Bridging Methods and Data in System-Level Prognostics: A Comprehensive Review

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ABSTRACT

System-level prognostics (SLP) is a core problem in prognostics and health management (PHM) that seeks to predict future health states or remaining useful life (RUL) in complex multi-component systems where degradations interact through functional and operational interdependencies. Despite significant progress, the SLP literature remains fragmented, and existing reviews largely offer taxonomies without systematically linking modeling assumptions, data availability, and validation choices to reported performance and reproducibility. This paper offers a data-centric synthesis of the SLP landscape by integrating insights from influential reviews, technical contributions, and publicly available prognostics datasets. We conduct an analysis to characterize publication trends and research domains, identify and quantify the coverage of recurring SLP challenges, and assess how current methodologies address (or overlook) these issues. We also curate a dataset catalog to quantify gaps between methodological ambitions and benchmarking resources. The study concludes by outlining priority directions for advancing reproducibility, data diversity, and deployment-oriented SLP research.

Keywords: Prognostics and Health Management, system-level prognostics, remaining useful life, component interdependencies, mission profile, multi-component systems

1. INTRODUCTION

As systems grow more complex, traditional component-level prognostics (CLP) become insufficient: practical decisions often require system-level predictions, because failures emerge from coupled degradations, cascading effects, and mission-dependent interactions among subsystems. SLP is therefore a necessity, but it is harder than CLP due to component interdependencies, heterogeneity, uncertainty propagation, and complex failure logic (Tamssaouet et al., 2023).

Although the SLP literature has expanded across modeling paradigms and application domains, it remains fragmented. Existing reviews provide useful taxonomies (Kim et al., 2021; Tamssaouet et al., 2023) but rarely connect modeling assumptions, data regimes, and validation practices to reported performance and reproducibility. The rise of data-driven, hybrid (Deng et al., 2023), and uncertainty-aware methods further diversifies the landscape and complicates holistic assessment. Meanwhile, SLP is constrained by limited public data. Unlike CLP, which offers several benchmark datasets (Solís-Martín et al., 2025), truly system-level datasets are scarce. Most available datasets are unimodal, component-centric, and concentrated in a few domains (notably batteries and bearings), limiting evaluation of interdependencies, mission variability, and system-level uncertainty under realistic conditions. This mismatch between methodological ambition and data availability motivates a unified, data-centric view of the SLP landscape beyond taxonomy.

The present paper addresses this gap by bringing together three main contributions: (i) identify and structure 14 key methodological challenges in SLP and quantitatively assess their coverage in the recent literature, highlighting both dominant research trends and underexplored yet critical issues; (ii) review publicly available prognostics datasets, explicitly distinguishing component- and system-level data, and reveal a strong predominance of component-centric, unimodal datasets; (iii) expose key limitations in domain diversity, data modality, and system observability, and outline priority directions for advancing scalable and deployable system-level prognostics.

The remainder of this paper is organized as follows. Section 2 presents a bibliometric analysis of the SLP literature, including the search methodology, publication trends, and the coverage of key system-level challenges, along with a characterization of publicly available prognostics datasets. Section 3 synthesizes the methodological landscape, introducing a motivating example before reviewing existing taxonomies, data constraints, and evaluation practices. Section 4 discusses the main limitations of current SLP research and outlines directions for future work. Finally, Section 5 summarizes the main findings and their implications for advancing system-level prognostics.

2. BIBLIOMETRICS ANALYSIS

This section provides a quantitative overview of the scientific landscape related to SLP within the broader field of PHM. In this work, the bibliometrics aim to (i) assess how frequently SLP-related studies appear in the literature, (ii) map the disciplinary domains in which these contributions originate, and (iii) understand how research efforts have evolved over time.

2.1. Literature research methodology

To obtain a comprehensive view of the research landscape, we used Web of Science (WoS), a major multidisciplinary bibliographic and citation database used for academic research. Each step of our search methodology is described in Figure 1.

