findings and persistent challenges, implications for practice, research, and industry bodies, the limitations of the review, and directions for future research. Section 4 concludes.

RESEARCH METHOD

Review Design

This study adopts an integrative narrative review design. An integrative review is appropriate where the relevant evidence is spread across engineering, information-systems, and management literatures, where much of it is conceptual rather than experimental, and where the goal is to build a framework rather than to estimate a pooled effect size. The review therefore combines a focused core of semiconductor-specific prognostics and health management studies with a broader body of related and semi-related work whose methods are transferable to fab equipment.

Sources and Search Strategy

Evidence was drawn from two sources. The first was a core set of peer-reviewed publications and benchmark documentation on semiconductor equipment fault detection, remaining useful life estimation, and predictive maintenance, identified through targeted searches using combinations of the terms predictive maintenance, prognostics, remaining useful life, fault detection and classification, semiconductor equipment, etch, and machine learning, supplemented by backward citation tracking. The second was a consolidated reference list of 1,056 unique records, deduplicated and organized by subject area, from which related and semi-related studies were screened.

Inclusion and Screening Criteria

Three inclusion criteria were applied. First, the source had to be published to date, consistent with the temporal scope of the review. Second, the study had to address at least one of the following: equipment reliability, maintenance strategy, condition monitoring, fault or anomaly detection, degradation and integrity, industrial safety in maintenance contexts, cybersecurity of connected industrial or data systems, data and cloud infrastructure for analytics, spare parts and procurement, facility and power reliability, or governance and quality of data-driven decisions. Third, the study had to be traceable

through complete bibliographic details. Applying the date criterion to the consolidated list left 171 records; relevance screening on title and subject classification retained 100 of these, excluding studies in unrelated fields such as animal nutrition, special-needs pedagogy, urban housing, and marketing. Together with 14 core sources, the final corpus comprises 114 references.

Analysis and Synthesis

Included studies were coded into seven thematic categories (Table 1) and mapped to the stages of the equipment health decision chain: data acquisition, detection, diagnosis, prognosis, and maintenance decision. Thematic synthesis was then used to identify convergent findings, methodological trends, and unresolved tensions, which informed the conceptual model in Section 3.2. Core semiconductor studies were used to establish the state of the art, while related studies were used to identify transferable mechanisms, enabling conditions, and organizational requirements.

RESULTS AND DISCUSSION

This section reports the results of the review in six parts: the literature synthesis (Section 3.1), the conceptual model derived from it (Section 3.2), a discussion of the findings and persistent challenges (Section 3.3), implications (Section 3.4), limitations of the review (Section 3.5), and directions for future research (Section 3.6).

Literature Synthesis

Reliability Metrics and Maintenance Strategies

Predictive reliability assessment in a fab is ultimately judged against RAM outcomes. Table 2 summarizes the metrics most frequently used to evaluate the business effect of a PdM program, together with the way PdM is expected to change them.

Maintenance strategies are commonly classified into run-to-failure, preventive, predictive, and prescriptive categories (Ran et al., 2019; Zhang et al., 2019). The distinction between the last two matters for this review. Predictive maintenance answers when a failure is likely; prescriptive maintenance additionally answers what action to take, on which component, and when to schedule it given production constraints. Several 2020 contributions explicitly targeted this step from prediction to prescription.

The transition from reactive to predictive regimes was examined for mechanical systems in 2020 (Sunday et al., 2020) and earlier for critical power and energy infrastructure, where condition monitoring underpins availability (Adaramola et al., 2018). A reliability-centered maintenance (RCM) concept for static mechanical equipment (Obetta, 2020), condition-based maintenance of bearings and swivels (Obetta & Ninduwezuor-Ehiobu, 2018), risk-based inspection for fitness-for-service assessment of ageing pressure vessels (Obetta, 2018), and reliability and integrity management of fired heaters and boilers (Obetta, 2019) illustrate how maintenance intensity can be matched to measured risk. Risk-based process engineering for natural gas infrastructure (Asibor & Isong, 2019) extends the same logic to whole processing systems. These templates transfer to fabs, whose tools combine rotating, static, and electronic subsystems, and whose support organizations face the same tension between operational continuity and cost that has been analysed for distributed IT support operations (Anyanwu, 2019; Anyanwu, 2020).

