

Review

Physics-Informed Machine Learning for Fatigue and Fracture Analysis and Prediction: A Scoping Review

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Abstract

Physics-Informed Machine Learning has emerged as a powerful paradigm for fatigue and fracture analysis, combining the data-driven flexibility of neural networks with the consistency of physical laws. This scoping review maps the extent, range, and nature of research on PIML applied to fatigue life prediction, crack growth and propagation, multiaxial fatigue, damage mechanics, prognostics and health management, and structural health monitoring, covering the literature published from 2018 up to August 2026. A comprehensive search strategy integrated the core terminology of the field with broader synonym terms, complemented by forward and backward citation searching and manual screening of the most productive venues. The combined strategy retrieved 124 records, of which 76 primary research articles satisfied the inclusion criteria and were charted and characterized in this review. The included studies are characterized through the lens of a three-bias taxonomy—observational, learning, and inductive—which organizes how physical knowledge enters the learning pipeline: through data-level constraints, loss-function modifications, and structural architectural changes, respectively. The review maps the architectural landscape of the field, from standard multi-layer perceptron-based PINNs to specialized variants including sequential attention models, physics-informed Kolmogorov–Arnold networks, geometry-aware finite encodings, graph neural networks, and probabilistic Bayesian formulations. The mapped literature indicates that PIML methods are reported to improve generalization from sparse and noisy experimental data, achieve computational gains over conventional simulation, and quantify prediction uncertainty. Persistent challenges nonetheless emerge across the mapped literature, including high training costs, sensitivity to hyperparameter and loss-weighting choices, limited transferability across problem configurations, and the black-box nature of deep models. The review identifies knowledge gaps and concludes with an agenda for future research, emphasizing generalizable and adaptive architectures, multi-scale and multi-physics formulations, and standardized benchmarks.



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1. Introduction

Fatigue and fracture represent critical failure mechanisms that significantly impact the safety, reliability, and lifespan of engineering structures across diverse sectors, including aerospace, automotive, civil infrastructure, and energy. The ability to accurately

predict and analyze these phenomena is paramount for robust design and maintenance [1]. This challenge is notably amplified within the paradigm of Industry 4.0, characterized by smart factories, digital twins, and advanced manufacturing techniques such as additive manufacturing. For instance, while AM offers unprecedented design freedom and rapid production, it introduces new complexities related to material properties, microstructural inhomogeneity, and the presence of process-induced defects—such as porosity and lack-of-fusion—which profoundly affect the fatigue and fracture performance of printed components [2–4]. Such challenges underscore the need for advanced predictive tools that can ensure the reliability and quality of AM parts, representing a significant concern for widespread industrial adoption [5,6]. However, the need for robust fatigue and fracture analysis extends far beyond AM, encompassing all engineering applications where structural integrity is paramount.

The task of structural assessment is fraught with inherent complexities due to the multi-scale nature of damage progression, ranging from microscopic material degradation to macroscopic crack propagation and ultimate failure [7,8]. Traditional methodologies, encompassing extensive experimental campaigns and purely physics-based computational models, often encounter limitations such as high computational demands, reliance on vast amounts of experimental data, difficulty in capturing complex non-linear material behaviors, and challenges in accounting for uncertainties in material properties and loading conditions [9–12]. Specifically, uncertainty in microscopic material parameters complicates the precise prediction of fatigue life, introducing noise and variability into failure time data [9]. Moreover, conventional fatigue models struggle with inconsistencies in data and often fail to accurately predict crack growth in high-stress regions rather than isolated peak points [13,14].

While traditional methods continue to face persistent challenges across various materials and structures, Physics-Informed Neural Networks, and later the broader concept of Physics-Informed Machine Learning, have emerged as transformative paradigms within the landscape of scientific computation. PINNs, notably pioneered by Raissi, Perdikaris, and Karniadakis, were initially developed to address partial differential equations systems across diverse engineering and scientific domains, such as fluid dynamics and mechanics [15–18]. It was only subsequently that researchers began applying this approach to more specialized problems like fatigue and fracture analysis [1,3,19,20]. This approach offers a powerful synergy by integrating data-driven machine learning capabilities with the foundational principles of physical laws [21–24]. For clarity, these methodologies, encompassing both machine learning and neural network methods, are collectively referred to as Physics-Informed Machine Learning throughout this work.

Although foundational studies have examined the application of conventional machine learning in structural integrity, a comprehensive mapping of the literature specifically addressing physics-informed methodologies is currently absent. There is a particular need to categorize the mathematical integration of physical laws into learning algorithms to mitigate the pervasive challenge of limited experimental data in fatigue analysis, applicable to both novel materials like those produced via Additive Manufacturing [2,3] and traditional materials where experimental data is costly or scarce. Unlike purely data-driven models that can exhibit physical inconsistencies and poor extrapolation outside their training data, or solely physics-based simulations that may be computationally expensive and struggle with incomplete information, PIML explicitly embeds governing equations, conservation laws, and boundary conditions directly into the learning process [18,25,26]. This hybrid methodology provides several compelling advantages: it allows models to be trained effectively even with sparse or limited data, ensures the physical plausibility and interpretability of predictions, enhances generalization capabilities to unseen conditions,

and can provide near real-time simulation results once trained [27–30]. Such methods are particularly valuable for inverse problems or complex systems where the exact underlying physical equations may be unknown or difficult to solve analytically [27,31,32]. This makes PIML well-suited for a wide range of Industry 4.0 applications, including those where process metadata and digital control necessitate robust models for defect detection, property grading, and quality assurance, as seen in AM [33].

To bridge this gap, this scoping review goes beyond a chronological survey by mapping and characterizing the state of the art, categorizing how PIML addresses the three fundamental biases: observational, inductive, and learning. By crossing traditional fatigue models with machine learning and neural network techniques, we characterize how these approaches enhance prediction and analysis accuracy while addressing the limitations of traditional methods in these domains. The scope literature search underpinning this review was conducted in two phases—the first in March 2026 and the second in August 2026—with the second phase incorporating an expanded set of keywords registered in the updated study protocol on the Open Science Framework. In accordance with that protocol, the results of the two phases are consolidated and reported throughout this paper as a single integrated review. The remainder of this paper is organized as follows. Section 2 introduces the foundations of Physics-Informed Machine Learning for fatigue and fracture, formalizing the three sources of bias—observational, learning, and inductive—that structure the analysis. Section 3 details the methodology: the search strategy, the inclusion and exclusion criteria, the six-step paper selection process, the information extraction and charting procedure, the coding of the three-bias taxonomy, and the descriptive characterization of the reporting completeness of the included studies. Section 4 presents the literature review, beginning with the bibliometric overview of the cohort, then characterizing the selected studies through the lenses of the three biases and of architectural diversity, and concluding with a summary of key findings. Section 5 discusses the results, covering trends and valuable findings, theoretical models and integration strategies, technical gains, disadvantages of PINN and PIML, and opportunities for research and applications. Finally, Section 6 closes the review with its key takeaways, limitations, and future directions.

2. Foundations of PIML

Physics-Informed Machine Learning, with Physics-Informed Neural Networks as a foundational component, represents a transformative paradigm that integrates data-driven machine learning with fundamental physical laws. This approach has rapidly emerged as a powerful tool for addressing complex engineering and scientific challenges, particularly those characterized by data scarcity, high computational costs, and the need for physically consistent predictions.

The concept of PINNs was notably pioneered by Raissi, Perdikaris, and Karniadakis, who developed this framework to address partial differential equations across diverse domains, including fluid dynamics and general mechanics [15–18]. The core mathematical model of a PINN approximates the solution to a PDE using a deep neural network. The neural network, denoted as $u_\theta(\mathbf{x}, t)$, is trained by minimizing a loss function that combines two primary components: a data-driven loss (L_d) and a physics-informed loss (L_p), for a generic PDE given by $\mathcal{F}(u, \mathbf{x}, t) = 0$.

Central to understanding PIML's efficacy is its unique approach to addressing various biases inherent in scientific modeling. This review adopts the established PIML taxonomy of three distinct biases: observational, inductive, and learning biases [34,35]. While these concepts apply to both general machine learning algorithms and neural network algorithms like PINNs, the specific methods of integration can vary. Figure 1 illustrates the three bias types considered in this review.

Observational bias arises from the challenges of acquiring comprehensive, high-quality data, leading to sparse, noisy, or limited datasets—a pervasive issue in many engineering fields. PIML mitigates this by leveraging physical constraints to enable models to learn and generalize more effectively from less data [35]. For instance, known physical relationships can be used to generate synthetic data or to constrain model outputs, making the most of scarce experimental observations.

Learning bias is primarily related to introducing physics into the training process—typically into the loss function of the model. This means the model’s fundamental architecture or structure remains largely generic, but its learning process is guided by penalizing solutions that violate known physical principles [34]. This approach ensures that the model converges to physically plausible outcomes without explicitly incorporating physical laws into its internal structure. In general ML algorithms, this might involve adding regularization terms derived from physics to the objective function, while in NNs, this translates to physics-informed terms in the network’s loss function.

Inductive bias, in the context of PIML, primarily involves modifying the architecture of part of the network—and possibly its activation functions—to adhere to physical principles [36]. This involves embedding physical properties directly into the model’s structural components, fundamentally altering how the model processes information. This could mean designing specialized layers that intrinsically represent physical operators, or using activation functions that enforce physical constraints. In broader ML algorithms, this might involve engineering features or kernel functions that inherently reflect physical relationships before feeding them into a standard model.

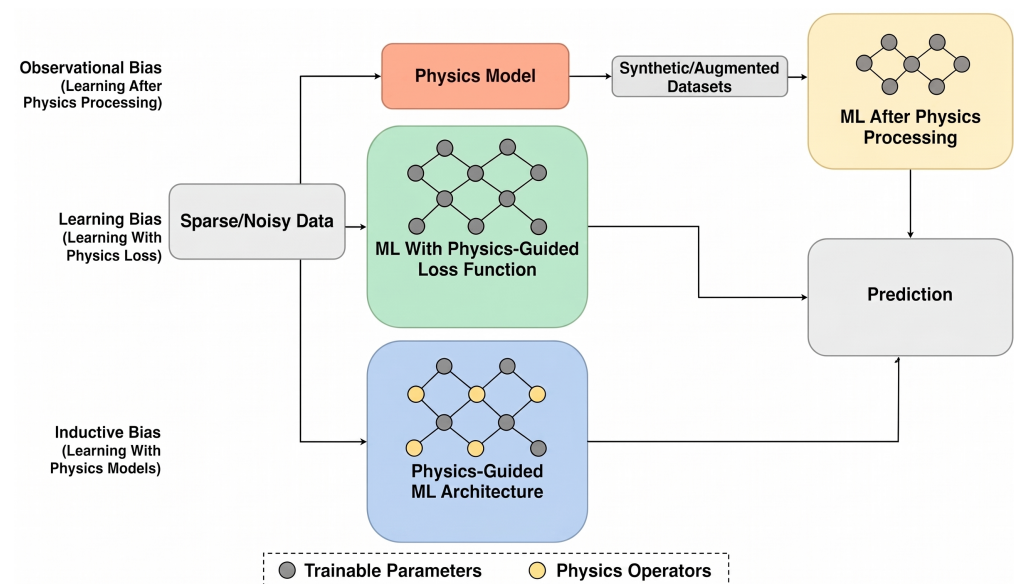


Figure 1. Physics-informed bias types (adapted from [37]).

