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Review

Recent Advances in Data-Driven Methods for Degradation Modeling Across Applications

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Abstract

Understanding degradation is crucial for ensuring the longevity and performance of materials, systems, and organisms. To illustrate the similarities across applications, this article provides a review of data-based methods in materials science, engineering, and medicine. The methods analyzed in this paper include regression analysis, factor analysis, cluster analysis, Markov Chain Monte Carlo, Bayesian statistics, hidden Markov models, nonparametric Bayesian modeling of time series, supervised learning, and deep learning. The review provides an overview of degradation models, referencing books and methods, and includes detailed tables highlighting the applications and insights offered in medicine, power engineering, and material science. It also discusses the classification of methods, emphasizing statistical inference, dynamic prediction, machine learning, and hybrid modeling techniques. Overall, this review enhances understanding of degradation modeling across diverse domains.

Keywords: degradation mechanisms; condition monitoring; prognostics and health management (PHM); remaining useful life (RUL); reliability modeling; predictive maintenance; machine learning; physics-informed modeling; uncertainty quantification; fault diagnosis

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1. Introduction

Degradation is defined as a process in which the quality or condition of a material, system, or organism deteriorates over time, leading to a decline in performance or functionality. This process is crucial to understand for technical, engineering, and economical reasons, as it influences the service life of various structures and materials. In this article, we present a summary of existing research on degradation modeling, encompassing a diverse range of approaches across applications in material science, engineering, and medicine.

In addition to application-specific studies, several review papers have already surveyed degradation modeling from different perspectives. For instance, Shahraki et al. provide a broad overview of degradation models and their engineering applications, with a particular focus on reliability assessment, remaining useful life prediction, and maintenance policies in industrial systems [1]. Other reviews emphasize predictive maintenance and sensor technologies in the context of Industry 4.0 and smart factories, where degradation is typically treated as a latent driver of equipment health indicators rather than as an explicit modeling target [2]. Classical surveys on stochastic degradation processes, such as the work of van Noortwijk on gamma–process–based models, have also played a central role in reliability-centered applications [3].

While these contributions summarize important strands of the literature, they remain largely confined to engineering and maintenance-oriented settings, and they seldom compare methodological choices across fundamentally different domains (materials, engineered systems, and human health).

The present review complements and extends these works in three ways. First, we explicitly adopt a data-driven perspective and organize the literature according to the families of statistical and machine learning models used to describe degradation, rather than according to a single industrial sector. Second, we juxtapose applications from materials science, engineering, and medicine under a unified terminology, highlighting how similar model classes are reused across domains that differ strongly in terms of time scales, observability of degradation, and data availability. Third, we discuss how data-based models can be combined with physical and knowledge-based components into hybrid approaches, which are increasingly relevant in modern prognostics and health management. This cross-disciplinary and method-focused view is, to the best of our knowledge, not covered in existing reviews and motivates the structure of the present paper.

Degradation modeling plays a crucial role in various fields, including engineering, reliability analysis, and system optimization. Understanding the behavior of degrading systems and predicting their remaining useful life is essential for effective maintenance, resource allocation, and system design. In this review, we will present various statistical methods that have been applied to degradation modeling, exploring both traditional statistical techniques and more advanced approaches, such as machine learning algorithms. By examining these methods, we provide insights into the strengths, limitations, and potential applications of each approach in degradation modeling.

Consequently, this review is guided by the following questions: (i) how are degradation phenomena operationalized and measured in materials science, engineering, and medicine; (ii) which data-driven model classes are most frequently used for degradation modeling in each domain and under which data conditions; and (iii) to what extent are hybrid or physics-informed approaches already adopted in practice? By answering these questions, we aim to provide practitioners with a structured map of available methods, their typical use cases, and open gaps where current approaches appear insufficient.

This paper is structured as follows: In Section 2 we introduce the key preliminaries on degradation modeling, including definitions, ISO standards across medicine, engineering and materials science, and the distinction between physical, data-driven and knowledge-based approaches. Section 3 surveys the existing literature, summarizing prior review papers and textbook treatments, and presents a comparative analysis of publication trends over time in the three application domains. In Section 4 we propose our classification of data-based methods into three main groups—statistical inference, dynamic prediction and machine learning—and describe each class in detail. Section 5 examines how these methods have been used in material science, power engineering and medicine, highlighting domain-specific preferences and hybrid combinations. Section 6 discusses open challenges and future research directions, such as uncertainty quantification, missing-data handling, data fusion, and scalability. Finally, Section 7 concludes with a summary of the main insights and recommendations for practitioners and researchers.

2. Review Methodology

The present review follows a structured, though not fully PRISMA-compliant, procedure for identifying, screening, and selecting publications on data-based degradation modeling in materials science, engineering, and medicine. The goal of this section is to document the search strategy and eligibility criteria in a transparent and reproducible way.

2.1. Databases and Search Strategy

We conducted a structured search in four major scientific databases that cover the target domains and methodologies: Scopus, Web of Science Core Collection, IEEE Xplore, and PubMed. The search was performed for articles published between 2010 and 2023 (inclusive), reflecting the period in which data-driven and machine learning approaches to degradation modeling became prominent.

The search strings combined terms related to degradation with methodological and application-related keywords. A generic template was used as follows:

```
(degradation OR ageing OR aging OR ‘‘remaining useful life’’ OR RUL) AND
(model* OR predict* OR prognos* OR ‘‘health index’’)
AND (Bayesian OR stochastic OR ‘‘gamma process’’ OR ‘‘Wiener process’’ OR
‘‘hidden Markov’’ OR ‘‘machine learning’’ OR ‘‘deep learning’’ OR
‘‘Gaussian process’’)
AND (material* OR engineering OR ‘‘power system’’ OR medical OR clinical
OR tissue OR organ)
```

The exact syntax was adapted to the query language of each database (e.g., field tags, truncation symbols). In addition, we used a forward–backward snowballing procedure: reference lists of key methodological papers and existing reviews (e.g., [1,4–6]) were scanned for further relevant publications, and citation searches were performed for highly cited degradation-modeling articles.

2.2. Eligibility Criteria and Screening

The initial search retrieved 909 records (Scopus: 320, Web of Science: 260, IEEE Xplore: 150, PubMed: 134, and 45 from snowballing). After removing duplicates across databases, 612 unique records remained for title and abstract screening.

The inclusion criteria were as follows:

- Peer-reviewed journal articles, conference papers, books or book chapters in English.
- Explicit focus on modeling of a degradation process, understood as a time-evolving loss of function, performance, or structural integrity.
- Use of data-based, statistical, stochastic, or machine learning methods (possibly in combination with physical or knowledge-based components).
- Application within materials science, engineering systems, or medicine (as defined in Section 3).

We excluded the following:

- Purely physical or mechanistic models without any statistical or data-driven inference component.
- Works dealing exclusively with reliability or maintenance optimization without modeling an explicit degradation trajectory.
- Studies focused on domains outside the scope of this review (e.g., software reliability, database degradation, general quality-management systems, or purely cognitive/psychiatric models).
- Non-scholarly documents such as theses, technical reports, patents, and non-English publications.

After title and abstract screening, 220 records were retained for full-text assessment. Of these, 120 were excluded because they did not provide an explicit degradation model, did not use data-based methods, or fell outside the target domains. The final corpus consists of 100 publications: 15 textbooks or monographs, 10 review papers, and 75 journal or conference articles presenting methodological developments or substantive case studies. Figure 1 summarizes the selection process in the form of a PRISMA-style flow diagram.

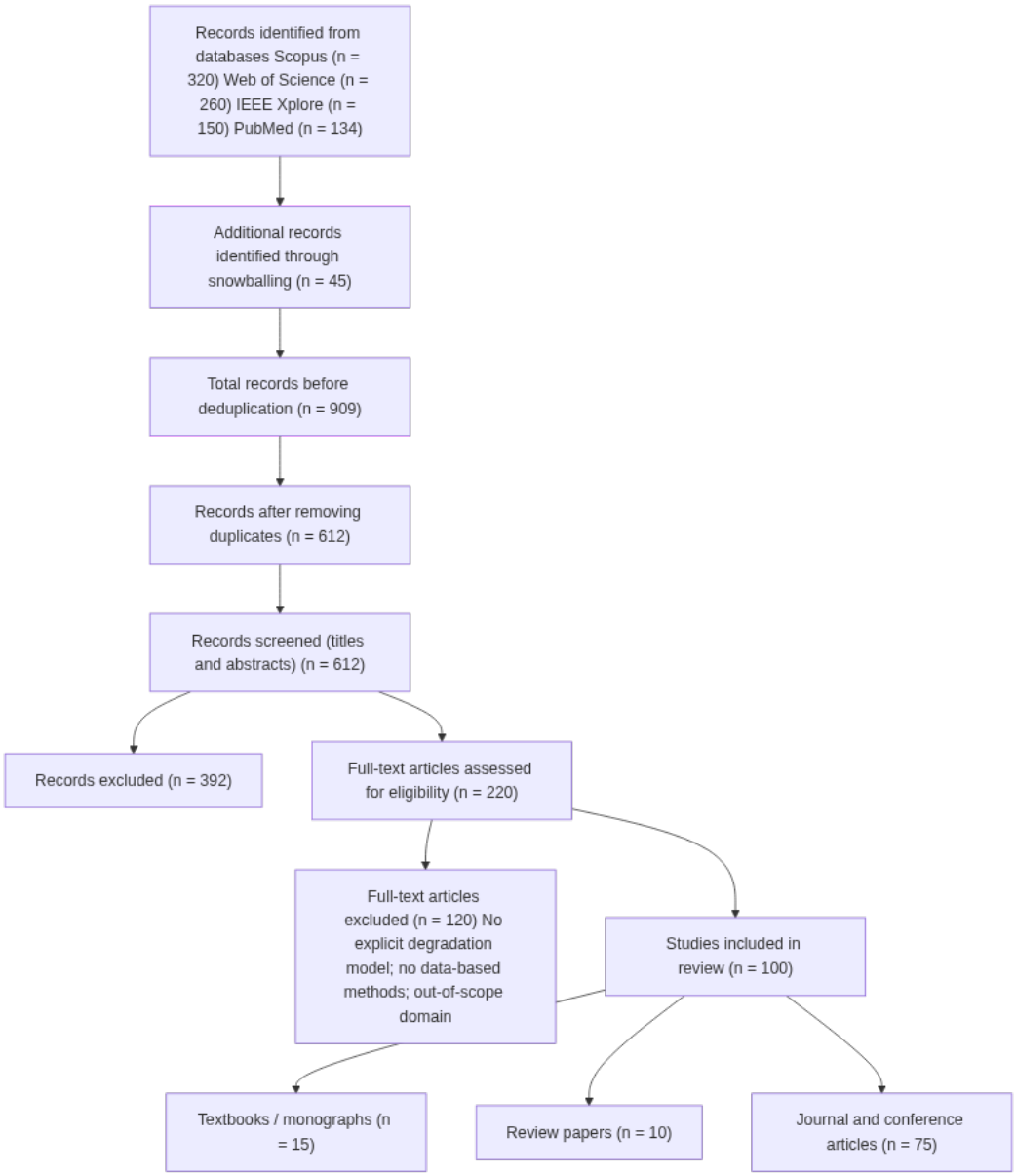


Figure 1. PRISMA-styleflow diagram of the literature selection process.

