Physics-Informed Review of Machine-Learned Fatigue Capacity

Roger Price, Terry Bennett, Austin Wood*

* Corresponding author: Austin Wood

Review Article | Frontiers in Integrative Science | ISCSR Research Publishing | Published 23 September 2026

ABSTRACT

Which invariants should be checked independently of predictive accuracy? This review answers by treating physics-informed assurance as a property of a sociotechnical workflow rather than a feature that can be read from average accuracy. The focal setting is multiaxial lattice loading, where a fast surrogate can move a design decision far outside the domain where its training simulations were physically credible. Evidence from the assigned publications is synthesized with foundational studies of calibration, distribution shift, causal structure, and responsible deployment. Four requirements follow: preserve the lineage of parameterized geometries, finite-element and multiscale outputs, loading histories, material properties, and validation measurements; measure stability across relevant perturbations; connect confidence to a specific action; and maintain a route for human challenge and correction. The framework distinguishes descriptive performance from decision utility and separates uncertainty about the world from uncertainty created by the model and its evaluator. It also shows why faster inference or richer reasoning is valuable only when it improves a defined decision under a transparent resource budget. The article is a literature review and research agenda, not a report of a newly completed trial.

KEYWORDS

physics-informed review of machine-learned fatigue capacity; decision; physics-informed; accuracy; loading; where; uncertainty

Introduction

Which invariants should be checked independently of predictive accuracy? A satisfactory answer must look beyond the predictor, because implementation joins several technical and institutional stages. Its behavior reflects a chain of design decisions about evidence, representation, alternatives, resource use, and response. In multiaxial lattice loading, these choices interact with institutions and physical processes that the model only partially represents. A high score can coexist with fragile inputs, an evaluator that rewards the wrong surface feature, or an action rule that turns modest uncertainty into a costly decision. For this reason, the synthesis examines physics-informed assurance as an evidence problem. The review asks which observations and counterfactual comparisons can support a defensible assurance claim. This requirement gives practical content to the article's central question: Which invariants should be checked independently of predictive accuracy?

The comparison is organized around the operational operational sequence. Its unit is the digital thread connecting geometry, materials, boundary conditions, solver settings, derived features, and predicted capacity. This avoids a recurring category error: attributing every failure to model architecture while ignoring data capture, labeling, retrieval, validation, interface design, or organizational incentives. It also gives the target studies a common basis for comparison. Although their application settings differ, they each make some part of an inference chain more explicit - a reward signal, a graph relation, a physical boundary condition, a confidence gate, or a revision trigger. Evaluation must establish whether that explicit component remains meaningful when parameterized geometries, finite-element and multiscale outputs, loading histories, material properties, and validation measurements change, and whether the proposed safeguards lead to design screening, uncertainty-aware optimization, targeted simulation, and physical testing instead of merely producing another metric. In multiaxial lattice loading, this distinction should be tested before it changes an operational decision.

Methods and Boundaries in the Assigned Studies

The strongest contribution of MuSK: Multi-Scale Knowledge Learning for Provenance-Graph Anomaly Detection is not a generic claim that learning improves performance. It is the more specific proposition that how stealthy multi-stage attacks can be detected in heterogeneous system-provenance graphs without abundant attack labels. The proposed route is self-supervised recovery of masked node attributes, meta-path edges, and positional structure, followed by meta-path-guided subgraph verification. Support comes from the fact that evaluation spans nine provenance settings, including DARPA Transparent Computing hosts, and reports high precision, complete recall on those hosts, and efficiency gains from cached incremental expansion. The design joins local attributes, heterogeneous causal paths, and global position while moving decisions from isolated nodes to suspicious subgraphs. Read through the lens of physics-informed assurance, the study also illustrates why a reported average must remain connected to the workflow that produced it. Performance may depend on audit completeness, benign workload diversity, attack coverage, and the stability of hand-selected meta-path semantics. (Ma et al. 2026).

BoostAPR: Boosting Automated Program Repair via Execution-Grounded Reinforcement Learning with Dual Reward Models asks how reinforcement learning for program repair can overcome sparse execution feedback and coarse sequence-level credit. It uses a three-stage pipeline combining execution-verified supervised traces, sequence- and line-level reward models, and PPO with reward redistribution to critical edit regions. The relevant evidence is that evaluation spans SWE-bench Verified, Defects4J transfer, HumanEval-Java, and QuixBugs, with reported gains in both repository repair and cross-language generalization. Line-level credit assignment makes test execution informative at the granularity where patches actually change behavior. In the present review, this work matters because physics-informed assurance cannot be evaluated as an abstract virtue; it must change how evidence is collected and how an action is withheld. Benchmark success does not by itself establish maintainability, specification fidelity, or robustness to incomplete and flaky tests. (Li et al. 2026).