2.1. Mathematical Formulations for Biases in PIML

To formalize the practical application of the three key physical biases in PIML, particularly within Physics-Informed Neural Networks, we derive their mathematical formulations below. These formulations, rooted in the foundational PINN framework [15–18,35,38], demonstrate how physics integration enhances model robustness, generalization, and physical consistency amid data scarcity and computational challenges.

Let $u_\theta(x)$ represent the output of a neural network (or PIML model) parameterized by θ at an input x . Let u_{data} be observed data points, and x_{data} be their corresponding input locations. Let $\mathcal{F}$ denote a generic physical law or Partial Differential Equation, such that $\mathcal{F}(x, u, \partial u, \partial^2 u, \dots) = 0$ represents the physical constraint.

The overall training objective in PIML typically involves minimizing a composite loss function L , which is a weighted sum of a data-driven loss L_D and a physics-informed loss

$$L = w_D L_D + w_P L_P \quad (1)$$

where w_D and w_P are weighting coefficients.

2.1.1. Observational Bias

Observational bias arises from sparse, noisy, or limited datasets [35]. PIML mitigates this by leveraging physical constraints to allow models to learn and generalize effectively from less data. While not a direct mathematical term for the bias itself, its mitigation is evident in how the model is trained to be robust despite data limitations. The data-driven loss component, L_D , quantifies the discrepancy between the model's predictions and the available data

$$L_D = \frac{1}{N_D} \sum_{i=1}^{N_D} \|u_\theta(x_{data}^{(i)}) - u_{data}^{(i)}\|^2 \quad (2)$$

where N_D is the number of available data points. The impact of observational bias is particularly significant when N_D is small or $u_{data}^{(i)}$ contains substantial noise. PIML addresses this by ensuring that even with a limited L_D component, the model can still learn physically consistent solutions due to the complementary L_P component, effectively reducing the model's reliance on extensive data.

2.1.2. Learning Bias

Learning bias in PIML is primarily introduced by incorporating physics directly into the model's training process—most commonly through the loss function [39]. The model's architecture remains largely general, but its learning process is guided by penalizing solutions that violate known physical principles. This is achieved through the physics-informed loss component, L_P :

$$L_P = \frac{1}{N_P} \sum_{j=1}^{N_P} \left\| \mathcal{F}(x_{col}^{(j)}, u_\theta(x_{col}^{(j)}), \partial u_\theta(x_{col}^{(j)}), \partial^2 u_\theta(x_{col}^{(j)}), \dots) \right\|^2 \quad (3)$$

Here, $x_{col}^{(j)}$ are collocation points (sampled within the domain where the physics holds), and N_P is the number of collocation points. Minimizing L_P forces the neural network's output $u_\theta(x)$ to satisfy the governing physical equations $\mathcal{F} = 0$, thereby embedding a strong learning bias towards physically plausible solutions.

Although this review is restricted to fatigue and fracture, the physics-only loss structure of Equation (3) is domain-independent. A canonical demonstration from outside structural mechanics is the use of PINNs to solve inverse problems in tokamaks, where the network is trained on the residual of the Grad–Shafranov equation with no data-fitting term at the collocation points [27].

2.1.3. Inductive Bias

Inductive bias, in the context of PIML, involves explicitly changing the architecture of the neural network or its activation functions to directly adhere to physical terms [40]. This means the physical properties are embedded directly into the model's structural components, influencing how it processes information. Unlike learning bias, which modifies the training objective, inductive bias alters the model $u_\theta(x)$ itself.

A generic mathematical representation for a neural network output with inductive bias could be

$$u_{\theta}(x) = \mathcal{G}(x; \theta, \Phi) \quad (4)$$

where $\mathcal{G}$ denotes a neural network architecture that has been explicitly designed or constrained by a set of physical operators or functions Φ . This could manifest as:

1. **Specialized Layers:** Layers f_k designed to compute specific physical operators (e.g., derivatives, integrals, or constitutive relations).
2. **Physics-Informed Activation Functions:** Activation functions $\sigma(z)$ that are chosen or modified to ensure physical constraints or properties (e.g., monotonicity, boundary conditions, and conservation laws) are intrinsically satisfied.
3. **Residual Connections:** The network might learn a residual from a known physical approximation, such that $u_{\theta}(x) = u_{physics}(x) + \Delta u_{\theta}(x)$, where $\Delta u_{\theta}(x)$ is learned by the neural network.

The core idea is that the internal workings and transformations of the network (its architecture) are tailored to reflect the underlying physics, leading to better interpretability [41].

The ability of PIML to embed physical principles and effectively manage these biases makes it well-suited for advancing research in fatigue and fracture analysis [42]. By combining the data-driven flexibility of machine learning with the rigorous constraints of physical laws, PIML offers a powerful framework to tackle the multi-scale complexities [43] and data scarcity [44] that traditionally limit accurate prediction and analysis in these critical engineering domains. This hybrid methodology ensures that models can learn robustly from limited experimental data [44], provide physically consistent [45] and interpretable predictions [41], and generalize effectively to unseen conditions [46], thereby offering solutions for structural integrity, predictive maintenance, and overall system reliability [47] problems.

3. Methodology

This scoping review was conducted in accordance with the methodological framework for scoping studies proposed by Arksey and O'Malley [48], further advanced by Levac et al. [49], and in line with the Joanna Briggs Institute guidance for scoping reviews [50,51]. The search and extraction strategies follow the PRISMA extension for Scoping Reviews reporting guidance [52] and were further adapted from established methodological guidelines for scoping reviews in engineering and computer science [53–55], ensuring comprehensiveness, objectivity, and replicability in identifying, selecting, charting, and describing the relevant literature, so as to provide a structured examination of the current state of research.

3.1. Materials, Research Protocol and Objectives

The following items were used as materials for the review and for preparing this manuscript:

Databases: Scopus, Web of Science, IEEE Xplore. These sources were selected for their established quality and broad coverage. Searches were conducted manually through each database's interface. The arXiv database was also included to support the most recent methodological trends.

Use of Generative AI: Authors used Gemini 3.1 Pro to support the following tasks:

- Formatting the references;
- Improving English language writing;
- Generating Figures 5–7;
- Formatting the manuscript in accordance with the publisher's template.

This scoping review was conducted to map the extent, range, and nature of research activity on Physics-Informed Machine Learning applied to fatigue and fracture analysis and prediction [48,49]. Specifically, the objectives are threefold:

1. **To map the extent, range, and nature** of PIML research in fatigue and fracture—covering the application domains addressed, the physical laws embedded, the bias-integration strategies adopted, and the architectural landscape of the field—thereby providing a comprehensive overview of the current state of the art.
2. **To characterize how the three fundamental biases**—observational, learning, and inductive—are operationalized across the included literature, describing how physical knowledge enters the learning pipeline at the data level, the training-objective level, and the architectural level, respectively [49].
3. **To identify gaps** in the existing literature and propose directions for future research.

Consistent with scoping review methodology, the study maps and describes the characteristics of the included evidence rather than producing a quantitative synthesis of pooled results [50,51].

The protocol for this study was registered on the Open Science Framework under the project “Scoping Review on Physics-Informed Machine Learning for Fatigue and Fracture Analysis and Prediction”, with DOI:10.17605/OSF.IO/CJD2H. For auditing purposes, the original project and its registration, created in March 2026, have been retained. An updated registration and revised files were submitted in August 2026 to reflect the updated version of the study.

3.2. Search Strategy

The search strategy combined the core terminology of the field—“Physics-Informed Machine Learning”, “Physics-Informed Neural Networks”—with the broader synonym families that have emerged in the literature, organized into concept blocks combined with Boolean operators. The concept blocks covered the families “physics-guided,” “physics-based,” “physics-encoded,” “theory-guided,” “knowledge-guided,” and “hybrid physics-data” approaches and were combined with the fatigue and fracture domains: “fatigue”, “fatigue life prediction”, “fracture”, “crack propagation”, “cumulative damage”, “remaining useful life”, and “structural health monitoring.” The combined string used was:

(“physics-informed” OR “physics-guided” OR “physics-based” OR
“physics-encoded” OR “theory-guided” OR “knowledge-guided” OR
“physics-embedded” OR “hybrid physics-data”) AND (“machine learning” OR
“neural network” OR “deep learning”) AND (“fatigue” OR “fatigue life
prediction” OR “fracture” OR “crack propagation” OR “cumulative damage” OR
“remaining useful life” OR “structural health monitoring”)

In addition to the database queries, three complementary identification techniques were applied to limit terminology bias, as recommended by the methodological guidelines and the peer-review process: (i) forward citation searching, in which the citing literature of the included primary studies and of the seminal PINN/PIML references was screened [15]; (ii) backward reference checking, in which the reference lists of the included studies and of the retrieved review articles were screened for eligible records missed by the strings; and (iii) supplementary manual searching of the tables of contents of the most productive venues in the field (e.g., International Journal of Fatigue, Engineering Fracture Mechanics, Computer Methods in Applied Mechanics and Engineering, Reliability Engineering & System Safety, Mechanical Systems and Signal Processing).

The searches were deliberately restricted to publications from 2018 onwards, aligning with the introduction of the modern PINN concept [15]. The combined strategy retrieved

124 records. Figure 2 presents the PRISMA 2020 workflow and the numerical results of the paper selection process. In addition, detailed information on each stage, including procedures such as consensus-based verification, is available in the referenced OSF project.