2.3. Data Extraction and Categorization

For each included publication, we extracted the following information:

- Application domain (materials science, engineering, medicine) and specific use case (e.g., corrosion, fatigue, power electronics, spinal disk degeneration).
- Type of degradation indicator $d(t)$ (direct physical measurement, derived health index, clinical score, etc.).
- Primary model family (statistical inference, stochastic degradation process, dynamic prediction model, machine learning, or hybrid/physics-informed).
- Data characteristics (sample size, sampling frequency, dimensionality, presence of censored or missing observations).
- Reported performance metrics (when available), such as prediction error, classification accuracy, or reliability-related measures.

These data were then used to construct the classification of methods presented in Section 5 and to populate the domain-specific analyses in later sections. Importantly, all quantitative summaries and figures (including publication counts over time) are based only

on the curated set of included studies and are not intended to represent global publication trends in the entire literature.

3. Preliminaries

3.1. Degradation Across Applications

A typical classification of degradation models discerns among three groups of models: physical models, data-driven models, and knowledge-based models [7]. Physical and knowledge-based models are typically application-specific because they describe particular phenomena occurring in a system. Conversely, data-based models focus on capturing the decline in performance or functionality regardless of the field of application. Despite the diverse applications of degradation, there are similarities in how degradation is described. Thus, similar data-based methods for degradation modeling can be used across disjoint applications.

In practice, many degradation models do not fall neatly into a single category. Mixed or hybrid approaches explicitly combine physical knowledge with statistical or machine learning components. A typical example is the use of stochastic degradation processes within a survival-analysis framework: a gamma process can be used to represent the underlying monotonic wear, while a Cox proportional hazards model links the failure intensity to operating conditions and covariates [3,8]. Similar hybrid strategies are explored in predictive maintenance, where physics-based models provide interpretable state variables and data-driven components improve prediction accuracy or extrapolation beyond the observed range [2]. In this review, we discuss such mixed approaches alongside purely data-driven models whenever the degradation mechanism is at least partially learned from data.

To illustrate the similarities across applications, this article provides a review of data-based method in materials science, engineering, and medicine. It is important to clarify how we distinguish between materials science and engineering applications in the sequel. In this review, materials science refers primarily to degradation phenomena at the level of material microstructure or specimen-scale properties (e.g., corrosion, fatigue crack growth, loss of stiffness or strength), typically studied under controlled laboratory conditions. Engineering applications, in contrast, concern the degradation of functional systems and components in their operational environment (e.g., bearings, power electronic converters, rotating machinery), where materials degradation is only one of several interacting mechanisms. Consequently, fatigue may appear in both categories: as a fundamental mechanism in materials studies, and as one of several degradation drivers in system-level engineering case studies.

In material science, degradation encompasses the deterioration of physical properties such as strength, ductility, and corrosion resistance of materials [9]. Understanding degradation processes is crucial for selecting materials that can maintain their performance over time, ensuring the reliability and safety of structures and components. This includes various degradation mechanisms, such as fatigue, creep, oxidation, and environmental degradation, which impact the structural integrity and reliability of materials and components.

In engineering, degradation refers to the decline in the performance or reliability of mechanical or electronic systems due to wear, fatigue, or aging [7]. This can include processes such as stress relaxation, thermal degradation, and chemical degradation, which affect the overall performance of materials and structures. Furthermore, the study of degradation in engineering involves the assessment of material degradation under different operational conditions, including temperature, humidity, and mechanical loading, to ensure the long-term functionality and safety of engineering systems.

In medicine, degradation focuses on the decline in the health or function of biological systems, such as tissues, organs, or physiological processes. This encompasses biodegradation and biodeterioration, where the vital activities of organisms lead to undesirable

changes in the properties of materials. In addition, the understanding of degradation in medicine extends to biomaterial degradation, including implant corrosion, drug delivery system degradation, and deterioration of biological tissues, with implications for the efficacy and safety of medical interventions. A notable example is the work of Yang et al. [10], where cognitive and emotional deterioration is modeled as a coupled degradation process in the context of Alzheimer's disease.

The notion of degradation is inherently domain-dependent and can, in principle, encompass a wide spectrum of phenomena, ranging from physical wear of components to loss of performance in information systems or deterioration of cognitive functions. In order to keep the scope of this review tractable, we restrict attention to (i) physical and chemical degradation of materials and engineered systems, and (ii) physiological degradation processes in medical applications that are directly linked to measurable biomarkers or clinical scores. We deliberately do not cover, for example, degradation of databases and information technology infrastructure, or chemical degradation in large-scale industrial processes, although similar data-driven methods could be applied in those contexts. Likewise, in medicine we focus on somatic and organ-level degradation and only touch briefly on mental health and cognitive decline. There exists a growing body of work where cognitive trajectories and emotional states are explicitly modeled as coupled stochastic degradation processes, for instance in Alzheimer's disease progression [10]. A comprehensive review of such cognitive and neuropsychiatric models would require a dedicated article and is therefore beyond the scope of the present paper.

Table 1 summarizes the definitions of degradation as outlined in ISO standards across the fields of medicine, engineering, and material science. Each application has specific standards that address the implications and management of degradation in their respective contexts.

Table 1. Definitions of degradation from ISO Standards.

Application	Definitions from ISO Standards
Medicine	ISO 10993-13:2010—the standard outlines methods for identifying and quantifying degradation products from polymeric medical devices, focusing on chemical alterations of the finished device [11]. ISO 10993-1:2018—the standard provides a framework for the biological evaluation of medical devices, including considerations for degradation and its impact on biocompatibility [12]. ISO 14971:2019—the standard addresses the application of risk management to medical devices, including risks associated with material degradation over time [13]. ISO 13485:2016—the standard specifies requirements for a quality management system where an organization needs to demonstrate its ability to provide medical devices that consistently meet customer and regulatory requirements, including those related to degradation [14].
Engineering	ISO 55000:2024—the standard provides an overview of asset management, including the management of degradation in engineering components to ensure reliability and performance [15]. ISO 9001:2015—the standard outlines quality management principles that include monitoring and managing degradation in engineering processes and products [16]. ISO 14001:2015—the standard focuses on environmental management systems, which include considerations for material degradation and its environmental impacts [17]. ISO 50001:2018—the standard provides a framework for managing energy performance, which includes addressing degradation in materials and systems to improve energy efficiency [18].
Material Science	ISO 15156-1:2020—the standard provides guidelines for materials used in oil and gas production, addressing degradation mechanisms such as corrosion and their impact on material selection [19]. ISO 6892-1:2019—the standard specifies the method for tensile testing of metallic materials, which includes considerations for degradation effects on mechanical properties [20]. ISO 11469:2016—the standard provides guidelines for the identification of plastics and their degradation characteristics, focusing on environmental impacts [21]. ISO 14040:2006—the standard outlines principles and a framework for life cycle assessment, which includes evaluating material degradation throughout the product life cycle [22].

Despite the specific manifestations of degradation in these fields, the common thread lies in understanding the degradation processes, identifying underlying degradation mechanisms, and predicting future behavior. This shared objective underscores the interdisciplinary nature of degradation analysis and emphasizes the necessity of a cohesive approach to analyzing and modeling degradation.

3.2. Data-Based Degradation Modeling

Mathematical models of degradation can be divided into analytical models, derived from first principles treating degradation as a physical phenomenon, and data-driven models, focused on describing degradation from experimental data [23] without explicit knowledge about the underlying physics [24]. Thus, developing models of degradation often relies on statistical inference to analyze degradation data, infer deterioration patterns, and provide reliability estimates and predictions based on historical data. Statistical inference methods consist of drawing conclusions about population parameters, making predictions, or testing hypotheses based on the estimated model. They often rely on model selection tools, such as the Akaike information criterion [25], or employ model-free techniques that dynamically adapt to the contextual affinities of a process and capture intrinsic characteristics of the observations.

Dynamic prediction methods model the dynamic evolution of degradation processes, considering time-dependent changes in degradation mechanisms, and predicting future degradation behavior. This approach enables the assessment of degradation over time and the prediction of future performance based on dynamic changes in degradation mechanisms.

Lastly, the recent rise in machine learning techniques allows capturing intricate degradation patterns, identifying underlying degradation mechanisms, and making precise predictions using extensive and diverse datasets [26]. These approaches facilitate the comprehensive analysis of degradation behavior and the development of predictive models for various degradation processes.

The three approaches are shown in Figure 2.

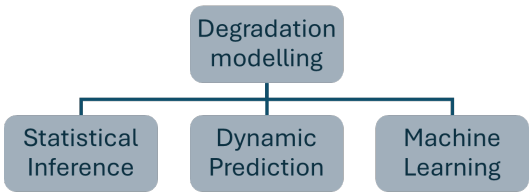


Figure 2. Main approaches to data-based modeling of degradation adopted in this work.

4. Background Analysis

4.1. Existing Reviews of Data-Based Degradation Modeling Methods

Table 2 provides an overview of methods for degradation modeling from textbooks, emphasizing the methods and proposed applications. The insights derived from these models contribute to the development of effective strategies for system maintenance, optimization, and reliability assessment. While the textbooks in Table 2 provide useful methodological introductions, they do not offer a systematic comparison of degradation-modeling approaches across application domains, nor do they discuss the suitability of specific methods under particular data conditions. Likewise, most existing literature reviews listed in Table 3 remain domain-specific or method-specific, and they typically concentrate on (i) physics-based and reliability-oriented models, (ii) machine learning approaches for prognostics, or (iii) accelerated aging and laboratory testing protocols. As

a result, the existing surveys do not articulate how statistical, stochastic, and machine learning models relate to one another, nor how they can be selected depending on data characteristics, observability of degradation, or the temporal structure of measurements. This methodological gap motivates the integrative perspective adopted in the present review. In particular, the books emphasize the fact that similar methods are used across applications. For instance, Bayesian modeling is discussed in [27–32] with application areas from economics and finance, through biostatistics and data analysis, to structural health monitoring.

Table 2. Degradation modeling in textbooks.

Ref.	Method	Application
[27]	regression analysis, Bayesian statistics	CNC machines
[28]	Markov Chain Monte Carlo, Bayesian statistics	machining tools
[33]	Markov Chain Monte Carlo, hidden Markov models	composite materials
[34]	supervised learning, deep learning	building materials
[35]	cluster analysis, regression analysis	industrial equipment
[36]	nonparametric Bayesian modeling of time series, Bayesian statistics	infrastructure systems such as bridges or highways
[29]	hidden Markov models, regression analysis	railway track geometry
[30]	Markov Chain Monte Carlo, Bayesian statistics	industrial machinery
[37]	Markov Chain Monte Carlo, supervised learning	brushless direct current motor
[38]	hidden Markov models, nonparametric Bayesian modeling of time series	machinery under different stressors
[39]	Markov Chain Monte Carlo, Bayesian statistics	metal components used in construction
[40]	hidden Markov models, nonparametric Bayesian modeling of time series	concrete structures
[31]	Bayesian statistics, regression analysis	structural components under stress
[32]	nonparametric Bayesian modeling of time series, Markov Chain Monte Carlo	modal properties of structural systems
[41]	Markov Chain Monte Carlo, Bayesian statistics	engineering assets and materials

It should be noted that the set of reviews included in Table 3 reflects the outcome of the literature selection protocol described in Section 2 and is therefore not intended to represent an exhaustive or unbiased sample of all available reviews. Instead, the table highlights representative examples illustrating the variety of methodological perspectives (statistical, mechanistic, stochastic, and machine learning-based) encountered in degradation-modeling research. This clarification is necessary to avoid overinterpretation of the relative prevalence of topics across the included reviews.

