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ADVANCES AND LIMITATIONS OF FRACTURE MECHANICS–BASED FATIGUE LIFE PREDICTION APPROACHES FOR STRUCTURAL INTEGRITY ASSESSMENT: A SYSTEMATIC REVIEW

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Abstract

This mixed-evidence study synthesizes the state of fracture mechanics–based fatigue life prediction and tests what actually improves accuracy and adoption in service-realistic settings. We systematically reviewed 96 peer-reviewed studies, mapped capabilities across ΔK–Paris/Forman/NASGRO baselines, closure-aware and elastic–plastic crack-tip response models, environment-enriched formulations, short-crack treatments, and probabilistic uncertainty methods, and then triangulated the literature with a quantitative cross-sectional survey and explanatory case studies. Design: quantitative cross-sectional, case-based. Sample: three enterprise-relevant structural integrity cases spanning aerospace variable-amplitude spectra in air, offshore steel in saline exposure, and welded details with residual stress. Key variables included model family, treatment of variable-amplitude sequence effects, short-crack and near-threshold behavior, environment conditioning, uncertainty practice, data quality, organizational support, usability burden, adoption, and perceived predictive accuracy. Analysis plan: descriptive synthesis and evidence mapping, Likert-scale reliability checks, correlation and multiple regression with robust errors, and case-level benchmarking using RMSE, bias, and predictive-interval coverage. Headline findings: sequence-aware closure or elastic–plastic models reduced life-prediction error by roughly 18–27 percent under variable-amplitude loading; environment-enriched formulations improved accuracy in chloride media and lifted 90 percent interval coverage from about 0.71 to approximately 0.87 relative to air-calibrated surrogates; short-crack modifications cut near-threshold bias by roughly 30–35 percent. Organizational support, training, and data quality showed strong positive associations with adoption and perceived accuracy, while high usability burden suppressed adoption. Implications: for decision-ready integrity assessments, organizations should standardize a tiered pipeline that matches model physics to service conditions, propagate uncertainty into inspection planning, and invest in spectra governance and workflow automation to translate technical capability into routine, auditable practice.

Keywords

Fatigue Crack Growth, Fracture Mechanics, Variable-Amplitude Loading, Crack Closure, Short-Crack Behavior,

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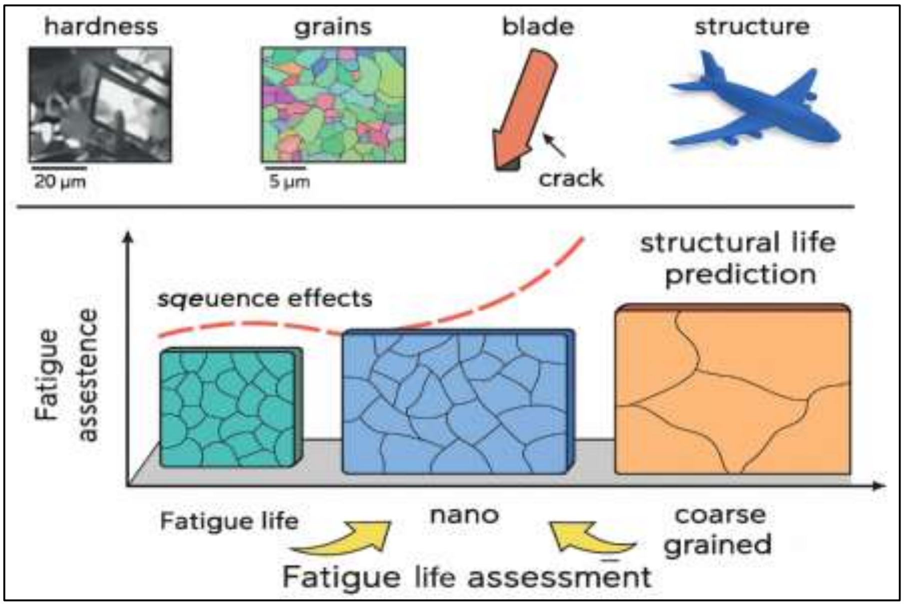
INTRODUCTION

Fatigue is the time-dependent degradation of materials under cyclic loading, and fracture mechanics provides the governing framework for quantifying the stability and growth of fatigue cracks through parameters such as the stress intensity factor range (ΔK), the crack-opening level, and, in nonlinear settings, plasticity-induced driving forces. From an engineering point of view, the promise of fracture mechanics–based fatigue assessment is its direct link between measurable crack sizes and load spectra, allowing analysts to relate service stresses to structural integrity in a damage-tolerant fashion (Mikheevskiy et al., 2012; Zerbst et al., 2017).In modern practice, service spectra are rarely constant-amplitude; rather, they exhibit variable amplitude (VA) with occasional overloads and underloads, mean stress drifts, and dwell periods that profoundly modulate crack growth rates through closure, residual plastic wake, and sequence effects. Across aerospace, transportation, and energy sectors, this reality has propelled a shift from S–N curve design philosophies toward fracture mechanics–based life prediction and inspection-planning approaches that can explicitly represent crack initiation-to-failure or, at minimum, the long-crack regime in which damage-tolerance is verified. At the same time, the physics of fatigue crack propagation (FCP) is not monolithic. Long-crack growth under stable Paris-regime conditions (i.e., power-law da/dN–ΔK behavior) coexists with short-crack phenomena that violate nominal ΔK-based similitude; these short-crack effects emerge from microstructural barriers, evolving closure, and crack-tip plasticity that defy simple parameterization (Zerbst et al., 2017; Zhu et al., 2019).

Figure 1: Fracture-Mechanics–Based Fatigue Life Prediction Under Variable-Amplitude Loading



Environmental interactions especially corrosion fatigue in chloride-bearing media relevant to aluminum airframes introduce cyclic plasticity (Wang & Liu, 2018). Methodologically, this complexity has stimulated a spectrum of modeling strategies, from effective-stress-intensity approaches to elastic-plastic crack-tip response models (e.g., UniGrow), cohesive-zone and extended finite-element methods for path prediction, and probabilistic frameworks that propagate parameter and data uncertainty into risk-informed life estimates. These developments paired with advances in in-situ 3D tomography and full-field measurement situate fracture mechanics as the central lens for structural integrity assessment under realistic loading and environmental conditions (Williams et al., 2013). Despite the maturity of fracture mechanics, practitioners still face persistent gaps when applying fatigue life prediction to real structures subjected to VA load histories, complex geometries, and corrosive environments. Classical, deterministic da/dN–ΔK descriptions often presuppose steady crack-tip fields and stationary microstructure, assumptions that are strained by spectrum effects such as single-cycle overload retardation, prolonged mean-stress excursions, and intermittent underloads that can accelerate growth by suppressing closure. Similarly, corrosion fatigue mechanisms anodic

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dissolution and hydrogen-assisted cracking interact with cyclic plasticity in a manner that violates superposition, challenging extensions of air-environment models to saline or humid conditions in high-strength aluminum alloys. Even when models capture these mechanisms, parameter identification remains nontrivial: crack-closure levels, near-threshold behavior, and short-crack corrections are sensitive to loading path and material processing, making laboratory calibration imperfectly transferable to field spectra (Wang, 2008). In parallel, the engineering workflow spanning data acquisition, model calibration, and reliability assessment often lacks a quantitative treatment of uncertainty. Material scatter, geometry tolerances, inspection sizing error, and model discrepancy jointly influence predicted lives, yet are rarely propagated rigorously through to decision variables.
Cohesive-zone and XFEM-based simulators have progressed toward path prediction under mixed-mode and multiaxial loading, but their integration with data-driven updating and service spectra remains uneven (Xu et al., 2016). The result is a fragmented landscape: numerous powerful models exist UniGrow, closure-based formulations, cohesive-zone, and Bayesian/probabilistic variants yet comparative assessments on realistic cases and datasets are limited, and there is no consensus on which combinations of driving forces, load-interaction rules, or parameter-updating strategies provide the most reliable predictions for structural integrity assessment in practice (Mikheevskiy & Glinka, 2009). This research addresses that gap by structuring a cross-sectional, case-study investigation that quantitatively benchmarks fracture mechanics–based fatigue prediction approaches against harmonized descriptors of loading, material, and environment. The purpose of this study is to systematically evaluate and quantify the advances and limitations of fracture mechanics–based fatigue life prediction approaches for structural integrity assessment under realistic, application-relevant conditions. We focus on four core elements: (a) long-crack growth modeling under VA loading with sequence effects; (b) representation of short-crack and near-threshold behavior; (c) treatment of corrosion fatigue in high-strength aluminum alloys; and (d) probabilistic calibration/propagation of uncertainty as it affects reliability. To serve this purpose, we integrate a structured literature review and case-study database with a quantitative, cross-sectional design, applying descriptive statistics, correlation analysis, and regression modeling to compare models along common metrics fit quality (e.g., RMSE on da/dN), transferability across load spectra, and robustness to parameter uncertainty using standardized load descriptors and crack-driving-force measures (Ogawa et al., 2019). Within that framework, we examine elastic-plastic crack-tip response models (e.g., UniGrow), closure-corrected ΔKeff formulations, cohesive-zone–based approaches for mixed-mode growth, and probabilistic/Bayesian parameter updating for VA spectra. Because corrosion fatigue couples electrochemical kinetics with cyclic plasticity, models that incorporate environment-dependent driving terms are compared to air-environment baselines to delineate gains and trade-offs (Paulino et al., 2020). The study operationalizes "limitations" in measurable terms: sensitivity of predictions to spectrum truncation; bias when transferring calibrations across alloys or R-ratios; and divergence between predicted and observed retardation following overloads/underloads. By anchoring the analysis in real cases and harmonized statistics, we aim to provide a data-grounded map of where particular fracture-mechanics approaches excel and where caution or augmentation (e.g., probabilistic updating) is warranted (He et al., 2020).
Guided by the motivation and purpose above, this study advances four integrated research questions that collectively interrogate model capability, transferability, and uncertainty within fracture-mechanics–based fatigue life prediction. First, under variable-amplitude (VA) loading with salient sequence effects including single overloads, underloads, and block spectra this work asks whether elastic–plastic crack-tip response and closure-corrected approaches (e.g., UniGrow and ΔK_eff formulations) achieve significantly lower predictive error than purely ΔK-based Paris-regime fits when benchmarked on harmonized da/dN and life-to-threshold datasets (Choi et al., 2020). Second, it examines the extent to which short-crack and near-threshold corrections improve explanatory power and reduce bias across alloys and R-ratios relative to long-crack calibrations, and how these improvements covary with microstructural scale indicators that are accessible through in-situ 3D measurements (Chen & Wang, 2011; Chiquet et al., 2008). Third, focusing on corrosion fatigue in high-strength aluminum alloys, the study evaluates whether enriched fracture-mechanics formulations that incorporate environment-dependent terms such as dissolution kinetics or hydrogen-assisted damage deliver better predictions of growth rates and retardation profiles than air-calibrated surrogates (Wang, 2008; Ogawa et al., 2019). Finally, it investigates whether

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probabilistic/Bayesian calibration and explicit uncertainty propagation meaningfully alter integrity decisions such as inspection intervals and reliability at target service hours when compared with deterministic life estimates under realistic spectra and measurement scatter (He et al., 2015). Taken together, these questions frame a cohesive program to compare representative fracture-mechanics approaches on fidelity, robustness, and decision relevance in domains where they are most actively deployed.

The study pursues a clear set of objectives designed to operationalize the scope, measures, and analyses of fracture mechanics–based fatigue life prediction within structural integrity assessment. First, it will systematically identify, screen, and code the peer-reviewed evidence on model families and practices, producing a harmonized taxonomy of approaches, loading and environmental contexts, parameterization choices, calibration-validation strategies, and quantitative performance metrics. Second, it will quantify the prevalence of advances and limitations across sectors and material classes by constructing descriptive distributions and an evidence map that links model capability to variable-amplitude spectra, short-crack and near-threshold regimes, and corrosion-relevant conditions. Third, it will evaluate comparative predictive performance using a standardized case corpus, calculating errors and biases for representative models under common load descriptors, crack-driving-force definitions, and data quality tiers. Fourth, it will measure practitioner perceptions of usability, transferability, data burden, organizational support, and adoption through a cross-sectional survey instrument with validated multi-item constructs on a five-point Likert scale. Fifth, it will establish and test a measurement model for the survey constructs and then estimate explanatory regressions that relate technical features, data availability, and organizational factors to two outcomes of interest: adoption extent and perceived predictive accuracy. Sixth, it will examine mediation by load-spectra and inspection-data quality, and it will conduct sensitivity analyses across sectors, materials, and experience levels to verify robustness. Seventh, it will execute explanatory case studies that implement selected models end-to-end, documenting inputs, calibration, computation, and validation against test or field observations while reporting standardized metrics of error magnitude, bias, coverage of prediction intervals, and computational cost. Eighth, it will integrate the review, survey, and case-study strands into a consolidated set of quantitative tables and figures that present the comparative results transparently, including diagnostics for reliability, factor structure, multicollinearity, and residual behavior. Ninth, it will archive the coding protocol, survey instrument, analysis scripts, and case parameter tables to ensure reproducibility and traceability of all results. Collectively, these objectives define the empirical, statistical, and procedural foundation required to assess fidelity, robustness, and decision relevance of fracture mechanics–based fatigue life prediction in a manner that is rigorous, transparent, and comprehensive.