Table 1: Composition of the related and semi-related seed corpus by theme (n = 100)

Theme	*Studies*	*Primary role in the synthesis*
Reliability, maintenance, and asset integrity	15	Maintenance strategies, RCM, risk-based inspection, degradation
Industrial safety and human factors	16	Maintenance safety, human error, leading indicators
Cybersecurity, identity, and data protection	15	Security of connected tools and analytics pipelines
Cloud, data integration, and remote inspection	12	Data platforms, ETL, scaling, non-contact monitoring
Supply chain, procurement, and contracts	14	Spare parts, uptime-oriented procurement, contracts
Energy, power, and facility systems	9	Power quality, grounding, on-site generation, HVAC
Governance, quality, and decision analytics	19	Auditability, risk-based decisions, operational embedding

Table 2: Equipment reliability metrics relevant to predictive maintenance

Metric	*Definition (after SEMI E10)*	*Expected effect of PdM*
MTBF	Productive time divided by number of failures	Increases as incipient failures are intercepted
MTTR	Mean elapsed time to restore a tool after failure	Decreases when diagnosis and parts are prepared in advance
Unscheduled downtime	Time lost to unplanned failures and repair	Converted partly into shorter scheduled downtime
Scheduled downtime	Time used for PM, qualification, and setup	Reduced by extending PM intervals where health allows
Operational availability	Share of time a tool is able to process	Increases overall
Overall equipment effectiveness	Availability x performance x quality	Improves through fewer excursions and less scrap

Equipment Data Sources

The data available for equipment health assessment are unusually rich. Status variable identification (SVID) traces record chamber pressure, RF forward and reflected power, matching network positions, gas flows, temperatures, and valve positions at rates from one to tens of hertz. Optical emission spectroscopy (OES) adds hundreds to thousands of spectral channels. FDC systems condense these traces into step-level summary statistics, while maintenance management systems log PM events, part replacements, and failure codes. Manufacturing execution systems contribute recipe, lot, and context information, and inline metrology provides wafer-level quality outcomes that serve as indirect health labels (Moyne & Iskandar, 2017).

Integrating these sources is an information-systems problem as much as an analytics one. ETL design and data integration for enterprise architectures (Badmus et al., 2019a), CI/CD pipeline strategies for platform deployments (Badmus et al., 2018), optimization of cloud-based databases (Odejobi et al., 2019), and performance evaluation of multi-tenant platforms under high concurrency (Odejobi & Ahmed, 2018b) address the data plumbing on which fab-wide models depend. Remote and aerial inspection platforms developed for power grids, transmission lines, and pipeline corridors (Dagodzo & Ahiaeke Patrick, 2020; Dagodzo, 2018a; Dagodzo, 2018b) show how non-contact sensing extends monitoring to assets that are difficult to instrument directly, a principle relevant to subfab and facility equipment.

This richness is accompanied by complications that shape every method reviewed below: traces vary in length from wafer to wafer, operating regimes change with recipe, sensors drift and are recalibrated, true failures are rare, and labels are frequently incomplete or recorded inconsistently by different technicians.

Deep Learning for Fault Detection on Raw Sensor Traces

Conventional FDC relies on engineers to define summary statistics (means, standard deviations, slopes) over recipe steps, then applies univariate limits or multivariate statistical process control such as principal component analysis with Hotelling T-squared and Q statistics. The 2019 to 2020 literature showed that convolutional and attention-based networks trained on raw traces can outperform this pipeline. Kim et al. (2019) introduced self-attentive convolutional neural networks that handle variable-length SVID sequences directly; using real production data, their model outperformed other deep learning baselines with less training time, and raw SVID data yielded better detection than condensed FDC data, while the attention weights pointed engineers to the time segments where abnormal patterns occurred.