Table 3 summarizes existing literature reviews on degradation modeling. This compilation shows a broad spectrum of methodologies and classifications within the field of degradation modeling and provides an overview of the various approaches and classifications in the field of degradation modeling.

Across these reviews, two limitations become evident. First, most surveys focus on a single industrial sector—such as photovoltaic degradation, lithium-ion batteries, composite materials, or rotating machinery—thus limiting their transferability to other domains with different degradation mechanisms or data structures. Second, the methodological scope is typically narrow: reviews emphasizing machine learning seldom discuss stochastic degradation processes, while reliability-oriented reviews often overlook modern probabilistic programming and hybrid physics–data approaches. As a result, the literature lacks a unified, cross-domain synthesis that systematically compares statistical inference, stochastic processes, dynamic prediction, and machine learning models within a single framework. The present review aims to address this gap.

Table 3. Literature reviews on degradation modeling.

Author	Ref.	Year	Classification
Firdaus, N., Ab-Samat, H., Prasetyo, B.T.	[4]	2023	defect detection model, Markovian model, machine learning-based predictive model
Jaime-Barquero, E., Bekaert, E., Olarte, J., Zulueta, E., Lopez-Guede, J.M.	[5]	2023	accelerated life testing model, physical-based model, machine learning-based model
Alimi, O.A., Meyer, E.L., Olayiwola, O.I.	[42]	2022	manual visual assessment model, condition monitoring model, statistical data analysis model
Berghout, T., Benbouzid, M.	[43]	2022	supervised learning model, unsupervised learning model, deep learning model
Zhao, S., Tayyebi, M., Mahdireza Yarigarravesh, Hu, G.	[44]	2023	mechanistic model, stochastic model, statistical model
Xue, K., Yang, J., Yang, M., Wang, D.	[45]	2023	machine learning model, statistical model, data-driven model
Papargyri, L., Theristis, M., Kubicek, B., Papanastasiou, P., Georghiou, G.E.	[6]	2020	statistical model, machine learning model, simulation model
Mondal, M., Kumbhar, G.B.	[46]	2018	neural network-based model, Monte Carlo simulation model, time series forecasting model
Zhang, M., Yang, S.	[47]	2024	support vector clustering model, deep learning model, statistical model
Chakurkar, P.S., Vora, D., Patil, S., Mishra, S., Kotecha, K.	[48]	2023	anomaly detection model, condition monitoring model, time-series analysis model

4.2. Comparative Analysis Across Years

Figure 3 illustrates the temporal distribution of the articles included in our review after applying the selection criteria described in Section 2. This figure should therefore not be interpreted as representing global publication trends in the field, but rather the characteristics of the curated dataset used in this review. Within this dataset we observe an increasing number of publications across all three domains, with the steepest growth in engineering applications. This pattern is consistent with the rising adoption of data-driven approaches in condition monitoring and industrial prognostics.

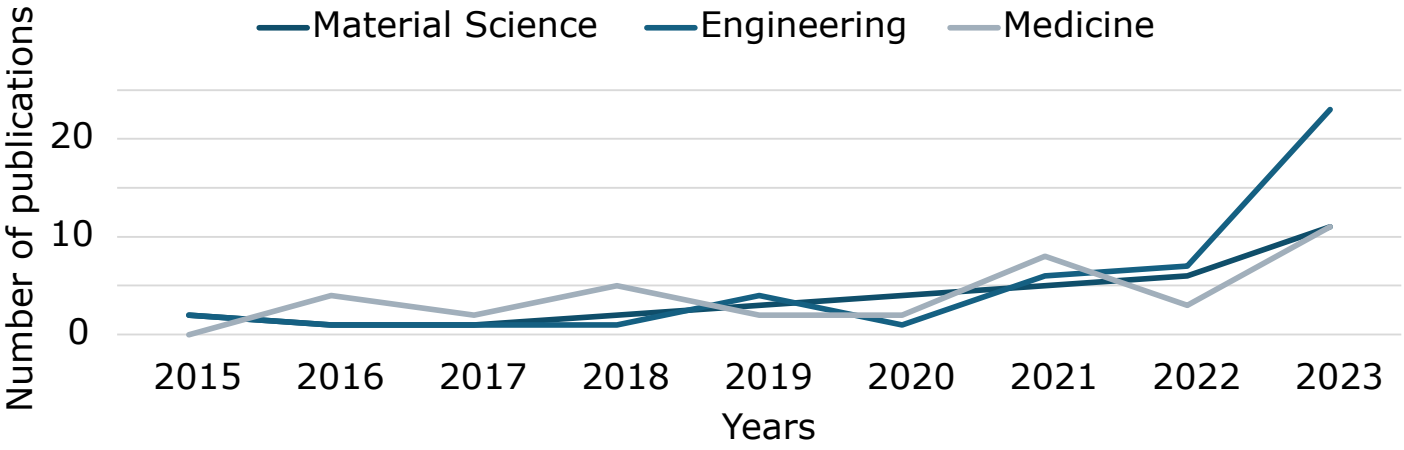


Figure 3. Number of articles over time in the three domains.

5. Classification with Respect to Methods

This section presents methods used for degradation modeling. The classification of methods adopted in the paper is shown in Figure 4. In the following, we denote by $d(t)$ a generic degradation indicator, which may represent a physical damage measure (e.g., crack length, loss of stiffness), a health index derived from multiple sensors, or a clinical score in medical applications. Depending on the method, degradation may appear either as

(i) an observed response variable y to be regressed on covariates, (ii) a latent state or factor driving the observed data, or (iii) a predicted quantity such as remaining useful life (RUL) or failure probability. Each subsection below explicitly indicates how the degradation quantity enters the corresponding model class.

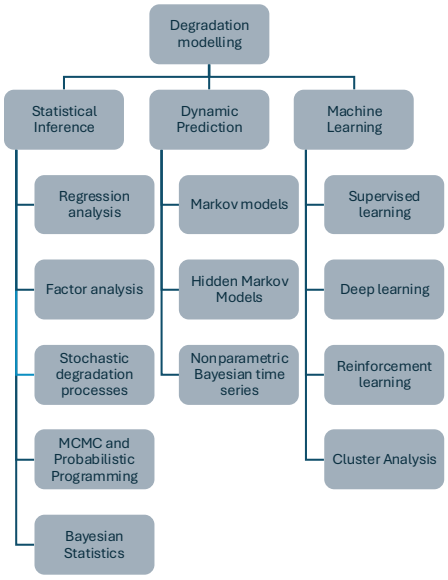


Figure 4. Classification tree of degradation modeling methods, adopted in this paper.

5.1. Statistical Inference

Statistical inference models are used to simulate and analyze the processes of tissue and organ degradation in human organisms [49]. These models allow for the analysis of the impact of factors such as aging, injuries, diseases, or the effect of drugs on the degradation of tissues and organs.

Statistical inference models are used to simulate and analyze technological processes in industry [50]. They are employed to forecast the behavior of technological systems, optimize production processes, and identify potential problems.

Statistical inference models are utilized to simulate and analyze various aspects related to the production, transmission, and use of energy [33]. They are used to forecast energy consumption, optimize energy processes, and identify potential areas for energy efficiency improvement. In degradation modeling, these statistical inference tools typically treat the degradation indicator $d(t)$ as either the response variable in regression-type formulations, or as part of a vector of condition indicators whose joint distribution is analyzed to infer underlying degradation mechanisms.

5.1.1. Regression Analysis

Regression analysis is a fundamental statistical tool for modeling the relationship between a dependent (response) variable and one or more independent (predictor) variables. In its simplest form, the linear regression model can be written as

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i, \quad i = 1, \ldots, n, \tag{1}$$

where y_i denotes the observed response, x_{ij} the value of the jth predictor for the ith observation, $\beta_0, \ldots, \beta_p$ are unknown parameters, and ε_i are random errors, typically assumed to satisfy $\mathbb{E}[\varepsilon_i] = 0$, $\mathrm{Var}(\varepsilon_i) = \sigma^2$, and $\varepsilon_i \perp\!\!\!\perp \varepsilon_j$ for $i \neq j$. In degradation modeling, y_i often represents a measurement of the degradation level at time t_i or after i load cycles (e.g., crack length, remaining capacity, stiffness loss), while the predictors x_{ij} encode stressors and operating conditions such as temperature, load, or chemical environment. The fitted

regression model then provides a parametric approximation of the degradation trajectory as a function of time and covariates.

Under these assumptions, the ordinary least squares (OLS) estimator for the parameter vector $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)^\top$ is given in matrix form by

$$\widehat{\boldsymbol{\beta}} = \left(\mathbf{X}^\top \mathbf{X}\right)^{-1} \mathbf{X}^\top \mathbf{y}, \tag{2}$$

where $\mathbf{X} \in \mathbb{R}^{n \times (p+1)}$ is the design matrix whose first column is all ones and $\mathbf{y} \in \mathbb{R}^n$ the vector of responses. The OLS solution minimizes the residual sum of squares,

$$\widehat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2.$$

Beyond ordinary least squares, parameters can be estimated by maximum likelihood, especially when the error distribution deviates from the Gaussian assumption or when heteroscedasticity is present. In a Bayesian formulation, priors $p(\boldsymbol{\beta}, \sigma^2)$ are specified and combined with the likelihood $p(\mathbf{y} \mid \boldsymbol{\beta}, \sigma^2, \mathbf{X})$ to obtain the posterior $p(\boldsymbol{\beta}, \sigma^2 \mid \mathbf{y}, \mathbf{X})$, from which posterior predictive distributions for future degradation levels can be derived. This is particularly useful when data are sparse or when uncertainty in extrapolating the degradation trajectory is critical for decision-making.

Regression analysis allows for hypothesis testing (e.g., $H_0 \colon \beta_j = 0$) and confidence interval estimation for coefficients, facilitating interpretability and inference. Extensions include weighted and generalized linear models to accommodate heteroscedasticity or non-Gaussian responses [51].

Key advantages: simplicity, parameter interpretability (effect of each covariate on degradation), availability of closed-form estimators in the linear–Gaussian case, and well-established diagnostic tools.
Limitations: reliance on linearity, independence, and homoscedasticity assumptions; sensitivity to extrapolation beyond the observed range; and potential misspecification when degradation dynamics are strongly nonlinear or regime-switching.
Usage: In the power industry, regression analysis precisely describes degradation processes by identifying the relationship between process variables and degradation [52]. This allows for the rapid prediction of degradation based on known process parameters, optimizing maintenance activities.

Regression analysis is also used in medicine to mathematically describe degradation processes in organisms, such as the breakdown of chemicals in tissues [53]. By employing regression analysis, researchers can determine the dynamics of degradation of medicinal substances in patients' bodies.

5.1.2. Stochastic Degradation Processes

Stochastic processes are a classical tool for modeling degradation as a random function of time. In this setting, the degradation indicator $d(t)$ is treated as a realization of a stochastic process $\{D(t), t \geq 0\}$, and failure is defined as the first time when $D(t)$ crosses a critical threshold. Such models are particularly suitable when monotonic or semi-monotonic deterioration is observed and when uncertainty in the rate of degradation must be explicitly quantified.