The first step consists of defining the *Topic search string*, submitted to WoS to retrieve relevant publications. The search string is constructed to cover all the relevant keywords in SLP. The initial search returned 1,225 records. In the second step, we restricted the scope to fields in which engineering-oriented SLP and PHM research is typically conducted, such as Aerospace, Engineering, Computer Science, etc., reducing the set to 700 papers. In the third step, we then applied a thesis-oriented filtering stage, further excluding irrelevant domains using the previously defined interfering vocabulary, and remove any duplicate items. Finally, a manual reading filter was performed to assess the relevance of each article to the scope of this review. This multi-stage process resulted in a final corpus of 248 publications explicitly addressing SLP.

2.2. Statistical analysis of SLP in PHM

Figure 2 represents the distribution of the research fields covered by studies on SLP in PHM. We find that the majority of papers fall under Engineering (Alaswad & Xiang, 2017), followed by Computer Science (Shi & Zeng, 2016), Operations Research & Management (Van Horenbeek & Pintelon, 2013), Automation & Control Systems (Skordilis & Moghaddass, 2020), and Instruments & Instrumentation (Liu et al., 2020). Only a small number of publications appear in fields such as physics and robotics (Sai et al., 2019). This distribution confirms that SLP research is predominantly situated within technical and engineering disciplines.

To get a more granular view of the scientific landscape, we next examine the distribution of specific SLP challenges discussed in existing SLP literature, as summarized in Figure 3. The results identify 14 recurring challenges that characterize the complexity of SLP:

Component interdependencies (C1) (Tamssaouet, Nguyen, Medjaher, & Orchard, 2021) capture the need to model degradation coupling and load sharing among subsystems, which fundamentally distinguishes SLP from CLP. **Uncertainty quantification and propagation (C2)** (Cao et al., 2024) concern the accumulation and transmission of epistemic and aleatory uncertainties across hierarchical system models. **Heterogeneity (C3)** (X. Zhang et al., 2023) reflects variability among components, sensors, and operating conditions, often exacerbated in multi-domain systems. **Mission profile variability (C4)** (Tamssaouet, Nguyen, & Medjaher, 2021) accounts for time-varying operational demands that significantly influence degradation trajectories.
Several challenges relate to model formulation and computational feasibility. **Nonlinear degradation mechanisms (C5)** (Tamssaouet, Nguyen, & Medjaher, 2021) arise from complex physical processes and dominate realistic SLP scenarios. **Model-construction difficulty (C6)** (Y. Zhang et al., 2024) highlights the challenge of building tractable yet accurate system-level models from limited data or partial physics. **Computational complexity (C7)** (Wang et al., 2025) addresses the scalability of inference and prediction algorithms as system size and dependency structure grow. Closely related, **scalability and adaptability (C8)** (Dobs et al., 2022) concern the ability of methods to generalize across system architectures and evolving configurations.
Data- and deployment-oriented challenges are also prominent. **Data quality issues (C9)** (Jose et al., 2026) encompass noise, missing data, and synchronization errors that degrade prognostic performance. **Decision-making integration (C10)** (Lu et al., 2026) emphasizes the need to connect SLP outputs with maintenance planning, resource allocation, and operational control. **Validation and certification (C11)** (Huang et al., 2025) address the difficulty of establishing trust, performance guarantees, and regulatory acceptance for system-level predictions. Finally, several challenges remain comparatively underexplored. **Intermittent-fault prognostics (C12)** (Xiao & Zheng, 2023) deal with sporadic and non-persistent failures that are challenging to detect and predict at the system level. **Failure threshold definition (C13)** (Lycksam et al., 2025) concerns the often arbitrary or component-specific criteria used to declare system failure. **Multi-indicator health assessment (C14)** (Zhou et al., 2024) reflects the challenge of fusing multiple degradation indicators into interpretable and decision-relevant system health metrics. It is important to note that the identification of SLP challenges in this work is based on a qualitative synthesis of recurring limitations reported across the reviewed corpus, rather than on isolated observations. Publication frequency is used only to reflect the level of research attention devoted to a given challenge and should not be interpreted as an indicator of its resolution. Many fre-

