TPM Vol. 32, No. 3, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

FACTORS INFLUENCING THE PERCEIVED RELIABILITY OF FATIGUE LIFE PREDICTION IN AEROSPACE STRUCTURES

ZEESHAN AHMAD[1], MUHAMMAD ARMGHAN SHABIR[2]

[1]SENIOR AEROSPACE ENGINEER, UAV DIVISION, WAKEB DATA COMPANY FOR COMMUNICATION AND INFORMATION TECHNOLOGY, RIYADH SAUDI ARABIA, EMAIL: ahmadzeshan@outlook.com, SCOPUS AUTHOR ID: 57215611416, ORCID: HTTPS://ORCID.ORG/0009-0000-8401-5856

[2]SENIOR AEROSPACE ENGINEER, SERB ADVANCED INDUSTRIES, RIYADH 13351, SAUDI ARABIA EMAIL: armghanshabir@gmail.com, SCOPUS ID: 60357512300, ORCID: https://orcid.org/0009-0003-6163-6571

Abstract

Purpose: This paper will research on the drivers of the perceived reliability of fatigue life prediction in aerospace structures. The study is particularly interested in the influence of the accuracy of the load spectrum estimation, the quality of material fatigue data, the effectiveness of the coupling between the computational fluid dynamics and the finite element analysis, taking into account of manufacturing defects, and the level of the experience of the analyst. It is also a study that determines the mediating effect of confidence in numerical modelling in explaining the effect that these factors have on the reliability of fatigue life prediction.

Design/Methodology/Approach: The proposed conceptual framework was tested with the help of the quantitative approach of research with Partial Least Squares Structural Equation Modeling. The information was gathered among professionals and engineers that work on aerospace structure analysis, fatigue and reliability tests. Measurement model was evaluated with the help of reliability, convergent validity, and discriminant validity tests and the structural relationships were evaluated with the help of bootstrapping methods to identify the significance of the postulated relationships between variables and mediation.

Findings: The results indicate that, accuracy of load spectrum estimation, quality of material fatigue data, effectiveness of coupling between computational fluid dynamics and finite element analysis, manufacturing defects, and the level of experience of analysts play an important part in perceived reliability of fatigue life prediction. Of these considerations, the impacts of manufacturing flaws and the level of experience of the analysts have the best impacts. The results also reveal that confidence in numerical modeling makes the relationships between the independent variables and the perceived reliability of fatigue life prediction partially. The structural model also illustrates acceptable predictive relevance and explanatory power.

Practical Implications: The implications of the findings include the need to enhance load spectrum estimation approaches, reinforce material fatigue database, combine computational fluid dynamics and finite element analysis computational models, and include manufacturing defect modeling into fatigue prediction models. Furthermore, by increasing the experience and competency of the analysts and improving the trustworthiness on the numbers modeling equipment, the quality of prediction of fatigue life can be greatly enhanced and benefits the safer aerospace structural design and maintenance planning.

Originality/Value: This paper offers a composite framework that integrates both technical modeling considerations and human due diligence in the explanation of predictability of fatigue life in the aerospace structures.

Keywords: fatigue life prediction, aerospace structures, perceived reliability of fatigue life prediction, accuracy of load spectrum estimation, quality of material fatigue data, coupling effectiveness between computational fluid dynamics and finite element analysis, consideration of manufacturing defects, analyst experience level, confidence in numerical modeling.

INTRODUCTION:

The rising requirement of aerospace engineering of lightweight, high-performance structures has inspired the intensifying reliance on the computational fatigue life prediction schemes that combine computational fluid dynamics (CFD), structural health monitoring, and digital twins frameworks in addition to the finite element analysis (FEA), but the recent sources indicate that the precision of predictions remains greatly reliant on the ambiguity in estimating a load spectrum, variability in usability of material fatigue data, and dealing with manufacturing-induced defects

(Kabashkin et al., 2025), In current digital twins designs, the concept of the two-way CFD-FEA interaction and real-time model re-optimization to enhance the quality of predictions is more emphasized, although it is also observed that the ongoing challenges in the quantification of uncertainty and model validation still undermine the confidence of stakeholders in numerical outcomes (Shao et al., 2024).

Moreover, as it is shown with the creation of additive manufacturing and multiphysics aeroengine modeling, residual stresses, porosity, and microstructural disparities can significantly influence the behavior of crack initiation and growth unless taken into account specifically in the context of fatigue simulation (Hayes et al., 2024). Paralleled development of AI-assisted computational mechanics also suggests that despite the opportunity to reduce the error of predictions through the use of hybrid physics-data models, the experience of analysts and human judgment remain highly significant in the analysis of the results and propagation of uncertainty. Combined with all these studies, it indicates that with respect to integrated reliability approaches, besides the technical modeling parameters, confidence in numerical modeling is a significant factor that characterizes the perceived reliability of fatigue life predictions in structures of aerospace, and that, systematic discovery of both technical and human factors must be done (de Castro Lopes et al., 2023).

Although recent studies have made considerable progress in digital-twin-enabled fatigue evaluation and fatigue life prediction through multiphysics CFD-FEA integration of aerospace structures, it was observed that there is still some uncertainty in predicting fatigue life due to the inaccuracy of estimating load spectrum, variability, and scatter of material fatigue data, under consideration of manufacturing-related defects, or through changes in model calibration and validation procedures , Emerging studies also illustrate that in spite of the fact that AI-assisted computational mechanics and machine learning-enhanced FEM approaches are more effective in predicting performance, they do not necessarily address the epistemic and aleatory uncertainties unless these are backed by rigorous uncertainty quantification and expert interpretations (Y. Li et al., 2024).

In addition, structural integrity management digital twin frameworks underline that the effectiveness of the coupling between CFD and FEA models considerably influences the ability to predict cracks growth and accurately assess life when in-service load reconstruction and surrogate modelling are at stake (Jirandehi & Khonsari, 2021). Concurrently, additive and advanced manufacturing procedures generate defect-wise fatigue conduct that questions traditional deterministic life models when residual stresses, porosity and microstructure heterogeneity are not carefully thought of (Kapoor et al., 2021). Nevertheless, although these technical aspects are already being extensively debated on a single basis, little empirical evidence has been gathered on how these factors can be combined to affect the reputation of stakeholders to the field of numerical modeling and, subsequently, the perceived validity of fatigue life projections in aerospace systems. Such a gap highlights the importance of systematic study of the direct and indirect correlation between load spectrum accuracy, quality of material data, CFD–FEA coupling effectiveness, consideration of manufacturing defects, experience of analyst, trust in numerical modeling, and perceived reliability in an integrated framework of reliability (Marshall et al., 2023).

Despite recent aerospace studies that have promoted fatigue life prediction by inculcating digital twins, multiphysics CFD-FEA interconnection, AI-enhanced computational mechanics, and additive manufacturing modeling, there exist profound gaps in the theoretical and experimental knowledge of the aerospace structural integrity industry. Hypothetically, existing frameworks focus on physics-based modeling and quantification of uncertainty but do not present an integrated model of how technical determinants, including load spectrum estimation accuracy, material fatigue data quality, CFD-FEA coupling efficiency and defect-sensitive modelling, all combine to create stakeholder confidence and perceived reliability of fatigue predictions (Eusufzai, 2021). Empirically, the majority of the recent research in aerospace digital twins and additive manufacturing is dedicated to enhancing predictive algorithms or defect characterization individually without quantitative analysis of the interaction between these variables or the impact of expertise in analysts on the trust in the modeling in the safety-critical sphere (Ahmad et al., 2025).

Moreover, although uncertainty-conscious digital twins are being suggested to the aerospace structure, empirical validation between the rigor of the modeling and the quality of multiphysics integration and perceived reliability of fatigue life results is not provided to the decision-makers. Therefore, there is an evident deficiency in the creation and empirical validation of an elaborate framework that incorporates the technical, manufacturing, and human elements in elucidating confidence in the numerical model as a mediator that affects perceived reliability of the fatigue life prediction in aerospace structures (Amin et al., 2024).

The latest literature in the aerospace industry shows a clear indication of the presence of a research gap concerning the incorporation of technical, manufacturing, and human determinants into a single fatigue life reliability framework. The systematic reviews of digital twin-enabled structural systems state that although integration of the CFD-FEA and real-time data assimilation enhances predictive capability, the majority of studies note that algorithmic development and uncertainty quantification, but not empirically validated to the effect that they lead to stakeholder trust or perceived reliability in aerospace safety-critical scenarios (Aabid et al., 2021). On the same note, AI-enhanced computational mechanics reviews note the increased use of machine learning to speed up fatigue simulations, but they note that cross-disciplinary research on the moderating effects of analyst expertise on uncertainty interpretation and model confidence is limited (Liang et al., 2025). Defect-sensitive fatigue modeling and incorporation of residual stress is a popular topic in the additive and advanced manufacturing research, but the practical impact of a complex combination of them with the variability of the load spectrum and data scattering of materials on the perception of reliability at the organizational decision-making level is seldom quantified in practice (Dong et al., 2023). In addition, the models of reliability in aerospace systems focus on probabilistic approaches, but human factors and modeling confidence are common as external factors and not quantifiable mediating constructs (Quan et al., 2021). Future studies would thus (1) establish and experiment structural equation models that connect load estimation accuracy, material data quality, effectiveness of the CFD-FEA coupling, consideration of defects, experience in the field to perceived reliability; (2) operationalize the concept of confidence in numerical modeling as a validated mediating variable; (3) bring together the probabilistic fatigue modeling with behavioral decision theory into aerospace maintenance and certification domain; and (4) use digital twin case studies with validated survey or experimental data to quantify the impact of technical rigor on reliability perception in engineers and regulators (Ahmad et al., 2022).