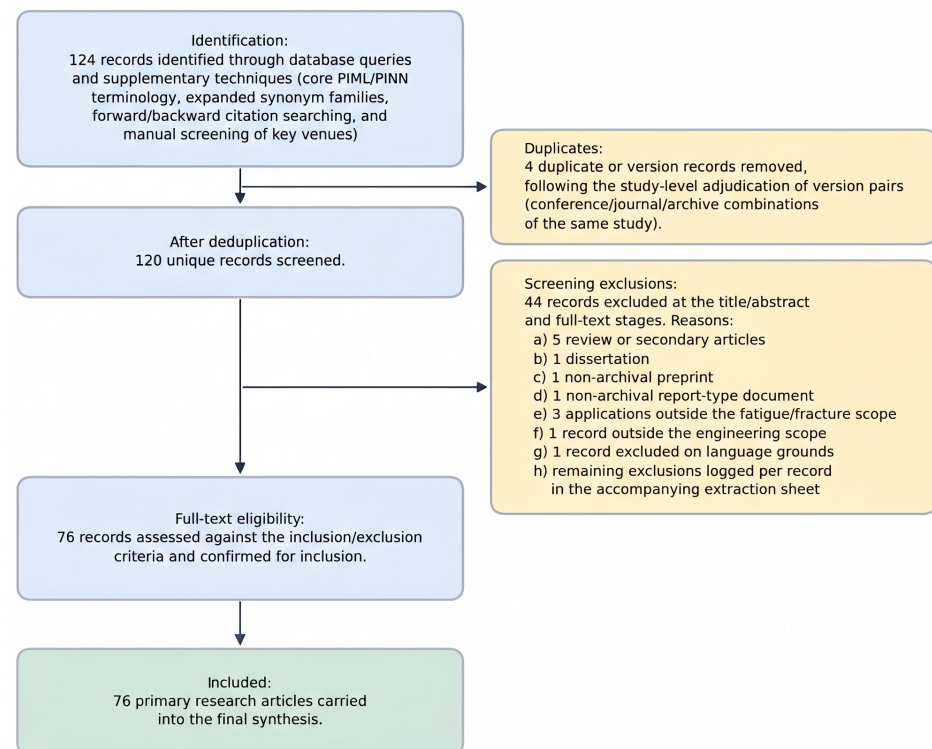


Figure 2. PRISMA 2020 compliant flow diagram for the study selection process.

3.3. Inclusion and Exclusion Criteria for Literature Selection

Following the search, retrieved articles were filtered to ensure their relevance to the review's scope. A set of inclusion and exclusion criteria was defined and applied to capture the recent evolution of the field, while maintaining a focus on primary research contributions and ensuring the quality and relevance of the mapped literature [53,56,57]. Table 1 summarizes the inclusion criteria applied to select studies for the review.

Table 1. Inclusion criteria.

Inclusion Criteria	Meaning
Topic Relevance	Studies explicitly applying PIML or PINN methodologies to predict, analyze, or monitor fatigue and/or fracture in engineering materials or structures, including applications in Prognostics and Health Management, Residual Life Prediction, and Structural Health Monitoring.
Publication Type	Peer-reviewed journal articles, conference papers, and reputable archival pre-prints.
Language	Articles written in English.
Content Focus	Papers presenting novel methodologies, significant applications, comparative analyses, or critical reviews directly pertinent to the integration of physics and machine learning for fatigue and fracture.
Publication Year	Studies published from 2018 onwards, aligning with the introduction of the modern PINN concept.

Table 2 details the exclusion criteria and their corresponding meanings, which were applied to filter the retrieved records against the review’s scope and prioritize primary empirical evidence.

Table 2. Exclusion criteria.

Exclusion Criteria	Meaning
Irrelevant Topic	Studies that mention PIML/PINN or fatigue/fracture but do not directly combine them within the specified engineering contexts, or those where the application is outside the scope of engineering materials and structures.
Publication Type	Non-archival or secondary sources such as book chapters, dissertations, patents, editorials, extended abstracts, or review articles are specifically excluded to prioritize primary research.
Duplicate Studies	Multiple publications by the same authors that cover the same body of work are excluded to avoid data redundancy.
Lack of Detail	Papers lacking sufficient methodological detail or results to contribute meaningfully to the review.

Studies addressing physical domains other than fatigue and fracture (e.g., plasma physics, fluid mechanics, climate modeling) were not admitted to the evidence cohort; they may be cited in this review only as methodological illustrations of the PIML formulations of Section 2.

3.4. Paper Selection Process

The selection of the included studies followed the six steps summarized in Figure 2 and detailed below. The per-record log of every decision—including reason for exclusion and version-pair adjudication—is maintained in the accompanying extraction sheet (Supplementary Materials).

Step 1—Identification. The search strategy identified 124 records through keyword-based queries combining the core PIML and PINN terminology with the expanded synonym families, complemented by forward citation searching, backward reference checking, and manual screening of key venues.

Step 2—Deduplication. After the removal of 4 duplicate or version records—adjudicated at study level, so that conference, journal, and archive versions of the same study are counted once—120 unique records remained.

Step 3—Title and abstract screening. The 120 unique records were screened against the inclusion and exclusion criteria (Tables 1 and 2). A total of 44 records were excluded at the title/abstract and full-text stages, with the reasons logged per record in the accompanying extraction sheet; the documented reasons include 4 review or secondary articles, 1 dissertation, 1 non-archival preprint, 1 non-archival report-type document, 3 studies outside the fatigue and fracture application scope, 1 record outside the engineering-applications scope, and 1 record excluded on language grounds (non-English publication).

Step 4—Full-text eligibility assessment. The 76 records that passed screening were assessed in full text against the eligibility criteria of Tables 1 and 2 and confirmed for inclusion in the review.

Step 5—Inclusion in the mapping. The 76 primary research articles were carried into the data extraction and mapping phase, in which study characteristics, bias coding, architectures, applications, and embedded physical laws were recorded.

Step 6—Logging, coding, and descriptive characterization. Every screening decision, version-pair consolidation, and coding assignment was logged per record (extraction sheet).

The multi-label bias coding of Section 3.6 was applied to the 60 distinct references appearing in Tables 7 and 8 (49 primary studies plus 11 of the 12 methodological anchors), while the descriptive characterization of Section 3.7 was applied to the full 76-study cohort.

3.5. Information Extraction and Charting

From each selected paper, critical information was systematically extracted and cataloged to facilitate comprehensive analysis. This approach ensures that the review process is comprehensive and replicable, following established guidelines for scoping literature reviews in engineering [53–55]. Table 3 details the information categories and the content extracted from each selected study.

Table 3. Extracted information.

Information Category	Description of Extracted Content
Bibliographic Details	Author(s), year of publication, journal or conference name, and the full title of the study.
PIML Methodology	The specific type of PIML model implemented, the method of incorporating physical laws (e.g., loss function vs. architecture), and any specialized techniques used.
Application Area	The specific engineering problem addressed, such as fatigue life prediction, crack propagation analysis, or structural damage detection.
System/Material	The type of material investigated (e.g., aluminum alloys, concrete, composites) or the specific structural system under study.
Key Contributions	Primary research findings, innovative methodological aspects, and quantifiable performance improvements achieved by the PIML model.
Observed Biases	Details on how the framework manages observational, inductive, and learning biases.
Limitations	Drawbacks, technical challenges, and proposed future research directions identified by the authors of each study.

By mapping this information thematically, the review identifies critical trends and common challenges in the field of structural integrity. This structured data extraction serves as the foundation for the subsequent Sections 4 and 5 of the document.

3.6. Coding of the Three-Bias Taxonomy

To operationalize the taxonomy introduced in Section 2.1 and ensure reproducible assignments, each of the 76 included studies was coded against the three bias categories [58]. Coding was performed on the full-text methodology sections, and each study could receive more than one label (multi-label coding), since frameworks frequently combine integration mechanisms. The following rules were applied:

1. **Observational bias (O)**—Physics enters at the data level, through physics-based generation or augmentation of training data (e.g., simulator-generated synthetic datasets), the selection and representation of physical measurements, and feature engineering grounded in known constitutive or empirical relationships.
2. **Inductive bias (I)**—Physics is hard-coded into the model architecture, for example, through specialized layers implementing physical operators, physics-informed activation functions, output transformations enforcing physical invariants (symmetry, conservation), or surrogate/hybrid architectures integrating discretization schemes.

3. **Learning bias (L)**—Physics steers the training process, through residual or physics-informed loss terms, physics-derived regularization, adaptive loss weighting, or meta-learning of training dynamics.
4. **Multi-label assignments**—All mechanisms explicitly described by the authors were recorded; a study implementing both physics-based data generation and a physics-informed loss received both O and L.
5. **Evidence rule**—A label was assigned only when the mechanism was explicitly described in the methodology; absence of an explicit mechanism was never inferred.
6. **Reliability**—Ambiguous cases were resolved through the consensus-based verification described in Section 3.7 (consistent with the registered protocol), and disagreements were documented. The resulting assignments are reported in Tables 7–9; the full per-study coding is provided in the accompanying extraction sheet.

3.7. Reporting Completeness and Descriptive Characterization

Consistent with scoping review methodology, no formal critical appraisal or risk-of-bias assessment was conducted on the included studies. In scoping reviews, assessment of the methodological quality or risk of bias of included studies is not a mandatory step and often does not occur, since scoping reviews are not designed to underpin practice decisions in the way synthesis for decision-making is [50]. The updated JBI guidance likewise recommends against critical appraisal in scoping reviews, as the aim is to map the available evidence rather than to provide a synthesized and clinically meaningful answer to a question [59]. Quality assessment is also uncommon in practice—a methodological review found that only 22% of scoping reviews reported one [60]—and scoping review protocols do not include a quality assessment step [61]. Accordingly, admission of the 76 primary research articles to the cohort was based exclusively on the eligibility criteria of Section 3.3, and no study was excluded, weighted, or ranked on quality grounds.

The methodology literature nonetheless recognizes the challenges of assessing methodological quality across the vast range of published and grey literature typically charted in scoping studies [49]. In light of this, instead of appraisal, the reporting transparency and methodological completeness of the included studies were characterized descriptively. Each paper was examined against three descriptive indicators:

1. **Clarity of Physical Integration:** Whether the underlying physical laws—such as the Paris Law, Basquin’s formula, or specific partial differential equations—were explicitly defined and mathematically integrated into the machine learning framework. Studies that lacked a clear definition of the governing equations were flagged during the screening phase (Section 3.3).
2. **Transparency of ML Architectures:** The degree of disclosure of neural network hyperparameters, optimization strategies (e.g., Adam, L-BFGS), and the specific architecture used (e.g., standard PINNs, PIKANs, or IFENN), with sufficient detail for methodological replicability [54].
3. **Validation and Physical Consistency:** The use of robust validation procedures, such as experimental test sets or k-fold cross-validation, and the performance of physical consistency checks verifying that model predictions adhere to fundamental mechanical constraints, such as non-negative crack growth or thermodynamic limits.

This descriptive characterization informed the narrative analysis of Sections 4 and 5 and supported the multi-label bias coding of Section 3.6; it did not serve to exclude or rank any study admitted to the cohort. Any ambiguities regarding the categorization of a study (particularly within the three-bias taxonomy) were resolved through a consensus-based verification process involving internal technical discussions among the research team to mitigate individual reviewer bias.