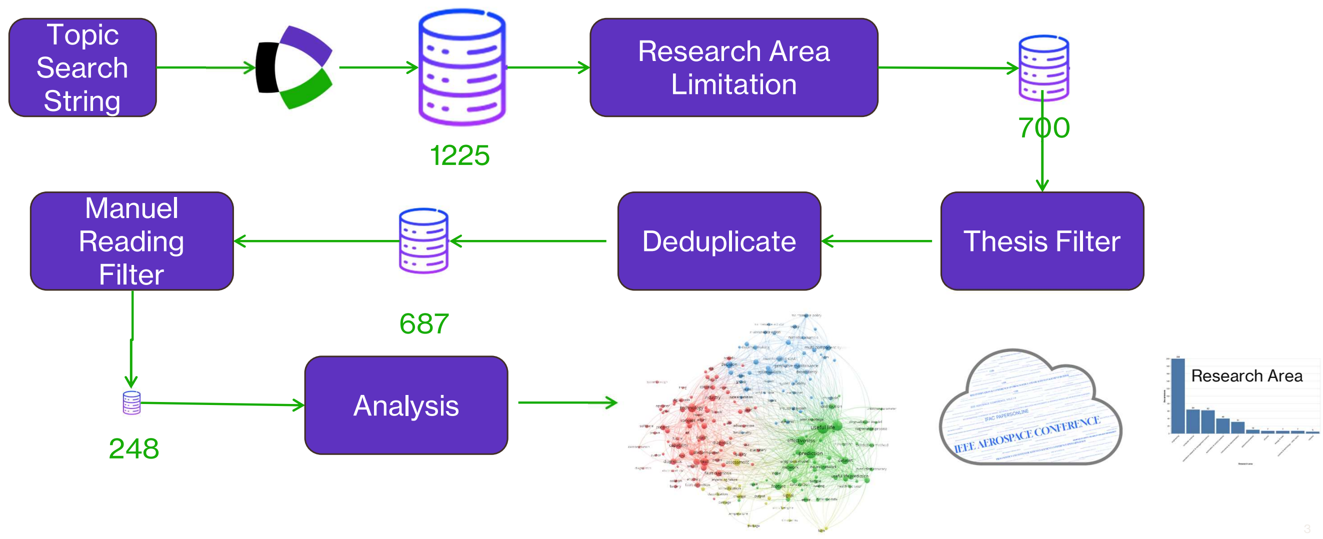

Figure 1. Search methodology flowchart.

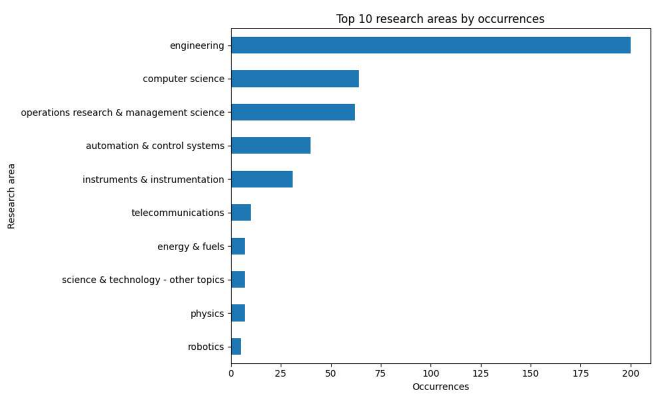

Figure 2. Top 10 research areas by occurrences.

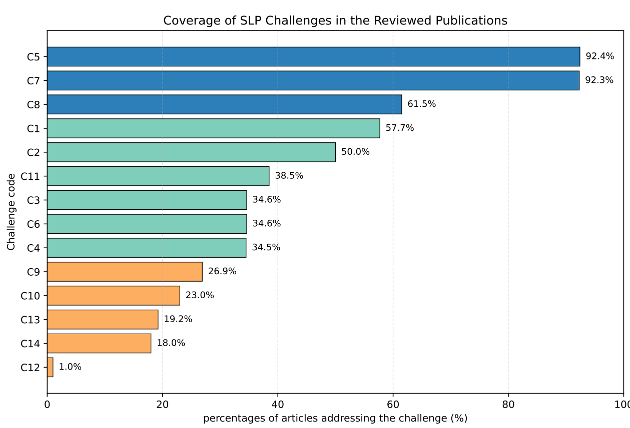

Figure 3. Coverage of SLP challenges in the reviewed publications. Each bar represents the proportion of articles addressing or tried to address a given challenge independently.

quently studied challenges remain only partially addressed under simplifying assumptions, while other less frequently discussed issues may have significant practical implications at a system scale. For example, interdependency modeling (C1) is often limited to pairwise or predefined structures, and computational scalability (C7) is rarely evaluated under realistic deployment constraints. Conversely, challenges such as intermittent-fault prognostics (C12) and system-level failure threshold definition (C13), though rarely studied, have disproportionate operational impact and remain largely underaddressed.