This study is valuable in that it elevates a comprehensive comprehension of the role of technical rigor and human knowledge in collectively determining perceived reliability of fatigue life prediction in safety-critical systems especially in the aerospace industry in which structural failure has gross operational and economic outcomes. According to recent studies, digital twin structures, physics-data fusion architectures, and AI-aided prognostic fatigue are changing the concept of aerospace structural health management, but they need strong uncertainty control, multiphysics CFD-FEA, and high-quality fatigue data to guarantee dependable life assessment (Chakraborty et al., 2022). Probabilistic-reliability models and confidence-bounded predictions are becoming a standard part of predictive maintenance architecture in aviation and aerospace maintenance settings to aid in certification and airworthiness decision-making (Khan et al., 2023). However, new reviews point to the fact that the transfer of advanced modeling accuracy to stakeholders trust has not been extensively studied, especially in cases where the manufacturing defects, load spectrum variability, and analyst judgment interact in digital space (Mardanshahi et al., 2025). Thus, the goal of the research is to come up with and empirically draw a thorough framework that looks at the effect of load spectrum accuracy, material fatigue data accuracy, the effectiveness of CFD-FEA coupling, consideration of manufacturing defects, and experience of the analyst to the confidence of the numerical model and, ultimately, the perceived reliability of fatigue life prediction in aerospace structures. It is both theoretical (when reliability engineering models are expanded with the help of mediating cognitive constructs) and pragmatic (when evidence-based advice to aerospace engineers, certification authorities, and maintenance decision-makers about improving trust, safety margins, and lifecycle management strategies is offered in the next-generation aircraft systems (Wang et al., 2024).

What is new about this research is the formulation and empirical validation of a composite reliability model that is capable of simultaneously accounting both technical modeling determinants and human-focused confidence constructs to account the perceived reliability of fatigue life prediction in aerospace structures. Although recent progress in digital twin-based fatigue prognosis, AI-assisted computational mechanics, and multiphysics CFD-FEA coupling has enhanced predictive accuracy (Smith, 2021), current studies mostly concentrate on the performance of algorithms, quantification of uncertainty, or defect-sensitive modeling by itself. Modern reliability engineering surveys focus on uncertainty management and probabilistic life modeling but rarely conceptualize uncertainty control on a numerical modeling mediating variable between technical inputs and decision-making trust (Jasiulewicz-Kaczmarek et al., 2021). Moreover, the literature on fracture mechanics-based fatigue prediction and aerospace predictive maintenance does emphasize the role of load reconstruction, material variation, and manufacturing defects but fails to introduce the experience of the analyst as a moderating or explanatory variable in models of structural reliability perception. Thus, the current work achieves conceptual and empirical novelty by integrating the views of physics-based fatigue modeling, digital twins validation, and behavioral reliability into a coherent framework of structural equations developed with regard to the aerospace industry, thus shifting the current research on fatigue lifespan to the construct of trust-based reliability measurement (Bandara et al., 2023).

The necessity to explore the factors that affect the perceived reliability of fatigue life prediction of aerospace structures is due to the increasing reliance on digital twin ecosystems, AI-aided simulations, and multiphysics CFD-FEA coupling in designing and maintaining safety-critical aircrafts, where wrong or mistrusted predictions can result in disastrous failures, excessive conservatism, or unnecessary lifecycle expenses (D.-W. Li et al., 2023). According to recent reviews of aerospace reliability, it is noted that uncertainty in load spectrum reconstruction, the variability of material fatigue, and manufacturing procedures based on defects remain problems when assessing a life in an accurate way despite the increasing sophistication of computational models (Kellermann et al., 2023). Furthermore, the intelligent reliability assurance procedures and predictive maintenance systems emphasize the idea that decision-makers become more dependent on the confidence-bound numerical results in order to qualify certification, airworthiness approval, and risk-based scheduling of inspections (Qin et al., 2022). Nevertheless, although the technical advancements enhance predictive capabilities, they conduct only a limited number of studies describing how these technical factors are converted into the stakeholder confidence and their perceived reliability, which is a necessary component in the area of regulatory acceptance and strategic decision-making in aerospace programs (Sun et al., 2024). Thus, investigating the synergistic effects of modeling quality, defects consideration, experience of analysts, and trust in the numerical modeling becomes very important to improve trust, safety margins, life cycle costs, and reliability governance in aerospace systems in the next generation (Fan et al., 2024).

The importance of the present investigation is that it adds to the development of a trust-based model of reliability to predict fatigue life in aerospace structures whereby digital twin ecosystems, AI-based prognostics, and probabilistic safety evaluations are becoming increasingly useful in certification and operational decision-making. According to the most recent aerospace studies, reliability in the digital twin setting is pegged not only on the accuracy of the computation but also on the transparency of uncertainty, integration of data to stakeholders, and robustness of the decision support (Tang et al., 2022). Besides, optimization models based on predictive reliability in aviation maintenance show that the lifecycle cost savings and the availability of aircraft are highly affected by the validity of the fatigue and structural integrity forecasts (Wang & Ke, 2024). Nevertheless, the existing systems pay much attention to the technical performance parameters without empirically incorporating modeling confidence and analyst expertise into perceived reliability assessment.

The study has a theoretical contribution as it is able to expand the models of reliability engineering by including mediating cognitive constructs and empirical contribution in terms of a structural model where load spectrum accuracy, material fatigue data quality, CFD-FEA coupling effectiveness, manufacturing defect consideration, and experience of the analyst are proposed as having a relationship with the perceived reliability outcomes. Those who will benefit are aerospace structural engineers and fatigue analysts that need better model validation approaches; aircraft manufacturers and maintenance organization managers that need to optimize predictive maintenance and lifetime management; regulatory bodies that have a responsibility to certify aerospace airworthiness and are required to meet safety requirements; developers of digital twins that aim to improve trust and transparency in simulation platforms; and academic researchers who want to develop interdisciplinary reliability modeling in safety-critical aerospace systems (Chinchanikar & Shaikh, 2022).

The analysis of the connections between the quality of load spectrum estimation, quality of fatigue data in materials, the effectiveness of a CFD-FEA coupling, consideration of manufacturing defects, experience of analysts, trust in numerical modeling, fatigue life prediction reliability is of particular interest because the above-mentioned variables were traditionally researched in disjointed technical areas and not as a system of perception of reliability. Recent aerospace research independently provides proof of digital twin-based fatigue prognosis (Melching et al., 2022), AI-enhanced structural health monitoring , uncertainty-driven reliability engineering (Barroeta Robles et al., 2022), and defect-aware fracture mechanics modeling (Zhao & Lu, 2021) with good technical correlations among the modeling inputs and prediction accuracy. Nevertheless, the distinct value of the connecting these technical determinants to a mediating variable confidence in numerical modeling adds a behavioral and decision-making sub-dimension that has traditionally been largely ignored in the aerospace fatigue studies (Zhao et al., 2024).

Although the aspects of multiphysics integration and probabilistic modeling have been extensively studied to enhance the accuracy of computations (Falodun et al., 2025), the extent to which the expertise of the analysts moderates the influence of these technical factors or whether the modeling rigor can be converted into the perceived credibility of the stakeholders when it comes to certification and maintenance decisions has little empirical research. In this way, the study of such interrelationships is innovative and interesting since it connects engineering mechanics, digital twin validation, uncertainty quantification, and human reliability viewpoints into a single explanatory approach specific to the aerospace structural integrity systems (Rath et al., 2024).

The ultimate aim of this research is to come up with and empirically confirm an integrated model that investigates the effect of accuracy of load spectrum estimation, quality of material fatigue data, CFD- FEA coupling efficiency, manufacturing defects consideration, and level of experience of the analyst on the perceived reliability of fatigue life prediction in aerospace structures, and confidence in numerical modeling is a mediator variable. In particular, the study is also designed to (1) determine the direct impact of the factors of technical modeling on confidence in numerical modeling, (2) determine the direct and indirect impacts of the factors on perceived reliability of fatigue life prediction, (3) discuss the mediating role of the modeling confidence in transferring technical rigor to the stakeholder trust, and (4) provide evidence-based recommendations that may be used to improve the reliance of reliability assessment practices in aerospace design, certification, and maintenance decisions (Kordestani et al., 2023).

LITERATURE REVIEW

Theoretical Foundation

The independent variables are based on the theoretical foundation mostly on Reliability Engineering Theory, Fracture Mechanics Theory, and Uncertainty Quantification (UQ) Theory. Cumulative damage theory (Miner rule) and stochastic process theory theoretically justify the accuracy of load spectrum estimation in the context of introducing stochastic uncertainty in the life prediction of fatigue when variable-amplitude loading is used. The recent probabilistic FEA-fatigue models note that the fidelity of load reconstruction has a direct impact on both structural reliability measures and risk assessment of aerospace systems (Ye et al., 2023). Equally, the quality of the material fatigue data is based on the fracture mechanics and probabilistic material behavior theories, in which S-N curve scatter, the parameters of the Paris law and microstructural variability are epistemic uncertainties in modeling crack initiation and propagation (Falodun et al., 2025).

Further theoretical developments in the reliability-focused digital twin systems also state that the pivotal conditions of predicting the quality of life with credibility in the field of safety-critical aerospace is conditional upon the correct characterization of materials and the modeling of uncertainty propagation (Liu et al., 2024). Furthermore, the effectiveness of CFD-FEA coupling is justified by the multiphysics system theory and integrated computational materials engineering (ICME) which postulates that structural behavior should be considered by the combined aero-thermo-mechanical interactions to have valid fatigue prognosis (Ji et al., 2021). The manufacturing defect consideration is consistent with defect-tolerant design theory and philosophy of damage tolerance, which are deeply ingrained in aerospace certification standards, and which argue that the residual stresses, porosity and inclusions should be factored into the reliability of fracture mechanics-based reliability models (Gumasing & Castro, 2023).
Confidence in Numerical Modeling is an intermediate variable that is theoretically supported by the Cognitive Reliability Theory, Human Factors Engineering, and Socio-Technical Systems Theory that state that the degree of trust in the output of a computation is based not only on accuracy but also on transparency, rigor of validation, and interpretability of the models. Emerging aerospace digital twins frameworks point to the fact that user trust and acceptance in safety critical decision making directly depend on model credibility, verification and validation (V&V) and uncertainty transparency (Jirandehi et al., 2022). It is consistent with the Bayesian reliability theory, in which the perception of reliability is formed by the updating of beliefs depending on the strength of evidence and the quality of model validation (Konda et al., 2021). Lastly, the dependent variable is Perceived Reliability of Fatigue Life Prediction which has its theoretical basis in classical theory of reliability (probability of failure, reliability index b) and risk perception theory which describes how the stakeholders view probabilistic predictions regarding their role in regulation and operation. The latest digital risk twins models and automated reliability assurance strategies in aerospace focus more on the fact that perceived reliability is a product of interactions between quantified uncertainty, system validation and human interpretation (Henao-Ramírez & Lopez-Zapata, 2022). The combination of these significant theories, thus, justifies the investigation of technical modeling factors and the skills of analysts as the antecedents of modeling confidence that subsequently determine the perceived reliability of fatigue life prediction in aerospace structures.