5.1.2.1. Gamma Process

The gamma process $\{D(t), t \geq 0\}$ is widely used for monotonic degradation. It has independent, non-negative increments

$$D(t+\Delta t) - D(t) \sim \text{Gamma}(\alpha\,\Delta t, \beta), \quad \text{Gamma}(\alpha\Delta t, \beta) = \frac{\beta^{\alpha\Delta t}}{\Gamma(\alpha\Delta t)} x^{\alpha\Delta t - 1} e^{-\beta x}$$

where $\alpha > 0$ and $\beta > 0$ denote the shape and scale parameters, respectively, and $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}\,\mathrm{d}t$. Its sample paths are almost surely non-decreasing, which matches many physical degradation mechanisms such as corrosion, crack growth, and insulation aging. In this context, $D(t)$ directly represents the cumulative degradation level, and the distribution of the time to reach a failure threshold can be derived analytically [3]. Gamma-process models have therefore become a standard reference in reliability-centered degradation modeling.

5.1.2.2. Wiener Process

For degradation signals that exhibit recovery effects or strong measurement noise, the Wiener process with drift,

$$D(t) = \mu t + \sigma W(t),$$

where $W(t)$ is standard Brownian motion, provides a flexible model. The drift μ represents the average degradation rate, and the diffusion coefficient σ captures environmental or operational variability. The observed degradation $d(t)$ is identified with $D(t)$, and the distribution of first-passage times of $D(t)$ through a threshold is used to model failure or end of life. Wiener-type models are commonly employed when degradation trajectories fluctuate around an overall downward (or upward) trend.

5.1.2.3. Inverse Gaussian and Related Processes

Inverse Gaussian processes extend Wiener-type models to strictly increasing sample paths, combining monotonicity with stochastic variability in the degradation rate. They have been applied to fatigue crack growth, creep, and other cumulative damage phenomena where the underlying physics dictates one-directional progression. More generally, compound Poisson or Lévy processes allow for jump components and are appropriate when degradation is driven by occasional shocks superimposed on gradual wear, which is frequently encountered in mechanical and electronic systems operating under random loading conditions [54].

Key advantages: natural representation of cumulative damage in continuous time; explicit modeling of uncertainty in degradation rate; closed-form results for failure probabilities and remaining useful life; parameters often have clear physical interpretation.
Limitations: require careful selection of process family (gamma, Wiener, IG); parameter estimation may be difficult with sparse or noisy observations; incorporating covariates or complex operating conditions may require hierarchical or hybrid extensions.
Usage: Gamma and Wiener processes are widely used for modeling monotonic or noisy degradation in materials (e.g., corrosion, fatigue), engineering systems (e.g., bearings, insulation, electronics), and selected biomedical indicators. They form the basis for reliability analyses and hybrid Bayesian–stochastic degradation models [3,54].

5.1.3. Factor Analysis

Factor analysis is a multivariate technique used to explain the covariance structure among a set of observed variables $\mathbf{x} = (x_1, \ldots, x_p)^\top$ in terms of a smaller number of

unobserved latent factors $\mathbf{f} = (f_1, \ldots, f_m)^\top$, with $m < p$. The classic common-factor model is

$$\mathbf{x} = \boldsymbol{\Lambda}\,\mathbf{f} + \boldsymbol{\varepsilon}, \tag{3}$$

where $\boldsymbol{\Lambda} \in \mathbb{R}^{p\times m}$ is the matrix of factor loadings, and $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \boldsymbol{\Psi})$ represents unique variances (specific plus error), with $\boldsymbol{\Psi}$ diagonal. The covariance structure implied by the model is

$$\mathrm{Cov}(\mathbf{x}) = \boldsymbol{\Sigma} = \boldsymbol{\Lambda}\boldsymbol{\Lambda}^\top + \boldsymbol{\Psi}. \tag{4}$$

In degradation applications, the observed variables $\mathbf{x}$ may correspond to multiple correlated condition indicators (e.g., vibration amplitudes, temperatures, laboratory measurements), while the latent factors $\mathbf{f}$ capture underlying degradation modes or health indices that drive the joint variation in these indicators. Tracking the evolution of factor scores over time provides an indirect representation of the degradation trajectory $d(t)$.

Estimating $\boldsymbol{\Lambda}$ and $\boldsymbol{\Psi}$ can be achieved via the following:

- *Principal axis factoring*, which iteratively estimates communalities $h_j^2 = \sum_{k=1}^{m} \lambda_{jk}^2$ and solves eigenvalue problems on the reduced correlation matrix.
- *Maximum likelihood (ML)*, which finds estimates $\widehat{\boldsymbol{\Lambda}}, \widehat{\boldsymbol{\Psi}}$ by maximizing the Gaussian log-likelihood under $H_0\colon \boldsymbol{\Sigma}(\boldsymbol{\Lambda}, \boldsymbol{\Psi}) = \mathbf{S}$, where $\mathbf{S}$ is the sample covariance.

Interpretation hinges on *rotated* solutions (e.g., varimax) to achieve "simple structure" and on assessing model fit via likelihood-ratio tests or information criteria.

Key advantages: dimensionality reduction, uncovering latent constructs, and parsimonious modeling.
Limitations: identifiability issues, sensitivity to distributional assumptions, and subjective choice of number of factors [55].
Usage: In engineering processes, factor analysis can be used to identify groups of process variables [56]. They have a significant impact on degradation, leading to a better understanding of the degradation process.

Similarly, in the energy sector, factor analysis is employed to identify significant factors influencing degradation [57]. It helps optimize maintenance activities and improve understanding of degradation processes.

5.1.4. Bayesian Statistics

Bayesian statistics provides a principled framework for learning about unknown parameters θ by combining prior beliefs $p(\theta)$ with evidence from data $\mathcal{D}$ through the likelihood $p(\mathcal{D} \mid \theta)$. The cornerstone is Bayes' theorem

$$p(\theta \mid \mathcal{D}) \;=\; \frac{p(\mathcal{D} \mid \theta)\, p(\theta)}{p(\mathcal{D})} \quad \text{where} \quad p(\mathcal{D}) = \int p(\mathcal{D} \mid \theta)\, p(\theta)\, d\theta. \tag{5}$$

In degradation modeling, the parameter vector θ typically includes degradation rates, threshold levels, or coefficients linking covariates to the degradation indicator $d(t)$. The posterior predictive distribution $p(\tilde{y} \mid \mathcal{D})$ then provides probabilistic forecasts of future degradation levels or remaining useful life, with full propagation of parameter and model uncertainty.

The posterior $p(\theta \mid \mathcal{D})$ quantifies updated uncertainty about θ. From it one can derive

- *Point estimates*, e.g., the posterior mean $\mathbb{E}[\theta \mid \mathcal{D}]$.
- *Credible intervals*, defined by $\int_a^b p(\theta \mid \mathcal{D})\, d\theta = 1 - \alpha$..

- *Posterior predictive distribution* for a new observation $\tilde{y}$,

$$p(\tilde{y} \mid \mathcal{D}) \;=\; \int p(\tilde{y} \mid \theta)\, p(\theta \mid \mathcal{D})\, d\theta.$$

Bayesian methods naturally handle hierarchical models by placing priors at multiple levels (e.g., $\theta \sim p(\theta \mid \phi)$, $\phi \sim p(\phi)$), and they explicitly propagate all sources of uncertainty. Computational tools such as Markov Chain Monte Carlo (MCMC) or variational inference allow approximation of posteriors when closed-form solutions are unavailable [58].

Key advantages: coherent uncertainty quantification, flexible modeling of complex structures, and direct probability statements about parameters.
Limitations: computational intensity, sensitivity to prior choices, and challenges in high-dimensional settings.
Usage: In the context of dynamic degradation processes of biologically active substances, Bayesian statistics is used to update knowledge about degradation parameters based on clinical trial results [1,59]. This allows patient-specific variability in physiological parameters to be incorporated into the model and improves prediction of future degradation states, which is crucial for dosing and safety assessment.

Bayesian statistics updates knowledge about the degradation of biologically active substances based on clinical trial results [1]. It enhances the modeling of dynamic degradation processes.

5.1.5. Markov Chain Monte Carlo and Probabilistic Programming

Markov Chain Monte Carlo (MCMC) comprises a class of algorithms for generating samples from a target probability distribution $\pi(\theta)$ when direct sampling is infeasible. A key property is that the Markov transition kernel $K(\theta' \mid \theta)$ satisfies the detailed balance condition

$$\pi(\theta)\, K(\theta' \mid \theta) \;=\; \pi(\theta')\, K(\theta \mid \theta') \quad \Longrightarrow \quad \int \pi(\theta)\, K(\theta' \mid \theta)\, d\theta = \pi(\theta').$$

In the Metropolis–Hastings algorithm, one proposes $\theta^* \sim q(\theta^* \mid \theta^{(t)})$ and accepts it with probability

$$\alpha = \min\Big(1,\; \frac{\pi(\theta^*)\, q(\theta^{(t)} \mid \theta^*)}{\pi(\theta^{(t)})\, q(\theta^* \mid \theta^{(t)})}\Big),$$

otherwise setting $\theta^{(t+1)} = \theta^{(t)}$. A special case is the Gibbs sampler, which updates each component θ_i by drawing from its full conditional $\pi(\theta_i \mid \theta_{-i})$.

Hamiltonian Monte Carlo (HMC) augments the parameter space with auxiliary momentum variables $p \in \mathbb{R}^d$ and uses simulated Hamiltonian dynamics to propose distant states with high acceptance probability [60]. One defines the Hamiltonian

$$H(\theta, p) = U(\theta) + K(p) = -\log \pi(\theta) + \tfrac{1}{2}\, p^\top M^{-1} p,$$

where M is a mass matrix. Trajectories are simulated via the *leapfrog* integrator

$$\begin{aligned} p\Big(t + \tfrac{\epsilon}{2}\Big) &= p(t) - \tfrac{\epsilon}{2}\, \nabla_\theta U\big(\theta(t)\big), \\ \theta(t+\epsilon) &= \theta(t) + \epsilon\, M^{-1} p\Big(t + \tfrac{\epsilon}{2}\Big), \\ p(t+\epsilon) &= p\Big(t + \tfrac{\epsilon}{2}\Big) - \tfrac{\epsilon}{2}\, \nabla_\theta U\big(\theta(t+\epsilon)\big). \end{aligned}$$

After L steps, the proposal (θ^*, p^*) is accepted with probability $\min\{1, \exp(-\Delta H)\}$.

Probabilistic programming languages (PPLs) such as Stan or BUGS allow users to specify complex hierarchical or latent-variable models in high-level syntax; the PPL runtime then automatically constructs and runs efficient MCMC chains (including HMC) to approximate posterior distributions of all parameters.

When applied to degradation models, the parameter vector θ often contains rates of deterioration, noise levels, or latent state parameters governing the evolution of $D(t)$; MCMC samples from $p(\theta \mid \mathcal{D})$ can then be used to compute predictive distributions for future degradation trajectories and remaining useful life.

Key advantages: flexibility to model arbitrary posteriors, efficient exploration in high dimensions (HMC), and automatic uncertainty quantification.
Limitations: convergence diagnostics required, choice of integrator step-size and path length in HMC, and potentially high computational cost.
Usage: In the context of variable energy conditions, MCMC accounts for uncertainties in modeling the degradation of biologically active substances [29]. It enables effective prediction of future degradation states based on previous observations.

MCMC efficiently samples complex probability distributions, which is crucial in modeling step degradation [61]. It facilitates effective prediction of future degradation states based on previous observations.

5.2. Dynamic Prediction

In material science, Markov models enable engineers to analyze temporal dependencies and transitions between different states in a process. This allows for the prediction of future states, identification of bottlenecks, and optimization of process parameters for improved efficiency and productivity. Hidden Markov Models can uncover hidden patterns and detect anomalies in processes, aiding in process control and optimization.