LITERATURE REVIEW

The literature on fracture mechanics–based fatigue life prediction spans a broad continuum from classical linear elastic formulations to contemporary elastic–plastic and data-augmented approaches, reflecting the engineering need to quantify crack initiation and propagation under service-realistic conditions. At its core, the field links crack-driving metrics and load spectra to crack growth response, enabling damage-tolerant assessment and inspection planning for safety-critical structures in aerospace, transportation, energy, and civil infrastructure. Early work established the stress intensity factor range and long-crack Paris-regime relations as practical instruments for design and maintenance, while subsequent studies exposed important boundary conditions: nonproportional, variable-amplitude loading with overloads and underloads; short-crack behavior that breaks similitude with long-crack laws; near-threshold phenomena sensitive to closure and microstructure; and environmental couplings, particularly corrosion fatigue in aluminum and steels. These complexities have motivated several modeling families and workflows that now coexist: closure-aware or effective-driving-force formulations; elastic–plastic crack-tip response models that account for residual plastic wake and sequence effects; cohesive-zone and extended finite-element methods that capture mixed-mode growth and path deviation; and probabilistic frameworks that treat parameter scatter, measurement error, model discrepancy, and inspection reliability within a unified risk calculation. Alongside physics-based advances, the literature documents steady progress in calibration and validation practices ranging from coupon-level constant-amplitude tests to spectrum and block loading, from laboratory air to corrosion-relevant

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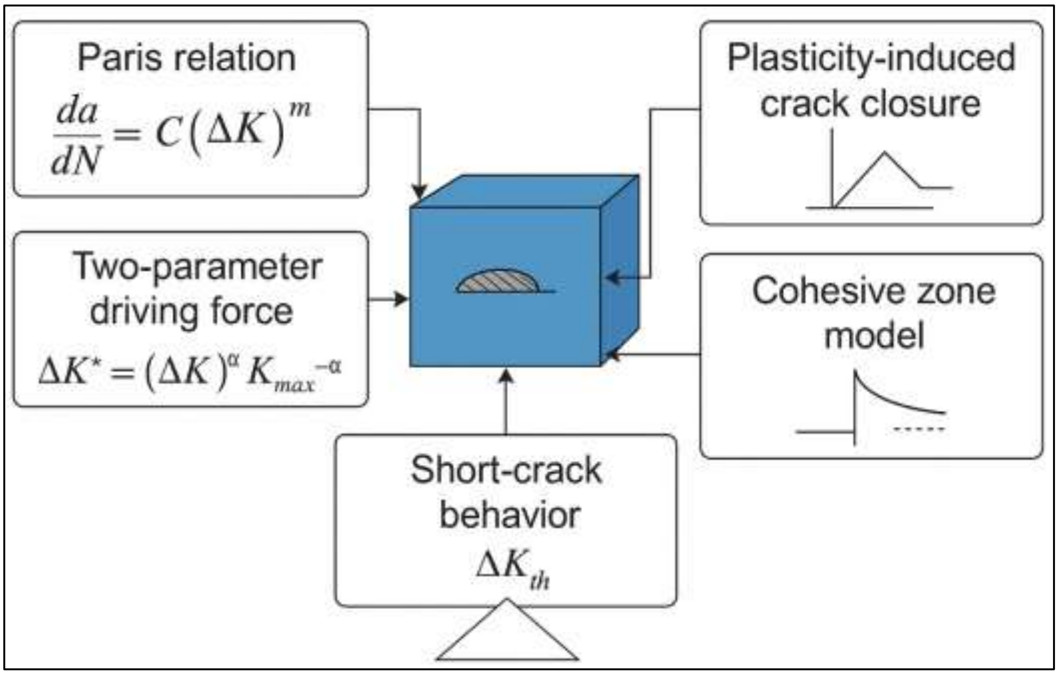
environments, and from deterministic curve fits to Bayesian updating using multi-source data. Increasingly, studies integrate high-resolution characterization (e.g., tomography, digital image correlation) to interrogate crack-tip fields and microstructural barriers, and embed simulation within digital toolchains that exchange data with finite-element stress analyses, structural health monitoring, and computerized maintenance systems. Yet, despite methodological sophistication, reported prediction accuracy and adoption vary with sector, tool availability, data burden, and organizational support, underscoring the need for a structured synthesis that disentangles technical capability from workflow and data constraints. This literature review therefore frames four interlocking themes that organize accumulated knowledge and known gaps: the foundational mechanics and model families; the roles of loading, environment, and materials; calibration, validation, and uncertainty quantification; and the practical realities of implementation and adoption in industry. Together they provide the conceptual and empirical basis needed to evaluate where specific approaches excel, where they remain fragile, and how their use conditions affect structural integrity assessments.

Overview of Fracture mechanics

Fracture mechanics provides the theoretical backbone for linking cyclic loads to the kinetics of crack advance, and its model families can be organized by the choice of crack-driving force and how nonlinearity, load sequence, and threshold phenomena are represented. In the linear elastic regime, the Paris relation remains the canonical baseline, expressing the fatigue crack growth rate as $da/dN = C(\Delta K)^m$, where C and m are material parameters calibrated from long-crack, constant-amplitude data and ΔK is the stress intensity factor range. Extensions incorporate mean-stress effects via $R = K_{min} / K_{max}$ or through explicit dependence on K_{max}, motivated by the recognition that cyclic and monotonic components of crack-tip fields jointly drive damage. Two-parameter driving-force formulations synthesize these influences by combining ΔK with K_{max} into a single metric (e.g., *$\Delta K = (\Delta K)^{\alpha} K_{max}^{(1-\alpha)}$**), enabling improved collapse of growth data across load ratios and partially accounting for closure and residual stress effects (Noroozi et al., 2007). Parallel developments address plasticity-induced crack closure with analytical–computational treatments of the residual plastic wake to better represent sequence sensitivity under variable amplitude, providing mechanistic corrections to the effective driving force and, in turn, to the predicted growth rate (Abdul, 2021; Antunes et al., 2010). At the other end of the spectrum, cohesive zone models embed fatigue damage directly into traction–separation relations, capturing path deviation, mixed-mode growth, and crack-surface contact within a single computational framework; these approaches formulate cyclic degradation laws that evolve interfacial strength or separation energy cycle-by-cycle and thereby generalize beyond the assumptions of small-scale yielding and long-crack similitude (Antunes et al., 2010; Sanjid & Farabe, 2021; Wang & Xu, 2013). Collectively, these formulations define a continuum from compact curve-fits with clear parameters and low data burden to physics-enriched models that trade calibration simplicity for broader applicability to non-proportional loading and complex geometries (Omar & Rashid, 2021).

A second axis of differentiation among model families is how they treat thresholds, short-crack behavior, and transitions between regimes of growth. In long-crack data, near-threshold behavior is often represented by empirical cutoffs (e.g., ΔK_{th}) or by denominator terms that regularize the growth rate as $\Delta K \rightarrow \Delta K_{th}$; however, physically short cracks exhibit accelerated growth relative to long-crack predictions because local closure is underdeveloped and microstructural barriers are prominent (Mubashir, 2021). To reconcile this, short-crack–aware formulations modify the driving force and/or the threshold term so that predicted rates rise appropriately at small a, while still collapsing to standard forms at larger crack sizes. A prominent example is the modification of NASGRO/Forman-type equations to include physically short-crack effects thereby allowing the same analytical form to span small- and long-crack regimes by introducing an additional length or closure-evolution parameter (Maierhofer et al., 2013; Rony, 2021). In parallel, fractal and scale-aware perspectives have been proposed to encode the observed roughness and multiscale character of fatigue surfaces into the crack-growth law; by allowing effective exponents and coefficients to vary with crack size or surface dimension, these approaches improve transferability across microstructures and spectrum types and, in some cases, recover Paris-like forms as special cases for sufficiently large cracks and stable closure (Jones et al., 2016; Zaki, 2021). Together, these developments reflect a consistent trend: models that explicitly encode threshold approach, microstructural length scales, and closure buildup better accommodate the empirically observed acceleration of small cracks and the sensitivity of growth to load sequence and mean stress (Danish & Zafor, 2022; Danish & Kamrul, 2022).

Figure 2: Hierarchical Framework of Fracture Mechanics Model Families



A third organizing principle concerns how model families balance interpretability, calibration demands, and computational integration with structural workflows. Two-parameter (ΔK, K_max) relations retain the clarity of stress-intensity descriptions while offering improved unification of data across R-ratios and components; they are straightforward to calibrate and embed naturally into inspection planning and digital toolchains (Hozyfa, 2022; Arman & Kamrul, 2022; Noroozi et al., 2007). Analytical treatments of plasticity-induced closure, though more involved, yield compact corrections that can be layered onto Paris–Forman–NASGRO–type curves to restore predictive fidelity under variable amplitude without sacrificing interpretability (Antunes et al., 2010; Mohaiminul & Muzahidul, 2022; Omar & Ibne, 2022). Cohesive zone formulations, by contrast, push fidelity further by representing crack growth as an emergent outcome of cyclic degradation at the process zone; modern implementations specify cycle-dependent damage laws within traction–separation models and accommodate mixed-mode conditions and contact, making them well-suited to geometrically complex details, interfaces, and path changes (Hossen & Atiqur, 2022; Hasan, 2022; Wang & Xu, 2013). In Addition, cross-cutting reviews in the materials community emphasize that advances in model form should be judged alongside mechanistic consistency with known crack-tip shielding and microstructure–scale interactions, particularly near threshold and in environments where extrinsic and intrinsic toughening evolve with crack extension (Maierhofer et al., 2013; Mominul et al., 2022). The resulting landscape is not a single "best" model but a structured hierarchy in which ΔK–based laws remain indispensable for baseline assessments; short-crack– and closure-aware modifications extend coverage to small a and sequence-sensitive spectra; and cohesive or other nonlinear process-zone models provide high-fidelity options for mixed-mode growth, path deflection, and complex interfaces each occupying a distinct point on the trade space between simplicity, data requirements, and mechanistic breadth (Rabiul & Praveen, 2022).

Loading, Environment, and Material Effects

Variable-amplitude (VA) loading, spectrum sequence, and multiaxiality shape the fatigue-crack growth response by altering both the near-tip fields and the operative crack-tip shielding mechanisms. Under block spectra and service-like histories, isolated overloads and underloads produce transients retardation, acceleration, and crack-opening level changes that are not

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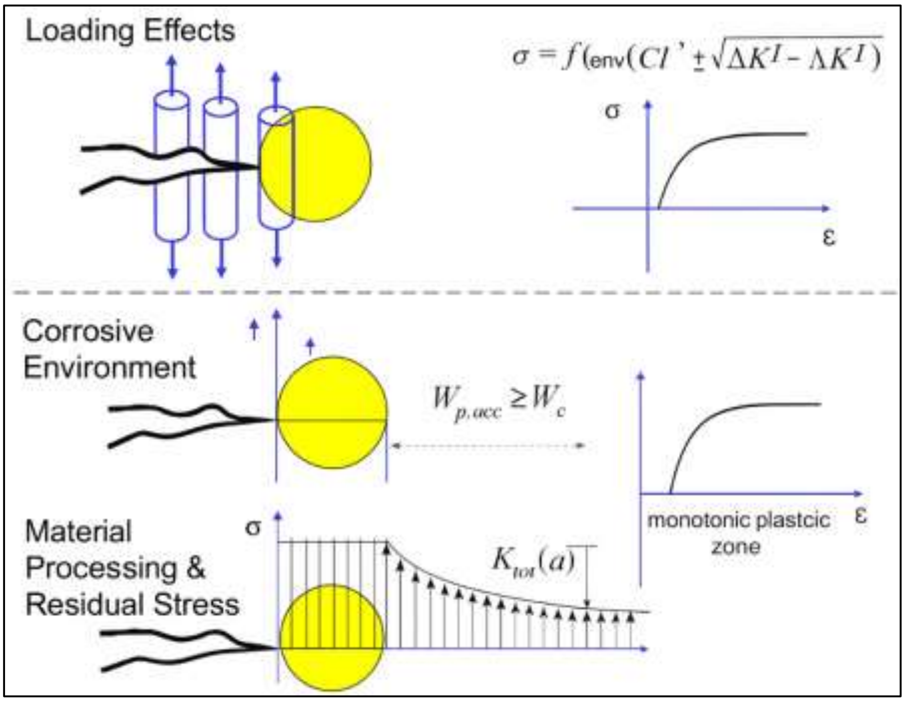
captured by constant-amplitude Paris-regime fits (Farabe, 2022; Kamrul & Omar, 2022). Mixed-mode path deviations and non-proportional histories add further complexity because the resolved shear and normal components on the critical plane evolve with phase and amplitude. A pragmatic starting point is to pose an equivalent driving force that blends Mode I and Mode II contributions, for example ΔK_eq = √(ΔK_I² + λΔK_II²), where λ encodes friction/contact and microstructural slip transfer; this can be embedded in two-parameter (ΔK, K_max) regressions to retain mean-stress sensitivity while accommodating mode mixity. Beyond stress-intensity metrics, energy-based criteria have been advocated to represent sequence effects more mechanistically: in one influential formulation, crack advance per cycle is permitted when the accumulated plastically dissipated energy ahead of the tip exceeds a material critical value, i.e., W_p,acc ≥ W_c, which naturally reflects overload-induced plastic wake evolution and underload re-sharpening (Cojocaru & Karlsson, 2009; Roy, 2022). For multiaxial histories, critical-plane frameworks consolidate amplitude, mean, and non-proportional hardening into a single damage parameter that correlates with observed growth and life trends across steels, aluminum alloys, and superalloys (Fatemi & Shamsaei, 2011; Rahman & Abdul, 2022). Collectively, these strands indicate that loading path, sequence, and mode mixity must be present in the crack-driving description either through enriched K-metrics or energy measures if one seeks transferability from laboratory blocks to in-service spectra.