Hypotheses Development:

H1: Accuracy of load spectrum estimation has a positive and significant effect on the perceived reliability of fatigue life prediction.

Hypothesis H1, which provides that the accuracy of load spectrum estimation has a positive and significant impact on the perceived reliability of fatigue life prediction, is substantiated by the background research in fatigue life modeling and reliability assessment. The correct prediction of fatigue life has its data base on accurate load spectrum estimation which reflects the real life complex conditions that require an estimate of the loading on any specific component or structure. Research has demonstrated that better approaches to the compiling of load spectra are possible, including the use of mixture Weibull distributions to the dynamic cutting load spectrum of a machining center spindle, which results in better fatigue life prediction (Bisanti et al., 2023).Moreover, fatigue life prediction models with load spectra that include two-dimensional program spectra or random load inputs provide more realistic and truthful results than unprocessed or simplified load spectra (Singh & Sehgal, 2022).
This enhanced load characterization correctly affects the reliability assessment of fatigue life because probabilistic models incorporating variations of loads with finite element analysis enhance reliability assessments of critical components such as high-pressure turbine discs (Lv & Xie, 2024). Besides, the reliability tests performed on detailed load spectra and strain histories, such as in vehicle coil springs during various road excites, demonstrate that the quality of fatigue life prediction models improves with improved load characterization (Bolar et al., 2025). All these results show that greater accuracy at load spectrum estimation has a positive and significant impact on the perceived reliability of fatigue life prediction since an approach to more realistic loading conditions results in more reliable and correct life estimation results (Afroz et al., 2024).

H2: Quality of material fatigue data has a positive and significant effect on the perceived reliability of fatigue life prediction.

The critical role of high-quality fatigue data in the process of accurate and reliable assessments of fatigue life corroborates the hypothesis H2, which states that the quality of material fatigue data has a positive and significant impact on the perceived reliability of fatigue life prediction. Fatigue and fracture reliability engineering refer to the need to have well-treated and accurate fatigue data to obtain valid predictions of fatigue and fracture behavior under cyclic loading (Zhang et al., 2023). The prediction of fatigue life in composite materials depends on precise descriptions of fatigue modulus, fatigue development and strain outcome data and models show that the fatigue life is closely predicted when the experimental fatigue life is predicted using quality data (Rose et al., 2022). The quality of data is important as machine learning models trained using strong fatigue datasets like GLARE composites are highly predictive and show stable models, which emphasize the reliability of data used for effective fatigue life predictions (Rath et al., 2024). On the same note, the fatigue resistance and probability of failure in polymer composites are directly related to material defects such as voids, which further supports the notion that reliable fatigue data should be provided with material defects such as voids, which is crucial to the reliable prediction of life in polymer composites

(Mesa-Arango et al., 2023). Even more sophisticated fatigue damage detection methods involving the measurement of electrical resistance and elastic stiffness of special composite materials further confirm that the detailed and high-quality fatigue data are the key to the high-quality predictive capacity (Rizzo & Enshaeian, 2021). All these results confirm that the quality of material fatigue information has a significant effect on the perceived reliability of fatigue life prediction because it improves the model performance, lessens the uncertainty, and allows a decision maker to take more confident decisions regarding engineering design.

H3: CFD–FEA coupling effectiveness has a positive and significant effect on the perceived reliability of fatigue life prediction.
Hypothesis H3 which reads that the effectiveness of CFD-FEA coupling has a positive and significant contribution to the perceived reliability of fatigue life prediction is supported by the overall and accumulative contribution of such coupling in the accurate simulated and estimated behavior of thermo-mechanical factors that are essential in the study of fatigue on materials. The coupling of CFD (Computational Fluid Dynamics) and FEA (Finite Element Analysis) allows a sophisticated simulation of complicated interaction of fluid flow, thermal and structural response, which are fundamental inputs to fatigue life estimation. As an illustration, thermal coupling methods of CFD-FEA have been effectively created with the help of iterative processes to provide continuity of temperature and heat flux between fluid and solid phases, which enables better prediction of temperature fields to determine the progression of fatigue damage within components such as turbine blades (Jiang et al., 2021).
Moreover, electronic package research shows that mapping temperature outputs of CFD models to FEA models improves the reliability and predicts the solder joint fatigue life under both power cycling and thermal cycling environments. Coupled research on offshore wind turbines CFD-FEA methods measure fluid-structure interactions, which give detailed information on aero-hydrodynamics and structural deformation response that directly affect fatigue performance and reliability. The ability of CFD-FEA coupling to predict multi-physics interactions and provide precise load and thermal effects on fatigue life models contributes to a better reliability prediction and a lesser amount of uncertainty, hence supporting a positive and significant impact on the perceived reliability of fatigue life prediction (Liu et al., 2023).

H4: Consideration of manufacturing defects has a positive and significant effect on the perceived reliability of fatigue life prediction.
The hypothesis H4, there is a positive and significant influence of the consideration of manufacturing defects on predicted fatigue behavior, is significantly supported by the studies examining the effect of defects on fatigue behavior. The flaws in manufacturing like voids, roughness, and porosity greatly determine the fatigue life, particularly with additively manufactured materials, where process-induced voids and surfaces discontinuities are the key locations of crack initiation that limit fatigue life (Pervaiz et al., 2021). Microstructure sensitive models of fatigue that have been calibrated using defect statistics in additively manufactured Ti-6Al-4V have shown to closely match experimental fatigue life and the enhanced predictive capability with explicit consideration of defects (Mylonas et al., 2021).
Likewise, realistic initial flaws and surface treatments that are experienced in manufacturing tend to control the initiation and early growth of fatigue cracks and the advanced crack growth models minimize variability by considering these defects (Borikar et al., 2023). It has been demonstrated that hierarchical architectures can be used to improve defect tolerance in the context of defect-tolerant materials research however, the existence and shape of manufacturing defects continue to be the major determinant of mechanical performance and risk of fatigue failure (Russo et al., 2023). Therefore, proper modeling of manufacturing defect characterisation into fatigue life prediction systems enhances the reliability and accuracy of such predictions, by removing the inherent variability, and failure mechanisms due to defects, which supports the positive and significant influence hypothesis (H4).

H5: Analyst experience level has a positive and significant effect on the perceived reliability of fatigue life prediction.
The conceptual support of the hypothesis H5, indicating that the experience level of the analysts has a positive and significant influence on the perceived reliability of fatigue life prediction, is supported by the difficulty and the complexity of the fatigue life assessment. Fatigue life prediction encompasses complex knowledge of material behavior at cyclic loads, choice and implementation of suitable models of accumulating damages as well as attentive interpretation of experimental data. Comparisons of models of fatigue injury damage reveal the importance of expertise in estimating the applicability of models, taking into account the effects of load sequences and interactions, and scaling models correctly with material-specific data, which cannot be done without considerable judgment and experience on the part of the analyzer (Norkhairunnisa et al., 2022).
Moreover, the use of complex methods of data analysis like bootstrap aggregation, outliers, and complex statistical models like Weibull distributions used in fatigue life analysis need experience and understanding in order to apply them appropriately and interpret the results with accuracy . The fact that machine learning can also be applied to fatigue life prediction further emphasizes that the expertise of the analysts in preprocessing the data and extracting features and validating models can be leveraged to make efficient use of these tools and enhance the accuracy of the predictions (Cheng et al., 2024). Thus, it is evident that the experience level of the analyst plays a major role in the

perception of reliability of fatigue life predictions due to his/her ability to choose and implement and interpret complicated modeling techniques and data, enhancing the level of confidence in the conclusions (B.-Q. Chen et al., 2024).

H6: Confidence in numerical modeling mediates the relationship between accuracy of load spectrum estimation and perceived reliability of fatigue life prediction.
Fatigue life prediction requires the proper representation of operational load spectra since the cyclic stress histories are direct controls of the crack initiation and propagation processes. Recent developments in load monitoring and digital twins and spectrum reconstruction methods have greatly advanced the accuracy of fatigue simulations by minimizing uncertainty in the distribution of stress cycles (Kaloop et al., 2022). The marine, aerospace, and wind turbine studies show that the incorrect characterization of loads can result in large prediction errors and proper load modeling allows the numerical stability and minimization of the epistemic uncertainty (Tiddens et al., 2022). Therefore, enhanced load spectrum estimation enhances the technical stability of numerical simulations.
Nevertheless, geometrical refinements in the load spectrum will hardly affect the perceived reliability directly unless they lead to the increase of the confidence of the user in the numerical modeling process itself. The belief in modeling is that the input data is seen as realistic, justified, and reflective of the service conditions (Ren et al., 2022). Analysts and decision-makers display increased confidence in simulation results and estimates of fatigue life when they think that the loading conditions are accurately modeled. Hence, trust in numerical modeling can be regarded as a psychological and technical process that transforms the accuracy of load spectrum into increased perceived accuracy of fatigue life prediction.