In power engineering, dynamic prediction methods play a vital role in forecasting electricity demand, optimizing power generation, and managing energy resources. Markov models can accurately forecast short-term and long-term load demand by modeling the temporal dependencies and transitions in power consumption patterns. Hidden Markov Models help identify hidden states and patterns in power generation and consumption, facilitating efficient energy management and resource allocation. Nonparametric Bayesian time series modeling considers factors such as weather conditions and time of day to predict electricity demand accurately.

In medicine, dynamic prediction methods have significant applications, ranging from disease prognosis to treatment optimization. Markov models can model disease progression and predict patient outcomes based on current health states. Hidden Markov Models are valuable for modeling latent variables and hidden dynamics in medical data, enabling early detection of diseases and personalized treatment strategies. Nonparametric Bayesian time series modeling captures the complex temporal dynamics of patient data, facilitating accurate predictions of disease progression, treatment response, and prognosis.

In all these dynamic settings, the latent or observed state variable is naturally interpreted as a discrete or continuous representation of the degradation level, whose evolution is governed by the chosen stochastic or Bayesian time series model.

5.2.1. Markov Models

Markov models are useful for modeling abrupt degradation by considering the nonlinear relationships between process variables and degradation [31]. They enable the forecasting of future degradation states based on previous observations and can incorporate dynamic changes in the degradation process. For degradation modeling, the state X_t typically encodes a discrete degradation level or health condition (e.g., “healthy”, “minor

damage", "severe damage", "failed"), and transitions between states represent the progression of degradation over time. Absorbing states correspond to failure, and mean times to absorption provide estimates of remaining useful life.

A (discrete-time) Markov model represents the evolution of a system through a finite (or countable) set of states $\mathcal{S} = \{1, \ldots, K\}$, where the probability of a transition depends only on the current state. If $X_t \in \mathcal{S}$ denotes the state at time t, the *Markov property* is

$$\Pr\big(X_{t+1} = j \mid X_t = i,\, X_{t-1}, \ldots, X_0\big) \;=\; \Pr\big(X_{t+1} = j \mid X_t = i\big) =: p_{ij}, \quad i, j \in \mathcal{S}. \tag{6}$$

The one-step transition probabilities p_{ij} form the transition matrix $P = (p_{ij})$, satisfying $\sum_j p_{ij} = 1$ for each i. The n-step transition probabilities are given by the Chapman–Kolmogorov equations,

$$p_{ij}^{(n)} \;=\; \Pr(X_{t+n} = j \mid X_t = i) \;=\; \big(P^n\big)_{ij}, \quad P^n = \underbrace{P \cdots P}_{n \text{ times}}. \tag{7}$$

If $\boldsymbol{\pi}^{(t)}$ is the row vector of state-probabilities at time t, then

$$\boldsymbol{\pi}^{(t+n)} \;=\; \boldsymbol{\pi}^{(t)}\, P^n.$$

For ergodic chains (irreducible and aperiodic), there exists a unique stationary distribution $\boldsymbol{\pi}^*$ satisfying $\boldsymbol{\pi}^* = \boldsymbol{\pi}^*\, P$; this can be used for long-term degradation prediction. In absorbing chains, mean time to absorption and absorption probabilities provide estimates of remaining useful life.

Key advantages: simple formulation, closed-form n-step predictions, and well-studied theory of long-run behavior.
Limitations: state-space discretization may be coarse, and the loss of history beyond the current state may oversimplify gradual degradation [62].
Usage: In the context of discontinuous energy processes, Markov models are important for modeling abrupt degradation and considering dynamic changes in the degradation process, especially under changing energy conditions [63]. They also allow for the inclusion of nonlinear relationships between process variables and degradation.

In medicine, Markov models can be used to model changes in patients' health status, predict the course of diseases, and assess the risk of drug degradation [64]. They consider the dynamic changes in patients' bodies and their impact on drug degradation.

5.2.2. Hidden Markov Models

Hidden Markov Models are used to model abrupt degradation by considering the nonlinear relationships between process variables and degradation [65]. They enable the forecasting of future degradation states based on previous observations.

A Hidden Markov Model (HMM) describes a system where an unobserved (hidden) state sequence $\{X_t\}$ evolves as a Markov chain over states $\mathcal{S} = \{1, \ldots, K\}$, and at each time t emits an observation Y_t according to a state-dependent distribution. An HMM is specified by

- Initial distribution $\pi_i = \Pr(X_1 = i)$.
- Transition matrix $A = (a_{ij})$ with $a_{ij} = \Pr(X_{t+1} = j \mid X_t = i)$.
- Emission probabilities $b_i(y) = \Pr(Y_t = y \mid X_t = i)$ (or density $b_i(y)$ for continuous Y_t).

The joint probability of a state sequence $\mathbf{x} = (x_1, \ldots, x_T)$ and observations $\mathbf{y} = (y_1, \ldots, y_T)$ is

$$\Pr(\mathbf{x}, \mathbf{y}) = \pi_{x_1} \, b_{x_1}(y_1) \prod_{t=2}^{T} a_{x_{t-1}, x_t} \, b_{x_t}(y_t).$$

Key computations include the following:

1. *Filtering/likelihood*: via the forward recursion $\alpha_t(j) = \left[\sum_i \alpha_{t-1}(i) a_{ij}\right] b_j(y_t)$.
2. *Decoding*: the Viterbi algorithm finds $\arg\max_{\mathbf{x}} \Pr(\mathbf{x} \mid \mathbf{y})$.
3. *Learning*: Baum–Welch (EM) updates π, A, b by maximizing the data likelihood.

HMMs capture abrupt or regime-switching degradation by modeling latent condition changes and corresponding observation patterns.

In degradation applications, the hidden state X_t is often interpreted as an unobserved degradation regime (e.g., normal operation, early damage, advanced damage), while the observations Y_t are condition indicators such as vibrations, acoustic emissions, or clinical measurements. The inferred state sequence thus provides an indirect estimate of the underlying degradation trajectory.

Key advantages: ability to model unobserved regimes, efficient inference via dynamic programming.
Limitations: choice of state-space size, assumption of conditional independence of observations [66].
Usage: In the context of discontinuous energy processes, Hidden Markov Models are important for modeling abrupt degradation [67]. It helps consider dynamic changes in the degradation process, especially under changing energy conditions.

Hidden Markov Models can be effectively used in medicine to model changes in patients' health, taking into account dynamic fluctuations in patients' bodies and their impact on drug degradation [68]. These advanced models allow for predicting the effectiveness of therapies.

5.2.3. Nonparametric Bayesian Time Series Modeling

Nonparametric Bayesian methods allow the model complexity to grow with data by placing priors on infinite-dimensional objects. Three widely used approaches in time series are

5.2.3.1. Dirichlet Process Mixtures

Partition the series $\{y_t\}_{t=1}^{T}$ into an unknown number of regimes, indexed by latent parameters $\{\theta_k\}$. A Dirichlet Process (DP) prior on the mixing measure G induces a countably infinite mixture

$$\begin{aligned} G &\sim \mathrm{DP}(\alpha, G_0), \\ \theta_t \mid G &\sim G, \quad y_t \mid \theta_t \sim F(y_t \mid \theta_t). \end{aligned} \tag{8}$$

Using the stick-breaking construction,

$$G = \sum_{k=1}^{\infty} \pi_k \, \delta_{\theta_k}, \quad \pi_k = \beta_k \prod_{l<k} (1 - \beta_l), \quad \beta_k \sim \mathrm{Beta}(1, \alpha),$$

one obtains an adaptive mixture that clusters observations into regimes with similar dynamics. Posterior inference (e.g., via Gibbs sampling) estimates both the number of regimes and their parameters.

5.2.3.2. Gaussian Process Regression

Model the latent signal $f\colon t \mapsto \mathbb{R}$ as a Gaussian Process (GP)

$$\begin{aligned} f(t) &\sim \mathcal{GP}\big(m(t),\, k(t,t')\big), \\ y_t &= f(t) + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2). \end{aligned} \tag{9}$$

The kernel $k(t,t')$ encodes smoothness or periodicity, and the GP posterior provides closed-form predictive distributions

$$f_* \mid \mathbf{y} \;\sim\; N\big(K_* K^{-1}\mathbf{y},\; K_{**} - K_* K^{-1} K_*^{\top}\big),$$

where $K = [k(t_i,t_j)]$, $K_* = [k(t_*,t_j)]$, etc.

5.2.3.3. Prophet

Prophet is an additive forecasting model designed for business time series, decomposing y_t into trend $g(t)$, seasonality $s(t)$, holiday effects $h(t)$, and noise

$$y_t = g(t) + s(t) + h(t) + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2). \tag{10}$$

The trend $g(t)$ is modeled as a piecewise linear (or logistic) function with automatic changepoint detection

$$g(t) = \big(k + a(t)^{\top}\boldsymbol{\delta}\big)\, t + \big(m + a(t)^{\top}\boldsymbol{\gamma}\big),$$

where $a(t)$ indicates segments, k, m are base rate and offset, and $\boldsymbol{\delta}, \boldsymbol{\gamma}$ are adjustments at changepoints. Seasonality $s(t)$ uses Fourier series

$$s(t) = \sum_{n=1}^{N} \Big[\alpha_n \cos\big(2\pi n t/P\big) + \beta_n \sin\big(2\pi n t/P\big)\Big],$$

and $h(t)$ includes user-specified events. Prophet is fitted via MAP estimation with weakly informative priors, yielding fast, interpretable forecasts [69].

When used for degradation modeling, the time series $\{y_t\}$ or latent function $f(t)$ is identified with the degradation indicator $d(t)$. Dirichlet process mixtures allow automatic discovery of degradation regimes and changepoints, while Gaussian processes provide flexible nonparametric priors over degradation trajectories, including uncertainty bands for future evolution.

Key advantages: automatic changepoint detection, interpretable components, and scalability to large datasets.
Limitations: assumes additive structure, may struggle with highly irregular dynamics, and limited probabilistic uncertainty beyond the MAP fit.

5.3. Machine Learning

Machine learning methods enable automatic detection of patterns in process data and construction of predictive models from historical observations [70]. In degradation modeling, they are typically used to learn mappings from multivariate condition indicators and operating variables to targets such as a continuous degradation measure $d(t)$, a discrete health state, or a remaining useful life (RUL) estimate. This facilitates adaptive degradation modeling in engineering processes using a wide range of predictive algorithms.

In the power industry, machine learning methods enable adaptive modeling of degradation [71]. It may consider changing process conditions and optimizing maintenance operations.

In medicine, machine learning methods can be used to predictively model drug degradation based on clinical and laboratory data [35]. They enable adaptive modeling of drug degradation, automatic detection of drug degradation patterns, and optimization of therapeutic doses.

5.3.1. Supervised Learning

Supervised learning aims to learn a mapping $f : \mathcal{X} \to \mathcal{Y}$ from input–output pairs $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$, where each y_i is a known label or response. The model $f(x;\theta)$, parameterized by θ, is trained by minimizing an empirical risk functional

$$\widehat{\theta} \;=\; \arg\min_{\theta} \; \frac{1}{n} \sum_{i=1}^{n} \ell\big(y_i,\, f(x_i;\theta)\big) \tag{11}$$

where $\ell(\cdot,\cdot)$ is a loss function (e.g., squared error $\ell(y,\hat{y}) = (y-\hat{y})^2$ for regression or cross-entropy $\ell(y,\hat{y}) = -\sum_k y_k \log \hat{y}_k$ for classification).