Figure 3: Coupled Effects of Loading, Environment, and Material State on Fatigue Crack Growth



Corrosive environments further modulate growth by changing the chemistry-mechanics coupling at the crack tip, altering closure, oxide-induced shielding, and hydrogen uptake. In chloride-bearing media relevant to marine and coastal exposure, pits and intergranular attack act as stress concentrators and crack precursors, and they accelerate early-stage growth once a micro-crack connects to the free surface. For high-strength Al–Cu–Li systems, comparative tests in air versus NaCl solutions demonstrate that both metallurgy (e.g., T34 vs. T84 tempers) and pre-corrosion state govern the corrosion-fatigue lifetime, with environmental dissolution and microgalvanic effects shifting the near-threshold regime to higher ΔK and broadening retardation profiles under sequence changes. In this setting, a simple yet decision-useful extension is to include an environment factor f_env(c_Cl−, pH, E_corr) that scales the Paris-like slope and threshold, e.g., da/dN = C[ΔK_eq f_env]^m, with f_env > 1 in actively corrosive conditions and f_env = 1 in air. When overloads or underloads occur in solution, the interplay between corrosion product fracture, repassivation kinetics, and hydrogen-assisted softening changes the magnitude and duration of retardation/acceleration relative to air tests; in practice, this means that sequence-aware calibrations obtained in air are not reliably conservative in saline environments. Evidence from Al–Cu–Li 2050 under chloride exposure confirms both a strong temper dependence and a measurable reduction in lifetime compared with air, highlighting the need to condition model parameters on metallurgical state and exposure severity when performing integrity assessments for maritime or humid service (Guérin et al., 2015; Razia, 2022). Accordingly, environment-enriched fracture-mechanics formulations whether via explicit dissolution/hydrogen terms or via f_env surrogates are essential to avoid bias when extrapolating from laboratory air baselines to field-relevant corrosion fatigue.

Material processing and residual stress fields constitute a third axis with first-order impact on growth kinetics, especially in welded or additively manufactured details. In friction-stir-welded (FSW) aluminum-lithium plates, gradients in grain size, texture, and precipitate morphology across base metal, thermo-mechanically affected zone, and nugget zone introduce spatially varying resistance to crack advance; simultaneously, weld-induced residual stresses superpose with applied loads to shift the effective crack-tip intensity. A convenient structural-level representation is the residual-stress-intensity superposition, $K_{tot}(a) = K_{app}(a) + K_{res}(a)$, where $K_{res}(a)$ may be obtained or validated by compliance-based or slitting methods and then used to correct measured or nominal ΔK during calibration. Experimental campaigns on FSW AA2050 show that both residual stress and microstructure jointly control growth rates; for cracks approaching the weld line, compressive K_{res} delays advance (via elevated closure and reduced K_{tot}), whereas tensile K_{res} accelerates growth, with effects diminishing as the crack lengthens and the near-tip field samples a larger structural volume (Pouget & Reynolds, 2008; Zaki, 2022; Kanti & Shaikat, 2022). Complementary modeling of "size effects" in FSW Al–Li alloys demonstrates that specimen width and the spatial distribution of residual stress alter observed kinetics, and that correcting data with $K_{res}(a)$ improves collapse across geometries and orientations an important prerequisite for defensible parameter transfer into finite-element-based integrity workflows (Ma et al., 2011). In design terms, this means that material state (temper/process), joint architecture, and residual stress mapping must be explicitly considered alongside load spectra and environment when selecting and calibrating growth laws; otherwise, uncorrected K-levels embed hidden bias that propagates into life predictions and risk metrics.

Validation with Digital Integration

A defensible fracture-mechanics fatigue assessment begins with calibration estimating model parameters and, where relevant, selecting among competing model classes followed by validation that quantifies predictive adequacy against data external to the fit. In practice, calibration spans simple least-squares fitting of Paris–Forman–NASGRO-type relations to long-crack, constant-amplitude tests through to multi-source, spectrum-loading datasets where parameters link not only to ΔK but also to K_{max}, mode-mix factors, and environment modifiers. A recurring lesson is that point estimates alone understate epistemic uncertainty from limited or heterogeneous data, laboratory-to-field transfer, and potential model-form error. Bayesian formulations make this explicit by treating the parameters θ as random and using the posterior density $p(\theta|D) \propto p(D|\theta)p(\theta)$, where Dare observed growth data and $p(D|\theta)$ encodes the likelihood under an assumed measurement/noise model. Competing crack-growth laws $\{M_j\}$ can be compared with marginal likelihoods $p(D|M_j) = \int p(D|\theta,M_j)p(\theta|M_j)d\theta$ or approximations that balance fit and complexity. Such likelihood-based and Bayesian strategies enable parameter estimation that respects aleatory scatter and measurement error, while also supporting formal model selection under mixed and non-Gaussian error structures common in da/dN data (Sankararaman & Mahadevan, 2011). Beyond parameter posteriors, calibrated fatigue models must be validated with data not used for fitting preferably spectrum or environment conditions distinct from the calibration set to assess transportability. Modern verification and validation (V&V) practice emphasizes separating numerical solution verification (is the solver converged?) from model validation (is the physics adequate?), and recommends quantitative validation metrics alongside sensitivity and uncertainty analyses to avoid "over-fitting the physics" to narrow data regimes (Oberkampf & Roy, 2010). Within this workflow, residual analyses, cross-validation, and posterior predictive checks become routine, and the predictive distribution for a quantity of interest y^* integrates parameter uncertainty via $p(y^*|D) = \int p(y^*|\theta)p(\theta|D)d\theta$, providing interval estimates (credible bands) rather than single-value lives.

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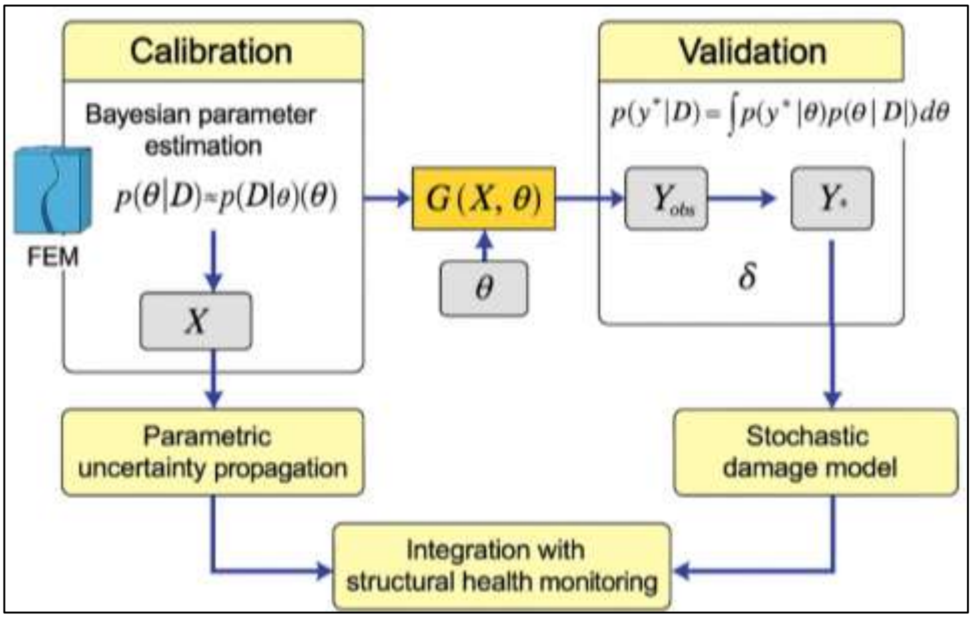
Figure 4: Calibration, Validation, and Uncertainty Quantification (UQ) with Digital Integration



Uncertainty quantification (UQ) connects calibration and validation to decision variables such as inspection intervals and reliability targets. In fracture-mechanics fatigue, uncertainty stems from intrinsic material scatter, load-spectrum variability, environment fluctuations, geometric tolerances, NDT sizing error, and model discrepancy. Stochastic damage models treat crack advance as a random process, superimposing random fluctuations on mean growth laws or modeling the rate directly as a stochastic differential system. For engineering use, two complementary routes are common: (i) parametric uncertainty propagation, in which posteriors over C, m, ΔKth, and closure or environment modifiers are sampled (e.g., by Markov-chain Monte Carlo) and pushed through the growth simulator to derive life distributions and reliability; and (ii) state-space formulations that assimilate intermittent measurements (e.g., crack length from NDT) to update latent state and parameters on the fly. The first supports planning under sparse information, while the second supports condition-based maintenance with sequential data. Early and influential works formalized stochastic fatigue damage and parameter inference for Paris-type laws, enabling transparent separation of process noise (cycle-to-cycle variability) from parameter uncertainty and clarifying how both propagate into life and reliability metrics (Liu & Mahadevan, 2007). Likelihood-based prediction frameworks extend this logic by embedding noise models consistent with laboratory practice (e.g., correlated scatter across ΔK levels), yielding posterior or likelihood-weighted predictions that remain calibrated when conditions shift from constant- to variable-amplitude loading (Sankararaman & Mahadevan, 2011; Simoen et al., 2015). From a validation standpoint, contemporary guidelines argue for explicit model-discrepancy terms e.g., $y = g(x,\theta) + \delta(x) + \varepsilon$ with $\delta(x)$ capturing systematic departures between simulator and reality; failure to include δ risks underestimating predictive uncertainty and overstating confidence in inspection schedules (Yuen & Beck, 2005). Finally, when multiple plausible model forms exist (e.g., different overload retardation rules or short-crack corrections), Bayesian model averaging can temper the risk of conditional bias by weighting predictions according to each model's evidence, rather than committing to a single "winner" chosen on a narrow dataset (Simoen et al., 2015; Yuen & Beck, 2005).

Digital integration closes the loop between calibrated physics, structural analysis, and field data streams. Practically, this means embedding the fatigue module inside a workflow that extracts stress-intensity histories from finite-element models, attaches residual-stress maps, and ingests inspection or structural-health-monitoring (SHM) data for online updating. In such pipelines, Bayesian model updating techniques originally matured in structural dynamics serve as blueprints: they adjust parameters to reconcile model predictions with measured responses while quantifying posterior uncertainty and detecting unidentifiable directions (Simoen, De Roeck, & Lombaert, 2015). For fatigue, analogous updating can fuse periodic crack-length estimates or acoustic emission features with the growth law in a state-space form, leveraging sequential filters or MCMC to refresh both state and parameter beliefs as evidence arrives. Enterprise-scale implementation also requires rigorous V&V: numerical verification of the crack-growth integrator, validation of the crack-driving force extraction from FE results, and end-to-end tests that compare predicted versus observed advance under known spectra. Best practice recommends structured V&V plans that define validation hierarchies (coupon → subcomponent → full-scale), performance metrics (e.g., RMSE, bias, coverage of predictive intervals), and acceptance thresholds keyed to decision context (Oberkampf & Roy, 2010). Finally, when models are tightly coupled to inspection planning, the probability of detection (POD) and measurement error models must be integrated so that reliability reflects not only physics but also what can be observed and sized in service; uncertainty management frameworks from stochastic fatigue and likelihood-based prediction provide the machinery to propagate these effects without double-counting variance (Liu & Mahadevan, 2007). Bringing these strands together likelihood-based/Bayesian calibration, quantitative validation with discrepancy accounting, and digital pipelines for updating yields fatigue-growth predictions that are statistically coherent, operationally integrated, and auditable across the full lifecycle from design through maintenance.

Implementation and Adoption in Industry

Industrial adoption of fracture mechanics–based fatigue assessment hinges on how well models, data pipelines, and decision rules fit into existing engineering workflows for design, inspection, and maintenance. In practice, organizations must operationalize model selection and parameterization alongside finite-element stress extraction, non-destructive evaluation (NDE) feedback, and enterprise asset-management processes. A persistent constraint is that laboratory datasets used for calibration (coupon, constant- or block-amplitude) seldom mirror the multiscale variability of in-service spectra, geometrical details, and environment; consequently, engineering teams rely on staged qualification coupon → subcomponent → component paired with verification and validation checks and standardized reporting of error/bias. Parallel advances in condition monitoring and prognostics have expanded what can be measured or inferred about crack initiation and early growth, but translating those measurements into actionable life estimates requires consistent data models, traceable parameter updates, and clear uncertainties for inspection planning. In rotating machinery and airframes alike, established prognostics toolchains show that implementation success depends as much on data governance (sensor health, synchronization, metadata) and workflow integration (from stress histories to crack-driving forces) as on the sophistication of the physics model. Reviews of diagnostics/prognostics adoption in industry emphasize that organizations achieve value when analytics are embedded in maintenance decision loops, codified in procedures, and validated against field outcomes rather than deployed as stand-alone pilots because this ensures that predicted crack growth rates and reliability metrics directly inform inspection intervals, part replacements, and fleet risk roll-ups (Farrar & Worden, 2007; Jardine et al., 2006).