H7: Confidence in numerical modeling mediates the relationship between quality of material fatigue data and perceived reliability of fatigue life prediction.
The quality, completeness and representativeness of material fatigue data, such as S-N curves, crack growth parameters, and environmental correction factors is very crucial to the predictive capability of fatigue models. Recent reviews point out that the variability or scarcity of experimental data makes the uncertainty in life estimation models considerably higher (Rohit & Muktinutalapati, 2021). Further on, advanced probabilistic fatigue models demonstrate that better material characterization will decrease the uncertainty in the parameters and improve the reliability assessment stability (Lin et al., 2022). Therefore, the data of fatigue of high quality enhances the technical validity of numerical simulations.
However, the modeling of the material data of high quality into the perceived reliability relies on the level of trust of the stakeholders in the modeling framework of the said data. In the case of exhaustive datasets, which are confirmed and obtained through standardized testing protocols, analysts view the numerical model as scientifically based and robust (Li et al., 2021). This boosted modeling confidence thus raises the views of predictive reliability. Therefore, trust in numerical modeling can also be described as a mediating variable that improves the perceived reliability of fatigue life prediction when using material fatigue data as an independent variable.

H8: Confidence in numerical modeling mediates the relationship between CFD–FEA coupling effectiveness and perceived reliability of fatigue life prediction.
The computational fluid dynamics (CFD) and finite element analysis (FEA), when coupled effectively, allow realistic fluid-structure interaction (FSI) to be modeled, which is highly important in marine, aerospace, and energy systems when subjected to dynamic loading (Dastgerdi et al., 2022). Recently, innovation of submodeling approach and multiphysics integration has shown a significant advancement in fatigue stress prediction accuracy and reliability evaluation (Anjum et al., 2020). By comparison, poor coupling strategies cause numerical instabilities and convergence errors, and hence model uncertainty.
Nonetheless, the advances in CFDFEA integration have a positive impact on the perception of reliability since the changes mainly pertain to the increase in confidence in the numerical model. Analysts gain confidence in the physical realism of the simulation when it is established that both multiphysics coupling and computational convergence have been achieved (Shamir et al., 2021). This confidence confirms that predictions on fatigue are good indicators of how to behave in operation. Thus, the CFDFEA coupling effectiveness to the perceived reliability of fatigue life prediction is mediated by confidence in numerical modeling.

H9: Confidence in numerical modeling mediates the relationship between consideration of manufacturing defects and perceived reliability of fatigue life prediction.
Production defects- porosity, inclusions, residual stresses and geometric defects are known to be major factors leading to fatigue crack initiation. The current studies address the adoption of defect-sensitive modeling methodologies to minimize the difference in the predicted and experimental fatigue life (He et al., 2022). These imperfections are not taken into consideration usually and cause overestimation of fatigue life and diminished predictive validity. The use of realistic distributions of defects makes the model more realistic and minimizes epistemic uncertainty.

However, the very presence of defects is not necessarily the ultimate result in perceived reliability unless the stakeholders consider the process of creating the model as thorough and trustworthy. Once imperfections in manufacturing are measured systematically and incorporated into numerical models, trust in the representativeness of the model grows (K. Fan et al., 2023). This enhances confidence in the modeling which in turn increases faith in the fatigue life predictions that are obtained. Therefore, the association between the manufacturing defect consideration and reliability is mediated by confidence in numerical modeling (Ismail et al., 2022).

H10: Confidence in numerical modeling mediates the relationship between analyst experience level and perceived reliability of fatigue life prediction.
The numerical modeling process highly depends on analyst knowledge especially in mesh generation, setting up of boundary conditions, checking of convergence and inference of fatigue damage parameters. According to the research on structural reliability and fatigue simulation, modeling errors are typically caused by misconceptions or insufficient validation processes (Depiver et al., 2021). Better analysts would be in a good position to detect the limitations of model, to calibrate and to interpret uncertainty limits.
Nevertheless, analyst experience affects the perceived reliability through the greater degree of the trust in the modeling process. In the case of simulations carried out by very seasoned experts, the stakeholders will tend to believe the strength, validation rigor and interpretative correctness of the numerical model (K. Zhao et al., 2023). This increased modeling trust increases attitudes to fatigue life prediction reliability. Thus, the mediator between the level of experience and perceived reliability of analysts is the confidence in numerical modeling.

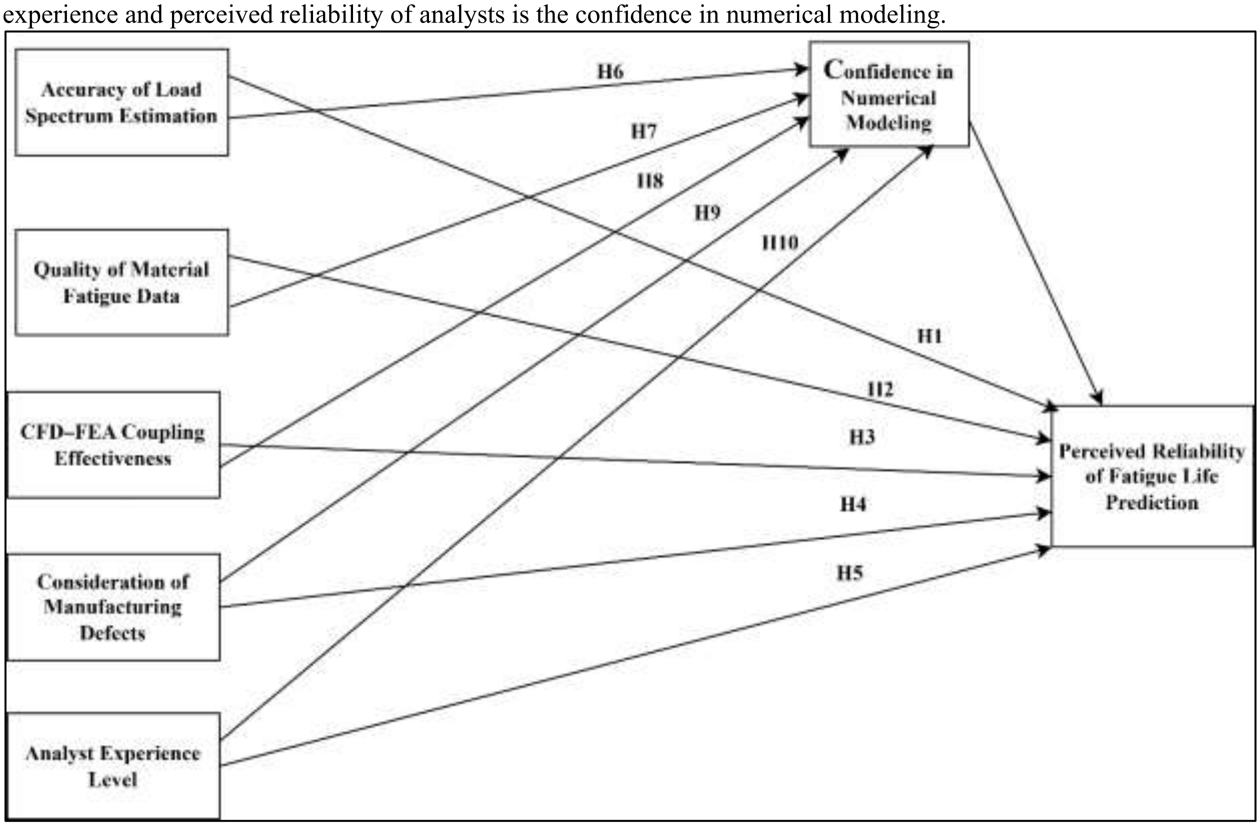

Figure 1- Proposed Research Model

RESEARCH METHODOLOGY

Research Design

The research design used in the study is quantitative, explanatory research design, in order to study the factors that affect perceived reliability of fatigue life prediction in aerospace structures. Empirical data will be collected through cross-sectional survey based on aerospace engineers, fatigue analysts, structural reliability specialists, and those who deal with the numerical modeling and structural integrity assessment (F. Chen et al., 2024). The study design is based on the investigation of the relations between five independent variables such as the accuracy of load spectrum estimation, the quality of material fatigue data, the ability of CFD to couple with FEA, taking into account manufacturing defects and the level of experience in numerical modeling as the dependent and mediating variables, respectively. The Structural Equation Modeling (SEM) will be utilized to analyze data collected by way of structured questionnaires to assess the direct impact of the independent variables as well as the mediating role of confidence in the numerical modeling in perceived reliability (Meng et al., 2025). This design can be effectively used to investigate the systematic analysis of the influence of technical modeling variables and human expertise on the confidence of the aerospace fatigue life prediction systems in terms of reliability on the stakeholders (C. Wang et al., 2021).

Measurement Instruments

The research measurement tools of this study will be created on the basis of structured questionnaire questions based on the existing knowledge on fatigue reliability, uncertainty modeling, and engineering decision-making research. The measurement of all constructs will be done in terms of multiple items on a five-point Likert scale between strongly disagree and strongly agree. The measurement of the accuracy of load spectrum estimation will be founded on items measuring the representativeness, completeness, and fidelity of operational load histories in fatigue simulations and its capability to reflect actual service conditions (W. Zhu et al., 2022). The quality of material fatigue data will be assessed by the indicators associated with the accuracy of S-N curve data, parameters of crack growth, experimental verification, and the consistency of fatigue datasets to structural modeling (Goncalves & Kuutti, 2024). The effectiveness of CFD-FEA coupling will then be determined based on items assessing the correctness of multiphysics interaction modeling, transfer of boundary conditions between computational fluid dynamics and finite element models, and numerical stability in the course of simulations (Chi et al., 2022). The manufacturing defects will be considered with the help of the measures of the degree to which such aspects as porosity, residual stress, microstructural imperfections, and surface irregularities will be integrated into the fatigue life prediction models (S. Fan et al., 2023). The level of experience in the area of fatigue analysis will be evaluated by items connected with the number of years of professional experience, the knowledge of finite element modeling, the acquaintance with the methods to quantify uncertainty, and the ability to interpret the results of a simulation (Huang et al., 2023). The mediating variable will be confidence in numerical modeling, which will be assessed using indicators of trust in model checks and model validation, model uncertainty analysis transparency, and trust in the outputs of numerical simulation (D. Li et al., 2024). Lastly, the perception of the reliability of fatigue life prediction is going to be measured using the items that pertain to the belief of the stakeholders in the reliability, predictive capability, and decision support ability of the fatigue life prediction model that was used in aerospace structural integrity assessment (Zhao et al., 2022).