The following two primary supervised tasks are described:

- *Regression*: $\mathcal{Y} = \mathbb{R}$, predicting continuous degradation measures (e.g., wear rate).
- *Classification*: $\mathcal{Y} = \{1, \ldots, C\}$, labeling discrete states (e.g., "healthy" vs. "faulty").

In degradation applications, regression tasks often predict the current degradation level or RUL, while classification tasks assign each observation to a health class or damage severity level, using expert labels or failure histories as supervision. Common algorithmic frameworks include linear models, support vector machines, decision trees and ensembles, and feed-forward neural networks. Model selection and regularization (e.g., ridge, lasso) control complexity and mitigate overfitting.

Key advantages: direct use of labeled data, flexibility across tasks, and mature theory for generalization (e.g., VC-dimension, Rademacher complexity).
Limitations: requires substantial labeled data, is sensitive to label noise, and has the potential for overfitting without proper regularization [72].
Usage: In the power industry, supervised learning methods enable adaptive modeling of degradation [73]. It considers changing process conditions, and optimizing maintenance operations.

In medicine, supervised learning allows for adaptive modeling of drug degradation based on individual patient characteristics [74]. It may optimize therapeutic doses and assess degradation risk.

5.3.2. Deep Learning

Deep learning refers to a class of machine learning methods based on artificial neural networks with multiple hidden layers, which can automatically learn hierarchical feature representations from raw data. A feed-forward deep neural network with L layers can be defined recursively as

$$\begin{aligned} \mathbf{a}^{(0)} &= \mathbf{x}, \\ \mathbf{z}^{(l)} &= W^{(l)}\mathbf{a}^{(l-1)} + \mathbf{b}^{(l)}, \quad l = 1, \ldots, L, \\ \mathbf{a}^{(l)} &= \phi\big(\mathbf{z}^{(l)}\big), \end{aligned} \tag{12}$$

where $\mathbf{x} \in \mathbb{R}^d$ is the input, $W^{(l)}$ and $\mathbf{b}^{(l)}$ are the weights and biases of layer l, and $\phi(\cdot)$ is a nonlinear activation (e.g., ReLU, sigmoid). The network's output $\hat{\mathbf{y}} = \mathbf{a}^{(L)}$ is compared to

the true label $\mathbf{y}$ via a loss function $\ell(\mathbf{y}, \hat{\mathbf{y}})$, and parameters are optimized by backpropagation and stochastic gradient descent

$$\theta \leftarrow \theta - \eta \, \nabla_\theta \frac{1}{n} \sum_{i=1}^{n} \ell(\mathbf{y}_i, \hat{\mathbf{y}}_i).$$

Extensions include convolutional neural networks (CNNs) for spatial degradation patterns and recurrent architectures (RNNs/LSTMs) for temporal degradation sequences. Deep models excel at capturing complex, nonlinear relationships in high-dimensional sensor or image data, which is critical for accurate degradation prediction and anomaly detection. Shallow neural networks, comprising a single hidden layer with a limited number of units, can be viewed as a special case of this framework. They remain attractive for moderate-sized degradation datasets due to easier training and improved interpretability of learned features, and they are still widely used in practice alongside deeper architectures [75].

Key advantages: automatic feature learning, state-of-the-art predictive performance in large datasets, and flexible architectures for diverse data modalities.
Limitations: large data and computational requirements, potential overfitting, and reduced interpretability of learned features [76].
Usage: In the field of power engineering, deep learning facilitates advanced pattern recognition in modeling degradation and predicting energy processes [34]. It enables adaptive modeling of degradation risk in energy processes.

In medicine, deep learning enables advanced recognition of drug degradation patterns [57]. It contributes to adaptive modeling, prediction of therapy efficacy, and assessment of degradation risk. In both cases, the network output corresponds either to a continuous degradation index, a predicted RUL, or a probability over discrete degradation states, which can be directly integrated into maintenance and decision-support systems.

5.3.3. Reinforcement Learning

Reinforcement learning (RL) addresses sequential decision–making under uncertainty by learning a policy $\pi(a \mid s)$ that maximizes expected cumulative reward in a Markov decision process (MDP). An MDP is defined by the tuple $(\mathcal{S}, \mathcal{A}, P, r, \gamma)$ where the following apply:

- $\mathcal{S}$ is the state space, $\mathcal{A}$ the action space.
- $P(s' \mid s, a)$ is the transition probability.
- $r(s, a)$ is the immediate reward.
- $\gamma \in [0, 1)$ is the discount factor.

The goal is to maximize the *return* $G_t = \sum_{k=0}^{\infty} \gamma^k \, r(s_{t+k}, a_{t+k})$. The state-value and action-value functions under policy π satisfy the Bellman equations

$$V^\pi(s) = \mathbb{E}_\pi\big[G_t \mid s_t = s\big] = \sum_a \pi(a \mid s) \Big[r(s, a) + \gamma \sum_{s'} P(s' \mid s, a) V^\pi(s') \Big], \tag{13}$$

$$Q^\pi(s, a) = r(s, a) + \gamma \sum_{s'} P(s' \mid s, a) \sum_{a'} \pi(a' \mid s') \, Q^\pi(s', a'). \tag{14}$$

For degradation-aware control and maintenance, the state s typically includes a representation of the current degradation level or health index, and the reward function $r(s, a)$ balances short-term performance against long-term costs associated with accelerated degradation or failure.

Model-free methods include the following:

- *Q-learning* (off-policy) $Q_{t+1}(s_t, a_t) \leftarrow Q_t(s_t, a_t) + \alpha\left[r_t + \gamma \max_{a'} Q_t(s_{t+1}, a') - Q_t(s_t, a_t)\right]$.
- *Policy gradient* (on-policy): optimize $J(\theta) = \mathbb{E}_{\pi_\theta}[G_t]$ via $\nabla_\theta J = \mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log \pi_\theta(a \mid s)\, Q^{\pi_\theta}(s, a)\right]$.

Deep RL integrates neural networks to approximate Q or π (e.g., DQN, actor–critic). In degradation modeling, RL can learn maintenance or control policies that dynamically trade off immediate performance versus long-term system health.

Key advantages: learns adaptive policies without explicit system models; handles stochastic, nonstationary environments.
Limitations: sample-inefficient; high variance in gradient estimates; requires careful tuning of hyperparameters [77].
Usage: In the field of power engineering, reinforcement learning is used for adaptive degradation modeling [78]. It considers dynamic changes in the degradation process, especially under changing energy conditions.

In medicine, reinforcement learning is employed for adaptive modeling of drug degradation [79]. It enables the prediction of therapy effectiveness and the assessment of degradation risk.

5.3.4. Cluster Analysis

Cluster analysis is an unsupervised learning technique that seeks to partition a set of n observations $\{x_i \in \mathbb{R}^d\}_{i=1}^n$ into K groups (clusters) $\{C_k\}_{k=1}^K$ such that observations within the same cluster are more similar to each other than to those in other clusters. In degradation modeling, clusters may correspond to distinct degradation patterns, operating regimes, or groups of components with similar health trajectories. Such unsupervised grouping can reveal heterogeneous degradation mechanisms and support the design of condition-based maintenance strategies tailored to each cluster.

Two common approaches are:

5.3.4.1. K-Means Clustering

Assign each x_i to the cluster with the nearest centroid μ_k, by minimizing the within-cluster sum of squares (WCSS):=

$$\{\widehat{C}_k, \widehat{\mu}_k\}_{k=1}^K = \arg\min_{\{C_k, \mu_k\}} \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2. \tag{15}$$

The standard algorithm alternates between (i) *assignment*: $C_k \leftarrow \{\, i : \|x_i - \mu_k\| \leq \|x_i - \mu_j\|\ \forall j\}$, and (ii) *update*: $\mu_k \leftarrow \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i$, until convergence.

5.3.4.2. Hierarchical Clustering

Builds a tree (dendrogram) of clusters either by agglomeration (bottom-up) or division (top-down). In agglomerative clustering, start with each point as its own cluster and at each step merge the pair (C_a, C_b) minimizing a linkage criterion, e.g.,

$$d_{\text{single}}(C_a, C_b) = \min_{x_i \in C_a, x_j \in C_b} \|x_i - x_j\|, \quad d_{\text{complete}}(C_a, C_b) = \max_{x_i \in C_a, x_j \in C_b} \|x_i - x_j\|.$$

By cutting the dendrogram at a chosen height, one obtains a desired number of clusters.

Key advantages: no need for labeled data; can discover unknown structure; interpretable via centroids or dendrograms.
Limitations: choice of K or cut-height is subjective; sensitive to scaling and noise; may find only spherical clusters (for K-means) or be computationally expensive ($\mathcal{O}(n^3)$ for naive hierarchical implementations) [80].
Usage: In the power industry, cluster analysis helps reduce data complexity by identifying important factors influencing degradation processes [81]. It enables mathematical modeling of various degradation cases, contributing to a better understanding of degradation processes.

Cluster analysis is also used in medicine to group degradation events based on similarities in their characteristics [53]. It helps identify groups of process variables that significantly impact the degradation of chemicals in organisms.

6. Classification of Methods and Their Usage Across Applications

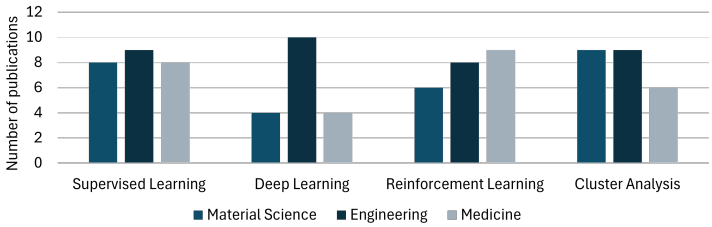
This section presents degradation modeling across domains such as material science, engineering, and medicine. In Table 4, we provide a comprehensive overview of the number of articles published in each domain, categorized by the methods employed. This analysis reveals the distribution of research efforts across the three domains, highlighting how each method contributes to the understanding and application of degradation modeling. It is important to emphasize that the numbers in Table 4 are based solely on the curated corpus of studies selected according to the review methodology described in Section 2. They should therefore not be interpreted as global publication statistics for the entire literature but rather as a summary of how methods are distributed within the specific set of 100 included publications.

Table 4. Overview of the number of articles published in each domain, categorized by the methods employed

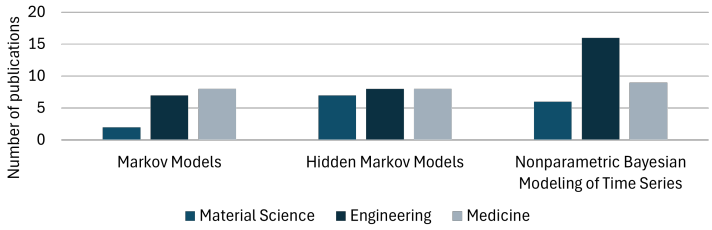
Method	Material Science	Engineering	Medicine
Statistical inference	25	41	34
Dynamic prediction	21	36	28
Machine learning	23	31	27

6.1. Individual Methods

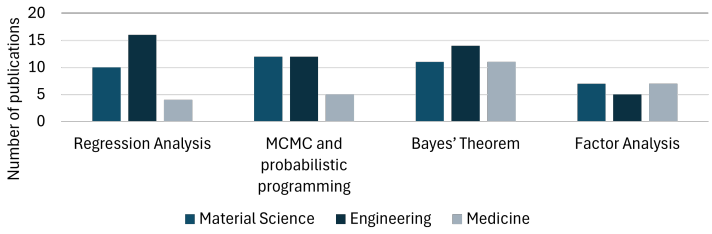
Figure 5 summarizes how frequently the three main method families—statistical inference, dynamic prediction, and machine learning—appear in the reviewed corpus across the three domains. These proportions reflect the characteristics of the included studies rather than global publication trends (see Section 2). For each method family, the model input typically consists of measurements or derived indicators capturing the degradation state, while the output is either a degradation level, a health-state classification, or a remaining useful life estimate.