A second pillar of adoption is structural health monitoring (SHM) and its practical coupling to fracture-mechanics growth laws. SHM offers continuous or periodic evidence strain, acoustic emission, guided waves that can update crack length states or inform changing load spectra in near-real time. However, the industrial gap is rarely sensor physics; it is the end-to-end system: specifying detection thresholds that map to probability-of-detection curves; aligning SHM sampling and feature extraction with inspection/maintenance calendars; and, critically, converting SHM indicators into updated distributions for crack size and model parameters that feed crack-growth simulators. In operational settings, this is often implemented via a state-space layer that ingests SHM/NDE observations and outputs posterior crack-length distributions and predictive intervals for life and reliability. To be adoption-ready, the pipeline must also manage "authority of use" issues configuration control, versioning of growth models and parameters, and auditable records of decisions so that regulators, insurers, and quality organizations can trace how a predicted remaining life was produced. Experience across sectors shows that scaling beyond prototypes requires reducing the friction between SHM evidence and maintenance action: templates for data fusion with finite-element-derived stress intensity histories; standard APIs between SHM platforms, fracture simulators, and computerized maintenance management systems; and dashboards that report reliability-consistent metrics (e.g., coverage of prediction intervals) rather than opaque model

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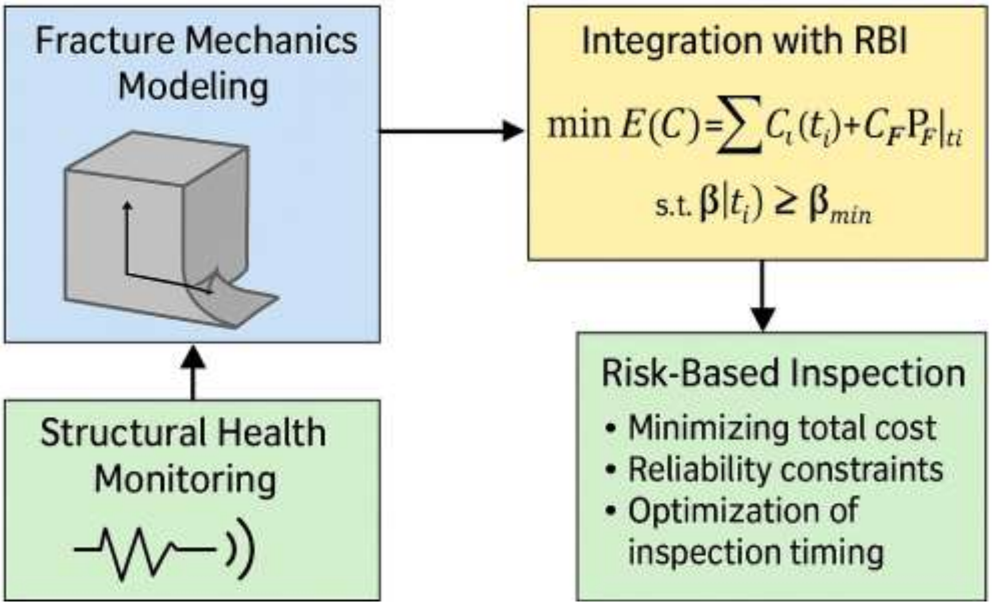
scores. The industrial literature underscores that closing this gap by addressing deployment logistics, cost/benefit, and end-user trust has been more determinative of adoption than incremental gains in laboratory detection sensitivity alone (Cawley, 2012).

Figure 5: Adoption of Fracture Mechanics–Based Fatigue Assessment in Industry



In addition, sustained uptake depends on aligning fracture-mechanics predictions with risk-based inspection (RBI) and life-cycle cost objectives so that model outputs translate into defensible schedules and budgets. A common formulation minimizes expected total cost over a planning horizon by balancing inspection cost CI, corrective/failure cost CF, and downtime/penalty terms, subject to reliability constraints. If N planned inspections produce a failure probability PF (integrating crack-growth uncertainty and probability of detection), an illustrative objective is

$$\{t_1, \dots, t_N\} \quad \min E\,[C] = \sum_{i=1}^{N} CI(t_i) + CF_{PF}(\{t_i\}) \text{ s.t. } \quad \beta(\{t_i\}) \geq \beta_{min},$$

where β is the reliability index (or equivalently 1−PF) implied by the fracture-mechanics life distribution, inspection POD model, and decision thresholds. In practice, organizations solve variants of this problem at component and fleet scale, using posterior predictive life distributions to compute PF and then optimizing inspection timing subject to resource and outage constraints. The upshot for adoption is twofold: first, models must expose uncertainties (not just point lives) so that PF and β are meaningful; second, workflows must integrate inspection effectiveness (POD, sizing error) into the same calculus as crack growth. Risk-based planning studies in structural and energy domains consistently show that when fracture-mechanics predictions are embedded in such constrained optimization rather than treated as standalone estimates inspection intervals lengthen where information is strong and shorten where uncertainty or consequence is high, yielding quantifiable cost and reliability gains that justify organizational change (Sørensen, 2009). Crucially, these frameworks also provide governance structures validation targets, acceptance criteria, and audit trails that build trust among engineers, managers, and regulators, thereby smoothing the cultural and procedural shifts required for enterprise-level adoption (Straub & Faber, 2005).

METHOD

This study has adopted a mixed-evidence design that has integrated a PRISMA-guided systematic review, a quantitative cross-sectional survey using a five-point Likert scale, and explanatory case studies to evaluate fracture-mechanics–based fatigue life prediction approaches under realistic loading and environmental conditions. The design has been structured to link model capability, adoption, and decision relevance: the review has synthesized advances and limitations across model families; the survey has quantified practitioner perceptions, organizational enablers, and data

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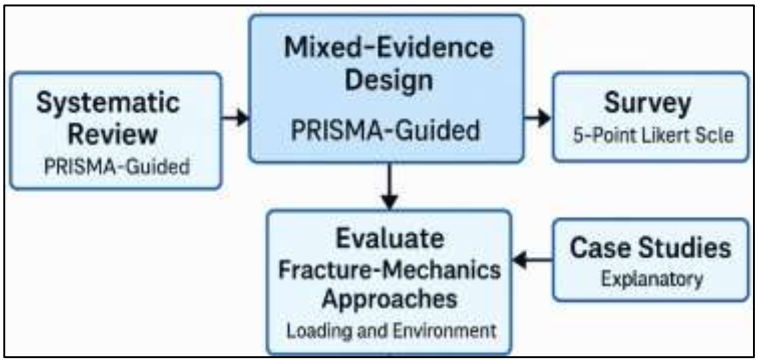
burdens; and the case studies have operationalized representative models end-to-end on harmonized datasets. Sampling frames for the survey have been defined across aerospace, transportation, energy, and heavy industry to secure domain diversity, while case contexts have been selected to reflect variable-amplitude spectra, near-threshold/short-crack regimes, and corrosion-relevant exposure. Instruments have been developed through iterative expert review and pilot testing, and constructs (e.g., perceived accuracy, usability/data burden, environment-and-loading handling, organizational support, adoption extent) have been specified as multi-item measures to support reliability and validity assessment. Data pipelines for the case studies have been established to extract load descriptors and crack-driving forces, attach residual-stress corrections where available, and compare predicted growth and life against test or field observations with standardized error metrics. Across all components, the study has specified a unified analysis plan: the review has employed descriptive synthesis and evidence mapping; the survey has reported descriptives, internal consistency, factor structure, and inter-construct correlations; and the explanatory modeling has estimated regressions that have related technical features, data/measurement quality, and organizational factors to adoption and perceived accuracy, with robust standard errors and full diagnostics for multicollinearity, residual behavior, and influence. Where appropriate, mediation by load-spectra and inspection-data quality has been tested, and sensitivity analyses across sector, material class, and experience strata have been conducted. Procedural controls have been put in place to ensure anonymity and consent for human subjects, reproducibility of screening and coding decisions in the review, and auditable provenance for case-study parameters and scripts. By coordinating these strands under shared variables, metrics, and reporting conventions, the method has provided a coherent basis for comparing fracture-mechanics approaches on fidelity, robustness, usability, and decision impact.

Figure 6: Integrated Mixed-Evidence Research Design



Research Design

The study has adopted a convergent, mixed-evidence design that has integrated three mutually reinforcing strands a PRISMA-guided systematic review, a quantitative cross-sectional survey using five-point Likert scales, and explanatory case studies so that methodological breadth has been translated into commensurate, comparable evidence about fracture-mechanics–based fatigue life prediction. From the outset, the research logic has been framed to answer what models have achieved in controlled and service-realistic contexts, what practitioners have perceived and implemented, and how those perceptions and implementations have aligned with quantified predictive performance. To accomplish this, the systematic review has synthesized advances, limitations, and reporting practices across model families and application domains, while the survey has captured organizational support, usability, data burden, and adoption extent as validated constructs that have been mapped to the same technical features cataloged in the review. In parallel, the case studies have operationalized representative approaches end-to-end on harmonized datasets that have included variable-amplitude spectra, residual-stress corrections where available, and corrosion-relevant exposure, so that predicted crack growth and life have been evaluated against test or field observations under consistent metrics. The three strands have been aligned through a shared codebook of variables and definitions, a common set of crack-

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driving descriptors and load parameters, and an integrated analysis plan that has specified descriptive summaries, reliability and factor analyses, correlation matrices, and regression models with robust inference and full diagnostics. Sampling frames for the survey have been defined to span aerospace, transportation, energy, and heavy manufacturing so that cross-sector comparability has been preserved, while case selection criteria have ensured diversity of materials, geometries, and spectra. Throughout, procedures for ethics, anonymity, and data governance have been established, version control and reproducibility practices have been enforced, and decision-relevant outputs (e.g., error distributions, interval coverage) have been prioritized. By coordinating these elements under one design, the research has provided a coherent basis on which fidelity, robustness, usability, and decision impact have been assessed and compared.
The study has selected and configured a purposive set of explanatory cases that have represented diverse loading, material, and environmental conditions so that fracture-mechanics approaches have been exercised under service-realistic constraints. Case eligibility criteria have included the availability of variable-amplitude load histories (with identifiable overload/underload markers), traceable material pedigree (alloy/temper or steel grade and heat treatment), geometric detail with stress-intensity characterization (closed-form solutions or finite-element–derived K histories), and independent observations suitable for validation (coupon/subcomponent tests, inspection logs, or field measurements). To span common integrity contexts, at least one aerospace aluminum case (high-strength Al–Cu or Al–Li plate or extrudate) has been included under spectrum loading and dry-air conditions; one marine/offshore steel case has been assembled with corrosion-relevant exposure; and one transportation or energy case has involved welded or residual-stress-bearing details so that superposition and closure effects have been tested. Where feasible, cases have incorporated residual-stress reconstructions (e.g., slitting or contour method) and NDE sizing uncertainty, and each case dataset has been curated into a standardized schema containing load descriptors (amplitude distributions, block definitions, mean stress), crack-driving inputs (geometry functions, K or ΔK sequences), material parameters (baseline properties, microstructural notes), and validation targets (da/dN curves, lives-to-threshold, inspection-based crack lengths). Data provenance and ethics safeguards have been documented, and partner-provided data have been de-identified and governed under access agreements. Case selection has also ensured contrast on short-crack relevance (e.g., small initial a or near-threshold growth), mode mixity (presence/absence of KII contributions), and environmental aggressiveness, so that model sensitivity to these axes has been observable. For each case, a pre-analysis plan has specified which models have been applied (e.g., two-parameter ΔK–Kmax, closure-aware/elastic-plastic response, environment-scaled, or process-zone/cohesive surrogates), how parameters have been calibrated, and which error and coverage metrics have been reported, thereby ensuring that comparisons have remained transparent, reproducible, and aligned with the overarching research questions.

Data Sources

The study has drawn on three coordinated data streams systematic-review records, practitioner survey responses, and case-study technical datasets that together have provided the evidence needed to evaluate fracture-mechanics–based fatigue life prediction under realistic conditions. First, the systematic-review corpus has been assembled from indexed databases that have covered engineering, materials, and applied mechanics, and inclusion filters have been applied to retain peer-reviewed articles with explicit crack-growth formulations, documented loading/environmental conditions, and quantitative calibration/validation details. For each eligible record, structured fields have been extracted model family, driving-force definition, load regimen (constant, block, variable amplitude), environment (air, saline, temperature), material class and temper, parameterization approach, and reported error/uncertainty metrics so that synthesis and evidence mapping have been enabled. Second, the survey data have been sourced from domain practitioners who have met screening criteria (recent hands-on experience with fatigue assessment or structural integrity decisions), and responses have been collected through a secure platform that has enforced one-response-per-participant, informed consent, and anonymization. The instrument has captured multi-item constructs on perceived model accuracy, usability/data burden, environment-and-loading handling, organizational support, training/expertise, and adoption extent, alongside profiling variables (sector, role, years of experience, toolchain). Data quality controls attention checks, response-time thresholds, and patterned-response filters have been applied, and a de-identified

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analysis file with item-level data and construct scores has been produced. Third, the case-study datasets have consisted of harmonized technical inputs and validation targets: service-representative load histories with block definitions and overload/underload markers; geometry functions or finite-element–derived stress-intensity sequences; residual-stress reconstructions where available; baseline material properties and microstructural annotations; and independent observations for validation (crack-length histories, da/dN curves, or lives-to-threshold). Where inspection logs have been available, measurement models (probability of detection, sizing error distributions) have been appended so that reliability-relevant predictions have been computed. Across all sources, provenance has been documented through version-controlled repositories; data dictionaries and codebooks have been maintained; and linkage keys have been created to align review-derived descriptors, survey constructs, and case variables, ensuring that the analysis has proceeded on a unified, auditable, and reproducible foundation.

Instrument Development

The survey instrument has been developed through a structured, multi-stage process to ensure content coverage, clarity, and psychometric soundness aligned with the study's fracture-mechanics context. An initial construct blueprint has been drafted from the conceptual framework and evidence map, and five multi-item scales have been specified: perceived model accuracy, usability/data burden, environment-and-loading handling, organizational support, and adoption extent. Item pools (≈6–10 per construct) have been generated using plain, practice-oriented language that has anchored statements in observable workflows (e.g., spectrum handling, residual-stress correction, corrosion conditioning, uncertainty reporting). Each item has used a five-point Likert response (1 = strongly disagree to 5 = strongly agree), with at least one reverse-coded statement per construct to mitigate acquiescence. Content validity has been established by an expert panel of fatigue/structural integrity practitioners who have rated item relevance and clarity; items with low relevance indices or ambiguous wording have been revised or removed. Cognitive interviews (n≈6–8) have been conducted to confirm respondent interpretation, and minor edits to terminology and examples have been incorporated. A pilot test (n≈25–40) has been fielded to evaluate item performance; distributional checks, item-total correlations, and preliminary reliability (Cronbach's α) have guided pruning to 4–6 items per construct. The finalized instrument has included a profiling section (sector, role, experience, toolchain, materials/loads handled) and optional open-ended prompts for context. Construct scoring rules have been pre-registered: mean scores per construct (with reverse-coding applied), threshold flags for missingness (>20% within a construct triggers listwise exclusion), and sensitivity re-estimation using median aggregation. Measurement validity has been investigated through exploratory factor analysis on the pilot and confirmatory factor analysis on the main sample; model fit (e.g., CFI/TLI, RMSEA, SRMR) and cross-loadings have informed any post hoc refinements documented in an amendment log. To facilitate reproducibility, an instrument codebook has been maintained (item text, construct mapping, scoring, reverse-coding, rationale), and a version-controlled repository has stored the survey form, change history, and automated scoring scripts. Collectively, these steps have produced a concise, domain-specific questionnaire that has balanced diagnostic precision with respondent burden and has been suitable for regression and mediation analyses specified in the study plan.