Fan et al. (2020) proposed a data-driven fault detection and diagnostic approach for semiconductor equipment that combined detection with diagnostic isolation of the responsible variables. Collectively these studies established two lessons: information discarded by summary statistics is often diagnostically valuable, and interpretability mechanisms such as attention maps are needed for engineers to trust and act on alarms.

Comparable detection problems were studied in adjacent domains to date. Intrusion detection and prevention models (Dosunmu & Ogundele, 2020), insider-threat classification and risk modeling in complex digital systems (Akeju et al., 2018), and automated incident response built on enterprise log analytics (Mbonu et al., 2019b) confront the same rare-event, high-volume, high-dimensional conditions as tool FDC. Predictive compliance monitoring that detects systemic safety risks from complaint data (Adeyelu, 2018) and predictive churn analytics (Oziri et al., 2020) illustrate how weak, imbalanced signals can be converted into early warnings, a problem directly analogous to sparse equipment fault labels.

Remaining Useful Life Prognostics and the PHM 2018 Benchmark

A major barrier to prognostics research in semiconductors has been the confidentiality of fab data. The PHM Society 2018 Data Challenge partially removed that barrier by releasing time-series sensor data from multiple ion mill etch tools operating under various conditions, with the objectives of detecting faults and predicting time remaining until the next failure (PHM Society, 2018). The dataset documented several failure mechanisms, including leaks between the flowcool and ion mill chambers, electric grid wear, and ion chamber wear.

Throughout 2019 and 2020 this dataset became the de facto benchmark for semiconductor RUL estimation. The approaches evaluated on it evolved from gradient-boosted regressors on engineered features toward recurrent networks (LSTM and GRU), temporal convolutional networks, and hybrid models that first issued an early degradation warning before regressing RUL. Two methodological insights emerged. First, operating-state awareness is essential: models that condition on recipe and regime outperform those that treat all samples identically. Second, the benchmark exposed how sensitive reported accuracy is to sample screening, censoring, and choice of error metric, which motivated calls for standardized evaluation protocols.

A broader body of prognostics theory, including systematic reviews of the pipeline from data acquisition to RUL prediction (Lei et al., 2018) and surveys of deep learning for machine health monitoring (Zhao et al., 2019), supplied the architectures that semiconductor researchers adapted. Multimodal modeling for long-term production forecasting (Nwangwu et al., 2020) and data-driven and spatially explicit risk models for tracking contaminant pathways (Azeez & Badmus, 2018; Lamidi & Olamide, 2018) demonstrate, in other physical domains, the fusion of heterogeneous measurements into forward-looking estimates under uncertainty, which is the essence of RUL estimation.

Degradation mechanisms studied in other asset-intensive sectors inform the physical side of prognostics. Corrosion management and material selection for marine equipment (Obetta et al., 2020), green corrosion inhibitors for steel protection (Atta et al., 2018), NDT-based integrity management and corrosion risk assessment for process equipment (Atta et al., 2020), and integrity assurance of turret mooring systems through inspection, monitoring, and life extension (Obetta & Ninduwezuor-Ehiobu, 2019) are relevant to corrosive process-gas handling, exhaust lines, and vacuum hardware. Optimization studies of single-phase induction motor losses and weight (Amayo & Popoola, 2017a; Amayo et al., 2015; Amayo, 2017) bear on the motors that drive pumps, chillers, and wafer-handling robots, whose electrical signatures are common health indicators.

Comparative Machine Learning for Failure Prediction

Alongside deep architectures, 2020 saw systematic comparisons of classical learners on production failure data. El Mourabit et al. (2020) compared several machine-learning algorithms for predicting semiconductor equipment failures during wafer manufacturing and selected a multilayer perceptron as the most effective, reporting an accuracy of 91.95 percent. Such studies built on the multiple-classifier PdM framework that Susto et al. (2015) had demonstrated on semiconductor equipment, in which classifiers trained at several prediction horizons allow maintenance decisions to trade unexpected-failure risk against wasted component life.