(**a**) Machine learning



(**b**) Deep Learning



(**c**) Statistical Inference

Figure 5. Usage of techniques.

6.1.1. Statistical Inference Usage

The distribution in Table 5 shows that statistical inference methods are used across all three domains, but with distinct preferences reflecting data characteristics and modeling needs. In most applications, the input consists of low- or medium-dimensional condition measurements (e.g., mechanical properties, sensor readings, laboratory biomarkers), while the output is either a degradation level $d(t)$, its rate of change, or a categorical health state.

Regression analysis dominates in engineering studies, where covariates such as load, temperature, or operating cycles are directly linked to degradation. Bayesian statistics and MCMC are widely used when uncertainty quantification or hierarchical structure is required, especially in medicine. Factor analysis appears primarily in settings where multiple correlated indicators must be reduced to a small number of latent degradation factors.

Table 5. Method used for degradation modeling with statistical inference.

Method	Material Science	Engineering	Medicine
Regression Analysis	[82–91]	[92–107]	[108–111]
Factor Analysis	[112–118]	[119–123]	[124–130]
Markov Chain Monte Carlo + probabilistic programming	[90,118,131–140]	[103,120,141–150]	[151–155]
Bayesian statistics	[87,115,156–164]	[101,165–178]	[108,125,126,128, 179–185]

6.1.2. Dynamic Prediction Usage

Table 6 refers to the number of applications of individual techniques from the dynamic prediction methods in each of the disciplines, which allows us to conclude the preferences and popularity of particular techniques in particular fields.

Dynamic prediction methods are applied in all three domains when degradation evolves over time and latent system states play a role. The input typically consists of sequential measurements or event histories, while the output is a predicted next state, a future degradation level, or an implied remaining useful life.

Markov and Hidden Markov Models are common in studies with abrupt changes or regime-switching behavior. They are particularly relevant in medicine, where disease progression is naturally represented by transitions between health states. Nonparametric Bayesian time-series models are more prevalent in engineering, where irregular sampling and complex temporal dependencies require flexible model structures.

Table 6. Method used for degradation modeling with dynamic prediction.

Method	Material Science	Engineering	Medicine
Markov models	[139,186]	[141,149,150,178,187–189]	[153,179,182,190–194]
Hidden Markov Models	[113,117,131,157,195–197]	[102,144,170,171,198–201]	[110,181,183,185,192,202–204]
Nonparametric Bayesian Time Series Modeling	[114,134–138]	[97,98,100,104,119,121–123,147,148,168,172,187,205–207]	[129,130,151,155,208–212]

6.1.3. Machine Learning Usage

Table 7 shows the use of different machine learning techniques in three disciplines: material science, power engineering, and medicine.

Machine learning methods are most often used when data are high-dimensional, noisy, or contain nonlinear relationships between inputs and degradation. The input typically includes multivariate sensor readings, images, vibration signals, or patient-specific clinical features, while the output is a predicted degradation indicator, remaining useful life, or a health-state class.

Supervised learning is used broadly across all domains when labeled degradation data are available. Deep learning appears mainly in engineering and materials science, especially with vibration or image data requiring automatic feature extraction. Reinforcement learning is used when the goal is decision-making under uncertainty (e.g., maintenance optimization, treatment strategies). Cluster analysis is applied to identify groups of components or patients sharing similar degradation patterns.

Table 7. Method used for degradation modeling with machine learning.

Method	Material Science	Engineering	Medicine
Supervised Learning	[82,84–86,132,140,159,196]	[95,96,99,106,174,199,201,213,214]	[127,180,184,204,208,210,211,215]
Deep Learning	[83,88,158,216]	[92,143,165,167,175,176,188,205,214,217]	[152,202,203,218]
Reinforcement Learning	[89,91,116,133,156,195]	[105,142,145,146,166,173,177,200]	[109,124,190,193,209,219–222]
Cluster analysis	[112,160–164,186,197,216]	[93,94,107,169,189,198,206,223,224]	[154,194,215,218,220,222]

6.2. Method Selection Guidelines Across Data Types and Degradation Scenarios

The counts in Tables 4–7 and the visual summaries in Figures 5–8 show how different methods are used across materials science, engineering, and medicine in the curated corpus of studies. However, for practitioners it is often more important to understand *which* methods are appropriate for a given type of degradation signal, data availability, and operational context. Table 8 summarizes recommended model families for representative scenarios, together with brief justifications. The recommendations synthesize patterns observed in the reviewed applications and insights from previous surveys [1,3,54].

The table is not intended as a rigid prescription but as a set of evidence-based guidelines. In practice, several model families can often be combined (e.g., gamma processes within a Bayesian framework, or HMMs with neural network emission models), which motivates the hybrid-methods discussion in the next subsection.

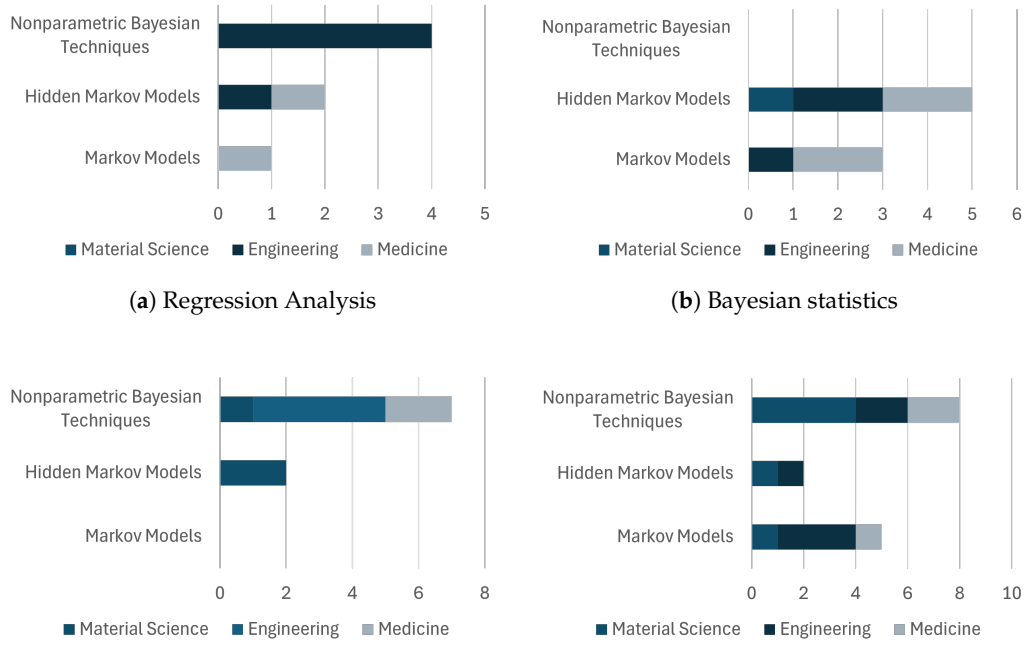
Table 8. Recommended model families for typical degradation scenarios.

Scenario	Typical Data Characteristics	Recommended Methods	Rationale
Monotonic physical degradation (e.g., corrosion, crack growth, insulation aging)	Low- to medium-frequency measurements of a scalar damage indicator; strictly increasing or nearly monotonic trajectories; moderate sample size	Stochastic degradation processes (gamma, inverse Gaussian); parametric or Bayesian regression on time and covariates	Gamma/IG processes naturally represent cumulative monotonic damage and allow analytical RUL estimates; regression captures covariate effects on the degradation rate [3,54].
Noisy, non-monotonic degradation with recovery effects	Dense or irregular time series; measurement noise and reversible effects (e.g., capacity recovery, load-dependent stiffness)	Wiener processes with drift; Gaussian process regression; state-space models	Drift–diffusion processes and GP regression model smooth but non-monotonic trajectories and provide uncertainty bands; state-space models separate latent degradation from measurement noise.
Abrupt regime changes or switching between health states	Time series or event sequences with sudden changes in behavior; latent operating modes; possibly sparse measurements	Markov models; Hidden Markov Models; switching state-space models	Markov and HMM frameworks explicitly represent transitions between discrete degradation states or regimes and are well suited for fault/health-state classification and prognosis.
High-dimensional sensor data (vibration, images, multichannel signals)	A large number of correlated features; possibly a high sampling rate; labels for health states or failures available for part of the data	Supervised machine learning (tree ensembles, SVMs, shallow ANNs); deep learning (CNNs, RNNs/LSTMs) for sufficiently large datasets	ML methods automatically extract nonlinear features from multivariate signals and achieve high predictive performance for health-state classification and RUL estimation, at the cost of interpretability and data requirements.
Small datasets with substantial uncertainty	Limited number of units or short time series; censored or missing observations; need for uncertainty quantification	Bayesian statistical models; hierarchical regression; stochastic degradation processes with Bayesian inference	Bayesian and hierarchical models can borrow strength across units, propagate parameter uncertainty, and provide credible intervals for degradation trajectories and RUL, which is crucial in high-reliability settings.
Complex operating conditions and multiple covariates	Multiple environmental and loading variables; mixture of continuous and categorical covariates; possible interactions	Generalized linear and additive models; mixed-effects models; hybrid physics–data models	These models flexibly incorporate covariates and random effects, capturing heterogeneity between units and linking physical understanding with data-driven components.

6.3. Hybrid Methods

6.3.1. Statistical Inference and Dynamic Prediction

Figure 6 presents combinations of methods from statistical inference and dynamic prediction. It demonstrates the usage of MCMC in material science, power engineering, and medicine for parameter estimation, exploring distributions, and Bayesian models. MCMC simulations are valuable for simulating complex systems and addressing uncertainty in diverse domains. Nonparametric Bayesian modeling is important in material science, while in power engineering and medicine, MCMC is used for uncertainty quantification and computational modeling.



(**a**) Regression Analysis (**b**) Bayesian statistics

(**c**) Factor Analysis (**d**) MCMC and probabilistic programming

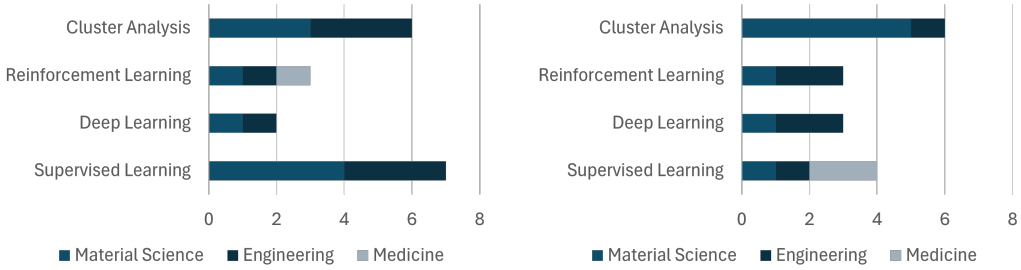
Figure 6. Combination of statistical inference and dynamic prediction methods.