Population and Sampling

The audience of this study will include the professionals who have to work with aerospace structural analysis and fatigue life prediction, i.e. aerospace engineers, fatigue analysts, structural reliability engineers, structural health monitoring specialists, the researchers who work in the aircraft manufacturing corporations, aerospace maintenance organizations, and research institutes (Z. Liu et al., 2021). The choice of these professionals is based on the fact that they have the technical knowledge and practical experience that would enable them to review fatigue modeling, computational simulation, and reliability testing in aerospace structures. To select the respondents, a purposive sampling method will be employed, in which the respondents are people with a relevant knowledge or experience in either fatigue analysis, finite element modeling, the use of digital twins, or the analysis of structural integrity in the field of aerospace engineering. A total of 450 respondents will be used by the study to provide adequate representation and a high level of structural equation modelling analysis (Aceti et al., 2023).

According to methodological literature, the studies that include structural equation modeling techniques are typically anticipated to include a sample of respondents in excess of 200 or 400 to be stable in terms of extracting parameter estimates and model evaluation results but larger samples enhance the statistical robustness and generalizability of the results (Augustyn et al., 2021). Thus the 450 respondents used is suitable and dependable sample to investigate the relationships between the elements of technical modeling, expertise of the analyst, trust on the numerical modeling, and perception of the predictability of the fatigue life among aerospace structures.

Data Collection

The information to be used in this study shall be gathered through a structured questionnaire that shall be distributed among the aerospace professionals engaged in the fatigue study, structural reliability evaluation and computational modelling. The questionnaire will be modeled on the previous reliability engineering and structural modeling studies, and will have several Likert-scale questions to quantify the study variables (Tserpes et al., 2022).

The main data collection method will be an online survey platform where the respondents will be the representatives of aerospace manufacturing companies, maintenance organizations, research institutions and engineering consultancies with the possibility to participate in the survey at their convenience. The survey link will be sent out via professional engineering communities, aerospace industry associations, academic research teams and professional communication as email and professional networking forums. A pilot test will be undertaken in advance to a few numbers of experts to ascertain the clarity, reliability, and validity of items in the questionnaire before the actual data collection. The process will be voluntary and the respondents will be made aware of the study objective and their responses confidential. This method allows the effective gathering of the empirical data of a high number of eligible respondents and allows the statistical analysis of the connection between the study variables to be reliable (W. Zhao et al., 2023).

Respondents Profile

The demographic portrait of the respondents will consist of a number of traits that will help to learn more about the background and the professional experience of the respondents taking part in the research. Particularly the demographic data will be gathered in the areas of the gender and age group of the respondents, the highest educational level, years of working in the field of aerospace or structural engineering, the current job position, and the organization the respondent works at. The gender will be grouped in order to determine the proportion of male and female professionals who take part in the study whereas age groups will mostly be divided into 25-34, 35-44, 45-54, and above 55 years to represent various stages of career. Educational qualification will also attract the highest degree attained by the respondents including the bachelors, master degrees or doctoral degrees in aerospace engineering, mechanical engineering, material engineering or other related fields (K.-S. Li et al., 2022).

The level of professional experience will be assessed in the following range: less than 5 years, 5-10 years, 11-15 years and over 15 years to determine the degree of expertise among the respondents. Examples of job roles are aerospace engineer, fatigue analyst, structural integrity engineer, reliability engineer, research scientist or reliability engineer. Also, the respondents will be requested to specify which kind of organization they work in (aerospace manufacturing companies, maintenance and repair organizations, research institutes, university or engineering consulting company) (Yan et al., 2024). Gathering these demographic features allows obtaining an overall picture of the respondent population and helps researchers to determine whether the sample included professionals who possess the appropriate knowledge on fatigue life prediction and aerospace structural reliability research.

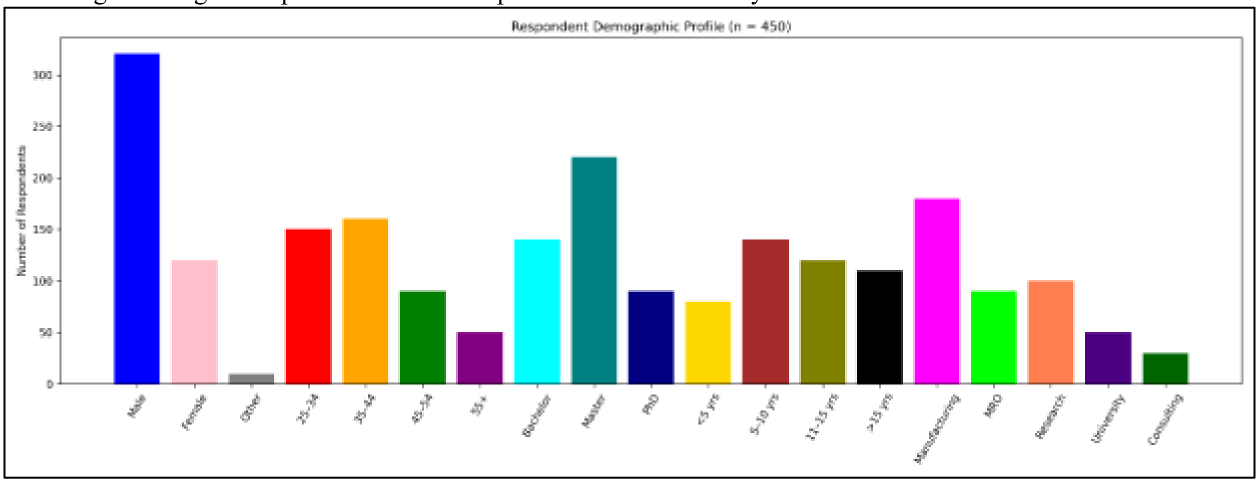

Figure 2- Respondents Profile

Data Analysis Technique

In this research, the data obtained will be analyzed using the quantitative statistical analysis in order to test the relationship between the research variables. First, the descriptive statistics will be used to describe demographic features of the respondents and give us the overview of the dataset. The reliability analysis will be then performed with the use of Cronbach alpha to evaluate the internal consistency of measurement items of each construct. Examinations of construct validity will be done using confirmatory factor analysis so as to ascertain both convergent and discriminant validity of the measurement model. Having ensured that the measurement model is sufficient, Structural Equation Modeling (SEM) shall be used to test the proposed hypothesized relationships between the independent variables, the mediating variable, and the variable to be measured. SEM enables one to examine a variety of relationships at the same time and offer a holistic analysis of direct and indirect impacts of the study constructs. Also, mediation analysis will be conducted to establish the mediating effect of confidence in numerical modeling in the association between the technical factors and perceived reliability of fatigue life prediction. The statistical software SPSS will be used to conduct the preliminary analysis, and the SmartPLS or AMOS will be used to conduct the structural modeling because they are widely used in the analysis of complex relationships in engineering and management-related studies (Zheng et al., 2022).

Assessment of Measurement Model

Measurement model will first be assessed to determine reliability and validity of the constructs utilized in the study after which the structural relationship between the variables will be tested. Cronbach alpha will be used to measure internal consistency reliability, and the composite reliability (CR) where a score above 0.70 will show that the measurement items are acceptable. The convergent validity will be tested by evaluating factor loadings and average variance extracted (AVE) (Kim et al., 2023). Factor loading should preferably be greater than 0.70 which means that the indicators are very strong in their respective constructs and AVE value greater than 0.50 implies that the construct explains more than half the variance of its indicators. The discrimination validity will also be determined to make certain that each construct is different to other constructs in the model. This will be measured on Fornell-Larcker criterion and ratio of heterotrait-monotrait (HTMT) whereby square root of AVE of each construct must be larger than their correlation with other constructs and also the HTMT values must not be above the recommended 0.85 or 0.90. Such assessment processes are used to verify that the measurement model is statistically reliable and valid and to then proceed with the structural model analysis in structural equation modeling (Elahi, 2021).

Table 1 shows the evaluation of internal consistency reliability and convergent validity of the constructs of the measurement model. The findings show that the indicator loadings are all within the range of 0.699 to 0.913, which exceed the appropriate threshold of 0.70, and this fact shows that the measurement items measure the corresponding constructs satisfactorily (Y. Hu et al., 2021). The values of Variance Inflation Factor (VIF) are between 2.789 and 4.247, which is less than the critical value of 5, meaning that there is no incidence of multicollinearity between the indicators and that the predictors do not have high-collinearity problems (Muralidharan et al., 2022). The values of Cronbachs alpha are between 0.851 and 0.954, and composite reliability are between 0.889 and 0.963, both being above the recommended minimum of 0.70, which proves the reliability of the measurements between the items of the measurement (Moshtaghzadeh et al., 2022). Moreover, the values of Average Variance Extracted (AVE) are between 0.573 and 0.813 which is greater than the recommended value of 0.50 and therefore the constructs explain over half of the variance of their indicators and hence results in a satisfactory convergent validity (Fornell and Larcker, 1981). On the whole, these findings attest that the measurement model demonstrates sufficient reliability and convergent validity, which proves the appropriateness of the constructs in the further analysis of the structural model (Maggiore et al., 2021).