The practical significance of this line of work is less the specific accuracy figure than the recognition that accuracy is a poor criterion for imbalanced failure data. Studies increasingly reported recall,

precision, F1, and cost-weighted metrics, and paired classifiers with resampling or anomaly-detection formulations. Machine-learning prediction was applied in parallel to cloud resource scaling (Ahmed et al., 2020) and to supply chain demand forecasting and inventory management (Aifuwa et al., 2020), which share the requirement that predictions be converted into capacity or stocking decisions.

From Prediction to Prescription

Perhaps the most consequential conceptual advance of 2020 was the explicit move toward prescriptive maintenance. Nemeth et al. (2020) proposed a conceptual model for etching equipment in which several machine-learning algorithms predict time-to-failure intervals for unplanned downtimes, Bayesian networks infer the probable root cause, and the resulting recommendations are fed into maintenance planning routines to raise availability, with the benefit demonstrated on an industrial etch use case.

This architecture addresses a recurring complaint from fab engineers: a health score or RUL estimate alone does not tell a technician which part to stage or which PM to pull forward. By linking prognosis to diagnosis and planning, prescriptive frameworks convert analytics into scheduled actions whose value can be measured in reduced MTTR and avoided unscheduled downtime. The approach is consistent with the cyber-physical system architecture for Industry 4.0, which progresses from connection and conversion through cyber, cognition, and configuration levels (Lee et al., 2015).

Prescriptive recommendations depend on parts, contracts, and capital. Models for inventory availability and plant uptime in energy facilities (Okonkwo et al., 2018b), strategic procurement optimization (Okonkwo et al., 2018a), cost reduction through contract negotiation and vendor governance (Okonkwo et al., 2019), GIS-enabled ERP procurement (Ahiaeke Patrick et al., 2020), and supply chain risk management for processing projects (Agbabiaka et al., 2019) link the decision layer to supply chain execution, while port logistics efficiency (Okonkwo et al., 2020) affects lead times for imported tool parts. Capital equipment financing and risk management in technology procurement (Okoli et al., 2020), automated risk assessment for regulatory deliverables (Uchechi & Ominyi, 2020), liability mitigation in high-value service contracts (Uchechi & Ominyi, 2019), and data-driven executive decision systems (Lawal & Oduleye, 2019b) frame the commercial side of decisions such as whether to repair, refurbish, or replace a subsystem.

Explainability, Governance, and Hybrid Modeling

Adoption of data-driven models in fabs depends on engineers being able to verify that an alarm reflects physics rather than an artifact of context. Around 2020, post-hoc attribution methods such as SHAP (Lundberg & Lee, 2017) began to be applied to FDC and PdM models to rank the sensors and time windows driving a prediction. In parallel, hybrid models that combine physical understanding (for example, the relationship between RF reflected power and chamber wall deposition, or between pump current and bearing wear) with learned components gained attention because they extrapolate more safely when operating conditions change and require fewer failure examples to train.

Explainability is also a governance requirement. Risk-based decision-making in good manufacturing practice environments (Aneke & Adesemoye, 2020) and traceability and chain-of-custody integrity (Aneke & Adesemoye, 2019) provide models for documenting how automated recommendations are reached and which data they used, while diagnostic quality systems (Yusuf & Abdulrazaq, 2018) show how measurement processes themselves are kept under control. Technology-enabled internal audit, risk-based internal control models, data-driven risk evaluation, and integrated governance and compliance strategies (Akomolafe & Agu, 2018; Akomolafe & Agu, 2019a; Akomolafe & Agu, 2019b; Akomolafe & Agu, 2019c) offer frameworks for auditing model-driven decisions, and legal and ethical risk modeling for data protection (Mbonu et al., 2018) together with comparative data protection and secure cloud implementation (Mbonu et al., 2019a) address the handling of equipment data that suppliers and fabs regard as proprietary.