4. Literature Review

This section presents a comprehensive review that begins by outlining the bibliometric results of the systematic search described in Section 3, whose 76 included primary studies form the evidence base of this work. It then provides an in-depth analysis of the selected papers, categorizing them by the types of biases they address, the specific architectures employed, and the foundational theoretical models they incorporate.

4.1. Application of Methodology and Bibliometric Overview

Based on the systematic search strategy of Section 3.2, updated to August 2026, 124 records were retrieved. After applying the inclusion and exclusion criteria of Section 3.3—which comprised the removal of 4 duplicate or version records and the exclusion of 44 records at the title/abstract and full-text stages—a final set of 76 primary research articles was deemed relevant for in-depth analysis. In total, 48 records were excluded before analysis. The documented exclusion reasons include review or secondary articles [62–65], a dissertation [66], a non-archival preprint [67], a non-archival report-type document [68], applications outside the fatigue/fracture scope [69–71], a record outside the engineering-applications scope [72], and a record excluded on language grounds [73]. The complete per-record exclusion log is provided in the accompanying extraction sheet.

The broader context deserves emphasis: neural-network modeling of fatigue is not new. A comprehensive survey published in 2022 already cataloged 251 publications between 1990 and July 2021 across five application classes—fatigue life prediction, fatigue crack, fatigue damage diagnosis, fatigue strength, and fatigue load [74]. What is recent is the physics-informed subset, which this review deliberately restricts to publications from 2018 onwards, the year the modern PINN framework was established [15]. The growth of this subset mirrors the trajectory of physics-informed learning at large: in the Web of Science alone, PINN publications in the mechanics and materials science category grew from 3 papers in 2019 to 65 in 2022 [75], and the field has since been characterized by dedicated bibliometric and scientometric analyses [76,77].

Figure 3 presents the publication trend of the 76 included studies between 2018 and August 2026 as a combined bar-and-line chart: the bars give the number of included studies published in each year, and the overlaid line tracks the cumulative count, which reaches 76 at the search cutoff. The per-year values are drawn directly from the study register in the accompanying extraction sheet, so the chart reflects exactly the cohort of this review. Because the literature search was concluded in August 2026, the 2026 bar is marked as a partial year, and the cutoff is indicated by a vertical marker; the 2026 count will likely evolve as the full publication cycle completes. The field is relatively young and in expansion: while earlier work focused on basic PINN implementations, the latest research demonstrates a shift toward specialized neural architectures, such as sequential attention models for fatigue crack growth [78] and physics-informed residual networks for multiaxial loading [79].

Regarding the top cited works, represented by Table 4, the collaboration between Shun-Peng Zhu and Lanyi Wang on defect-driven frameworks and state-of-the-art reviews that bridge the gap between traditional mechanics and deep learning represents the most-cited entry in the field, with 172 summed citations [3,47]. Other significant contributions include the uncertainty-aware probabilistic models developed by Haijie Wang [2,80] and the physics-based fracture mechanics architectures pioneered by Aldakheel and Baktheer [81]. Recent efforts by Zhiying Chen [20] and Ehsan Akbari [82] further expand the application of PIML to complex crack propagation and multiaxial fatigue scenarios.

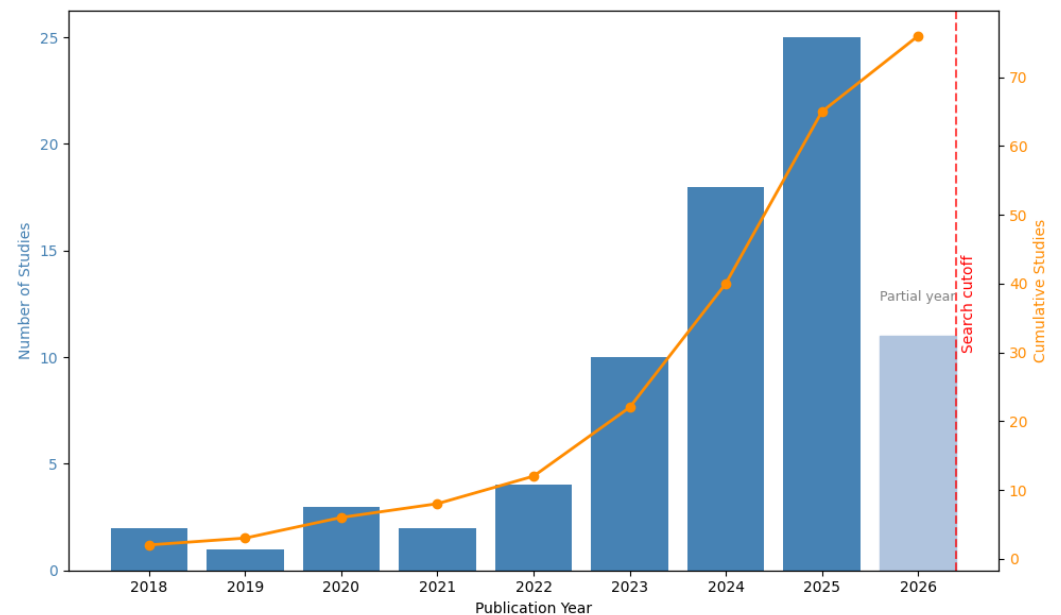


Figure 3. Annual publication trend of the 76 included studies.

Table 4. Top 5 cited research entries in PIML for fatigue and fracture (as of August 2026, Google Scholar).

Rank	Primary Research Entry	Summed Citations	Included Papers
1	Zhu, S.-P./Wang, L.	172	“Physics-informed ML and its structural integrity applications: state of the art” [47] (143 citations); “Defect driven PINN framework for fatigue life prediction” [3] (29 citations).
2	Haijie Wang	36	“Uncertainty-aware fatigue-life prediction of Hastelloy X” [2] (35 citations); “Multi-physics information-integrated neural network” [80] (1 citation).
3	Aldakheel, F./Baktheer, A.	31	“Physics-based ML for computational fracture mechanics” [1] (19 citations); “Physics-based machine learning for fatigue lifetime prediction” [81] (12 citations).
4	Zhiying Chen	22	“Crack propagation simulation and overload fatigue life prediction via enhanced PINNs” [20] (22 citations).
5	Ehsan Akbari	18	“Physics-Informed Neural Networks for Multiaxial Fatigue Life Prediction of Aluminum Alloy” [82] (18 citations).

Figure 4 maps the relationship between bias type and application domain as a heatmap built from the multi-label coding of Section 3.6. The rows correspond to the seven coding categories of Table 8—observational (O), learning (L), and inductive (I) bias and their combinations (I+L, I+O, L+O, I+L+O)—and the columns correspond to the seven application domains of Table 9: fatigue crack growth, multiaxial fatigue, extreme environments, geometric complexity, computational speed, diverse materials, and structural health monitoring and prognostics. Each cell reports the number of coded studies in that bias $\times$ domain combination, with shading intensity proportional to the count. Since frameworks frequently address more than one domain, a study may contribute to more than one column, and row and column totals therefore need not sum to 76. Read across the

rows, the figure confirms that applications decrease in number as the complexity of bias implementation increases—from observational bias, which primarily operates at the data level; to learning bias, which modifies the loss function and the training dynamics; and to the most demanding inductive bias, which restructures the internals of the model.



Figure 4. Distribution of the 76 included studies across bias categories and application domains. Studies addressing more than one domain contribute to more than one column; row and column totals therefore need not sum to 76.

The bibliometric landscape from 2018 to 2026 reveals a maturing field that has transitioned from foundational neural network approximations to more coupled, specialized frameworks for structural integrity such as the ones proposed by [18,83]. A significant thematic shift has emerged in the most recent literature (2025–2026), moving away from deterministic point estimates toward uncertainty quantification and the development of sequential attention mechanisms to capture the temporal complexities of crack growth [78,84]. Furthermore, as illustrated in the relationship between bias type and application domain, there is a notable decrease in the number of studies as implementation complexity increases. While observational and learning strategies—such as custom loss functions—are increasingly mature [81], the structural modification of neural networks to embed physical laws (inductive bias) remains an active and challenging research frontier [1,79]. This quantitative overview of the literature’s evolution and its key contributors provides the necessary foundation for the subsequent qualitative analysis of how these frameworks explicitly manage physical biases across diverse engineering domains.

4.2. Analysis of the Selected Literature

This part of the review examines the selected papers, focusing on the specific approaches taken to integrate physics into machine learning models for fatigue and fracture. It also categorizes the literature by how different PIML frameworks address inherent biases and the architectural diversity employed to achieve their objectives.

Physics-Informed Machine Learning frameworks effectively address inherent biases in scientific modeling, enabling robust predictions in data-scarce domains like fatigue and fracture. As introduced in the preceding section, we adopt the established PIML taxonomy of three distinct biases: observational, inductive, and learning [34,35]. While these

concepts apply broadly to both general machine learning and neural network algorithms, the specific methods of integration can vary. The search strategy deliberately broadened the terminology families (physics-guided, physics-based, physics-encoded, theory-guided, knowledge-guided, and hybrid physics–data) to capture studies that integrate physical knowledge into learning models regardless of the terminology adopted. Across the 76 included studies, the literature demonstrates strategies for embedding prior knowledge and addressing these biases, with different architectural choices and loss function formulations guiding model behavior and influencing predictive accuracies across diverse loading conditions and material properties [81].

4.2.1. Observational Bias

Observational bias in Physics-Informed Machine Learning arises from the challenges inherent in acquiring comprehensive, high-quality datasets—a pervasive issue in fatigue and fracture experimentation due to the high costs and time demands of testing [7,9,35]. PIML effectively mitigates these limitations by leveraging physical constraints to enable models to learn and generalize more robustly from sparse, noisy, or limited data [24,35]. Earlier strategies focused on embedding physical mechanisms through customized loss functions to improve fatigue damage prediction [85] or utilizing feedforward neural networks to incorporate constraints from experimental evidence in non-uniform loading scenarios [81]. In the domain of additive manufacturing, defect-driven PINNs have enhanced generalization by embedding critical defect information into their loss functions to address small sample conditions [2,3]. Furthermore, observational bias is managed in fracture mechanics by utilizing ϕ ML frameworks that generate physics-based synthetic datasets from simulations to supplement or replace extensive experimental campaigns [1,81].