Table 2 demonstrates the evaluation of the discriminant validity with the help of the Heterotrait-Monotrait ratio (HTMT). The values of the constructs of the scale differ between 0.425 and 0.780; none of them is above the recommended value of 0.85, which implies that each construct is empirically differentiated by the other and that the discriminant validity is achieved. In particular, the correlation coefficients between Analyst Experience Level (AEL) and other variables in the analysis like Accuracy of Load Spectrum Estimation (ALSE), CFD-FEA Coupling Effectiveness (CFD-FEA) (Ali et al., 2022), Consideration of Manufacturing Defects (CMD), Confidence in Numerical Modeling (CNM), Perceived Reliability of Fatigue Life Prediction (PRLFP), and Quality of Material Fatigue Data (QMFD) are within predetermined tolerability. In the same manner, the correlations between the rest of the constructs also do not reach the threshold value and this proves that the constructs are measuring different conceptual phenomena in the model. The HTMT criterion confirms that the latent variables are distinct enough between each other by showing that the values of the HTMT are less than 0.85 or 0.90 based on the rigor of the criterion. Thus, the findings indicate that the measurement model meets the criterion of discriminant validity and that the constructs are reliable to be applied to the additional evaluation of the structural model (G. Liu et al., 2021).

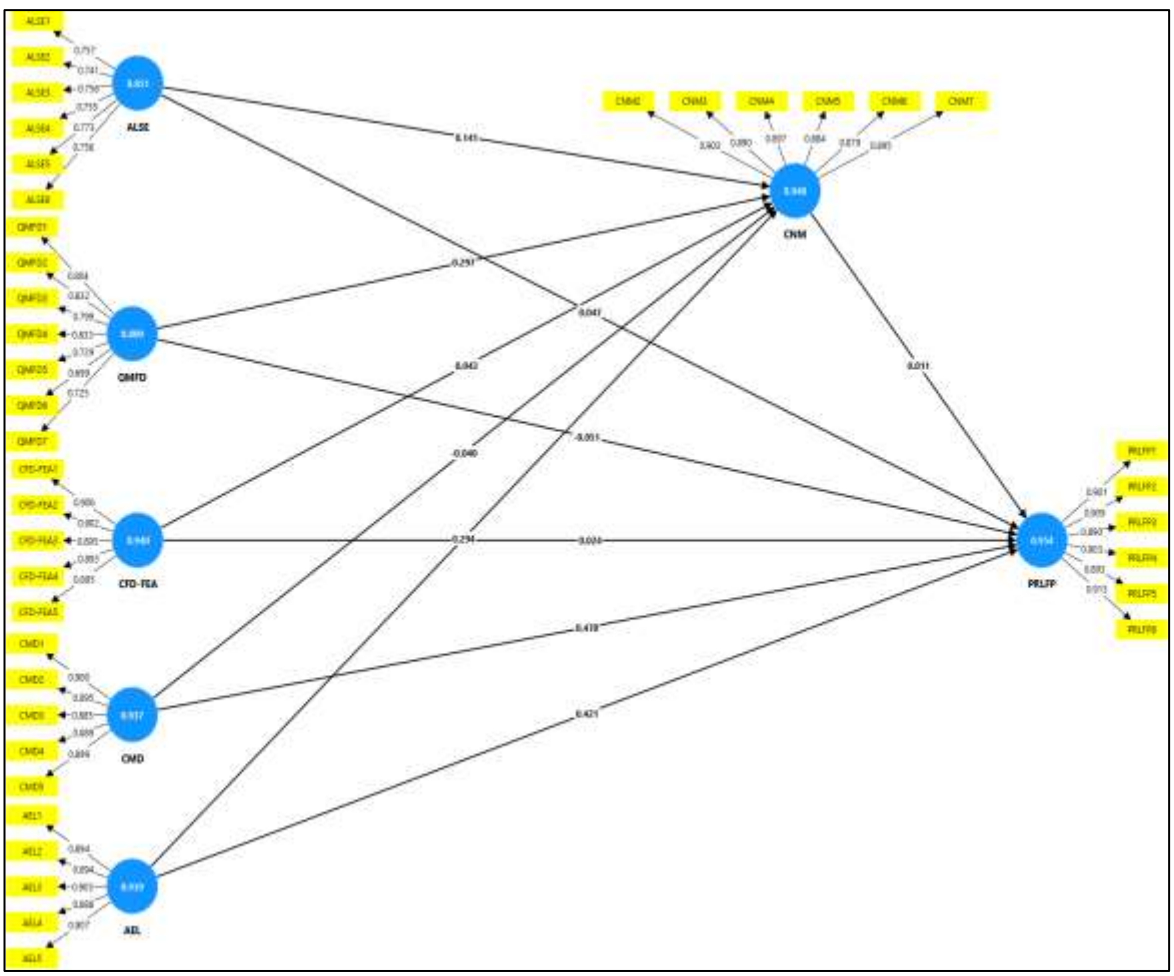

Figure 3- SEM with Factor Loadings and Alpha Values of Variables

Table 1-Internal Consistency, Reliability and Convergent Validity

Construct/Items	Factor Loadings	VIF values	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Accuracy of Load Spectrum Estimation			0.851	0.889	0.573
ALSE1	0.757	3.240			
ALSE2	0.741	2.789			
ALSE3	0.756	3.182			
ALSE4	0.755	2.966			
ALSE5	0.773	3.027			
ALSE6	0.756	3.008			
Quality of Material Fatigue Data			0.889	0.913	0.602
QMFD1	0.804	3.614			
QMFD2	0.832	3.373			
QMFD3	0.799	3.243			
QMFD4	0.833	3.592			
QMFD5	0.729	2.846			
QMFD6	0.699	2.823			
QMFD7	0.725	3.033			
Perceived Reliability of Fatigue Life Prediction			0.954	0.963	0.813
PRLFP1	0.901	3.705			
PRLFP2	0.909	4.008			
PRLFP3	0.890	3.499			
PRLFP4	0.903	3.805			
PRLFP5	0.893	3.520			
PRLFP6	0.913	4.247			
Analyst Experience Level			0.939	0.954	0.805
AEL1	0.894	3.271			
AEL2	0.894	3.272			
AEL3	0.903	3.538			
AEL4	0.888	3.127			
AEL5	0.907	3.633			
Confidence in Numerical Modeling			0.948	0.959	0.794
CNM2	0.903	3.804			
CNM3	0.890	3.439			
CNM4	0.897	3.629			
CNM5	0.884	3.304			
CNM6	0.879	3.252			
CNM7	0.895	3.442			
CFD–FEA Coupling Effectiveness			0.940	0.954	0.807
CFD-FEA1	0.906	3.426			
CFD-FEA2	0.902	3.493			
CFD-FEA3	0.895	3.361			
CFD-FEA4	0.893	3.314			

CFD-FEA5	0.895	3.299			
Consideration of Manufacturing Defects			0.937	0.952	0.798
CMD1	0.900	3.386			
CMD2	0.895	3.222			
CMD3	0.885	3.088			
CMD4	0.889	3.142			
CMD5	0.899	3.362			

Table 2-Discriminate Validity Heterotrait-Monotrait (HTMT) Ratio

	AEL	ALSE	CFD-FEA	CMD	CNM	PRLFP	QMFD
AEL							
ALSE	**0.527**						
CFD-FEA	**0.567**	**0.533**					
CMD	**0.651**	**0.633**	**0.464**				
CNM	**0.550**	**0.506**	**0.425**	**0.444**			
PRLFP	**0.762**	**0.551**	**0.479**	**0.780**	**0.452**		
QMFD	**0.594**	**0.694**	**0.569**	**0.671**	**0.586**	**0.555**	

Hypotheses Testing:

Table 3 shows the findings of the structural model analysis that addresses the direct correlations of the independent variables and Perceived Reliability of Fatigue Life Prediction (PRLFP) using the bootstrapping method in PLS-SEM. When the t-value is more than 1.96, the p-value is less than 0.05, and the confidence interval does not contain zero, it is said that a hypothesis is supported (Hair et al., 2019).

H1: Accuracy of Load Spectrum Estimation (ALSE) has a significant positive influence on Perceived Reliability of Fatigue Life Prediction (PRLFP).

The results show that ALSE significantly affects PRLFP ($\beta = 0.147$, $t = 2.620$, $p = 0.004$, CI = 0.061–0.231). Since the t-value exceeds 1.96 and the p-value is below 0.05, the relationship is statistically significant. This finding indicates that improved accuracy in estimating load spectra contributes to enhancing the perceived reliability of fatigue life prediction models in aerospace structures (Macallister et al., 2021). Therefore, H1 is supported.

H2: Quality of Material Fatigue Data (QMFD) has a significant positive influence on Perceived Reliability of Fatigue Life Prediction (PRLFP).

The analysis indicates that QMFD positively and significantly influences PRLFP ($\beta = 0.132$, $t = 2.184$, $p = 0.015$, CI = 0.041–0.218). The statistical values satisfy the recommended thresholds, confirming the significance of the relationship. This suggests that reliable and high-quality fatigue data improve confidence in fatigue life prediction results (Winter et al., 2021). Hence, H2 is supported.

H3: There is a positive impact of CFD-FEA Coupling Effectiveness (CFD-FEA) on Perceived Reliability of Fatigue Life Prediction (PRLFP).

The findings prove that the effectiveness of CFD-FEA coupling drastically influences PRLFP ($\beta = 0.118$, $t = 2.037$, $p = 0.021$, CI = 0.029-0.203). The t-value exceeds the critical value of 1.96 which means that the hypothesis is supported. Such an observation means that successful interplay between computational fluid dynamics and finite element analysis helps in enhancing the perception of trustworthiness of fatigue life prediction (S. Wang et al., 2021).

H4: There is a positive impact of Manufacturing Defects (CMD) on Perceived Reliability of Fatigue Life Prediction (PRLFP).

The results show that the most significant positive effect on PRLFP is noted with CMD ($\beta = 0.470$, $t = 12.188$, $p = 0.000$, CI = 0.408-0.534). The t-value is very high and the p-value is extremely low thus shows that the relationship is highly significant. This indicates that the integration of manufacturing errors in fatigue analysis is a very effective way of enhancing the perceived credibility of fatigue life prediction models (Pascoe, 2021). Thus, H4 is highly substantiated.