Figure 6 shows how statistical inference and dynamic prediction methods are combined in practice. Such hybridizations arise when covariate effects (handled by regression or Bayesian inference) coexist with latent temporal structure (handled by Markov or Hidden Markov Models). Inputs typically include sequential measurements and operating conditions, while outputs involve state probabilities, predicted trajectories, or uncertainty-quantified degradation forecasts.

6.3.2. Statistical Inference and Machine Learning

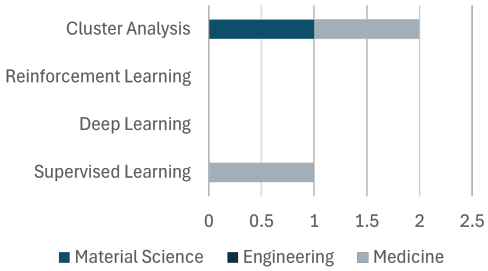
Figure 7 presents combinations of techniques from the area of statistical inference methods and machine learning techniques.

Figure 7 illustrates combinations of statistical inference and machine learning. These hybrids are used when statistical models provide interpretability or uncertainty quantification, and machine learning contributes nonlinear feature extraction. The input commonly consists of multidimensional condition measurements, and the output is either a predicted degradation value or a classification of health state.

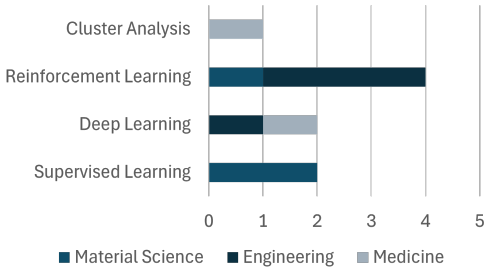


(**a**) Regression Analysis

(**b**) Bayesian statistics



(**c**) Factor Analysis

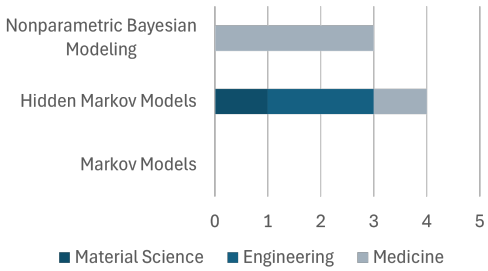


(**d**) MCMC and probabilistic programming

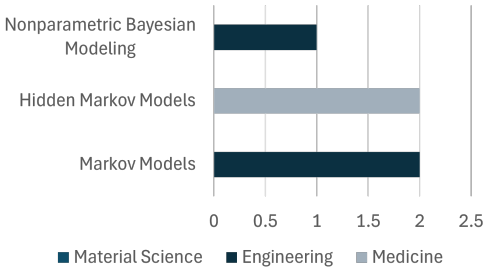
Figure 7. Combination of statistical inference and machine learning.

6.3.3. Dynamic Prediction and Machine Learning

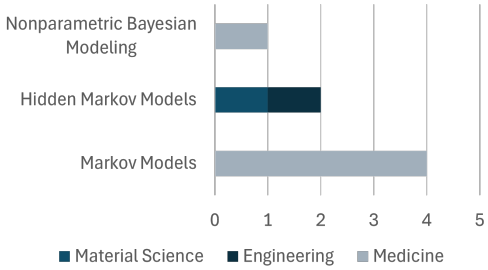
Figure 8 presents the combination of machine learning techniques and dynamic prediction in scientific fields. Figure 8 showcases the relevance of different combinations of methods in various disciplines, including Material Science, Engineering, and Medicine.



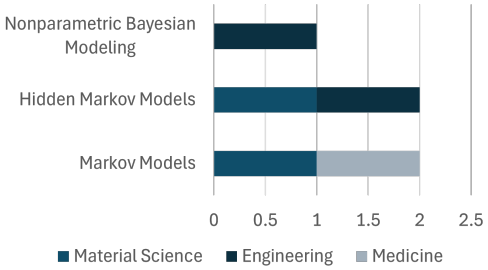
(**a**) Supervised Learning



(**b**) Deep Learning



(**c**) Reinforcement Learning



(**d**) Cluster Analysis

Figure 8. Combination of dynamic prediction and machine learning.

Figure 8 presents combinations of dynamic prediction and machine learning methods. These approaches are applied when time-dependent degradation must be modeled together with nonlinear dependencies in the data. Inputs usually comprise temporal sensor signals

or images, and outputs are derived degradation trajectories, predicted states, or remaining useful life.

7. Discussion and Challenges

7.1. Discussion

The analysis across Sections 5–6.2 shows that no single modeling paradigm universally dominates degradation modeling across the three domains. Instead, method choice is largely driven by (i) the structure of the available data (scalar trajectories, time series with regime switching, high-dimensional sensor channels), (ii) the purpose of modeling (explanatory analysis vs. predictive maintenance), and (iii) the level of uncertainty that must be quantified. Statistical inference remains the most interpretable approach, particularly when covariates or uncertainty quantification are essential. Dynamic prediction methods are preferred when temporal dependencies or latent states drive the degradation process. Machine learning methods dominate when high-dimensional or nonlinear patterns are present. These trends are consistent with previous reviews [1,3,54].

Table 9 presents an overview of the advantages and disadvantages of the methods for degradation modeling in this paper.

Table 9. Comparison of strengths and weaknesses of each class of methods. Statistical approaches are more interpretable, but can be more costly to compute, however machine learning when provided enough data has great predictive performance.

	Methods	Advantages	Disadvantages
Statistical inference	Regression analysis	Fast computation, Easily interpretable	Linear relationships, Strong assumptions
	Factor analysis	Interpretability	Highest expert knowledge requirements
	MCMC & probabilistic programming	Specification of complicated models,	Mostly Bayesian applications, Computational costs
	Bayesian statistics	Most flexibility, interpretability	Computational problems, untraceablity of direct analytical formulas
Dynamic prediction	Markov models	Widely understood, Good short term predictions	Limited long term accuracy
	Hidden Markov models	Improved prediction quality, more flexibility	Difficult interpretability
	Bayesian time series	Ease of application (esp. Prophet), decomposition of effects	Computational costs
Machine learning	Supervised learning	Flexibility, wide adoption	Difficult interpretability, large dataset requirements
	Deep learning	Flexibility, predictive performance	High dataset requirements, no interpretability, computational costs
	Reinforcement learning	Very promising results	High dataset requirements, no interpretability, computational costs
	Cluster analysis	Limited expert knowledge required, detection of atypical cases	Data requirements, Problems with traceability

Overall, the comparative analysis suggests that the most robust solutions often combine multiple classes of methods. For example, combining Markovian dynamics with

Bayesian inference enables transparent uncertainty quantification in temporal settings, while integrating machine learning with probabilistic models offers improved predictive power for high-dimensional signals. These hybrid configurations correspond well with the patterns summarized in Section 6.2.

7.2. Open Challenges

Despite significant progress across the three domains, several open challenges remain that limit the robustness and generalizability of degradation models. The most important challenges identified in the reviewed literature are summarized below.

1. Data quality, missingness, and heterogeneity.

Many degradation datasets suffer from sparsity, irregular sampling, sensor dropouts or missing covariates. Existing imputation approaches are often ad hoc and rarely benchmarked. Moreover, degradation datasets differ substantially across units, environments and operating regimes, requiring models that can explicitly handle heterogeneity (e.g., hierarchical Bayesian models or domain-adaptation methods).

2. Limited availability of benchmark datasets.

A recurring limitation across the reviewed literature is the reliance on bespoke datasets, which prevents reproducible comparisons across methods. There is a strong need for publicly available benchmark datasets that cover monotonic and non-monotonic signals, regime-switching behavior, and multimodal sensor information. Standardized benchmarks would also enable fair comparisons between probabilistic, ML-based and hybrid approaches.

3. Uncertainty quantification and reliability of predictions.

Machine learning models often provide point predictions without calibrated uncertainty estimates, which limits their suitability for safety-critical domains (e.g., energy, medicine). Conversely, probabilistic models with rich uncertainty quantification are computationally expensive and difficult to scale. Developing models that jointly deliver accuracy and trustworthy uncertainty remains an unresolved challenge.

4. Integration of physics-based and data-driven models.

Physics-based models encode mechanistic understanding but may be difficult to calibrate. Data-driven models capture empirical behavior but lack interpretability. Integrating these approaches—e.g., via physics-informed Gaussian processes, neural differential equations, or Bayesian hybrid models—is a promising but still emerging research direction.

5. Real-time and scalable degradation modeling.

Many real-world systems require near real-time inference for maintenance decision-making. However, current methods (especially MCMC-based and deep-learning-based approaches) may be computationally prohibitive. Efficient inference schemes, online learning, streaming algorithms, and dimensionality reduction for high-frequency sensor data are critical developments.

6. Cross-domain generalization.

Most methods are evaluated within a single domain (materials, engineering or medicine). Little work investigates whether degradation patterns or model architectures transfer across domains or application contexts. This represents an important research gap, particularly for high-risk systems where domain-specific data are scarce.

Addressing these challenges will support more reliable deployment of degradation models in operational settings and will motivate new methodological advances bridging statistical inference, dynamic prediction, and machine learning.

8. Conclusions

This review synthesizes degradation modeling approaches across materials science, engineering and medicine, focusing on three major methodological families: statistical inference, dynamic prediction and machine learning. The comparative analysis demonstrates that no single method dominates across all domains. Instead, model suitability is driven primarily by the structure of available data, the temporal characteristics of the degradation process, and the intended use of the model (explanation, prediction or decision support).

Statistical inference methods remain essential when interpretability, covariate effects and uncertainty quantification are required. Dynamic prediction methods, including Markov and Hidden Markov Models as well as nonparametric Bayesian time-series techniques, are preferred when degradation follows a temporal or regime-switching structure. Machine learning methods become advantageous for high-dimensional or nonlinear sensor data, offering strong predictive performance when sufficient training examples are available.

A key finding is the growing importance of hybrid modeling strategies. Combinations such as Bayesian inference with state-space dynamics, machine learning with probabilistic layers, or physics-informed neural models increasingly address the limitations of individual method classes. These hybrid approaches appear particularly promising for noisy, irregular and multimodal degradation data.

Across all domains, common challenges include data sparsity, heterogeneity, lack of benchmark datasets, and limited uncertainty quantification in high-capacity predictive models. Addressing these issues—together with improving scalability and cross-domain generalization—remains essential for reliable deployment of degradation models in real-world applications.

Overall, this review provides a structured overview of the methodological landscape, clarifies which approaches are most suitable for particular degradation scenarios, and highlights open challenges that motivate future research. The synthesis aims to support both practitioners selecting appropriate methods and researchers developing the next generation of interpretable, scalable and uncertainty-aware degradation models.

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Abbreviations

The following abbreviations are used in this manuscript:

ISO	ISO
OLS	Ordinary Least Squares
AIC	Akaike Information Criterion
MCMC	Markov Chain Monte Carlo
HMC	Hamiltonian Monte Carlo
HMM	Hidden Markov Model
PPL	Probabilistic Programming Language
GP	Gaussian Process
DP	Dirichlet Process
MAP	Maximum a Posteriori (estimation)
EM	Expectation–Maximization (algorithm)
MDP	Markov Decision Process
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory (network)
RUL	Remaining Useful Life
VC	Vapnik–Chervonenkis (dimension)
H_2S	Hydrogen sulfide

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