This data-level strategy spans both component and microstructure scales. Simulation-generated training data now support graph neural networks that reproduce crack coalescence and propagation from XFEM-generated datasets [86], three-dimensional FEA-based surrogates for damage-tolerant fatigue crack growth life assessment [87], and neural networks trained on ensembles of finite-element and Monte Carlo life predictions for real-time crack propagation under uncertainty [88]. At the microstructure level, Bayesian networks trained on multimodal crystal-plasticity simulations and in-situ 4D experiments predict the growth rate of small cracks [89], while machine learning frameworks built on crystal-plasticity-based micromechanical features track microstructure-sensitive crack paths in 3D [90]. A physics-guided GNN-transformer extends this data-level strategy to concrete structures, integrating microstructure topology and random load spectra for multi-scale fatigue life prediction of railway track slabs [91], and a PINN for crack growth in welded joints of orthotropic steel decks complements limited field data with simulation-augmented training samples and self-updating crack parameters [92].

Recent studies have expanded these capabilities, particularly through the use of sequential attention mechanisms that handle the temporal nature of fatigue crack growth. These frameworks allow models to prioritize critical observational sequences, effectively managing the bias introduced by time-dependent damage accumulation [78]. Similarly, interleaved deep learning approaches facilitate “cycle jumping” in simulations of microstructurally small fatigue cracks, significantly reducing the density of temporal data required for accurate prognosis [93]. For extreme environments, such as nuclear applications, specialized PINNs now integrate sparse experimental data from irradiated materials with governing physical laws to predict low-cycle fatigue with higher fidelity [94]. Hybrid models have also evolved to supplement limited experimental data with energy-based physical models, particularly for materials like concrete [95].

Managing experimental noise and statistical variability remains a central theme, with techniques like dimensionality reduction, path-slicing, and re-weighting employed to capture rare events in digital-twin scenarios [96]. Recent frameworks combine probabilistic neural networks with physics-informed features—such as those derived from the Basquin model—to provide robust uncertainty quantification [84,97]. These models utilize negative log-likelihood loss functions to better represent scatter and account for “run-out” data points typically discarded in purely data-driven methods [78,84]. Additionally, observational bias in complex multiaxial loading is addressed by incorporating non-proportionality measurements directly as observational inputs into residual networks [79,82]. Novel architectures like Finite-Pinn, which utilizes finite geometric encoding, maintain high fidelity to the physical domain even when trained on sparse point-cloud data from experimental measurements [98]. Finally, some recent models move toward the data-driven discovery of partial differential equations, using observed crack propagation to identify governing equations where analytical models are incomplete or unknown [99,100]. Figure 5 represents the implementation of the observational bias in the context of fatigue and fracture.

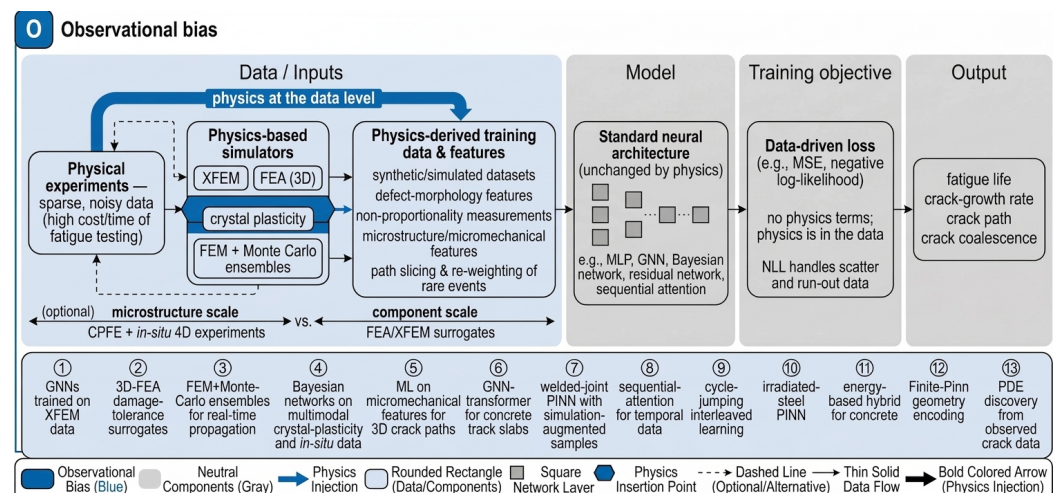


Figure 5. Implementation of PIML under observational bias (L generic): physics enters at the data level through simulator-generated training sets (XFEM/FE/CPFE) and physics-derived features, supplementing sparse experimental data.

4.2.2. Learning Bias

Learning bias in Physics-Informed Machine Learning is primarily characterized by the inclusion of physical constraints within the model’s objective function, effectively penalizing solutions that deviate from governing physical laws [25,34,35]. This strategy allows for a relatively generic architecture while ensuring the resulting model adheres to fundamental scientific principles without explicitly encoding laws into the internal structure [34]. In the context of fatigue analysis, this bias is frequently introduced by embedding empirical or phenomenological laws into the loss function, such as the Basquin formula for life prediction in irradiated steels [94] and other metal alloys [84]. Similarly, the Geometric Multiaxial Fatigue Life method has been integrated into PINN loss functions to improve predictions for aluminum alloys under complex loading [82]. Other researchers have successfully embedded the cyclic cohesive zone model and specialized crack growth rate models within the loss terms of enhanced PINNs to simulate crack propagation and overload fatigue behavior [20,101].

The loss-level strategy is also reinforced by physics-guided and physics-based variants outside the PINN label. A novel physics-guided neural network embeds fatigue physics into the objective while predicting fatigue-relevant parameters rather than loads, which al-

lows extrapolation beyond the trained load regimes [102]. A defect-based physics-informed framework constrains the training procedure with fracture-mechanics information on defect morphology, improving fatigue-finite-life prediction for additively manufactured components [103]. A probabilistic physics-guided prognostic calibrates Paris Law-based crack-growth models through optimization and explicit uncertainty quantification, with reported accuracy gains of approximately 15–20% when combined with weighting and pre-processing strategies [104]. The welded-joint PINN mentioned in Section 4.2.1 likewise relies on a physics-consistent composite loss with self-updating crack parameters [92].

Recent advancements in late 2025 and 2026 have refined these learning mechanisms by integrating more complex physical priors and hybrid models. For instance, energy-based fatigue models are now incorporated into the objective functions of hybrid PIML frameworks to accurately predict the fatigue life of concrete [95]. In fracture mechanics, learning bias is heavily leveraged through the minimization of energy functionals, a technique central to the Deep Ritz method for phase-field modeling of brittle fracture [105]. This approach is complemented by gradient-free PINN formulations that rely on continuum fracture mechanics principles integrated directly into the loss function [106]. Furthermore, Bayesian frameworks integrate established physical curves, such as El Haddad's, as prior knowledge within the loss to ensure physically consistent probabilistic predictions of fatigue endurance limits [107]. Physics-based machine learning for high-strength concrete embeds the physical constraints as loss terms and trains on continuum-damage simulations [108], while coupled feedforward networks for cyclic damage evolution enforce thermodynamics-consistent objectives directly through energy dissipation and irreversibility terms [109]. Even safety-factor estimation has been reformulated with mathematically modeled physics inside the objective, producing physically feasible predictions outside the training range [110].

The landscape of learning bias has also expanded to include nonlocal mechanics and equation discovery. Peridynamic-informed neural networks explicitly enforce peridynamic governing equations within their loss functions to capture brittle damage without the need for traditional spatial discretization [111]. Innovative methodologies now combine physical deep symbolic regression with deep learning to discover iterative crack tip correction algorithms that respect physical unit constraints [112]. Moreover, the discovery of governing partial differential equations directly from data allows the use of “discovered” equations as regularization terms, which has been shown to improve generalization even when analytical models are initially incomplete or unknown [100]. Further diverse applications include utilizing structure-preserving formulations that ensure thermodynamic conservation in multi-physics simulations by modifying optimization objectives [32]. Transfer-learned Kolosov–Muskhelishvili-informed networks further couple the objective and the architecture, satisfying the governing elastic fields during training while learning crack-propagation criteria across tasks [113].

Complementing these objective-level integrations, recent training-side developments have introduced more sophisticated optimization and adaptation techniques to address the inherent difficulties of PINN training. Adaptive weighting schemes, for example, employ annealing coefficients or neural tangent kernel-guided strategies to balance competing loss terms (L_{data} , L_{phys} , L_{bc}); neural tangent kernel-guided weighting has been reported to substantially accelerate convergence [18], and adaptive weighting remains an active area of methodological development [114]. In multiaxial fatigue, meta-learning frameworks have been applied to quantify weight corrections for non-proportional loading effects within residual connections, as exemplified by physics-informed residual networks with meta-learning [79]. Figure 6 represents the implementation of the learning bias in the context of fatigue and fracture.

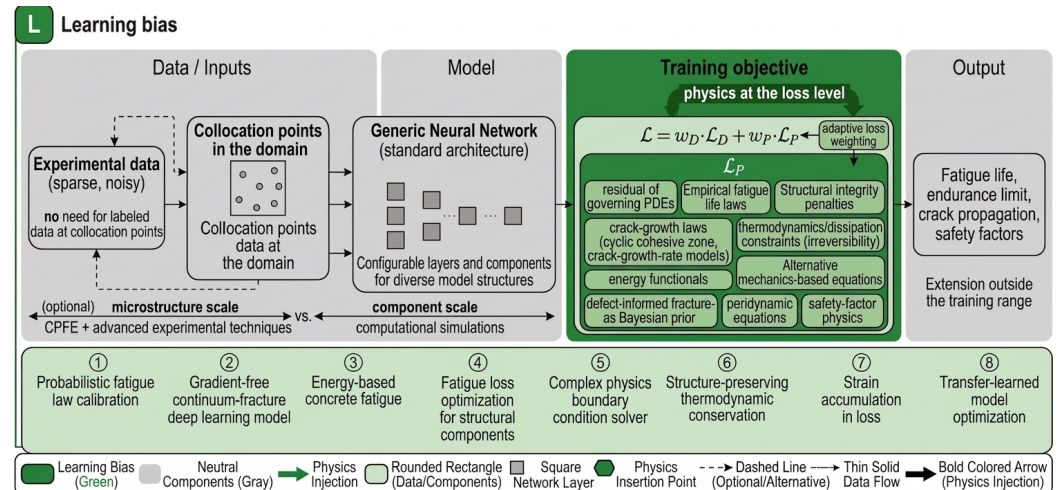


Figure 6. Implementation of PIML under learning bias: physics enters at the training-objective level through the weighted physics-informed loss $L = w_D L_D + w_P L_P$, enforcing governing laws, empirical fatigue laws, and discovered equations.