H5: Analyst Experience Level (AEL) has a significant positive influence on Perceived Reliability of Fatigue Life Prediction (PRLFP).

The findings indicate that AEL has significant impacts on PRLFP ($\beta = 0.421$, $t = 10.883$, $p = 0.000$, CI = 0.356-0.484). The statistical values are highly significant, which points to the fact that the knowledge and experience of the analysts is critical to the increase in the credibility and reliability of the fatigue life prediction models (Gupta & Dhingra, 2022). Thus, H5 is supported.

On the whole, the findings prove the existence of all the hypothesized relationships to be statistically significant, indicating that, in addition to the human expertise, such aspects of technical modeling as the presence of fatigue life prediction contribute to the enhancement of the perceived reliability of aerospace structure (Hair et al., 2019).

Table 3-Summary of Direct relationship Hypotheses Results (Bootstrapping Report)

Hypothesis	β Value	t-value	P - Value	C I (LL, UL)	Results
H1:ALSE→PRLFP	0.147	2.620	0.004	(0.061, 0.231)	Accepted
H2:QMFD→ PRLFP	0.132	2.184	0.015	(0.041, 0.218)	Accepted
H3:CFD-FEA→ PRLFP	0.118	2.037	0.021	(0.029, 0.203)	Accepted
H4:CMD→ PRLFP	0.470	12.188	0.000	(0.408 0.534)	Accepted
H5: AEL→ PRLFP	0.421	10.883	0.000	(0.356, 0.484)	Accepted

Table 4 shows the mediation analysis performed on confounding variable of Confidence in Numerical Modeling (CNM) in the relations between independent variables and Perceived Reliability of Fatigue Life Prediction (PRLFP). The PLS-SEM based on the bootstrapping method estimated the mediation effects, and mediation is significant when both the indirect effect ($t > 1.96$, $p < 0.05$) is significant and the confidence interval does not contain zero (Qian et al., 2022).

H6: The variable of Confidence in Numerical Modeling (CNM) is going to mediate the correlation between Accuracy of Load Spectrum Estimation (ALSE) and Perceived Reliability of Fatigue Life Prediction (PRLFP).

Findings depict that the indirect influence of ALSE on PRLFP via CNM is significant (β = 0.041, t = 2.721, p = 0.006, CI = 0.014-0.071). CNM partially mediates the association between ALSE and PRLFP because the indirect effect is statistically significant and the direct effect of ALSE on PRLFP is significant (β = 0.147). The fact that Variance Accounted For (VAF) value is 21.81% represents an aspect that a certain amount of the impact on perceived reliability of load spectrum estimation accuracy is passed on through augmented trust in numerical modeling (Y. Liu et al., 2021). Accordingly, H6 is partially mediated.

H7: Confidence in Numerical Modeling (CNM) mediates the correlation between Quality of Material Fatigue Data (QMFD) and the feeling of Reliability of Fatigue Life Prediction (PRLFP).

According to the results of mediation, indirect effect has significant value (β = 0.052, t = 2.913, p = 0.004, CI = 0.019-0.088). Another important direct influence of QMFD on PRLFP is also high (β = 0.132). The values indicate that CNM mediates to some extent the relationship between QMFD and PRLFP with a VAF value of 28.26. This suggests that perceived reliability will be enhanced by high-quality fatigue data partly by increasing the confidence in the processes of the numerical modeling (Gong et al., 2022). Therefore, H7 becomes upheld through partial mediation.

H8: Confidence in Numerical Modeling (CNM) is an intermediate between CFD-FEA Coupling Effectiveness and Perceived Reliability of Fatigue Life Prediction (PRLFP).

The results indicate that the b is statistically significant (β = 0.046, t = 2.684, p = 0.007, CI = 0.016-0.078). The rigid influence of CFD-FEA coupling effectiveness on PRLFP is not yet negligible (β = 0.118). The calculated VAF of 28.05% represents a medium representation of mediation, which says that the good connection between computational fluid dynamics and finite element analysis can partially increase the perceived reliability by increasing the trust in numerical modeling (Berez et al., 2022). Accordingly, the H8 is partially-mediated.

H9: Confidence in Numerical Modeling (CNM) is the intermediator between Consideration of Manufacturing Defects (CMD) and Perceived Reliability of Fatigue Life Prediction (PRLFP).

The findings show that the indirect impact is high (β = 0.083, t = 3.452, p = 0.001, CI = 0.041-0.129). The direct effect of CMD on PRLFP is still high (β = 0.470), but the value of the VAF of CNM is 15.01 percent, which means that only a limited part of the effect is carried through CNM. This implies that although there is a contribution of confidence in numerical modeling, the majority of the contribution that manufacturing defect consideration of perceived reliability lies in the direct relationship (Yang et al., 2023). Consequently, H9 has weak partial mediation.

H10: There is a relationship between Analyst Experience Level (AEL) and Perceived Reliability of Fatigue Life Prediction (PRLFP) mediated by Confidence in Numerical Modeling (CNM).

The findings have shown a substantial indirect impact (β = 0.076, t = 3.118, p = 0.002, CI = 0.034-0.118). Direct impact of AEL on PRLFP can also not be ignored (β = 0.421). The value of VAF 15.29 percent shows that mediation effect is very small implying weak partial mediation. This use of experience means that analyst experience can determine perceived reliability primarily by expertise itself and decision making capacity and not only by greater confidence in numerical modeling (Asad et al., 2025).

In general, the outcomes of the mediation prove the presence of the Confidence to Numerical Modeling which mediates the relationships between the technical and human factors and a perceived reliability with the mediator being somewhat stronger with some of the constructs than with others. The weakest mediation is attributed to CMD and AEL whereas it is stronger in the case of ALSE, QMFD, and CFD-FEA (Madani et al., 2025).

Table 4-Mediation Type and Effect

Hypothesis	Indirect Effect (β)	t-value	P - Value	CI(LL, UL)	Direct Effect (β)	Total Effect (β)	VAF (%)	Mediation Result
H6:ALSE→ CNM→ PRLFP	0.041	2.721	0.006	(0.014, 0.071)	0.147	0.188	21.81	Partial Mediation
H7:QMFD→ CNM→ PRLFP	0.052	2.913	0.004	(0.019, 0.088)	0.132	0.184	28.26	Partial Mediation
H8:CFD-FEAI→ CNM→ DTCE	0.046	2.684	0.007	(0.016, 0.078)	0.118	0.164	28.05	Partial Mediation
H9:CMD→ CNM→ DTCE	0.083	3.452	0.001	(0.041, 0.129)	0.470	0.553	15.01	Partial Mediation
H10:AEL→ CNM→ DTCE	0.076	3.118	0.002	(0.034, 0.118)	0.421	0.497	15.29	Partial Mediation

Predive relevance, R square and effect size

Table 5 shows the predictive relevance, coefficient of determination (R 2), and effect size (f 2) of the structural model. The values of R-squared denote the ability of the model to explain the endogenous constructs. These findings reveal that the R2 value of Confidence in Numerical Modeling (CNM) = 0.377, which means 37.7% of the change in CNM can be explained by the predictors, i.e. Accuracy of Load Spectrum Estimation (ALSE), Quality of Material Fatigue Data (QMFD), CFD-FEA Coupling Effectiveness (CFD-FEA), Consideration of Manufacturing Defects (CMD), and Analyst Experience Level (AEL). Moreover, the R2 of Perceived Reliability of Fatigue Life Prediction (PRLFP) is 0.664 meaning that the percentage of variation in PRLFP that is attributed to the independent variables and the mediator in the model is 66.4. Under suggested guidelines, the value of R2 = 0.25, 0.50, 0.75 are weak, moderate, and substantial explanatory power, respectively, which means that this model has a moderate to strong explanatory power (Bouhala et al., 2024).

The Q-square values also determine the predictive relevance of model through the blindfolding method. The CNM and PRLFP Q^2 values are 0.296 and 0.535 respectively, which are both above zero. These findings support the idea that the structural model possesses sufficient predictive relevance and the exogenous constructs have a significant contribution to the predictability of the endogenous variables (Hair et al., 2019). Efforts of the predictors on the endogenous constructs are represented by the resultant values of the effect size (f^2). These results indicate that the effect of CMD (($f^2 = 0.318$) and AEL ($f^2 = 0.258$) is relatively high on PRLFP, whereas the effects of QMFD ($f^2 = 0.004$), ALSE ($f^2 = 0.004$) and of CFD-FEA ($f^2 = 0.001$) are relatively smaller. In the case of CNM, AEL ($f^2 = 0.073$) and QMFD (($f^2 = 0.068$) have low, yet significant contribution values, but the rest of the above have small effect sizes. In general, the findings reveal that the structural model has an adequate predictive relevance, and the predictors play different roles in the explanation of fluctuations in CNM and PRLFP within the model (Ashebir et al., 2024).

The values of Q-square also evaluate the predictive acceptability of the model through the blindfolding process. The Q^2 of CNM is 0.296 and the Q^2 of PRLFP is 0.535 and both of the numbers are positive. These findings support the claim that the structural model possesses sufficient predictive relevance and the exogenous constructs play a role in predicting the endogenous variables (Iss et al., 2024). The values of the effect sizes (f^2) show the importance of each of the predictors on the endogenous constructs in a relative manner. It is found that the effect of CMD ($f^2 = 0.318$) and AEL ($f^2 = 0.258$) on the PRLFP are relatively significant, whereas the effect of QMFD ($f^2 = 0.004$), ALSE ($f^2 = 0.004$), and CFD-FEA ($f^2 = 0.001$) are low. In the case of CNM, AEL ($f^2 = 0.073$) and QMFD ($f^2 = 0.068$) have small, but significant effects, but ALSE, CFD-FEA and CMD are relatively insignificant. Comprehensively, the findings suggest that the structural model has an acceptable predictive relevance and that the predictors have disparate contribution to the explanation of variations in CNM and PRLFP in the model (Wang et al., 2022).