Enabling Infrastructure: Data Platforms and Cloud Services

Methodological progress was supported by infrastructure changes. Higher-bandwidth equipment

data interfaces made sub-second traces available to analytics platforms, and big-data architectures in semiconductor fabs enabled the storage and processing of years of multi-tool data required to observe rare failures (Moyne & Iskandar, 2017). Edge computing near the tool allowed models to score each wafer in near real time, while centralized platforms retrained models across fleets.

Cloud research published to date addressed the services on which such platforms run: scalable and secure cloud messaging architectures (Ahmed & Odejobi, 2018a), energy-efficient virtual machine placement (Ahmed & Odejobi, 2018b), constraint satisfaction in cloud network resource allocation (Ahmed et al., 2019), identity and access management for hybrid, distributed, and federated systems (Mbonu et al., 2020c; Oshoba et al., 2019), infrastructure-as-code governance (Mbonu et al., 2020b), blockchain-enabled audit trails for configuration management (Oshoba et al., 2020), and agile supply chain digital transformation with embedded IT risk controls (Mbonu et al., 2020a). Experience with directory services and offline assessment of security-critical systems (Ladapo et al., 2018; Ladapo et al., 2019) is relevant to the authentication layer that separates tool networks from enterprise systems.

Facility, Power, and Subsystem Reliability

Many tool failures originate outside the chamber. Power quality events, voltage sags, and grounding faults cause RF generator trips and wafer aborts, and fabs are increasingly integrating on-site generation. Grounding system design optimization for medium-voltage distribution (Adeniji et al., 2020), voltage control in the presence of distributed generation (Oshevire et al., 2017), optimization of electrical load distribution for hybrid solar installations (Sunday & Omoegun, 2019), solar integration in manufacturing industries (Sunday & Omoegun, 2018), programmatic renewable energy integration (Yeboah & Ike, 2020), co-optimization of performance in smart solar microgrids (Komi & Adeniji, 2020), and hydrogen as a secondary energy carrier in national grids (Shittu et al., 2019) inform the reliability of the electrical supply on which tools depend. Statistical solar radiation modeling (Odejobi & Ahmed, 2018a) supports forecasting of on-site generation, and studies of telecommunication network quality (Amayo & Popoola, 2017b) bear on the communication links that carry equipment data.

Thermal and environmental subsystems are equally important. Thermodynamic efficiency and control strategies for air conditioning systems (Sunday et al., 2019) relate to the chillers, heat exchangers, and clean-room air handling whose instability propagates to process temperature control. Chemical safety decision frameworks (Okojie & Abioye, 2020) are relevant to the management of process chemicals and their effect on component degradation.

Conceptual Model

The contributions synthesized in Section 3.1 address different stages of a single decision chain. Figure 1 organizes them into a five-layer conceptual model of predictive reliability assessment. The data layer integrates sensor traces, FDC summaries, maintenance logs, and manufacturing context. The detection layer flags abnormal wafers or runs. The diagnosis layer isolates the subsystem and probable root cause. The prognosis layer estimates health indicators, RUL, and failure probability over relevant horizons. The decision layer translates these estimates into maintenance actions, schedules, and spare-parts plans. A feedback path returns confirmed maintenance outcomes as labels, which is essential because label scarcity is the main limit on model quality.

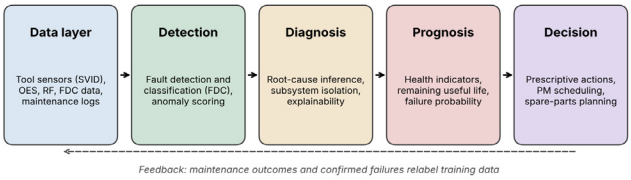


Figure 1: Integrated detection, diagnosis, prognosis, and decision framework for semiconductor equipment

Several design principles follow from the 2020 literature. Models should be operating-state aware, either by conditioning on recipe and context or by training separate models per regime. Detection and prognosis should share learned representations where possible, since both depend on the same degradation

Table 3: Comparison of predictive reliability approaches for semiconductor equipment