4.2.3. Inductive Bias

Inductive bias in Physics-Informed Machine Learning involves structural modifications to the model, such as tailoring its architecture and activation functions to intrinsically represent physical operations [36]. This approach fundamentally alters how information is processed, leading to potentially faster convergence, improved training stability, and greater interpretability [35,40,115]. Foundational strategies include ϕ ML Feedforward Networks that embed continuum mechanics and constitutive laws directly into their architecture to ensure thermodynamic consistency in modeling both brittle and ductile fractures [1]. Multi-physics Information-Integrated Neural Networks further this by embedding damage mechanics models and fatigue limits into activation functions, enhancing the transparency of the decision-making process [80]. Similarly, mechanics-informed autoencoders and probabilistic PINNs modify internal representations to capture structural damage characteristics and physical heteroskedasticity [2,116]. Residual-based connections, as seen in PIResANN, simplify the learning task by focusing on the deviation from a known physical approximation, thereby improving assessment accuracy for complex assets [79,117].

Structurally encoded physics is likewise present in recurrent and layered hybrids. Physics-informed recurrent cells have been embedded in cumulative damage models for fleet-level fatigue crack growth, where the physics participates in the network dynamics rather than only in the training objective [118]. A related hybrid architecture pairs physics-informed layers with data-driven bias layers to estimate missing physics in cumulative damage models—demonstrated for corrosion fatigue [119]. In prognostics and health management, a physics-informed neural network for wind turbine main bearing fatigue combines an L10-based physics-informed layer with a data-driven layer that models grease degradation [120]. Transfer-learned Kolosov–Muskhelishvili networks push the same principle further, guaranteeing that the governing equations are satisfied by construction of the architecture and reducing training effort by more than 70% through transferred crack-propagation criteria [113].

Furthermore, the integration of transfer learning and surrogate schemes, such as the Integrated Finite Element Neural Network, has been reported to substantially reduce training times by leveraging spatial coupling information to generalize across unseen loading paths and diverse geometries [121,122]. These advancements are often supported by physics-informed transfer learning via feature selection, which leverages data across populations of similar structures to overcome the lack of labeled data in new monitoring

domains [123]. Additionally, physical deep symbolic regression and the discovery of governing equations through PDE-based networks continue to guide the development of physically-informed architectures, ensuring that learned algorithms respect unit constraints and consistency [99,100,112]. Figure 7 represents the implementation of the inductive bias in the context of fatigue and fracture.

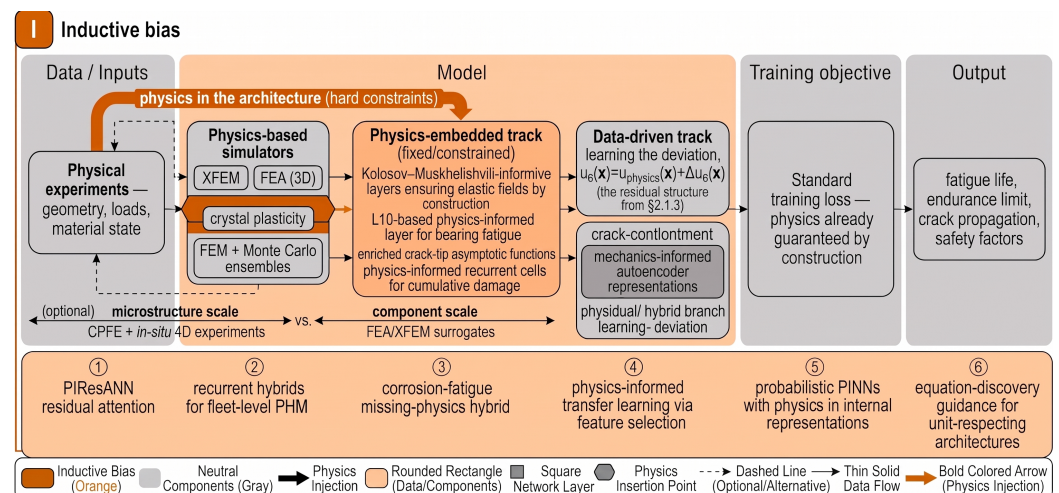


Figure 7. Implementation of PIML under inductive bias: physics is embedded directly into the network architecture via specialized physics layers, physics-informed activation functions, and residual hybrid structures, guaranteeing physical consistency by construction.

4.2.4. Architectural Diversity

The architectural choices for PIML models are highly diverse, specifically tailored to the characteristics of the fatigue and fracture problems addressed and the complexity of the physical laws integrated into the learning process.

Standard Physics-Informed Neural Networks remain the foundational architecture in the literature. These models typically utilize multi-layer perceptrons augmented with custom loss functions that penalize violations of governing equations [15]. Recent applications include predicting the low-cycle fatigue life of irradiated nuclear steels [94] and modeling brittle fracture without the need for traditional gradient damage formulations [106]. Additionally, standard PINNs have been effectively deployed for structural health monitoring of Kirchhoff–Love plates, where the network directly enforces boundary conditions and plate-bending PDEs within the loss function [124], and for fatigue crack growth in welded joints of orthotropic steel decks, where self-updating crack parameters are integrated during training [92].

Specialized PINN Variants. Beyond the standard architectures, specialized PINN variants have emerged that incorporate nuanced physical understanding directly into their structure to enhance predictive capabilities and interpretability. Table 5 categorizes the specialized PINN variants identified in the reviewed literature and their reported usage, now covering the 76-study cohort.

This architectural diversity reflects a strategic shift from generic neural networks toward designs that are intrinsically linked to the underlying physics of the problem, ensuring both computational efficiency and physical consistency.

Other Machine Learning Models with Physics Integration. Beyond explicit PINN structures, physical knowledge is increasingly integrated into other machine learning frameworks. This classification distinguishes broader machine learning frameworks and hybrid approaches from the specific neural network variants previously discussed, highlighting their unique roles in maintaining physical consistency and computational efficiency.

Table 6 presents the alternative machine learning frameworks, distinct from explicit PINN structures, that integrate physics into modeling.

Table 5. Specialized PINN variants and their usage.

Specialized PINN Variant	Usage
Sequential and Attention-Based PINNs	Capturing the temporal evolution of damage and prioritizing critical observational sequences to improve fatigue crack growth prognosis [78].
Physics-Informed Kolmogorov–Arnold Networks	Replacing fixed activation functions with learnable spline-based functions to enhance both predictive accuracy and interpretability [17].
Defect-Driven PINNs	Explicitly embedding geometric defect features into the loss function to account for the high scatter observed in additively manufactured materials, with fracture-mechanics defect information [3,4,103].
Enriched and Equation-Informed PINNs	Incorporating crack-tip asymptotic functions or analytic fields into the displacement representation to compute Stress Intensity Factors accurately without dense mesh refinement, including transfer-learned Kolosov–Muskhelishvili potentials [113,125].
Multiaxial and Residual Architectures	Integrating criteria like Geometric Multiaxial Fatigue Life and pairing residual networks with meta-learning to handle non-proportional loading [79,82].
Geometry-Aware Models	Utilizing finite geometric encoding and NURBS-based representations to ensure physical fidelity on complex solid mechanics domains [29,98].
Graph Neural Networks and Transformers	Simulating multi-crack coalescence and propagation from XFEM-generated data, with reported 6–25× speed-ups over XFEM, and multi-scale fatigue life prediction of concrete track slabs via a physics-guided GNN-transformer [86,91].
Equation-Discovery & Symbolic Regression	Discovering governing PDEs directly from data or identifying iterative crack tip correction algorithms that respect physical unit constraints [99,100,112].
ϕ ML & Feedforward Architectures	Integrating continuum mechanics and constitutive laws directly into the network structure to ensure thermodynamic consistency in fracture modeling, extended to high-strength concrete fatigue and cyclic damage evolution [1,81,108,109].
Probabilistic and Bayesian Variants	Integrating Bayesian methods and probabilistic layers to quantify uncertainty, heteroskedasticity, and fatigue life scatter, including Bayesian networks on multimodal experimental–simulation data [2,84,89,104,107].
Physics-Guided Networks (non-PINN)	Embedding fatigue physics in the objective to predict fatigue-relevant parameters, enabling extrapolation beyond trained load regimes [102].
Interleaved and Hybrid Frameworks	Facilitating “cycle jumping” for microstructurally small cracks or combining data-driven layers with physics-based models for grease degradation, corrosion fatigue, and energy-based concrete life prediction [93,95,118–120,126].
Energy-Minimization Models	Solving fracture PDEs by leveraging variational principles to minimize energy functionals [105].

In summary, the evolution of PIML architectures in the domains of fatigue and fracture reflects a decisive shift from generic neural networks toward designs that are intrinsically linked to the underlying physics of the problem. By transitioning from foundational multi-layer perceptrons to specialized architectures—such as sequential attention models for temporal damage accumulation, geometry-aware Finite-PINNs, spline-based PIKANs,

and graph-based or recurrent physics-embedded hybrids—researchers are effectively overcoming the constraints of earlier frameworks. These architectural innovations do not merely improve predictive accuracy for complex phenomena like multiaxial loading and irradiated material behavior; they also ensure that the resulting models are computationally efficient and physically consistent. Ultimately, the increasing diversity and specialization of these architectures underscore a move toward more robust and interpretable prognosis in real-world engineering environments.

Table 6. Alternative ML frameworks and their usage.

ML Framework	Usage
ϕ ML and Feedforward Networks	Integrating continuum mechanics and constitutive laws directly into neural architectures to ensure thermodynamic consistency when modeling brittle and ductile fractures, extended to high-strength concrete and cyclic damage evolution [1,81,108,109].
Interleaved Physics-Based Deep Learning	Utilizing surrogate models as a “cycle jumping” approach to accelerate microstructurally small fatigue crack growth simulations [93].
Hybrid Frameworks	Combining data-driven layers with physics-based models for specialized applications like bearing grease degradation, missing-physics estimation in corrosion fatigue, fleet-level cumulative damage, and energy-based life prediction for concrete [95,118–120,126].
Deep Ritz Method	Solving fracture PDEs by leveraging variational principles to minimize energy functionals during phase-field modeling [105].
Mechanics-Informed Autoencoders	Enabling the automated detection and localization of unforeseen structural damage by learning refined physical representations [116].
Simulation-Trained Surrogates and Statistical Learners	Training on physics-generated data: FEA-based damage-tolerance surrogates, neural networks on FEM-plus-Monte Carlo life ensembles, Bayesian networks on crystal-plasticity and in-situ 4D data, and ML frameworks on micromechanical features for crack-path prediction [87–90].
Physical Deep Symbolic Regression	Discovering governing equations or identifying iterative crack tip correction algorithms that intrinsically respect physical unit constraints [99,100,112].