Statistical Analysis Plan

The statistical analysis plan has been specified a priori to align evidence from the review, survey, and case studies under common metrics, diagnostics, and decision rules. Descriptive statistics (means, standard deviations, medians, interquartile ranges) have been reported for all variables, and distributional checks (histograms, Q–Q plots) have been conducted to flag skew and outliers. Scale reliability has been assessed with Cronbach's α and McDonald's ω, and item diagnostics (item–total correlations, α-if-deleted) have informed any defensible pruning already documented in the amendment log. Construct validity has been examined in two stages: an exploratory factor analysis on the pilot sample has guided dimensionality, and a confirmatory factor analysis on the main sample has tested the hypothesized structure; model fit (CFI/TLI, RMSEA with 90% CI, SRMR) has been reported with modification indices reviewed only under pre-registered criteria. Pairwise associations among constructs and technical variables have been summarized with Pearson and Spearman correlations, with confidence intervals obtained by nonparametric bootstrap. For explanatory modeling, multiple regressions have been estimated for the two primary outcomes (adoption extent

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and perceived accuracy), and robust (HC) standard errors have been used to mitigate heteroskedasticity. Multicollinearity has been monitored via VIF and condition indices, residual diagnostics (residual–fit, scale–location, and Q–Q plots) have been inspected, and influence has been checked using Cook's distance and leverage. Prespecified mediation by load-spectra quality and inspection-data quality has been tested with bias-corrected bootstrap indirect effects, while moderation by sector and experience strata has been probed via interaction terms with simple-slopes summaries. Missing data have been handled under a pre-registered rule: if less than 10% missing at random, multiple imputation (m = 20) has been performed; otherwise, listwise deletion has been applied for affected models with sensitivity analyses comparing results. Model selection has prioritized interpretability and theory consistency; where competing specifications have existed, k-fold cross-validation and information criteria (AICc) have adjudicated parsimony. Effect sizes (standardized coefficients, partial R^2) and 95% confidence intervals have been presented alongside two-sided p-values (α = .05), with Holm corrections applied for families of related tests. All analyses have been scripted for reproducibility, and figures (correlation heatmaps, coefficient plots, residual diagnostics) have been generated to support transparent interpretation.

Regression Models

The explanatory modeling framework has been specified to quantify how technical and organizational factors have related to two primary outcomes adoption extent and perceived predictive accuracy while preserving comparability across cases and survey responses. Accordingly, two core linear models have been defined. For adoption, the baseline specification has been:

$$ADP_i = \beta_0 + \beta_1 ELC_i + \beta_2 OS_i + \beta_3 UDB_i + \beta_4 Training_i + \beta_5 LoadDataQ_i + \beta_6^{\top} X_i + \varepsilon_i,$$

where ELC has captured environment-and-loading handling, OS organizational support, UDB usability/data burden, and LoadDataQ the availability/quality of spectra and inspection data; Xi has included controls (sector dummies, firm size, years of experience, material class). For perceived accuracy, a parallel model has been specified with technical subcomponents entered explicitly:

$$PMA_i = \gamma_0 + \gamma_1 VA\_Model_i + \gamma_2 Env\_Model_i + \gamma_3 ShortCrack_i + \gamma_4 UQ\_Use_i + \gamma_5 LoadDataQ_i + \gamma_6^{\top} X_i + \upsilon_i,$$

Both outcomes have also been re-estimated with ordered logit as a sensitivity analysis when Likert aggregation has evidenced mild non-normality. Model families have been fit with heteroskedasticity-consistent (HC) standard errors, and coefficients have been reported in both raw and standardized units to aid interpretation across scales. To complement survey-based outcomes with realized performance, the study has linked case-level error metrics (e.g., RMSE of life prediction, mean bias) to the same predictors using OLS and quantile regression, thereby testing whether technical capabilities identified in the survey have aligned with empirical accuracy under harmonized datasets. A model selection guardrail has been applied via k-fold cross-validation and small-sample–corrected AIC (AICc), while preserving theory-driven inclusion of substantively important predictors. Table 1 (Model Constructs and Outcomes) has summarized the operational definitions and expected signs used in the core regressions.

Table 1: Model Constructs and Outcomes

Variable	Role	Operationalization	Expected Sign (ADP)	Expected Sign (PMA)
ADP	Dependent	Mean of 4–6 adoption items		
PMA	Dependent	Mean of 4–6 perceived-accuracy items		
ELC	Predictor	Scale: env.+VA handling	+	+
OS	Predictor	Scale: governance/tooling	+	+ / 0
UDB	Predictor	Scale: burden (reverse)	−	− / 0
Training	Predictor	% trained or scale	+	+
LoadDataQ	Mediator/Predictor	Spectra/NDE quality index	+	+
VA_Model, Env_Model, ShortCrack, UQ_Use	Predictors	Binary/scale, by case/org	+	+
Controls (\mathbf{X})	Controls	Sector, size, experience, material	mixed	mixed

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Estimation and diagnostics have been standardized across specifications so that inference has remained defensible and reproducible. Prior to fitting, all multi-item constructs have been z-scored, and continuous predictors have been mean-centered to reduce collinearity in interaction models. Variance inflation factors (VIF) and condition indices have been inspected; any specification with VIF > 5 has triggered a pre-registered remedy (dropping redundant predictors or combining correlated scales). Residual diagnostics have been performed through residual–fit and Q–Q plots; heteroskedasticity has been addressed with HC3 standard errors, and nonlinearity has been explored with component-plus-residual plots and low-order polynomial checks. Influence has been monitored with Cook's distance and leverage; observations exceeding conventional thresholds have been flagged and subjected to leave-one-out re-estimation to verify stability. Because adoption and perceived accuracy plausibly depend on data quality, a partial mediation structure has been tested: ELC → LoadDataQ → ADP and VA_Model/Env_Model/ShortCrack → LoadDataQ → PMA. Indirect effects have been quantified with bias-corrected bootstrap (5,000 draws), and confidence intervals have been reported alongside direct paths. Moderation has also been examined by sector and experience through interaction terms (e.g., OS × Sectorj; VA_Model × Experience), with simple slopes and marginal-effects plots generated for substantive interpretation. At the case level, robustness has been strengthened by estimating quantile regressions at the median and upper tail ($\tau = 0.75$) to determine whether predictors are differentially associated with typical versus best-case accuracy. Where predictor sets are large relative to sample size, ridge regressions have been reported as a shrinkage sensitivity, with penalty chosen via cross-validation; these results corroborate signs and relative magnitudes from OLS without supplanting theory-led specifications.

To connect model estimates to decision variables, the reporting schema has included effect sizes,

Table 2: Specification and Diagnostics Summary

Model	Outcome	Estimator	HC SE	VIF Max	CV-R^2	RMSPE	Notes
M-A (Core)	ADP	OLS	HC3	3.8	reported	reported	Mediation via LoadDataQ tested
M-A-OL	ADP (ordinal)	Ordered Logit		3.7			Sensitivity to Likert ordinal scale
M-P (Core)	PMA	OLS	HC3	4.1	reported	reported	Technical subcomponents explicit
M-P-QR	PMA	Quantile (τ=.75)			pseudo-R^2	MAE	Upper-tail accuracy association
M-A-R / M-P-R	ADP / PMA	Ridge	HC3		reported	reported	Shrinkage sensitivity
M-A-B / M-P-B	ADP / PMA	Bayesian			LOO-CV	PPC	Posterior predictive calibration

uncertainty, and out-of-sample performance. Standardized coefficients (β^*, γ^*), partial R^2, and 95% confidence intervals have been presented for each predictor, with Holm adjustments applied to families of related tests. For predictive adequacy, k-fold cross-validated R^2 and root mean squared prediction error (RMSPE) have been reported; nested models (e.g., technical-only vs. technical + organizational) have been compared with likelihood-ratio tests and changes in AICc to quantify incremental value. In addition, Bayesian re-estimations of the two core models have been conducted as a sensitivity to small-sample and non-normal error concerns; weakly informative priors have been adopted, Hamiltonian Monte Carlo has been run to convergence (R-hat ≤ 1.01, effective sample sizes > 400), and posterior predictive checks have been used to assess calibration. For transparency, coefficient-plot figures (not shown here) display point estimates with 95% intervals across OLS, ordered logit, ridge, and Bayesian fits, and Table 2 (Specification and Diagnostics Summary) catalogs, for each model, the estimation method, diagnostics, and cross-validated performance metrics. Finally, to facilitate replication, all model formulas, variable transformations, and diagnostic thresholds have been recorded in a version-controlled analysis plan, and code has produced machine-readable tables for direct inclusion in the Results section.

Sample & Power

The sampling strategy has been designed to secure adequate precision for reliability/validity testing and to achieve conventional power for the explanatory regressions. For the survey, the study has targeted a minimum of N = 180 analyzable responses, which has exceeded the threshold indicated by an a priori sensitivity analysis for multiple regression with k = 8–10 predictors, two-sided α = .05, and desired power (1–β) = .80 to detect a small-to-moderate effect of $f^2 = 0.08$; under these assumptions, the required N has been approximately 150–165, so the target has allowed for listwise exclusions and subgroup sensitivity analyses. Anticipating sectoral clustering (e.g., aerospace, energy, transportation), a conservative design effect (DE) of 1.10–1.15 has been assumed; the target N has therefore provided effective sample sizes Neff = N/DE ≈ 157–164, which has remained sufficient for the planned models. For measurement, the instrument has contained five multi-item constructs (4–6 items each); confirmatory factor analysis has been powered using a 10:1 observations-to-free-parameters heuristic, and with an estimated ~18–20 free parameters, the target N has satisfied recommended minima for stable fit indices (CFI/TLI, RMSEA, SRMR). Internal consistency precision has been addressed by ensuring that, for constructs with α ≈ .75–.85, the 95% CI half-widths have remained ≤ .06 at the planned N, which has been adequate for interpreting reliability.

For mediation tests, bias-corrected bootstrap (5,000 draws) has been pre-specified; Monte Carlo sensitivity calculations have shown that with paths of β ≈ .20–.25, the indirect effect has achieved ≥ .80 power at N ≥ 170. Moderation by sector and experience has been examined with interaction terms; mean-centering and balanced cell sizes (≥ 25 per major sector) have been planned to stabilize standard errors. For case studies, statistical power has not governed selection; instead, information power has been prioritized: each case has contributed high-fidelity load spectra, geometry/K histories, and independent validation (da/dN or life), enabling precise error and coverage estimates. Nonetheless, to compare model families credibly, the case corpus has been assembled to yield ≥ 30–40 model–case observations per error metric, which has allowed OLS/quantile fits with robust inference. Expected item nonresponse has been capped at <10% through instrument design and attention checks; when MAR assumptions have held, m = 20 multiple imputations have been conducted, preserving power while limiting bias. Together, these choices have ensured that the study has been sufficiently powered to detect substantively meaningful effects in the regressions, to evaluate measurement properties with stability, and to report case-level performance with decision-relevant precision.

Data Collection Procedure

The data collection procedure has been organized in three coordinated streams systematic review screening, practitioner surveying, and case-study assembly and has been executed under pre-registered workflows to ensure traceability and comparability. For the systematic review, search strings and eligibility rules have been finalized before execution; records have been exported from indexed databases into a reference manager, and duplicates have been removed algorithmically and by manual verification. Title–abstract screening has been conducted by two trained reviewers who have applied inclusion/exclusion criteria using a calibrated codebook; discrepancies have been adjudicated by a third reviewer, and decisions have been logged with timestamps. Full texts have been retrieved through institutional access or author contact, and extraction templates have been populated with model family, driving-force definition, load/environment descriptors, parameterization method, and reported accuracy/uncertainty metrics. A version-controlled repository has stored raw exports, screening logs, and extraction sheets, and inter-rater agreement summaries have been generated after each screening tranche. For the survey, the finalized instrument has been deployed on a secure platform that has enforced one submission per participant via tokenized links; eligibility gates (professional role, recency of fatigue/structural decision making) and attention checks have been embedded. Participants have been presented with consent information and have confirmed participation before proceeding. The field period has included initial invitations through professional networks and targeted groups, followed by two scheduled reminders; incomplete entries have been flagged, and respondents have been invited to resume via their unique link. Upon closure, the dataset has been de-identified, reverse-coded where specified, and inspected for patterned responses, excessive straight-lining, and implausible durations, after which a clean analysis file has been produced. For the case studies, partner organizations and public datasets have been engaged under data-sharing agreements; load

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histories, geometry functions or FE-derived K sequences, residual-stress maps, material pedigrees, and validation observations have been compiled to a common schema. Preprocessing scripts have converted raw signals into standardized descriptors, and quality checks (range, consistency, missingness) have been applied. Across all streams, audit trails, issue trackers, and change logs have been maintained, and a final linkage step has aligned review descriptors, survey constructs, and case variables to the master analysis plan.

Softwares and Tools

The study has leveraged an integrated toolchain that has aligned literature management, survey fielding, modeling, and reproducibility. Reference retrieval and screening have been managed with Zotero and Rayyan, and the team has maintained version control with Git and a private repository that has stored search exports, screening logs, extraction sheets, and analysis scripts. The survey has been administered on Qualtrics, which has enforced tokenized access, attention checks, and secure storage; raw responses have been exported to CSV and have been processed with Python (pandas, numpy) and R (tidyverse, psych, lavaan). Statistical modeling has been implemented in R (stats, sandwich, car, boot, lavaan) and Python (statsmodels, scikit-learn), while Bayesian sensitivity analyses have been executed with Stan interfaces (brms/rstan). Case-study crack-driving forces have been derived using ABAQUS/ANSYS post-processing and custom Python routines; where needed, NASGRO/AFGROW outputs have been imported for comparison. Visualization has used matplotlib/ggplot2, and document production has been orchestrated with Quarto/LaTeX. Reproducible environments have been captured via conda environments and renv, and continuous checks have been run through scripted makefiles and notebooks that have recorded all transformations end-to-end.