While the analysis of SLP challenges reveals the methodological issues addressed in the literature, these challenges are closely tied to the characteristics and availability of data used for model development and validation. SLP research relies on heterogeneous datasets that vary in scale, modality, and accessibility, which directly conditions the extent to which system-level behaviors and interdependencies can be effectively investigated. Accordingly, we analyze the statistical characteristics of 30 public prognostics datasets (spanning both component- and system-level settings) with respect to their application domains, data sources, and data modalities, to assess how well existing data resources support current SLP research challenges.

Figure 4 provides insight into the application domains covered by publicly available Prognostics datasets. The distribution is strongly skewed toward the battery domain, which accounts for the majority of available datasets, with 13 battery-specific datasets identified. This is followed by bearing systems, represented by four datasets. A subset of datasets is labeled as Unknown, corresponding to cases where the data providers did not disclose the specific application domain or equipment type due to confidentiality constraints. Notably, several impor-

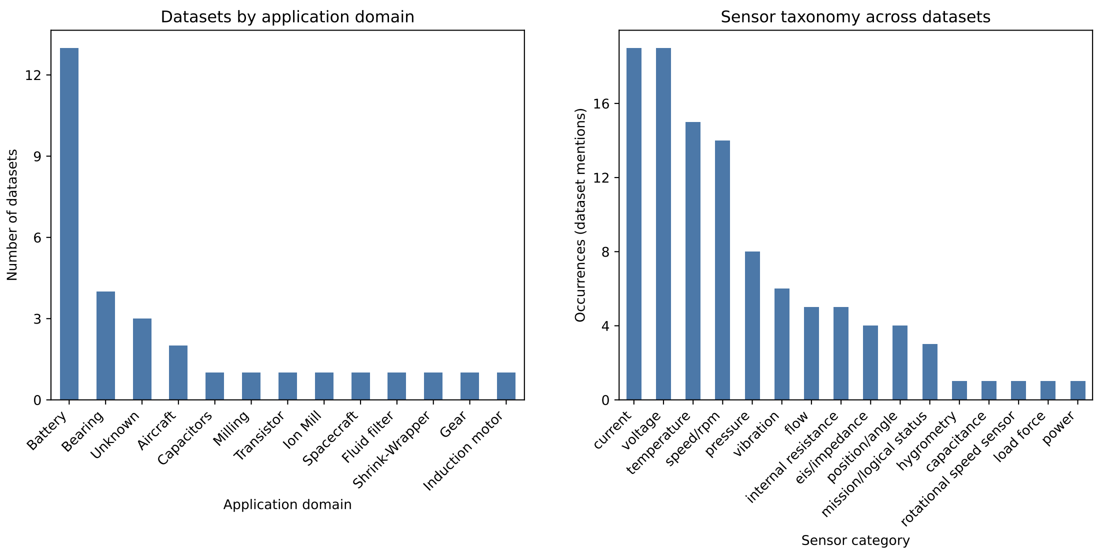

Figure 4. Datasets application domains and Sensor category charts.

tant industrial domains (such as milling machines, spacecraft systems, gear transmissions, and other complex assets) remain largely unrepresented in terms of publicly accessible prognostic datasets. This imbalance highlights a significant limitation in current benchmarking resources and underscores the need for broader data sharing across diverse application domains.