4.3. Summary of Key Findings

The comprehensive analysis of the 76 included studies reveals a transition from generic data-driven surrogates to specialized physics-embedded frameworks. Modern PIML models effectively address the challenges of sparse and noisy experimental data, which are common in fatigue and fracture studies, by leveraging physical constraints to guide the optimization process and improve generalization [7,9,35]. Recent developments highlight a trend toward architectural innovation, where standard multi-layer perceptrons are being replaced by designs that intrinsically capture the temporal evolution of damage [78,85], handle geometric complexities without dense meshing [98], and quantify the inherent statistical scatter in material behavior [2,84,107]. Across the cohort, the multi-label coding of Section 3.6 confirms that frameworks frequently combine integration mechanisms—in 14 of the 60 coded references, two or more bias mechanisms are combined. Table 7 maps the integration strategies identified across the reviewed studies, the physical laws embedded, and the corresponding model architectures.

Table 7. Mapping of integration strategies and methodologies.

Integration Strategy	Physical Law/Prior Embedded	ML Model/Architecture	Key References
Learning Bias (n = 26)	PDEs, Boundary Conditions, Energy Functionals, Fracture Mechanics Laws, Meta-Learning, Adaptive Loss Weighting	PINNs, PIKANs, Deep Ritz Method, Peridynamic-Informed NNs, Physics-Guided NNs, Bayesian PINNs	[15,17,20,25,32,34,35,82,84,92,94,95,100–113]
Inductive Bias (n = 22)	Continuum Mechanics, Constitutive Laws, Thermodynamic Consistency, L10-Based and Kolosov–Muskhelishvili Physics Layers, Architecture-Encoded Units	ϕ ML, IFENN, Mechanics-Informed Autoencoders, Residual-based Attention, Physics-Informed RNN Cells, Physics-Encoded Layers	[1,2,18,35,79–81,99,100,112–123,127]
Observational Bias (n = 28)	Experimental Data, Simulator-Generated Data (XFEM/FEM/CPFE), Multiaxiality/Non-proportionality, Sequential Observations, Microstructural Features	Residual NNs, Sequential Attention PINNs, GNNs, Hybrid Models, Bayesian Networks, Symbolic Regression, Surrogates	[1–3,7,9,35,78,79,81,82,84–100,128]

Regarding the compilation in Table 7, it is important to note the following about the background and methodological sources. The reference list distinguishes between three classes of sources. First, the 76 primary research articles form the evidence cohort of this review and are the exclusive basis for the counts, trends, and conclusions reported in Sections 4 and 5. Second, 12 methodological anchors—the taxonomy sources and foundational physics-informed methods and review works (e.g., the introduction of the PINN formulation [15], the Physics-Informed Machine Learning surveys, and the three-bias taxonomy papers)—are cited in Table 7 to anchor the classification rather than as coded evidence; they are identified in Section 4.3 and excluded from the coding counts (60 coded references = 48 primary studies + 12 anchors). Third, additional background sources—general PINN and PIML surveys, bibliometric and scientometric analyses, and methodological papers on training stability, hyperparameter sensitivity, and calibration—are cited for context and definitions (e.g., the PINN foundations, the PIML survey literature, the bibliometric analyses, and the technical studies supporting the disadvantages discussion). Consistent with the screening criteria, review and secondary articles identified during selection were not admitted as primary studies, and none of the anchor or background sources are counted in the 76-study cohort. This separation ensures that every quantitative claim in the analysis traces exclusively to primary evidence.

Table 8 reports the coding categories that result from the reference lists of Table 7. The counts were obtained by set arithmetic applied to the three strategy rows: the Learning Bias row lists 26 references, the Inductive Bias row 22, and the Observational Bias row 28, producing 76 individual row entries across 60 distinct references. Because frameworks frequently combine integration mechanisms, references appearing in more than one row are counted in more than one category, in accordance with the multi-label coding rule (Section 3.6).

Twelve of the references—[7,15,17,18,25,34,35,114,115,127,128]; ref. [27]—are methodological anchors: the taxonomy sources and foundational PINN/PIML methods and review works. They are cited in Table 7 to anchor the taxonomy rather than as coded evidence; ref. [35], for instance, is a taxonomy-anchor review cited in all three rows of Table 7 and is not treated as a primary study. Removing the 12 anchors leaves 48 distinct references corresponding to primary studies coded in at least one bias category, confirming that the expanded terminology families (physics-guided, physics-based, physics-encoded, theory-guided, knowledge-guided, and hybrid physics–data) map onto the same bias taxonomy rather than introducing new categories. The remainder of the 76-study cohort (28 studies)

is not coded in Tables 7 and 8 because it appears only in the architectural and application tables (e.g., [4,29,124,125,129]). One additional record ([73]) was excluded during screening because its full text is not in English and is therefore not part of the cohort (see Sections 3.3 and 4.1).

Table 8. Multi-label distribution of the three-bias coding.

Coding Category	Mechanism	References	n
Learning bias only (L)	Physics in the training objective only	[15,17,20,25,32,34,101–111]	17
Inductive bias only (I)	Physics in the architecture only	[18,80,114–123,127]	13
Observational bias only (O)	Physics at the data level only	[3,7,9,78,85–91,93,96–98,128]	16
Inductive + Learning (I+L)	Architecture and training objective	[112,113]	2
Inductive + Observational (I+O)	Architecture and data level	[1,2,79,81,99]	5
Learning + Observational (L+O)	Training objective and data level	[82,84,92,94,95]	5
Inductive + Learning + Observational (I+L+O)	Architecture, training objective, and data level	[35,100]	2
Total	—	60 distinct references (76 row entries)	60

Table 9 summarizes the key application domains addressed in the literature and the associated research contributions. The ability to discover governing equations directly from crack-propagation data [100] and reduce training times via spatial coupling information in architectures like IFENN [122] addresses traditional bottlenecks in computational mechanics. As the field integrates more advanced architectures such as Physics-Informed Kolmogorov–Arnold Networks [17], robust sequential attention frameworks [78], and simulation-trained graph and surrogate models [86,88], these tools are expected to provide better levels of reliability and physical transparency in structural integrity assessments.

Table 9. Key applications and associated research contributions.

Application Domain	Key Objective	Performance Gain/Innovation	Key References
Fatigue Crack Growth	Life prognosis, damage accumulation, and crack-path prediction	Temporal attention prognosis, symbolic crack-tip correction, self-updating crack parameters, simulation-trained surrogates, probabilistic calibration, microstructure-resolved crack paths, multi-crack coalescence	[20,78,81,85–90,92,93,96,99,100,104,112,118,119,125]
Multiaxial Fatigue	Loading under complex stress states	Management of non-proportional loading mechanisms	[42,79,82,101]
Extreme Environments	Irradiated nuclear reactor materials	Reliable prediction with limited, high-cost data	[94]
Geometric Complexity	Solid mechanics on general domains	Mesh-independent and geometry-aware encoding, transfer-learned crack-tip fields	[29,98,113,121,122,125]
Computational Speed	Accelerated simulations and real-time monitoring	Cycle-jumping, transfer-learning surrogates, 6–25× speed-ups over XFEM, >70% training-time reductions	[86,93,113,117,121,122]

Table 9. Cont.

Application Domain	Key Objective	Performance Gain/Innovation	Key References
Diverse Materials	Additive manufacturing, concrete, composites	Defect handling, energy-based models, safety-factor criteria, cyclic damage evolution, heteroskedasticity	[1–4,7,33,81,91,95,103,105,107–111]
Structural Health Monitoring and Prognostics	Damage localization, asset and fleet management	Physics-informed feature selection, mechanics-informed autoencoders, L10-informed bearing layers, fleet-level cumulative damage	[78,84,97,116–121,123,124]

In summary, the descriptive analysis of the 76-study cohort confirms three converging findings. First, the field has matured from proof-of-concept PINNs toward architectures that are intrinsically coupled to the underlying physics—sequential attention for temporal damage accumulation, geometry-aware encodings for complex domains, graph and recurrent hybrids for multi-crack and fleet-level problems, and equation-discovery frameworks where analytical models are incomplete [78,86,98,100,118]. Second, uncertainty quantification has become a defining feature of the most recent literature, with probabilistic and Bayesian formulations capturing fatigue-life scatter, heteroskedasticity, and prediction confidence rather than deterministic point estimates [2,84,104,107]. Third, the bias taxonomy remains a reliable organizing principle: observational strategies dominate because simulation-generated data are the most accessible form of physics integration, learning strategies are now well established through loss-level constraints, and inductive strategies remain the most demanding yet fastest-growing frontier [1,81,113]. The full per-study characteristics and coding that support these tables are provided in the accompanying extraction sheet, consistent with the registered protocol.

5. Results and Discussion

The scoping review of the 76-study cohort reveals a sophisticated and rapidly expanding research landscape that bridges the gap between classical fracture mechanics and deep learning. Since the foundational resurgence of physics-informed methods in 2018, the field has accelerated, extending into August 2026, transitioning from basic neural network approximations of physical fields to deeply coupled frameworks that solve complex, multi-physics structural integrity problems [18,21,83]. The expanded search confirmed that the terminology families surrounding the field—“physics-guided,” “physics-based,” “physics-encoded,” and “theory-guided” approaches—map onto the same three-bias taxonomy rather than defining separate categories, which strengthens the validity of the mapping [26,130].

5.1. Trends and Valuable Findings

Bibliometric and qualitative analyses indicate that PIML has moved beyond the proof-of-concept stage to become a robust methodology for addressing the chronic data scarcity and high experimental costs associated with fatigue testing [18,47,83]. This growth mirrors the broader trajectory of physics-informed learning, which expanded in the mechanics and materials science category of the Web of Science from 3 papers in 2019 to 65 in 2022 [75] and has since been characterized by dedicated bibliometric and scientometric analyses [76,77]. A prominent trend in the most recent literature is the departure from standard Multi-Layer Perceptrons toward specialized architectures such as Physics-Informed Kolmogorov–Arnold Networks, which utilize learnable spline-based functions to solve the partial differential equations of fracture mechanics [17]. Furthermore, there is a clear shift toward Probabilistic Physics-Informed Learning, where the focus has moved from deterministic point estimates to comprehensive Uncertainty Quantification [84,127], exemplified

by sequential attention models that not only predict fatigue crack growth but also quantify the confidence intervals of those predictions, a critical requirement for safety-sensitive aerospace and nuclear components [9,24,78]. A further visible trend is the consolidation of the physics-guided, physics-informed, and physics-encoded distinction, with frameworks increasingly classified by where the physics enters the learning pipeline rather than by model family [26,130]. Overall, the community is moving toward “Physics-Embedded” solutions that have been reported to improve generalization compared to purely data-driven models, effectively leveraging physical knowledge to extract maximum value from limited sensor data [47,131].