Approach	*Typical inputs*	*Strengths*	*Limitations*
Multivariate SPC (PCA, T-squared, Q)	FDC summary statistics	Mature, fast, interpretable contributions	Misses temporal patterns; sensitive to regime changes
Classical ML classifiers (RF, SVM, MLP)	Engineered features, failure labels	Simple to deploy; good with modest data	Requires feature design; accuracy misleading on imbalanced data
CNN and attention models on raw traces	Raw SVID and OES time series	Learns features automatically; handles variable length; attention aids diagnosis	Needs large labeled sets; risk of learning context artifacts
Recurrent and temporal convolutional RUL models	Run-to-failure sequences	Captures degradation dynamics; direct RUL output	Few complete failure histories; sensitive to censoring and metrics
Prescriptive frameworks (ML plus Bayesian networks)	Predictions, failure codes, maintenance plans	Links prediction to root cause and action	Requires curated failure taxonomies and process integration
Risk-based and reliability-centered programmes	Failure modes, consequences, inspection data	Prioritizes effort by risk; auditable	Relies on expert judgement; slow to update

signals. Every alarm should carry an explanation that maps to a subsystem an engineer recognizes. Finally, the decision layer should evaluate actions by expected cost, accounting for the asymmetric cost of a missed failure versus an unnecessary PM.

The model also embeds three enabling conditions identified in the synthesis. Secure and governed data infrastructure is a precondition for the data layer (Adegbite et al., 2020; Badmus et al., 2019a; Oshoba et al., 2019). Parts, contracts, and capital availability condition whether a decision can be executed (Okoli et al., 2020; Okonkwo et al., 2018b). Safety and human-factors controls condition how maintenance actions are carried out (Obogo et al., 2020c; Obriki & Arumosoye, 2020). From the model, four propositions are advanced for empirical testing.

- **P1.** Fault detection models trained on raw sensor traces achieve higher detection performance than models trained on summary FDC statistics, provided operating context is explicitly represented.
- **P2.** Prognostic estimates reduce unscheduled downtime only when coupled to a diagnosis layer that identifies an actionable subsystem and a decision layer that schedules intervention.
- **P3.** The availability benefit of predictive maintenance is moderated by spare-parts lead time and procurement responsiveness.
- **P4.** Engineer trust in, and use of, predictive alarms increases with the interpretability of the explanation provided and the auditability of the decision record.

Discussion

The synthesis shows that progress to date was uneven across the decision chain. Detection and prognosis advanced rapidly through deep learning and a shared benchmark, whereas diagnosis, decision support, and organizational integration remained less developed and were addressed mainly in conceptual work. The related literature is strongest precisely where the semiconductor-specific literature is weakest: on risk-based maintenance programmes, safety, security, procurement, and governance.

Comparative Assessment of Approaches

Table 3 compares the principal classes of methods that were prominent around 2020, drawing on the studies reviewed in Section 3.1.

No single class dominates. In practice, fabs that reported success combined fast statistical detection as a first screen, deep models for subsystems with abundant data, and prognostic or prescriptive layers only for high-impact components such as RF generators, electrostatic chucks, and dry pumps where the economics justified the engineering effort.

Beyond equipment-specific models, decision-analytics research published to date supplies methods for turning health estimates into operational action. Reviews of digital transformation in operations management through automation, analytics, and process redesign (Agboada et al., 2018), standard operating procedures as change infrastructure (Agboada et al., 2019), governance alignment among multiple stakeholders (Eyetsemitan et al., 2020),

analytical frameworks for infrastructure delivery efficiency (Nwafor et al., 2019b), and predictive analytics for forecasting and inventory (Aifuwa et al., 2020) describe how analytic outputs are embedded in routines, ownership structures, and performance reviews. In a fab, these mechanisms determine whether a predicted failure actually changes a PM schedule or a parts order.