From a system-level perspective, a more critical limitation is that only approximately 30% of the identified datasets can be considered genuinely system-level, in the sense that they provide a holistic view of the monitored asset. The majority of datasets remain component-centric, offering isolated measurements that do not capture interactions, dependencies, or degradation propagation across subsystems. This predominance of component-level data constitutes a major bottleneck for SLP research and highlights a clear mismatch between available data resources and the requirements of system-level modeling and inference. Concerning the data modalities used in the available public datasets, all currently accessible prognostics datasets are unimodal, containing only a single type of data, typically time-series signals such as current, voltage, temperature, vibration, hygrometer readings, or load force. Although many datasets include heterogeneous time-series collected from different sensors, and some occasionally provide complementary tabular metadata, they still do not constitute true multimodal datasets in the PHM sense. To the best of our knowledge, no publicly available multimodal dataset for prognostics currently exists. Several research works report the use of multimodal data (Jose et al., 2025, 2024; Kang et al., 2025), but the corresponding datasets are not publicly released. This gap highlights a significant opportunity for future contributions, as multimodal datasets are essential for advancing system-level prognostics, since they contain richness of information and provide more contextual understanding for interdependency modeling in complex systems.

3. DISCUSSION OF SLP LANDSCAPE

This section builds on the previous analysis by examining how SLP methods are structured and applied in practice. To ground the discussion, we first introduce a motivating example that illustrates how key SLP challenges naturally arise in real-world systems. Then we review existing taxonomies, data constraints, and evaluation practices that shape current approaches.

Aircraft Systems as a Motivating Example for SLP Challenges. An aircraft system provides a representative and intuitive context in which the identified SLP challenges naturally emerge. Aircraft degradation processes are inherently system-level, as the health evolution of major subsystems such as propulsion, avionics, flight control, thermal management, and power distribution is tightly coupled through load sharing, feedback loops, and operational constraints (C1). Uncertainty quantification and propagation (C2) become critical in this setting, as local estimation errors originating from individual subsystems can accumulate and interact across hierarchical diagnostic and prognostic models. Aircraft operations are also characterized by highly variable mission profiles (C4), where phases such as takeoff, climb, cruise, descent, and landing impose distinct and non-stationary stressors, further amplified by heterogeneity (C3) in components, environmental conditions, and usage histories across flights and fleets. These effects are governed by nonlinear degradation mechanisms (C5), often only partially understood, making system-level model construction (C6) particularly challenging. From a data perspective, sensor noise, missing measurements, and synchronization issues across distributed avionics and monitoring systems directly impact prognostic reliability (C9). Operationally, integrating prognostic outputs into maintenance scheduling, dispatch decisions, and flight operations (C10) is non-trivial, especially given stringent requirements for validation and certification in safety-critical domains (C11). Additional complexity arises from intermittent faults (C12), such as transient sensor or control anomalies, and from the difficulty of defining system-level failure thresholds (C13), which are typically tied to performance margins or safety envelopes rather than single component failures. Finally, synthesizing multiple degradation indicators into an interpretable and actionable system-level health assessment (C14) remains essential for effective decision-making.

SLP taxonomy: Across the reviewed corpus, SLP methods are commonly organized according to established taxonomies. These include distinctions between health-index–based approaches, component-level RUL aggregation, influenced-component modeling, and multiple failure-mode strategies (Kim et al., 2021), as well as between simplified and holistic system-level modeling frameworks (Tamssaouet et al., 2023). More generally, the literature also converges around the widely adopted classification into physics-based, data-driven, knowledge-based, and hybrid approaches. Synthesizing findings across these complementary categorizations reveals consistent trade-offs when methods are applied at a system scale. Physics-based approaches are widely recognized for their interpretability and ability to extrapolate under varying mission profiles; however, their applicability is often constrained by the difficulty of modeling interacting degradation mechanisms and estimating parameters in complex, multi-component environments (Cubillo et al., 2016). Conversely, data-driven approaches demonstrate strong capability in capturing nonlinear behaviors and exploiting large volumes of sensor data, but their effectiveness at the system level is fundamentally limited by data availability, incomplete observability, and the predominance of component-level, unimodal datasets, which restrict their capacity to represent system-level interactions (Nguyen et al., 2022). Knowledge-based methods facilitate transparency and alignment with operational decision processes, yet they suffer from scalability issues and combinatorial complexity as system size increases (Chiachío et al., 2019). Taken together, these observations indicate that no single methodological family adequately satisfies the combined system-level requirements of interdependency modeling, scalability, uncertainty propagation, and deployability. In this context, hybrid approaches are increasingly explored not merely as paradigm combinations, but as structured responses to system-level limitations, aiming to balance interpretability, data efficiency, and robustness. This evolution reflects a broader transition in SLP research from method-centric comparisons toward system-centric design considerations grounded in realistic operational conditions.