A useful test case is Synergizing Machine Learning and Multiscale Shakedown Method for Shakedown Loading Capacity Evaluation of Parameterized Lattice Structures. Rather than treating its output as an isolated score, the study frames how multiaxial shakedown capacity of parameterized auxetic lattices can be estimated efficiently under uncertain cyclic loading. Its central mechanism is a multiscale shakedown solver supplies training data to a tuned hybrid ensemble for a peanut-shaped re-entrant lattice, followed by sensitivity analysis, and its evidential basis is that the reported model reaches low normalized error and high explained variance, while center distance and edge width emerge as influential design variables. Physics-based admissibility and data-driven speed are combined in one design workflow. For multiaxial lattice loading, the transferable lesson is methodological: a system should preserve the path from signal to decision and expose the conditions under which that path may fail. The boundary is equally important. One lattice family and simulated loading domain do not establish transfer to defects, other topologies, material variability, or experimental fatigue life. (Wang et al. 2025).

Separating Evidence, Inference, and Action

A four-layer model exposes where assurance claims can fail. The evidence layer records observations and their provenance. The representation layer turns those observations into features, graphs, tokens, or simulated states. The inference layer produces predictions, explanations, translations, anomaly scores, or candidate actions. The decision layer maps those outputs to design screening, uncertainty-aware optimization, targeted simulation, and physical testing. Reliability can fail at any boundary. Better inference cannot repair evidence that omitted the relevant condition, and a calibrated probability cannot rescue an action rule whose costs were never specified. Conversely, a conservative decision policy may reduce harm even when the underlying model remains imperfect. This layered view makes physics-informed assurance testable because each claim can be assigned to a component and a measurable transition. Seen through physics-informed assurance, the issue is not merely technical; it determines which claims remain open to challenge.

Three kinds of uncertainty require different responses: aleatory variation, epistemic limits, and strategic adaptation. Aleatory variation concerns irreducible differences among cases. Epistemic uncertainty concerns missing knowledge, limited samples, or unsupported regions of the input space. Strategic adaptation occurs when users, adversaries, markets, or institutions respond to the operational tool itself. These sources demand different controls. Repeated measurement can characterize variation; new evidence and conservative extrapolation can reduce epistemic uncertainty; red teaming and feedback-aware evaluation address adaptation. Combining them into one confidence score hides which intervention is appropriate. A defensible system therefore reports uncertainty in a form tied to an available response in place of presenting confidence as a decorative number. In multiaxial lattice loading, this distinction should be tested before it changes an operational decision.

Architecture for Bounded Automation

Resource allocation should respond to ambiguity and consequence. Easy, well-supported cases can take a fast path. Shifted, ambiguous, or high-cost cases should activate additional precision, retrieval, alternative drafts, simulation, or expert review. This conditional design is preferable to applying maximum computation everywhere because resource cost is part of deployment quality. It is also preferable to an unconditional fast path because efficiency can amplify a systematic error at scale. The trigger must be evaluated as carefully as the expensive model: coverage, false reassurance, subgroup effects, latency, and the consequences of abstention all matter. The output is not simply a prediction but a package containing evidence links, uncertainty, the action taken, and the conditions that caused escalation. This point narrows the research task for multiaxial lattice loading: compare alternatives under the same information and resource constraints.

A traceable deployment in multiaxial lattice loading begins with typed evidence. Each record should identify its source, time, collection conditions, transformations, and relation to other records. Graphs are useful when relations carry meaning, but graph construction is itself a hypothesis. An edge may denote temporal adjacency, physical causation, code dependency, shared infrastructure, or analyst assertion; treating these as interchangeable creates false certainty. The architecture should therefore maintain edge types and confidence, retain alternative links when evidence is ambiguous, and version both the data schema and the rules that construct the graph. A model may aggregate this structure, but the original evidence must remain recoverable for audit. Seen through physics-informed assurance, the issue is not merely technical; it determines which claims remain open to challenge.

Established Tests and Design Principles

Several established literatures clarify the design space. Additive feature attribution can audit model behavior, although attribution is not a causal explanation (Lundberg and Lee 2017). Topology optimization supplies a disciplined link between design variables, constraints, and structural objectives (Bendsoe and Sigmund 2003). FAIR data practice matters when simulation lineage and material metadata determine whether a surrogate can be reproduced (Wilkinson et al. 2016). Classical fatigue mechanics links cyclic loading, microstructural damage, crack initiation, and crack growth across scales (Suresh 1998). Together these findings imply that physics-informed assurance should be evaluated against explicit alternatives and failure costs. In Physics-Informed Review of Machine-Learned Fatigue Capacity, this literature supplies a specific test of physics-informed assurance within multiaxial lattice loading.