Persistent Challenges

- **Class imbalance and label scarcity.** True failures are rare and maintenance logs are noisy, so supervised models face severe imbalance. Semi-supervised, one-class, and anomaly-detection formulations partly compensate but complicate threshold setting.
- **Maintenance-induced drift.** Each PM, part replacement, or chamber clean resets the baseline. Models must recognize these discontinuities rather than interpreting them as faults, and must adapt quickly during seasoning.
- **Chamber-to-chamber and tool-to-tool variability.** Nominally identical chambers behave differently, limiting transfer of models across a fleet. Transfer learning and domain adaptation were identified as priorities but were not yet mature in 2020.
- **Evaluation inconsistency.** Studies reported accuracy, RMSE, scoring functions, or percentage errors under different screening rules, which made comparisons on even a shared benchmark difficult.
- **Data access and confidentiality.** Fab data are commercially sensitive, so public benchmarks remain few and may not reflect the diversity of production tools.
- **Cybersecurity of connected tools.** As tools connect to analytics platforms, the equipment network becomes an attack surface, often running legacy operating systems. Work on securing operational technology networks in electric utilities (Adegbite et al., 2020), security audit and enterprise risk assessment for resilient information systems (Dosunmu & Ogundele, 2019), risk-based cybersecurity assurance and data availability (Fadayomi et al., 2019), privacy-centric security engineering for cloud systems (Okoruwa et al., 2020), and the intrusion detection and insider-threat models noted earlier (Akeju et al., 2018; Dosunmu & Ogundele, 2020) applies directly to fab equipment networks.
- **Human factors and safety.** Maintenance is where equipment reliability and personnel safety meet. Studies of near-miss and hazard observation data (Arumosoye & Obriki, 2019), data-driven occupational safety risk control in energy infrastructure (Obriki & Arumosoye, 2018), human error causation in high-risk industrial activities (Obriki & Arumosoye, 2020), safety management in oil and gas maintenance projects (Obogo et al., 2020c), internal QHSE audit systems (Obogo et al., 2020a), contractor safety governance (Arumosoye & Obriki, 2020), operational integrity in high-risk drilling (Nwangwu et al., 2018), heat stress risk in industrial operations (Arumosoye & Obriki, 2018), and risk management for heavy lifting operations (Obogo et al., 2020b) inform maintenance work planning. Research on safety culture, walkthrough frequency, construction safety governance, and hazard identification (Obogo et al., 2019a; Obogo et al., 2019b; Obogo et al., 2019c; Obriki & Arumosoye, 2019), together with adaptive safety management systems and AI-driven risk quantification in aviation (Adeyelu, 2019; Adeyelu, 2020), shows how leading indicators can be combined with equipment health signals.
- **Spare parts and supply continuity.** Supply chain fragility in 2020 limited part availability and extended MTTR. Force majeure and contractual resilience in energy supply chains (Uchechi et al., 2020), ESG-integrated sustainable procurement (Okojie et al., 2020), predictive demand forecasting for inventory (Aifuwa et al., 2020), and the procurement and inventory models discussed in Section 3.1.6 (Agbabiaka et al., 2019; Okonkwo et al., 2018b) are relevant to parts logistics for fabs, where critical spares often have long lead times and single sources.
- **Organizational integration.** Predictions create value only when they change maintenance plans, parts logistics, and dispatching. Integrating

analytics with computerized maintenance management and scheduling systems is often harder than building the model, and business continuity planning (Fadero et al., 2020) must account for analytics platforms that have become operationally critical.

Implications

Implications for Practice

For fab maintenance and equipment engineering organizations, the findings suggest a staged adoption path: retain statistical FDC as a first screen, apply deep models where trace data and labels are abundant, and reserve prognostic and prescriptive layers for high-impact subsystems. Maintenance records should be treated as a data asset, with standardized failure codes and confirmed root causes captured at each intervention, since label quality limits every downstream model. Predictive alarms should be integrated with work-order, parts, and scheduling systems so that predictions change actions, and procurement policies should be aligned with predicted demand for critical spares (Aifuwa et al., 2020; Okonkwo et al., 2018b). Safety procedures for maintenance work (Obogo et al., 2020a; Obogo et al., 2020c) and cybersecurity controls for tool connectivity (Adegbite et al., 2020; Dosunmu & Ogundele, 2019) should be updated as analytics platforms become operationally critical.