Role of data and its constraints. As mentioned earlier, only about 30% of identified datasets are truly system-level, and public resources are largely unimodal and time-series-only, with a strong skew toward batteries and, to a lesser extent, bearings (Figure 4). This data landscape naturally favors time series models and hinders progress on challenges that require richer observability, e.g., interdependency modeling (C1), heterogeneity (C3), and decision integration (C10). The scarcity of multimodal public datasets and the limited availability of run-to-failure traces (C9) constrain generalization to real operations and slow the community's ability to benchmark their SRUL pipelines (C2, C4). These observations strengthen the case for community efforts to release curated, privacy-preserving, multimodal, system-level datasets with explicit mission profiles.

Evaluation practices and reporting. To move toward more dependable SLP, we advocate standard reporting of: (1) mission profile definitions and coverage; (2) uncertainty calibration metrics alongside deterministic scores; (3) system-level target definitions (SRUL vs. component RUL aggregation) and how dependencies are encoded; (4) computational footprint (latency, memory) to quantify real-time feasibility; and (5) ablation studies that separate the effect of physics priors, data augmentation, and fusion strategies. Where public data are limited, protocols such as domain randomization (Tobin et al., 2017), and co-training (Abdelgayed et al., 2018) are recommended to be used and documented, and cross-domain tests should be encouraged to probe adaptability.

4. LIMITATIONS AND FUTURE DIRECTIONS

Limitations: Despite recent advances, current SLP research continues to face several substantive limitations. A primary concern is the dominance of component-level datasets, which restricts the study of system-level dynamics, including cross-component dependencies and emergent behaviors. This challenge is compounded by the scarcity of publicly available multimodal datasets, limiting observability and constraining the modeling of complex interactions across subsystems. While this scarcity is not solely a consequence of technical challenges such as sensor heterogeneity, data synchronization, and multi-indicator fusion. It is also driven by structural and organizational constraints inherent to industrial contexts. In safety-critical domains such as aerospace, energy, and transportation, operational data are often subject to strict data ownership policies, intellectual property protection, and confidentiality requirements. In addition, concerns related to commercial competitiveness and liability further limit data sharing, particularly when datasets may reveal system vulnerabilities or performance limitations.

The aforementioned data constraints consequently translate into significant methodological limitations. System-level uncertainty quantification and propagation are insufficiently addressed taking into account component dependencies, al-