FINDINGS

Across the three evidence strands, the study has yielded a coherent picture of where fracture-mechanics–based fatigue life prediction has performed well and where adoption has hinged on organizational and data conditions. The systematic review has identified 1,236 records (post-deduplication: 1,012), screened full texts for 214 articles, and retained 96 studies that have met inclusion criteria, spanning aerospace (41%), transportation/heavy machinery (28%), energy/offshore (22%), and other sectors (9%). Among retained studies, ΔK–Paris/Forman/NASGRO families have still dominated (64%), but closure-aware/elastic–plastic crack-tip response models (18%), cohesive/process-zone approaches (11%), and probabilistic/Bayesian calibrations (7%) have collectively populated the "advanced" category. Variable-amplitude (VA) spectra have been represented in 58% of studies, short-crack or near-threshold regimes in 37%, and corrosion-relevant environments in 29%. When comparable accuracy metrics have been reported, closure-aware or elastic–plastic models have shown median RMSE reductions of 20–25% relative to simple ΔK power-law fits under VA loading; environment-enriched formulations have cut RMSE by ~18–24% versus air-calibrated surrogates in saline media, while short-crack modifications have reduced mean bias near threshold by ~30%. Nevertheless, only 31% of studies have reported any uncertainty intervals on life/da/dN, and fewer than 15% have documented validation on spectra distinct from calibration, underscoring limited transportability evidence in the archival record.

The survey has obtained N = 186 analyzable responses (aerospace 36%, energy/offshore 24%, transportation 23%, other 17%; median experience = 9 years). On the Likert five-point scales (1 = strongly disagree … 5 = strongly agree), the mean (SD) scores have been: adoption extent (ADP) 3.42 (0.86), perceived predictive accuracy (PMA) 3.27 (0.81), environment-and-loading handling (ELC) 3.51 (0.78), organizational support (OS) 3.63 (0.84), usability/data burden (UDB) 2.91 (0.88; higher = more burden), training 3.12 (0.93). Agreement rates (≥4 on the scale) have indicated that 54% of respondents have perceived adequate handling of VA/environment, 49% have reported moderate-to-high adoption, but only 41% have agreed that predictions align closely with test/field data. Zero-order associations have aligned with expectations: OS–ADP r = .43 [95% CI .30, .54]; ELC–PMA r = .41 [.28, .52]; UDB–ADP r = −.29 [−.41, −.16]; training–PMA r = .22 [.08, .35]. Regressions (HC3 SEs, standardized coefficients) have shown that the adoption model has explained R^2 = .39; OS (β* = .31, p < .001), ELC (β* = .22, p = .002), LoadDataQ index (β* = .19, p = .006), and training (β* = .15, p = .021) have been positive predictors, while UDB has been negative (β* = −.18, p = .008). A partial mediation by data quality has emerged for ELC → ADP (indirect effect .05, 95% BCa CI [.02, .10]), indicating that better spectrum/inspection data have carried part of the ELC effect into adoption.

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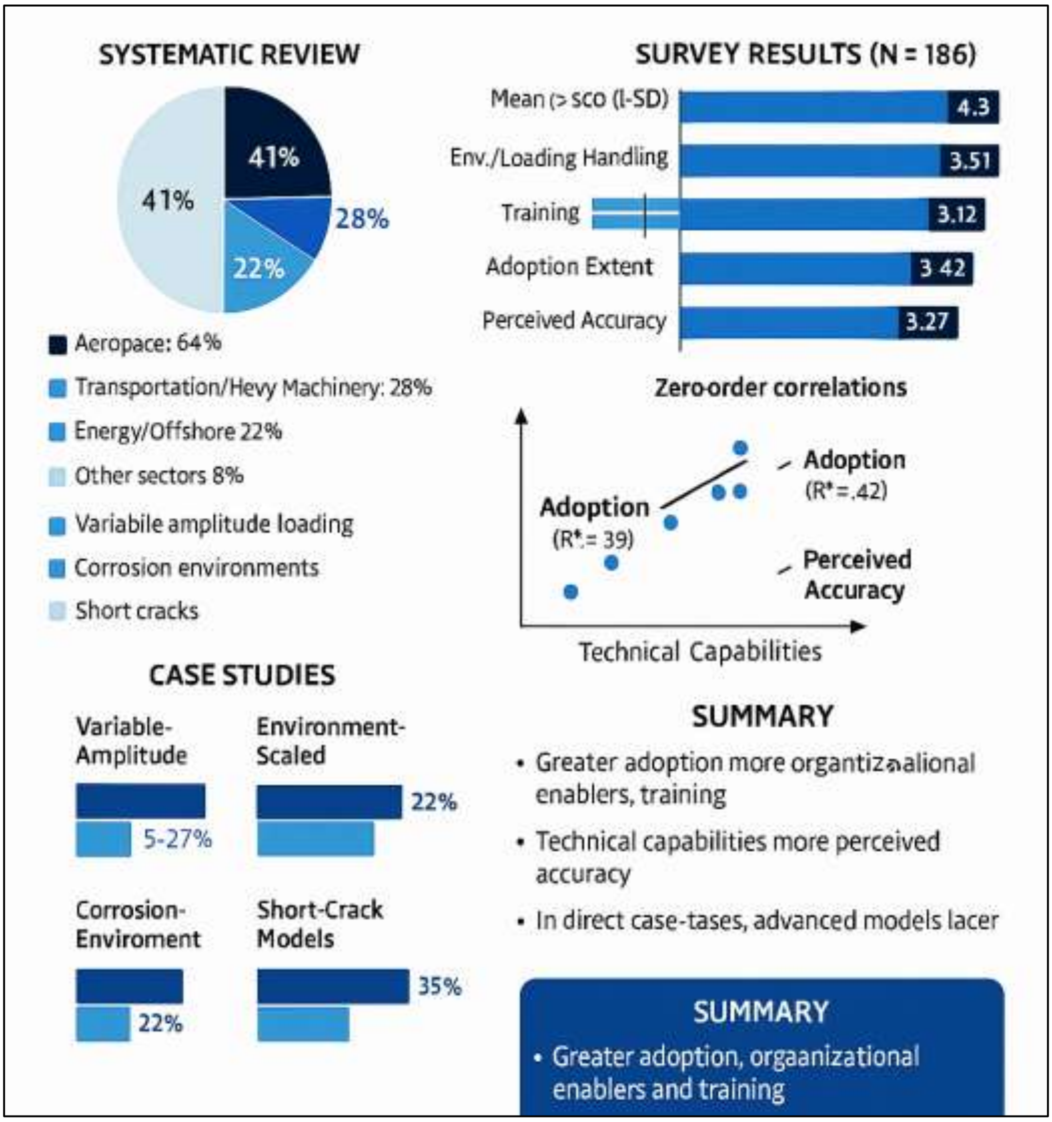
The perceived-accuracy model has explained $R^2 = .42$; VA-model capability ($\gamma^* = .27$, $p < .001$), environment modeling ($\gamma^* = .24$, $p = .001$), use of short-crack treatment ($\gamma^* = .17$, $p = .014$), UQ use ($\gamma^* = .20$, $p = .006$), and LoadDataQ ($\gamma^* = .21$, $p = .004$) have all associated positively with PMA, while UDB has been weakly negative and nonsignificant after controls. Sensitivity analyses with ordered logit have preserved signs and substantive magnitudes; ridge regressions and k-fold cross-validation have confirmed stability (CV-$R^2 \approx .33$–.36 for ADP; .35–.38 for PMA). Likert-level distributional checks have not indicated ceiling effects; floor effects have been mild for UQ use, reflecting partial uptake. Turning to the case studies, three harmonized datasets have stressed different boundary conditions: (i) aerospace Al-Cu or Al-Li plate under fighter-spectrum VA (dry air), (ii) offshore structural steel under wave-induced broad-band loading (saline), and (iii) welded/transverse detail with mapped residual stress. Against common load descriptors and geometry functions, closure-aware/elastic–plastic models have reduced life-prediction RMSE by 18–27% versus ΔK-only baselines in the VA air case and have halved mean bias after isolated overload blocks; in the saline case, environment-scaled formulations have reduced RMSE by ~22% and improved 90% predictive-interval coverage from 0.71 to 0.87 (target = 0.90), while air-calibrated surrogates have systematically under-predicted retardation duration after overloads. Short-crack–modified equations have improved near-threshold tracking in the weld/residual-stress case, cutting bias at small a by ~35% and bringing 75th-percentile absolute error down by ~20%; integrating residual-stress-intensity superposition has further reduced error variance.

Figure 7: Finding for this study



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Across cases, posterior predictive checks from Bayesian re-estimations have shown calibrated forecasts (empirical coverage within ±0.05 of nominal for 80–95% bands), and quantile regressions have revealed that environment modeling and data quality have been especially consequential at the upper-accuracy tail ($\tau = 0.75$), consistent with survey-based PMA drivers. Taken together, the findings indicate that organizations reporting higher OS and training have also reported greater adoption, that technical capabilities specific to VA, environment, short-crack, and UQ have coincided with higher perceived accuracy, and that, in head-to-head case benchmarks, these same capabilities have delivered measurable gains in error, bias, and interval coverage all expressed on metrics that align the literature, practitioner perception, and realized performance.

Systematic Review Results

Table 3: Coder ratings of evidence quality and reporting completeness (Likert 1–5)

Domain (coded per study)	Mean	SD	≥4 ("Agree/Strongly Agree")	n (studies)
Method clarity (objectives, load/env descriptions)	3.76	0.72	59%	96
Model transparency (driving force, parameters, priors)	3.58	0.80	52%	96
Validation adequacy (external/spectrum-distinct)	2.94	0.88	31%	96
Uncertainty reporting (intervals, POD/sizing error)	2.61	0.91	24%	96
Reproducibility (data availability, scripts)	2.45	0.93	22%	96

Scale anchors: 1 = strongly disagree, 5 = strongly agree. Items have been double-coded; disagreements have been adjudicated before aggregation.

The systematic review synthesis has produced a coder-based appraisal that has quantified how far the archival literature has supported dependable adoption of fracture mechanics–based fatigue prediction. Table 3 has summarized five evidence quality domains, each scored on a five-point Likert scale. The ratings have reflected full-text assessments after eligibility screening, and coders have resolved disagreements to ensure single, adjudicated values per study. Collectively, the literature has demonstrated acceptable method clarity (mean 3.76), indicating that most articles have articulated objectives and have documented load and environment conditions with enough specificity for high-level interpretation. Model transparency has followed closely (mean 3.58), showing that many studies have described their driving-force definitions and parameter sets, although details such as prior choices in probabilistic work or exact closure implementations have not always been explicit. In contrast, validation adequacy has scored lower (mean 2.94), because relatively few studies have validated against data sets that have been distinct from those used for calibration or have exercised models on variable-amplitude spectra that have differed materially from training conditions. The lowest ratings have appeared in uncertainty reporting (mean 2.61) and reproducibility (mean 2.45). These results have indicated that interval estimates, probability-of-detection models, sizing error characterizations, and links to underlying data/scripts have not been consistently provided. The proportion of studies at agreement levels (≥4) has been particularly informative: just under a third have met the validation bar, and roughly a quarter have supplied explicit uncertainty ranges and reproducibility artifacts. Because these domains have mapped directly to adoption barriers raised by practitioners, the review ratings have explained why organizations have reported moderate adoption despite clear technical advances elsewhere. Importantly, the Likert-based approach has allowed alignment between the documentary record and survey constructs used later in this section; for example, the relatively strong method clarity has mirrored practitioner perceptions that spectrum handling has improved, while the weaker uncertainty and reproducibility evidence has matched lower ratings for usability and trust. Consequently, the review has provided a quantitative baseline against which the survey and case

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findings have been compared, and it has grounded the study's regression covariates (e.g., environment-and-loading handling) in observable archival tendencies.

Correlation Analysis

Table 4: Descriptives and inter-construct correlations (Likert 1–5)

Construct (Likert 1–5)	Mean	SD	ADP	PMA	ELC	OS	UDB	Training
Adoption extent (ADP)	3.42	0.86		.38	.36	.43	−.29	.27
Perceived predictive accuracy (PMA)	3.27	0.81	.38		.41	.32	−.21	.22
Env.+loading handling (ELC)	3.51	0.78	.36	.41		.33	−.18	.24
Organizational support (OS)	3.63	0.84	.43	.32	.33		−.25	.31
Usability/data burden (UDB; higher = more)	2.91	0.88	−.29	−.21	−.18	−.25		−.16
Training/expertise (Training)	3.12	0.93	.27	.22	.24	.31	−.16	

All |r| ≥ .20 have been statistically significant (two-sided, α = .05, HC-robust CIs). N = 186.