Implications for Research

For researchers, the review highlights the need for evaluation protocols that report cost-weighted and recall-oriented metrics on imbalanced data, explicit treatment of maintenance-induced discontinuities, and validation across multiple chambers and tools. It also shows that equipment reliability research would benefit from engaging with the risk-based maintenance, safety, and governance literatures, which offer mature constructs for prioritization, accountability, and organizational adoption (Akomolafe & Agu, 2018; Aneke & Adesemoye, 2020; Obetta, 2018; Obetta, 2020). The propositions in Section 3.2 provide testable starting points.

Implications for Equipment Suppliers and Industry Bodies

For equipment suppliers, the findings support embedding health indicators, standardized data interfaces, and explainable diagnostics in tools, and offering prognostic services that respect customer data ownership (Mbonu et al., 2018; Mbonu et al., 2019a). For standards bodies and industry consortia, the scarcity of public datasets and inconsistent metrics point to the value of shared, anonymized benchmarks and common reporting conventions that extend the RAM definitions of SEMI E10 to predictive maintenance outcomes (SEMI, n.d.).

Limitations

Several limitations should be noted. First, the review is integrative and narrative rather than a protocol-registered systematic review, so the selection and interpretation of studies involve researcher judgement. Second, the temporal restriction to publications published to date excludes subsequent developments, including later transformer-based prognostics and more mature digital-twin implementations. Third, relevance screening of the related corpus was based on titles and subject classification rather than full-text appraisal, and many related studies are conceptual frameworks from adjacent sectors rather than empirical studies on semiconductor equipment; their transferability is argued rather than demonstrated. Fourth, proprietary fab data and unpublished industrial practice are, by their nature, underrepresented. Finally, no quantitative meta-analysis was attempted, because reported metrics and datasets were too heterogeneous to pool.

Future Research

Building on the synthesis, the conceptual model, and the limitations above, several directions for future research emerge. Future studies should test propositions P1 to P4 using multi-tool production data and controlled field trials. Transformer and attention architectures promised better handling of long, multi-rate sequences. Federated and privacy-preserving learning offered a route to share model improvements across fabs or between suppliers and customers without exchanging raw data, building on secure identity and data protection frameworks (Mbonu et al., 2019a; Oshoba et al., 2019). Physics-informed learning and digital twins aimed to reduce dependence on failure examples. Uncertainty quantification for RUL estimates was recognized

as necessary for risk-based scheduling, in the spirit of risk-based inspection and RCM (Obetta, 2018; Obetta, 2020). Joint optimization of maintenance and production scheduling, in which predicted health directly influences dispatching decisions, represented the logical endpoint of the prescriptive trend.

Quality and governance methods offer complementary structure for embedding these capabilities. Standard operating procedures (Agboada et al., 2019), QHSE audit (Obogo et al., 2020a), GMP-style risk-based decision-making (Aneke & Adesemoye, 2020), and diagnostic quality systems (Yusuf & Abdulrazaq, 2018) provide the routines through which predictive insights become standard work and remain auditable as models are retrained.

CONCLUSION

The period around 2020 marked a transition in how semiconductor manufacturers assess and protect equipment reliability. Deep learning on raw sensor traces showed that information lost in conventional FDC summaries could improve fault detection and point engineers to the responsible time segments. The PHM 2018 ion mill etch dataset gave the community a shared benchmark for RUL prognostics and revealed the importance of operating-state awareness and consistent evaluation. Comparative studies clarified the strengths and limits of classical learners, and prescriptive frameworks began to close the loop between prediction, root-cause inference, and maintenance planning. Research published to date in energy systems, offshore asset integrity, industrial safety, cybersecurity, cloud infrastructure, and supply chain management supplies transferable methods for risk-based maintenance, degradation assessment, secure data handling, and parts logistics. The remaining obstacles, notably label scarcity, maintenance-induced drift, cross-chamber variability, secure connectivity, and organizational integration, define the agenda for continued research and deployment.

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