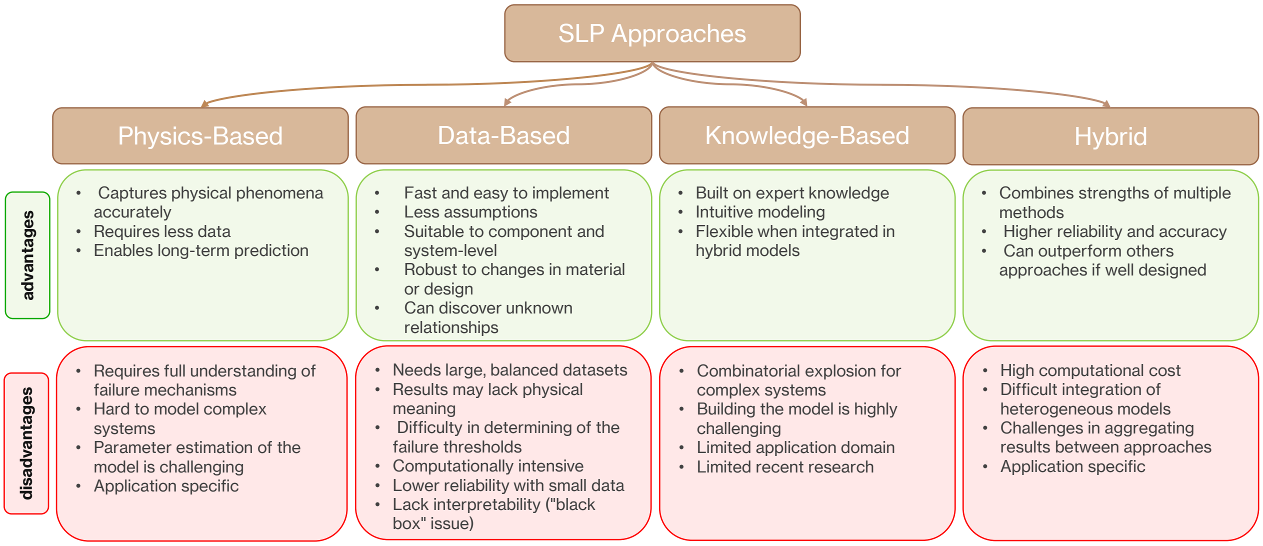

Figure 5. A high-level overview of SLP approaches in the literature highlighting the main advantages and disadvantages of each methodological family.

though many SLP methods introduce substantial computational overhead and this issue is increasingly acknowledged in recent studies—there remains a need for deeper discussion regarding their real-time feasibility. Furthermore, the linkage between SLP outputs and downstream decision-making processes, such as maintenance planning, remains weak. Progress is further impeded by the lack of standardized evaluation protocols, which undermines rigorous comparison across methods. Finally, limited attention to validation, certification, and trustworthiness constitute a major barrier to industrial adoption.

Future research directions: To address these limitations, several research directions warrant priority attention. First, the development and release of system-level, multimodal, and privacy-preserving datasets with explicit mission profiles is essential for advancing benchmarking capabilities. Second, the design of hybrid SLP models that combine physics-based priors with scalable data-driven methods, such as physics-informed machine learning, offers promise for improving both accuracy and interpretability. Third, explicit modeling of component interdependencies and degradation propagation at the system level should be prioritized, along with the incorporation of intermittent-fault prognostics into SLP frameworks. The systematic integration of uncertainty-aware prediction with decision support, and the development of computationally efficient, edge-aware SLP methods suitable for real-time deployment, are also critical. Finally, closer coupling between SLP and maintenance, logistics, and operational decision-making, alongside the adoption of standardized benchmarking and reporting practices that include uncertainty and computational cost metrics, will facilitate broader industrial adoption.

5. CONCLUSION

This paper presented a comprehensive and data-centric landscape of SLP, integrating insights from review articles, technical studies, and publicly available prognostics datasets. By jointly analyzing these three dimensions, we revealed how methodological advances, modeling assumptions, and data availability shape current SLP research. The bibliometric analysis demonstrated that SLP publications remain concentrated in engineering-oriented domains, with persistent gaps in research areas such as robotics, and complex industrial systems. Our challenge-oriented synthesis further showed that although significant attention has been given to non-linearity, computational efficiency, and uncertainty propagation, other key issues—such as interdependencies, multi-indicator fusion, mission profile variability, and intermittent-fault prognostics remain comparatively underexplored. The dataset analysis exposed a significant misalignment between the challenges addressed in the literature and the data resources available for benchmarking. Most accessible prognostics datasets are component-level, and almost all of them are unimodal with time-series modality and predominantly centered around batteries or bearings. This limited data diversity restricts the development and validation of SLP approaches that require multimodal information, component interactions, and realistic operational variability, weakening reproducibility and hindering their applicability in real complex assets. Although we also acknowledge the non-technical barriers that contribute to the shortage of data.

Future research should focus on developing standardized benchmarks, exploring scalable architectures, and designing validation protocols that reflect realistic industrial conditions. Advancing these directions will enable more robust, interpretable, and industry-ready SLP solutions. Ultimately, by bridging the gaps between methodological innovations, empirical evidence, and data foundations, this work aims to expose systematic mismatches between methodological assumptions, data regimes, and validation practices to support more informed development of next-generation prognostics approaches capable of addressing the full complexity of modern engineered systems.

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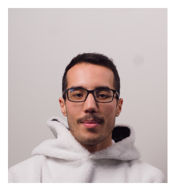
BIOGRAPHIES



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