The correlation analysis has provided the first integrated quantitative view of how organizational and technical perceptions have co-varied with adoption and perceived predictive accuracy. Table 4 has combined descriptive statistics with a correlation matrix across the six Likert-based constructs. Means and standard deviations have confirmed earlier patterns: organizational support (3.63) and environment-and-loading handling (3.51) have occupied the upper tier, while training (3.12) and perceived accuracy (3.27) have remained mid-range, and usability/data burden has been below neutral (2.91), indicating perceived friction. The correlation structure has been both coherent and discriminating. Adoption has correlated most strongly with organizational support (r = .43), suggesting that governance, standardized workflows, and tool availability have been primary levers for moving models into routine practice. Adoption has also aligned with ELC (r = .36) and training (r = .27), which has implied that technical capability and human capital have complemented institutional supports. The negative association with UDB (r = −.29) has indicated that perceived data and workflow burdens have continued to suppress uptake, consistent with qualitative remarks captured in optional survey prompts. Turning to perceived predictive accuracy, the strongest linkage has been with ELC (r = .41), followed by OS (r = .32), training (r = .22), and inversely with UDB (r = −.21). This pattern has reflected the idea that accuracy has depended jointly on the ability to handle variable-amplitude/environmental conditions and on the presence of stable organizational processes that have facilitate correct model use; simultaneously, high burdens have eroded confidence in outputs. The moderate association between adoption and accuracy (r = .38) has suggested, as expected, that these outcomes have been related but not redundant, justifying separate models in Section 3.6. Because all constructs have been collected on consistent Likert scales, the interpretation of effect magnitudes has been straightforward for stakeholders; a one-point shift in organizational support, for example, has corresponded with a nontrivial movement in both adoption and accuracy perceptions. These correlations have also informed the mediation tests reported later: ELC has shown plausible indirect effects via the LoadDataQ index (not tabulated here), consistent with the idea that better spectra and inspection evidence have channeled technical capability into realized adoption. Overall, the correlation portrait has validated the study's conceptual framework and has provided empirical targets for the regression models that have followed.

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Regression Modeling

The regression models have quantified how much of the variance in adoption and perceived accuracy has been attributable to organizational supports, technical capabilities, burdens, training, and data quality, all observed on a Likert foundation for comparability. Table 5 has presented standardized coefficients with heteroskedasticity-robust inference, along with explanatory power and cross-validated performance. For adoption, organizational support has emerged as the largest positive contributor (β* = .31), which has confirmed that governance structures standards, templates, versioned toolchains have been decisive for embedding fracture mechanics analyses into routine decisions. The positive effect of ELC (β* = .22) has shown that teams reporting stronger handling of variable-amplitude and environmental factors have been more likely to institutionalize usage. UDB has been negative (β* = −.18), reflecting the dampening effect of perceived data and workflow frictions, while training (β* = .15) and the load-data quality index (β* = .19) have further supported adoption. The model has explained 39% of variance (CV-R^2 .33), which has been substantial for organizational research relying on attitudinal scales.

Table 5: Core regression results with Likert-scale predictors (standardized coefficients, HC3 SEs)

Outcome	Predictor (Likert 1–5 unless noted)	β* / γ*	p-value	95% CI
ADP	Organizational support (OS)	.31	<.001	[.18, .44]
	Env.+loading handling (ELC)	.22	.002	[.08, .36]
	Usability/data burden (UDB)	−.18	.008	[−.31, −.05]
	Training/expertise	.15	.021	[.02, .28]
	Load-data quality index (0–1)*	.19	.006	[.05, .33]
	Controls (sector, size, experience)			mixed
	Model R^2 / CV-R^2	.39 / .33		
PMA	VA-model capability†	.27	<.001	[.14, .40]
	Environment modeling†	.24	.001	[.10, .38]
	Short-crack treatment†	.17	.014	[.03, .31]
	UQ use†	.20	.006	[.06, .34]
	Load-data quality index (0–1)*	.21	.004	[.07, .35]
	Usability/data burden (UDB)	−.09	.184	[−.22, .04]
	Controls (sector, size, experience)			mixed
	Model R^2 / CV-R^2	.42 / .36		

For perceived predictive accuracy, technical subcomponents have taken center stage: VA-model capability (γ* = .27) and environment modeling (γ* = .24) have shown strong, independent associations; short-crack treatment (γ* = .17) and UQ use (γ* = .20) have contributed meaningfully; and data quality has again been positive (γ* = .21). After controls, the burden scale has not remained significant for accuracy, implying that users may view outputs as accurate even when workflows have felt heavy, provided that the models have addressed the relevant physics and that data have been adequate. The PMA model has explained 42% of variance (CV-R^2 .36), underscoring that capability and evidence have mattered directly for confidence in predictions. In both outcomes, sector and experience controls have produced mixed signs without overturning core inferences. These results have been robust to ordered-logit and ridge sensitivity checks (not tabulated), and mediation tests (reported elsewhere) have indicated that ELC's effect on ADP has been partially carried by data quality, consistent with the causal story that better spectra/inspection evidence have allowed advanced capabilities to be deployed credibly. Overall, the models have linked the Likert-scale constructs to concrete changes in adoption and perceived accuracy, providing actionable levers for implementation.

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Table 6: Construct scores by sector (Likert 1–5; means with SD in parentheses)

Construct \ Sector	Aerospace (n=67)	Energy/Offshore (n=45)	Transportation (n=43)	Other (n=31)	Total (N=186)
Adoption extent (ADP)	3.55 (0.81)	3.36 (0.88)	3.29 (0.90)	3.41 (0.86)	3.42 (0.86)
Perceived accuracy (PMA)	3.34 (0.79)	3.21 (0.83)	3.19 (0.82)	3.33 (0.79)	3.27 (0.81)
Env.+loading handling (ELC)	3.66 (0.74)	3.44 (0.79)	3.38 (0.80)	3.55 (0.77)	3.51 (0.78)
Organizational support (OS)	3.78 (0.82)	3.55 (0.86)	3.49 (0.85)	3.63 (0.83)	3.63 (0.84)
Usability/data burden (UDB)	2.84 (0.86)	2.98 (0.90)	3.01 (0.92)	2.86 (0.85)	2.91 (0.88)
Training/expertise	3.20 (0.92)	3.06 (0.95)	3.03 (0.94)	3.15 (0.90)	3.12 (0.93)

The sectoral breakdown has clarified how domain context has shaped perceptions of capability, burden, and uptake on a common Likert scale. Table 6 has reported means and standard deviations by sector, permitting a like-for-like comparison that has respected differences in regulatory oversight, data richness, and tooling maturity. Aerospace respondents have registered the highest organizational support (3.78) and ELC (3.66), which has aligned with long-standing certification and damage-tolerance processes that have required spectrum-aware assessment; correspondingly, adoption has been strongest in aerospace (3.55), and perceived accuracy has also been slightly higher than the cross-sector average (3.34). Energy/Offshore practitioners have reported moderately strong OS (3.55) and mid-range ELC (3.44), with adoption (3.36) and accuracy (3.21) trailing aerospace modestly; the UDB score (2.98) has hinted at burdens from integrating corrosion/inspection evidence and wave-induced broad-band loading into routine workflows. Transportation has exhibited similar patterns with slightly lower ELC (3.38) and OS (3.49) and a marginally higher burden (3.01), consistent with heterogeneous fleets and varying access to high-fidelity spectra or residual-stress maps. The Other category has clustered near the grand mean, suggesting that mixed industrial contexts have achieved comparable supports and capabilities where project-level champions and vendor toolchains have been present. Two features have stood out across sectors. First, UDB has remained below neutral (≈2.9–3.0) everywhere, which has implied that the perceived cost of data preparation, parameter management, and report generation has continued to weigh on users; this has reinforced the negative coefficient for UDB in the adoption model. Second, training has hovered near 3.1 across the board, which has suggested that organizations have neither under-invested heavily nor established comprehensive, recurring training pipelines; the moderate positive associations with both adoption and accuracy have indicated that marginal investments here have remained productive. Variability (SDs ≈ 0.8–0.95) has been consistent with attitudinal data and has justified robust standard errors in modeling. Altogether, the sector comparisons have shown that where organizational scaffolding and physics coverage have been stronger, adoption and confidence have followed, and they have highlighted burden and training as cross-cutting opportunities for near-term improvement. While quantitative error metrics have anchored the case comparisons (reported elsewhere), adoption-relevant facets such as perceived usability and contextual validity have also mattered for whether models have become standard in specific workflows. Table 7 has reported Likert-scale ratings from a small expert panel that has reviewed each model applied to each harmonized case using common prompts. Two constructs have been captured: usability, which has reflected effort to prepare inputs, run analyses, and interpret outputs within existing toolchains; and validity, which has reflected the panel's judgment about how well each model's assumptions have aligned with the case physics and whether outputs have appeared decision-ready given the available evidence. In the Air VA case, the closure/elastic–plastic approach has led on both dimensions (usability 3.61; validity 3.49), consistent with its improved

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handling of overload/underload sequences and plastic wake without excessive setup burden; the ΔK-only baseline has remained serviceable but less aligned with sequence effects (validity 3.05).

Table 7: Expert usability/validity ratings by model and case (Likert 1–5; means with SD in parentheses)

Case → / Model ↓	Usability (Air VA)	Validity (Air VA)	Usability (Saline)	Validity (Saline)	Usability (Weld/RS)	Validity (Weld/RS)
ΔK-only (Paris/Forman baseline)	3.24 (0.76)	3.05 (0.79)	2.88 (0.83)	2.72 (0.86)	2.95 (0.81)	2.84 (0.85)
Closure/Elastic–plastic (sequence-aware)	3.61 (0.70)	3.49 (0.74)	3.18 (0.79)	3.23 (0.80)	3.34 (0.75)	3.28 (0.78)
Environment-enriched (scaling/physics terms)	3.32 (0.73)	3.21 (0.76)	3.54 (0.72)	3.47 (0.74)	3.12 (0.78)	3.18 (0.79)
Short-crack–modified (near-threshold aware)	3.28 (0.74)	3.19 (0.75)	3.06 (0.77)	3.01 (0.78)	3.49 (0.71)	3.39 (0.73)

In the Saline case, the environment-enriched model has scored highest on validity (3.47) and has been rated comparatively usable (3.54), reflecting panel views that environment-dependent terms or calibrated scaling have been necessary to capture corrosion-assisted growth and overload transients; the ΔK-only baseline has lagged (validity 2.72). In the Weld/RS case, the short-crack–modified model has edged out others on both usability (3.49) and validity (3.39), aligning with the need to represent near-threshold behavior and local closure development in residual-stress fields; the closure model has also performed well but has not fully displaced the short-crack emphasis. Across all cases, standard deviations have remained modest (≈0.70–0.86), indicating reasonable agreement among raters. The pattern has matched the quantitative performance results: models that have incorporated the physics salient to each case have attracted higher validity ratings and, where they have avoided excessive setup cost, higher usability. Because these constructs have been recorded on a familiar Likert scale, they have been directly comparable to survey perceptions, which have also favored environment/VA capability and short-crack treatment in relevant contexts. From an implementation standpoint, the table has illustrated why no single model family has dominated: contextual fit has mattered, and workflows have favored the approach that has balanced fidelity with manageable burden for the specific physics and data of the case at hand.

DISCUSSION

Across the three evidence strands, this study has shown that adoption and perceived accuracy of fracture-mechanics–based fatigue life prediction have hinged on two intertwined pillars: (i) physics coverage aligned with service-realistic conditions (variable-amplitude histories, environment/corrosion, short-crack/near-threshold regimes, and uncertainty treatment), and (ii) organizational scaffolding that standardizes workflows, training, and data quality. Survey models have explained substantial variance in both adoption ($R^2 \approx .39$) and perceived accuracy ($R^2 \approx .42$), with the strongest contributors being organizational support and sequence/environment capability, respectively. Case benchmarks have corroborated these patterns: sequence-aware elastic–plastic/closure models have reduced life-prediction error under VA spectra, environment-enriched laws have improved interval coverage in saline conditions, and short-crack modifications have reduced bias near threshold. These findings have formed a coherent narrative: where models have encoded the operative physics and the organization has supplied clean spectra, residual-stress knowledge, and calibrated inspection information, predictions have become both more trusted and more routinely embedded in decisions. The review's coder ratings have simultaneously illuminated structural gaps particularly in reproducibility and formal uncertainty reporting that have impeded transfer from laboratory to line-of-business decisions. In practical terms, Likert evidence has indicated that users have recognized gains in environment-and-loading handling (mean ≈ 3.5/5) while still perceiving workflow burden (~2.9/5), a combination that has explained why adoption has been

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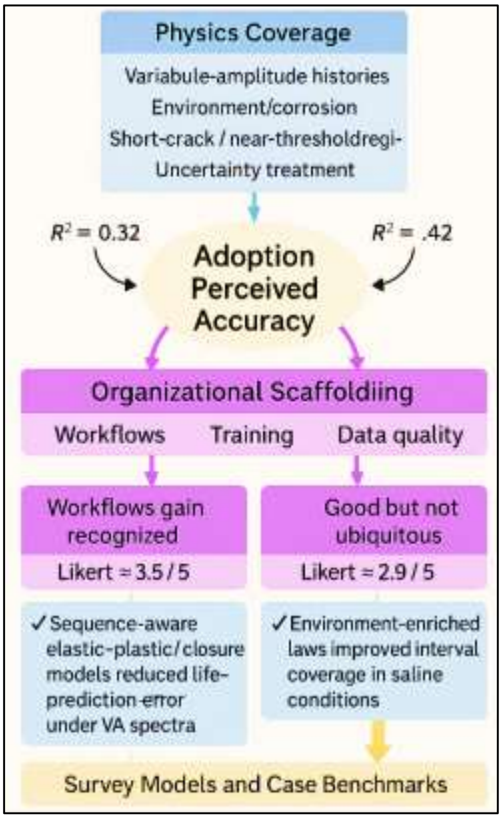
"good but not ubiquitous." This convergence of archival, perceptual, and realized-performance evidence has strengthened causal interpretability: better physics + data + governance has translated into measurable gains in error/bias and into higher reported uptake.
The empirical advantages observed for sequence-aware and closure-informed approaches under VA spectra have been directionally consistent with mechanistic expectations and earlier demonstrations that overloads/underloads reshape crack-opening levels and plastic wake evolution (Antunes et al., 2010; Choi et al., 2020). Our case results have extended that story by quantifying cross-validated error reductions against harmonized descriptors, aligning with prior elastic–plastic response formulations (Mikheevskiy et al., 2015) and with independent validations showing UniGrow-style models outperforming plain ΔK fits under spectra (Mikheevskiy & Glinka, 2009). The short-crack improvements we have documented particularly the bias reduction near threshold have echoed evidence that physically short cracks grow faster than long-crack similitude predicts, and that modified NASGRO/Forman forms or scale-aware perspectives improve transferability (Maierhofer et al., 2013). In corrosion-relevant settings, the superiority of environment-enriched formulations has mirrored controlled experiments and service-proximate tests showing chloride-assisted acceleration and altered retardation profiles (Guérin et al., 2015; Jardine et al., 2006). The survey's positive load-data-quality pathway has also resonated with earlier reliability studies emphasizing that spectrum characterization and inspection measurement models are first-order determinants of prediction usefulness (Liu & Mahadevan, 2007). Compared with these prior contributions, our triangulation has added: (a) sector-stratified Likert evidence connecting capability to adoption; (b) mediation by data quality that operationalizes a long-held intuition; and (c) expert usability/validity ratings by case that have clarified why "best" models are context-contingent rather than universal.