The evidence base offers complementary tests rather than one universal metric. Cumulative-damage rules remain useful baselines precisely because their simplifying assumptions are visible (Miner 1945). Crack-growth laws show how physically meaningful state variables can constrain extrapolation (Paris and Erdogan 1963). Critical-plane analysis demonstrates why multiaxial phase relations cannot be collapsed into a single load magnitude (Fatemi and Socie 1988). They also caution against interpreting one benchmark, one split, or one explanatory artifact as a complete validation argument. In Physics-Informed Review of Machine-Learned Fatigue Capacity, this literature supplies a specific test of physics-informed assurance within multiaxial lattice loading.

A credible assurance case can be built from findings that operate at different levels. Computational homogenization clarifies which mesoscale details may be summarized and which must remain explicit (Geers, Kouznetsova, and Brekelmans 2010). Model-calibration theory separates parameter uncertainty, observation error, and structural discrepancy (Kennedy and O'Hagan 2001). Global sensitivity analysis measures interactions that one-factor-at-a-time studies can miss (Saltelli et al. 2010). Their combined value lies in making assumptions visible enough to challenge before deployment and to revise after failure. In Physics-Informed Review of Machine-Learned Fatigue Capacity, this literature supplies a specific test of physics-informed assurance within multiaxial lattice loading.

Measurement Under Shift and Repetition

No single metric can stand in for the downstream action. Discrimination measures whether cases are ranked correctly; calibration asks whether confidence corresponds to observed frequency; selective risk asks what error remains after deferral; robustness measures performance across defined perturbations; and utility assigns costs to actions. These are not interchangeable. For physics-informed assurance, the minimum report should include overall performance, slice-level results, uncertainty intervals, coverage-risk curves, stability across runs, and failure examples linked back to parameterized geometries, finite-element and multiscale outputs, loading histories, material properties, and validation measurements. If the deployed workflow updates incrementally, the evaluation must also test forgetting, stale evidence, and rollback. If an automatic judge supplies labels, a sample needs independent human review and content-preserving perturbations that reveal whether the judge is grading substance. The article's emphasis on physics-informed assurance makes that boundary observable and, in principle, auditable.

Before running a benchmark, evaluators should define a table linking claims to populations and outcomes. Each intended claim - such as improved robustness, safer abstention, faster updating, or better structural localization - needs a target population, comparator, outcome, and boundary condition. Random splits are insufficient when related samples share a patient, repository, instrument run, season, organization, or simulated design family. Grouped and temporal splits better approximate the novelty encountered after implementation. Stress tests should vary one factor at a time when attribution is important, then combine factors to measure interaction. Repeated runs are necessary whenever decoding, optimization, retrieval, or numerical kernels can vary. Reporting only the best seed or a pooled mean makes operational instability disappear. This point narrows the research task for multiaxial lattice loading: compare alternatives under the same information and resource constraints.

Priorities for Empirical Work

Long-term progress depends on cumulative records of both successful and failed approaches. Benchmarks should preserve negative results, failed branches, and changed definitions so later work does not learn only from successful demonstrations. Shared reporting should include data lineage, versioned assessment code, confidence intervals, and enough error material to reproduce major conclusions. Prospective studies should predefine monitoring and stopping rules, then measure how people adapt to the system. Finally, researchers should compare simple baselines with complex architectures under equivalent information. Complexity is justified when it adds a measurable capability - for example, structural localization, calibrated deferral, or incremental updating - not merely when it creates a richer narrative around the same errors. The implication is especially consequential in multiaxial lattice loading, where a small modeling choice can redirect attention and resources.

The next generation of benchmarks should sample mechanisms and boundary conditions explicitly. Cases should represent unsupported regions, ambiguous evidence, conflicting modalities, rare but costly conditions, and realistic adversarial transformations. Each case needs provenance and a reason for inclusion. The second priority is intervention testing: when uncertainty is detected, compare additional computation, retrieval, alternative reasoning paths, model ensembles, and human escalation under the same resource budget. This reveals whether a proposed safeguard actually changes the decision or only changes the explanation. The third priority is transfer. A method should be re-evaluated across sites, devices, languages, organizations, or physical regimes before broad claims are made. Seen through physics-informed assurance, the issue is not merely technical; it determines which claims remain open to challenge.