5.2. Theoretical Models and Integration Strategies

The integration of theoretical knowledge into PIML frameworks has become increasingly sophisticated, moving from simple penalty terms in loss functions to the structural embedding of physical laws. In fatigue analysis, foundational empirical laws such as Basquin’s formula and the Paris Law are frequently utilized as soft constraints to ensure that the network’s predictions for life expectancy and crack growth rates remain within physically plausible bounds [84,94,96,132]. Recent 2025–2026 research has expanded these strategies by incorporating energy-based fatigue models for materials like concrete [95], El Haddad’s curve as a Bayesian prior for probabilistic endurance-limit evaluation [107], and non-proportional loading measurements for multiaxial fatigue in aluminum alloys [42,79,82]. Physics-guided networks that predict fatigue-relevant parameters rather than loads have been shown to extrapolate beyond trained load regimes [102], and probabilistic calibrations of Paris Law-based crack-growth models have reported accuracy gains of approximately 15–20% when combined with weighting and pre-processing strategies [104].

In the domain of fracture mechanics, integration has evolved to include ϕ ML frameworks that embed continuum mechanics and constitutive laws directly into the feed-forward architecture, thereby ensuring thermodynamic consistency in the modeling of elastic-viscoplastic failures [1,81], with extensions to thermodynamics-consistent cyclic damage evolution [109] and fatigue safety-factor estimation [110]. The Deep Ritz method is a widely adopted integration strategy for phase-field fracture, utilizing variational principles to minimize energy functionals and capture complex crack branching without explicit spatial discretization [105]. Crack-tip asymptotic enrichment and transfer-learned Kolosov–Muskhelishvili potentials have been introduced into network formulations to compute stress intensity factors accurately without dense mesh refinement [113,125]. Furthermore, a significant emerging strategy is the data-driven discovery of governing equations, where PDE-based neural networks and physical deep symbolic regression identify the underlying physical laws directly from observed crack propagation paths, subsequently using these discovered laws as regularization terms to enhance model robustness [83,99,100,112].

5.3. Technical Gains

The strategic coupling of physics and machine learning has yielded significant technical gains, particularly in terms of data efficiency, computational throughput, and geometric flexibility [130,133]. One of the most significant gains is the ability of PIML models to generalize from sparse and noisy experimental datasets, which is essential for characterizing additively manufactured materials with high microstructural variability or components in extreme environments [2,3,94]. For example, sequential attention mechanisms have demonstrated the ability to prioritize critical temporal data points in fatigue crack growth, leading to more accurate long-term prognosis [78], while interleaved physics-based deep learning frameworks enable “cycle jumping” that substantially reduces the density of temporal data required for microstructurally small fatigue crack simulations [93].

Computational efficiency has also seen significant improvements; surrogate schemes such as the Integrated Finite Element Neural Network leverage spatial coupling information to accelerate simulations and reduce training times relative to traditional finite element methods [121,122], and domain-decomposition-based schemes have been reported to achieve fivefold speed-ups [18]. Simulation-trained surrogates built on three-dimensional FEA and on finite-element-plus-Monte Carlo ensembles support real-time crack propagation predictions under uncertainty [87,88]; graph neural networks trained on XFEM-generated data reproduce multi-crack coalescence and propagation with reported speed-ups of $6\text{--}25\times$ relative to XFEM [86]; and transfer-learned Kolosov–Muskhelishvili networks have been reported to reduce training effort by more than 70% through transferred crack-propagation criteria [113]. In high-dimensional spaces, physics-informed formulations have been reported to achieve cost reductions of up to 72% compared with finite element methods [18]. Additionally, the introduction of geometry-aware architectures like Finite-PINN has enabled mesh-independent simulations on general solid mechanics domains, overcoming the Euclidean coordinate limitations of standard PINNs [29,98].

5.4. Disadvantages of PINN and PIML

Despite these significant advancements, PIML frameworks are associated with several persistent disadvantages and technical hurdles. A primary concern is the high computational cost of training and convergence, as PINNs often encounter “stiffness” in the optimization landscape when dealing with complex or high-dimensional boundary value problems [114]. The reliance on automatic differentiation to calculate physical residuals can become prohibitively expensive for PDEs involving higher-order derivatives, which frequently occur in intricate fracture simulations [114,115]. Furthermore, these models are often extremely sensitive to hyperparameter selection, requiring extensive tuning of network depth, activation functions, and the weighting coefficients of the various loss terms to prevent the optimization from converging to physically incorrect local minima [134–136].

The “black-box” nature of neural networks persists, although initial efforts to mitigate this issue have emerged, such as gray-box regime-aware frameworks that convert learned discrepancies into compact analytical corrections [137]. While physics integration improves interpretability, the internal reasoning processes of the weights and biases remain difficult to fully explain [2,79]. Additionally, many PINN implementations are instance-specific, meaning the model must be completely retrained for any change in problem parameters, boundary conditions, or material properties [114]; the exceptions reported in the literature rely on extensive transfer-learning schemes [113,121]. Finally, in practical structural health monitoring, PIML is often limited by a lack of precise knowledge regarding exact loading conditions or the specific governing equations needed to describe unforeseen structural damage patterns [116,138]. The review further highlighted that frameworks relying on discovered equations inherit uncertainty about the completeness of the identified physics [100], and that safety-factor and cyclic-damage applications still require careful validation before deployment in certification workflows [109,110].

5.5. Opportunities for Research and Applications

The current limitations of PIML provide a roadmap for future research opportunities. There is a pressing need for the development of more generalizable and adaptive models, such as those utilizing meta-learning or transfer learning, which can adapt to new geometries and loading conditions without needing full retraining [79,114,121,123]. Another critical opportunity lies in expanding PIML to encompass multi-scale modeling for heterogeneous materials, such as advanced fiber-reinforced composites, where multiple damage modes like matrix cracking and delamination must be captured simul-

taneously [7,8]; physics-guided graph–transformer architectures already point toward feasible multi-scale formulations, for instance for concrete railway track slabs [91].

Research should also focus on establishing universal links between empirical damage laws to unify brittle and ductile fatigue models within a single physics-informed framework [139] and on consolidating probabilistic calibration frameworks that propagate uncertainty through the entire life-prediction pipeline [2,104,107]. The data-driven discovery of governing equations offers a pathway to trustworthy models where analytical descriptions are incomplete [99,100,112], while fleet-level and PHM applications—from wind-turbine main bearings to bridge networks—demonstrate the potential of physics-informed recurrent and transfer-learned hybrids for industrial monitoring [118–121]. Furthermore, the development of automated, physics-aware hyperparameter optimization tools would significantly lower the barrier for industrial adoption [134–136]. Finally, the community must work toward establishing standardized benchmarks and open-source datasets for structural integrity problems to ensure that emerging methodologies can be objectively compared and validated [83]. By addressing these areas, PIML is poised to become a reliable building block for digital twins development and predictive maintenance in high-risk engineering sectors [78,84,95].

6. Conclusions

This scoping review maps the extent, range, and nature of research on Physics-Informed Machine Learning for fatigue and fracture analysis and prediction, covering the literature published from 2018 up to August 2026. The combined strategy retrieved 124 records, of which 76 primary research articles satisfied the inclusion criteria and were charted and characterized in this review, after the removal of duplicate or version records and the exclusion of records before the descriptive analysis.

The mapped literature confirms that the three-bias taxonomy—observational, learning, and inductive—provides a robust organizing principle for the field, and that the expanded terminology families map onto these same categories rather than defining separate classes of methods. Observational strategies remain the most widespread form of physics integration, primarily because simulation-generated data from finite element, XFEM, and crystal plasticity frameworks are the most accessible source of physical knowledge. Learning bias through loss-level constraints is now well established, with Basquin-type laws, energy functionals, defect-informed penalties, and discovered governing equations frequently embedded in objective functions. Inductive bias—embedding physics structurally inside the architecture—remains the most demanding yet fastest-growing frontier, exemplified by equation-informed networks, physics-embedded recurrent cells, and transfer-learned crack-tip representations. Architecturally, the field has decisively moved beyond standard multi-layer perceptrons toward specialized designs: sequential attention and probabilistic formulations that quantify uncertainty rather than delivering deterministic point estimates, spline-based Physics-Informed Kolmogorov–Arnold Networks, geometry-aware Finite-PINNs with mesh-independent encodings, and graph, transformer, and recurrent hybrids for multi-crack, multi-scale, and fleet-level problems. These advances have produced concrete technical gains, including reported speed-ups of 6–25× over XFEM for crack coalescence simulations, training-effort reductions of more than 70% through transferred physics, “cycle jumping” that drastically reduces the temporal data required for microstructurally small crack simulations, and accurate real-time crack propagation predictions under uncertainty.

At the same time, persistent limitations temper these gains. Training remains computationally expensive and prone to optimization stiffness, and models are highly sensitive to hyperparameter selection and loss-weighting schemes. Many implementations

remain instance-specific, requiring full retraining when parameters, boundary conditions, or material properties change, with only transfer-learning schemes offering partial relief. The black-box nature of neural networks persists despite physics-informed interpretability improvements, and frameworks that rely on discovered equations inherit uncertainty about the completeness of the identified physics. Fatigue and fracture applications also continue to face the practical challenge of uncertain loading conditions and incomplete governing laws in real structural health monitoring scenarios.

These limitations define a clear agenda for future work. Generalizable and adaptive models based on meta-learning and transfer learning, multi-scale formulations for heterogeneous materials such as composites and concrete, and unified frameworks bridging empirical damage laws across brittle and ductile regimes would considerably widen the applicability of the approach. Probabilistic calibration pipelines that propagate uncertainty through the entire life-prediction chain and physics-aware automated hyperparameter optimization would strengthen reliability and ease of use, while standardized benchmarks and open datasets for structural integrity problems would allow emerging methodologies to be objectively compared and validated.

Furthermore, there is a critical need to bridge the gap between PIML methodologies and microstructural failure analysis. Current machine learning frameworks in this domain lack better accounting for the complex, continuous microstructural evolution that fundamentally dictates failure in advanced metallic systems. Future research must aim to integrate phenomena such as phase transformations, abnormal grain growth, and the localized effects of inclusion contents during processing directly into the predictive learning process. For example, the predictive modeling of new commercial dual-phase steels with controlled additions of niobium, zirconium, or molybdenum, as well as advanced Al-Zn-Mg alloys, requires algorithms capable of capturing continuous variations in strain hardening exponents and the nucleation of brittle iron-bearing intermetallic phases that induce microcracking. Embedding these high-resolution microstructural mechanics into PIML architectures remains a significant, yet highly promising, frontier for true industrial-scale failure prediction.

By addressing these areas, Physics-Informed Machine Learning is well positioned to become a reliable building block for digital-twin development and predictive maintenance in high-risk engineering sectors as the field continues to expand.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/app16199720/s1>, Table S1: PRISMA-ScR checklist; Table S2: Extraction—single-bias studies (O, L, I), n = 37; Table S3: Extraction—multi-bias studies (I+L, I+O, L+O, I+L+O), n = 12; Table S4: Anchors, excluded records, background.

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