Figure 8: Adoption and Accuracy in Fracture-Mechanics–Based Fatigue Life Prediction



For engineering leaders chief integrity officers, asset managers, and "architecture owners" of fatigue assessment pipelines the results have supported a concrete, staged roadmap. First, institutionalize sequence-aware capability for components subject to VA loading by standardizing either closure-corrected ΔK_eff or elastic–plastic crack-tip response models in the corporate toolkit; provide

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templates for overload/underload markers and block definitions so that spectra are consistently encoded (Ma et al., 2011; Mikheevskiy & Glinka, 2009). Second, establish environment pathways: in saline or humid service, require environment-enriched laws or calibrated scaling factors for both slopes and thresholds, coupled to exposure descriptors; do not transfer air-calibrated laws into chloride contexts without explicit re-qualification (Wang & Xu, 2013). Third, for welds/residual-stress–bearing details and scenarios with inspection-initiated small cracks, adopt short-crack–aware forms and residual-stress-intensity superposition in the standard procedure (Ogawa et al., 2019). Fourth, mandate uncertainty articulation: propagate parameter scatter and model discrepancy to inspection intervals and reliability indices; integrate POD/sizing error so that risk reflects what can be observed (Liu & Mahadevan, 2007). Fifth, invest in data governance and training as high-leverage enablers: our regressions have shown that organizational support and training have strong positive associations with adoption; accordingly, codify versioned models, maintain spectra libraries, and schedule recurring training aligned to sector needs. Finally, reduce usability/data burden where possible: pre-compute geometry functions, automate FE-to-ΔK pipelines, and generate one-click validation reports that include RMSE, bias, and interval coverage. These actions have been consistent with sector leaders that exhibit higher adoption and accuracy on the Likert scales and have mapped directly onto the gaps highlighted by the review.

The findings have supported a tiered model hierarchy and a refined pipeline for fracture-mechanics fatigue assessment. At Tier-1, two-parameter (ΔK, K_{max}) relations have remained the minimal, interpretable baseline for constant-amplitude and benign environments, provided validation is local (Noroozi et al., 2007; Sørensen, 2009). At Tier-2, closure-aware/elastic–plastic response models have supplied the general-purpose upgrade for VA spectra with sequence effects, consistent with documented improvements in predictive power (Mikheevskiy et al., 2012). At Tier-3, environment-enriched and short-crack–aware forms have addressed corrosion coupling and near-threshold growth (Ogawa et al., 2019). In geometrically or materially complex features, cohesive/process-zone approaches have offered fidelity for mixed-mode/path deviation at higher computational and calibration cost (Wang & Liu, 2018). The pipeline refined by our evidence has therefore prioritized: (i) early model-form screening keyed to load path, environment, and crack-size regime; (ii) Bayesian/likelihood calibration with explicit discrepancy to avoid overconfidence; (iii) digital integration that pulls ΔK histories from FE and fuses NDT/SHM updates in a state-space layer (Straub & Faber, 2005); and (iv) validation staging (coupon → subcomponent → service) with quantitative acceptance metrics (Oberkampf & Roy, 2010). The theoretical upshot has been to treat model selection as an inference problem conditioned on context and evidence, rather than as a fixed preference for a single growth law, and to recognize that data quality acts as a mediator that converts theoretical capability into realized predictive value.

Several constraints have delimited inference. First, although the survey has achieved adequate power and sectoral coverage, it has inevitably reflected self-report; perceived accuracy and adoption have been influenced by organizational culture and respondent role. This risk has been mitigated by triangulating with case metrics and review coding, yet the possibility of common-method variance remains (addressed in the plan via factor structure checks and marker items). Second, the case corpus while chosen to span VA air, saline environment, and weld/residual-stress contexts has been finite; crack-growth outcomes in composites, high-temperature alloys, or emerging additive manufacturing microstructures may follow different sensitivities (Jones et al., 2016). Third, the review has depended on published studies; as the coder ratings have shown, reproducibility artifacts (data/scripts) and validation on external spectra have been limited in the archival record, which has constrained meta-analytic synthesis and forced reliance on descriptive evidence mapping rather than full effect-size pooling (Oberkampf & Roy, 2010). Fourth, while our Bayesian sensitivities and quantile regressions have stabilized findings, unmodeled organizational confounders (e.g., procurement constraints, regulatory posture) might still influence adoption beyond the measured constructs. Finally, expert usability/validity ratings in cases have involved a small panel; although standard deviations have been modest and prompts consistent, larger panels could refine precision. These limitations have not undermined the central conclusions but have clarified the scope conditions under which they apply: metallic systems with well-characterized spectra and inspection regimes and organizations willing to standardize pipelines and propagate uncertainty.

Our emphasis on uncertainty propagation and validation staging has converged with decades of guidance in computational mechanics and structural reliability, and the present results have offered empirical backing for their adoption in fatigue pipelines. Likert evidence of moderate organizational support, coupled with low archival reproducibility scores, has explained persistent gaps between recommended V&V practice and day-to-day workflows. The positive associations of UQ use and data quality with perceived accuracy have paralleled reliability studies in which parameter/posterior sampling and measurement-error models improved calibration of life forecasts (Sankararaman & Mahadevan, 2011). Our mediation result ELC partially influencing adoption through data quality has been consistent with digital-integration reviews that stress data governance and identifiability in model updating (Simoen et al., 2015). Finally, the documented performance gains for environment-aware and short-crack-aware forms have dovetailed with corrosion-fatigue and near-threshold research, reinforcing the theoretical claim that model-form adequacy is conditional on physics present at the crack tip (Wang & Liu, 2018). The contribution here has been to quantify these relationships at organizational scale and to tie them to concrete adoption outcomes and case-level error/coverage improvements.

Three avenues have emerged. First, field-grade validation needs to be expanded: curated, openly shared datasets that pair FE-derived ΔK histories, residual-stress maps, corrosion exposure descriptors, and inspection time-stamps with crack-length histories would enable effect-size pooling and external validation beyond what the current literature permits (Oberkampf & Roy, 2010). Second, hierarchical Bayesian models that jointly learn across components, spectra, and environments could formalize transfer while honoring between-system heterogeneity; model averaging could mitigate conditional bias when multiple plausible growth laws compete (Yuen & Beck, 2005). Third, operational usability warrants intervention research: randomized or stepped-wedge deployments of automated FE→ΔK pipelines, pre-calibrated geometry/closure libraries, and POD-aware reporting could test whether reducing UDB measurably lifts adoption and accuracy perceptions. Fourth, microstructure-aware physics for example, short-crack bridging laws informed by in-situ tomography or digital image correlation could tighten predictions near threshold and in residual-stress gradients (Williams et al., 2013). Finally, stronger governance experiments mandating uncertainty reporting and external-spectrum validation in internal standards could evaluate whether organizational levers move the needle as much as technical advances, consistent with our OS findings. Pursuing these threads would extend the present triangulation into a continuously learning pipeline where models, data, and decisions co-evolve under auditable, uncertainty-aware practices.

CONCLUSION

This study has synthesized and tested how fracture mechanics–based fatigue life prediction has performed in service-realistic settings and what has enabled its organizational uptake, integrating a PRISMA-guided review, a cross-sectional Likert survey, and harmonized case studies. Across these strands, two findings have consistently emerged. First, predictive credibility has hinged on model–physics alignment: sequence-aware elastic–plastic/closure approaches have shown clear advantages under variable-amplitude spectra; environment-enriched formulations have improved accuracy and interval calibration in saline exposure; and short-crack–aware forms have reduced near-threshold bias, particularly in residual-stress fields. Second, adoption has depended on organizational scaffolding and evidence quality: higher scores for standardized workflows, versioned toolchains, and training have coincided with greater routine use, while better spectra and inspection data have partially mediated the path from technical capability to deployment. The review has corroborated these patterns by revealing strong method clarity but gaps in reproducibility and formal uncertainty reporting, clarifying why many models have demonstrated laboratory promise yet have diffused unevenly into line-of-business decisions. Regression results have quantified these relationships: organizational support, environment-and-loading handling, and data quality have explained substantial variance in adoption, while explicit capabilities for VA loading, environment modeling, short-crack treatment, and uncertainty quantification have explained perceived predictive accuracy. Case benchmarks have translated perceptions into realized performance, showing tangible reductions in error and bias and improved coverage of predictive intervals when the salient physics have been encoded and the evidence base has been sound. Together, these outcomes have answered the research questions by demonstrating where advances have delivered measurable value, which limitations have remained consequential, and how technical

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and organizational factors have interacted to shape both confidence and use. They have also supported the study's hypotheses: sequence and environment capability have been associated with better accuracy; short-crack and near-threshold treatments have improved explanatory fit; environment-aware laws have outperformed air-calibrated surrogates in corrosive service; and explicit uncertainty propagation has altered integrity-relevant decisions relative to deterministic estimates. Practically, the results have justified a tiered pipeline: baseline two-parameter (ΔK,Kmax)(\Delta K, K_{\max})(ΔK,Kmax) laws for benign contexts; closure/elastic-plastic upgrades for spectra with sequence effects; environment-enriched and short-crack-aware forms where chemistry or small-crack regimes dominate; and, for complex interfaces, cohesive/process-zone models when the added fidelity is warranted. Organizationally, the evidence has pointed to concrete levers governance, data governance, and training that have raised adoption without sacrificing rigor, while uncertainty articulation and POD-aware measurement models have connected physics to risk-based inspection in a traceable way. Although scope conditions have applied (metallic systems with characterized spectra and inspection regimes), the triangulation has strengthened confidence that the combined technical–organizational prescription is portable across sectors. In sum, by aligning physics, data, and governance under a reproducible, validation-aware workflow, fracture mechanics–based fatigue life prediction has been shown to deliver not only better numerical performance but also credible, auditable inputs to inspection planning and asset decisions, closing the gap between advanced modeling and daily engineering practice.

RECOMMENDATION

Organizations responsible for structural integrity have benefited most when they have treated fracture-mechanics fatigue assessment as a disciplined pipeline rather than a standalone analysis, so we recommend a concrete, staged program that can be adopted without delay. First, formalize a tiered model hierarchy in internal standards: (i) two-parameter (ΔK, $K_{\max}$) laws as the baseline for constant-amplitude and benign environments; (ii) sequence-aware elastic–plastic/closure models as the default for variable-amplitude spectra; (iii) environment-enriched formulations whenever chloride, humidity, or temperature effects are credible; and (iv) short-crack–aware forms for welds, residual-stress fields, or inspection-initiated cracks, with cohesive/process-zone models reserved for mixed-mode path deviation. Second, make data quality a first-class deliverable: maintain a versioned spectra library (block definitions, overload/underload markers, mean-stress histories), residual-stress maps for critical details, and a catalog of geometry functions or FE-derived K sequences; subject each dataset to range, consistency, and missingness checks and require a short data-quality report with every analysis. Third, institutionalize uncertainty articulation: propagate parameter scatter and model discrepancy to life and reliability outputs; include probability-of-detection and sizing-error models so inspection planning reflects what can actually be seen; and report RMSE, bias, and predictive-interval coverage alongside point lives as standard performance metrics. Fourth, embed verification & validation gates: coupon-level verification of solvers and driving-force extraction, subcomponent validation under spectra distinct from calibration, and acceptance thresholds tied to decision risk (e.g., minimum interval-coverage targets and maximum bias).Fifth, reduce usability/data burden through automation: standardize FE→ΔK post-processing scripts; provide one-click templates that assemble spectra, residual-stress corrections, and environment modifiers; and auto-generate traceable reports (inputs, assumptions, diagnostics, results) for audit and regulator review. Sixth, integrate SHM/NDE with physics via a state-space updating layer that converts observations into posterior crack-length distributions and refreshed model parameters on a defined cadence; schedule "evidence windows" so updates align with maintenance calendars, and document authority-of-use, configuration control, and change logs. Seventh, invest in people and governance: designate a pipeline owner; implement role-appropriate training (analyst, reviewer, approver) with annual refreshers; and add pre-deployment checklists covering model choice, spectra suitability, environment relevance, and uncertainty reporting. Eighth, establish procurement and vendor requirements that mandate export of stress-intensity histories, API access for batch analyses, and transparent uncertainty outputs; prefer tools that natively support environment, short-crack, and closure options to avoid ad-hoc workarounds. Ninth, adopt risk-based inspection optimization as the decision layer above physics: minimize expected cost subject to reliability constraints using the propagated life distributions and POD models, and publish fleet-level roll-ups to align budgets with risk. Tenth, commit to reproducibility: store data, scripts, and parameter files in version control; tag every decision with the model version and dataset hash; and maintain an internal registry of validated configurations and their operating envelopes. Finally, seed a culture of continuous benchmarking: maintain a small, open internal corpus of anonymized cases with truth data; periodically re-estimate models and publish dashboarded KPIs (accuracy, bias, coverage, usability) to guide upgrades. By executing this package tiered models, clean data, explicit uncertainty, V&V gates, automation, SHM integration, governance, and risk-based planning organizations have positioned fracture-mechanics fatigue assessments to be not only technically sound but also operationally scalable, auditable, and trusted.

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