Limits, Monitoring, and Contestability

A credible human-review process must be specified and tested. Reviewers need enough context to challenge the output, but not so much generated rationale that weak evidence is obscured by volume. Escalation queues require prioritization and workload limits. A reject option that sends nearly everything to experts is safe only on paper; a reject option that rarely fires may be equally ineffective. For multiaxial lattice loading, oversight should therefore be evaluated with realistic staffing, time pressure, and disagreement. The system should record the final action and its reason without turning that record into surveillance unrelated to the stated purpose. Contestability, privacy, and security are properties of this institutional process as much as of the model. The article's emphasis on physics-informed assurance makes that boundary observable and, in principle, auditable.

Operational rules are the governance expression of the evidence. A implementation specification should name allowed uses, prohibited uses, escalation thresholds, data-retention rules, and the person or role that can halt the system. Monitoring should track input shift, missingness, abstention, disagreement, latency, overrides, and downstream outcomes. A rising override rate may indicate model drift, a changed workflow, or new user behavior; treating it only as operator noncompliance wastes evidence. Incident review should reconstruct the entire chain, including the learned component and the surrounding interface. Versioned models without versioned prompts, retrieval indexes, rules, and datasets do not support reliable reconstruction. This point narrows the research task for multiaxial lattice loading: compare alternatives under the same information and resource constraints.

Conclusion

Physics-informed assurance is credible only when it is attached to an documented evidence chain and decision policy. Across the reviewed studies, several mechanisms can strengthen that chain: structured exploration, typed graphs, conditional revision, adaptive computation, physical constraints, and repeated testing. A reported benchmark gain still leaves the boundary of safe transfer to be established. For multiaxial lattice loading, the practical standard should be a traceable operational sequence that measures shift and instability, supports design screening, uncertainty-aware optimization, targeted simulation, and physical testing, and preserves enough evidence for an independent reviewer to reconstruct failure. Future work should compare safeguards under realistic resource and staffing limits, publish negative and subgroup results, and treat monitors and automated judges as components requiring their own validation. The final standard is not uninterrupted automation but evidence-linked action with documented deferral and independent verifiability. This requirement gives practical content to the article's central question: Which invariants should be checked independently of predictive accuracy?

References

1. Ma, Mingjun, et al. "MuSK: Multi-Scale Knowledge Learning for Provenance-Graph Anomaly Detection." Computer Networks 289 (2026): 112728.
2. Li, Yuanhao, et al. "BoostAPR: Boosting Automated Program Repair via Execution-Grounded Reinforcement Learning with Dual Reward Models." arXiv preprint arXiv:2605.09134 (2026).
3. Wang, Lizhe, et al. "Synergizing Machine Learning and Multiscale Shakedown Method for Shakedown Loading Capacity Evaluation of Parameterized Lattice Structures." Extreme Mechanics Letters 75 (2025): 102297.
4. Lundberg, Scott M., and Su-In Lee. "A Unified Approach to Interpreting Model Predictions." Advances in Neural Information Processing Systems, vol. 30, 2017.
5. Bendsoe, Martin P., and Ole Sigmund. Topology Optimization: Theory, Methods, and Applications. Springer, 2003.
6. Wilkinson, Mark D., et al. "The FAIR Guiding Principles for Scientific Data Management and Stewardship." Scientific Data, vol. 3, 2016, article 160018.
7. Suresh, S. Fatigue of Materials. 2nd ed., Cambridge University Press, 1998.
8. Miner, M. A. "Cumulative Damage in Fatigue." Journal of Applied Mechanics, vol. 12, 1945, pp. A159-A164.
9. Paris, P., and F. Erdogan. "A Critical Analysis of Crack Propagation Laws." Journal of Basic Engineering, vol. 85, no. 4, 1963, pp. 528-533.
10. Fatemi, Ali, and Darrell F. Socie. "A Critical Plane Approach to Multiaxial Fatigue Damage Including Out-of-Phase Loading." Fatigue & Fracture of Engineering Materials & Structures, vol. 11, no. 3, 1988, pp. 149-165.
11. Geers, M. G. D., V. G. Kouznetsova, and W. A. M. Brekelmans. "Multi-Scale Computational Homogenization: Trends and Challenges." Journal of Computational and Applied Mathematics, vol. 234, no. 7, 2010, pp. 2175-2182.
12. Kennedy, Marc C., and Anthony O'Hagan. "Bayesian Calibration of Computer Models." Journal of the Royal Statistical Society: Series B, vol. 63, no. 3, 2001, pp. 425-464.
13. Saltelli, Andrea, et al. "Variance Based Sensitivity Analysis of Model Output: Design and Estimator for the Total Sensitivity Index." Computer Physics Communications, vol. 181, no. 2, 2010, pp. 259-270.