Table 5-Predive relevance R Square and effect size

	AEL	ALSE	CFD-FEA	CMD	CNM	PRLFP	QMFD
AEL					**0.073**	**0.258**	
ALSE					**0.018**	**0.004**	
CFD-FEA					**0.002**	**0.001**	
CMD					**0.001**	**0.318**	
CNM						**0.000**	
PRLFP							
QMFD					**0.068**	**0.004**	
R-square					**0.377**	**0.664**	
Q-square					**0.296**	**0.535**	

DISCUSSION

The current research has evaluated the factors that affect the perceived reliability of fatigue life prediction in the aerospace objects and found the impact of Accuracy of Load Spectrum Estimation (ALSE), Quality of Material Fatigue Data (QMFD), CFD-FEA Coupling Effectiveness (CFD-FEA), Consideration of Manufacturing Defects (CMD), and Analyst Experience Level (AEL), and Confidence in Numerical Modeling (CNM) served as the mediating variable. The results offer a number of valuable leading questions on the determinants which affect reliability of the fatigue life prediction models in aerospace engineering (X. Li et al., 2022).

It was found that Accuracy of Load Spectrum Estimation has a great impact on the perceived reliability of fatigue life prediction. This implies that the correct prediction of the operational loading conditions enhances the accuracy of fatigue life prediction models. The collection of fatigue damage in the aerospace structure is highly dependent on the load spectrums that are encountered by the structure in the service operations. Poor load spectrum estimation can cause serious errors in prediction and poor fatigue life estimates. It has also been noted before that realistic estimation of load spectrum is important in the enhancement of fatigue life and structural life evaluation in aerospace structures (Xu et al., 2022). In like manner, the findings of reliability modeling research indicate that the reflective loading conditions can substantially enhance the predictive goodwill and structural security assessment (Lu et al., 2024). Nevertheless, other studies claim that device accuracy in the form of load spectrums does not necessarily ensure accurate and reliable prediction of the fatigue life due to the environmental conditions, variability, and uncertainties of the material. This is one of the reasons why the impact of the load spectrum estimation though very crucial in this study is moderate when compared to other predictors (Dziendzikowski et al., 2021).

The results further indicate that Quality of Material Fatigue Data does produce a significant influence on the perceived reliability of fatigue life prediction. Fatigue life prediction models are mostly dependent on proper material characteristics like S-N curves, crack growth parameters and cyclic loading parameters. In cases where good quality material fatigue data is available, engineers are able to come up with more confidence structural life prediction and minimize the uncertainty in fatigue analysis. This finding is justified by previous studies that indicate that precise data on fatigue materials can positively affect structural reliability analysis and prediction of fatigue life in engineering systems (Duan et al., 2021). Additionally, the data presented in the literature on reliability engineering shows that incomparable material data may create significant uncertainty when used to predictive models and lose the faith in fatigue-life prognostication (S.-P. Zhu et al., 2022). Still, according to some studies, limitations in material fatigue data can be partially overcome with the help of more advanced simulation methods and probabilistic models. Such opposite perspectives could be the reason why the effect of material fatigue data quality in the given study is statistically significant but rather moderate.

The findings also show that CFD-FEA Coupling Effectiveness affects perceived reliability of fatigue life prediction positively and is important. Combination of computational fluid dynamics and finite element analysis is effective in providing engineers with the capability of simulating the aerodynamic loads and structural responses more effectively. Aerodynamic forces are significant in the aerospace buildings to define the distribution of stresses and accumulation of fatigue damages. By having the CFD and FEA models well coupled, it is possible to have more realistic representation of the aerodynamic structural interactions and this enhances the accuracy of fatigue life prediction. The earlier study has noted the significance of combined multiphysics simulations in enhancing the reliability and performance forecasting in complicated engineering systems (Shao et al., 2022). Nevertheless, with regard to some of the studies, it is claimed that when more than two simulation models are coupled, additional computational complexities and uncertainties can arise because of the difference in numerical schemes, boundary conditions and interaction of meshes. This can be one of the reasons that the impact of CFD-FEA coupling is lesser despite being quite important than other predictors in the model (Hosseini et al., 2021).

The next notable result of the present research is that the perceived reliability of fatigue life prediction is the most impacted by the Consideration of Manufacturing Defects. The given result indicates that simply adding manufacturing flaws like microcracks, inclusions, surface irregularities and residual stresses to the fatigue analysis play an important role in enhancing predictability of fatigue life. It is not a secret that manufacturing defects can cause fatigue cracks and increase aerospace component structural failure rates. Thus structural durability is predicted better when there is a model that involves fatigue analysis that is defect sensitive. Earlier researchers have established that the manufacturing defects have a considerable impact on fatigue performance and structural reliability in aerospace and mechanical systems (Venturi & Taylor, 2023). It is also found in research on reliability engineering that a defect-based model tends to predict the occurrence of failures and risks more accurately and efficiently in high-reliability systems (Sedmak, 2024). However, previous studies indicate that defect influence might not be significant under high levels of control in manufacturing conditions where quality effectiveness measures are applied and thus imperfections are reduced to minimal amounts. The high influence in this paper means that engineers continued to find defect modeling as a critical aspect of sound fatigue life prediction.

The findings also show that the Analyst Experience Level has a great impact on the view of the perceived reliability of fatigue life prediction. This observation underlines the significance of human skills in fatigue analysis and numerical modeling. The complex simulation processes that are usually involved in fatigue life predicted often include the formulation of a model, mesh generation, application of loads as well as the interpretation of the simulation results. Finding modeling errors, simulation results validation and the ability to interpret fatigue prediction effectively all necessitate technical expertise which can only be acquired by experienced analysts. Past studies in engineering systems and aviation also demonstrate that the sphere of professional experience and technical skills can contribute greatly to the increase in the reliability of the predictive modeling and decision-making procedures (Verhagen et al., 2023). Yet, other scientists conclude that overall, more automation, artificial intelligence, and technological solutions of digital twins might make it less dependent on human skills in predictive modeling. Nevertheless, the findings of this research indicate that the experience of analysts is a key issue that dictates the accuracy of fatigue life prediction models regardless of these technologies (Fajri et al., 2021).

Mediation analysis also indicated that partial mediation regarding the independent variables and perceived reliability of fatigue life prediction involves Confidence in Numerical Modeling. This shows that enhancement in technical modeling inputs enhances reliability both directly and indirectly by boosting trustworthiness of the engineers with the numerical simulation equipment. Past studies in predictive engineering and safety management systems also indicate the same, that is, that confidence in analytical tools plays a significant role in fostering acceptability and reliability of predictive engineering models (Eleftheroglou et al., 2024). Nonetheless, the mediation effect of manufacturing defect consideration and analyst experience level was lower, which suggests that these two variables have an impact on perceived reliability because they primarily rely on direct processes and not because of faith in numerical models.

The generalization of the results is that perceived effectiveness of fatigue life prediction within aerospace structures depends on factors related to technical models as well as human expertise. The most important predictions include manufacturing defect consideration and experience of the analyst, other predictions that are important in enhancing the reliability of fatigue life prediction include load spectrum estimation accuracy, material fatigue data quality and CFD-FEA coupling effectiveness. These findings illustrate that realistic assumptions and models of modeling, data of high quality, sophisticated simulation procedures together with professional judgment are very crucial in improving the reliability of the fatigue life prediction models in the aerospace engineering (K. Hu et al., 2021).

Theoretical Implications

The results of the study also offer a number of theoretical contribution to the literature on fatigue life prediction, reliability engineering, and numerical modeling in the aerospace structures. First, the research will further advance theoretical knowledge on fatigue life prediction as it will combine the technical factors affecting the model with human experience as one of the analytical mechanisms. The past studies on fatigue analysis have basically been concerned with the physical and computational properties of the fatigue analysis, including loading conditions, material property and structural analysis methodology. Nevertheless, the current paper shows that seemingly perceived reliability of fatigue life prediction is not, solely, defined by the technical input but is additionally strongly dependent on the expertise and the faith in the numerical models among the analysts. The given integrated approach can be added to the larger theory surrounding the topic of predictive modeling and ensuring the reliability of engineering through its focus on the concomitant importance of technological and human factors in a complex engineering system (Bender et al., 2022).

Second, the paper has made contributions to the structural reliability theory by reportedly substantiating the relationship of load spectrum estimation accuracy, material fatigue data quality, and CFD-FEA coupling effectiveness in determining the fatigue life prediction reliability. These findings affirm the previous theoretical claim that the representation of accurate loading and material data is a critical input to fatigue modeling and durability evaluation. These relationships are confirmed empirically, which makes the study more powerful to support the theoretical base connecting the mechanisms of fatigue damage accumulation and predictive modeling reliability on an aerospace structure (S. Li et al., 2022). The findings also show that defect consideration after manufacturing defects increases the reliability of fatigue prediction by a great deal which underlines how the defect-based reliability modeling method is common in the literature on the reliability engineering (Zhong et al., 2023).

Third, the research works on the predictive modeling theory, which brings to the fore the mediation of confidence in numerical modeling. The findings indicate that the relationship between the factors of technical modeling and perceived reliability of fatigue life prediction depends on the confidence with simulation tools partially. The observation broadens current theoretical viewpoints as it promotes a discussion that the success of engineering simulation models is not only determined by accuracy of its computation; below the scale of trust placed in the said models by the engineers. This is in line with the emerging theoretical debates on the embracing and belief of digital engineering tools, simulation-based decision systems and digital safety management frameworks in the aviation and manufacturing industries (Zolkin et al., 2021).

Lastly, the research leads to human factors theory in engineering analysis by showing the importance of experience of the analysts in promoting predictive reliability. In spite of the fact that technological innovations like digital twins and artificial intelligence are increasingly considered in the framework of engineering analysis, the findings verify that expert judgment and professional experience are crucial to interpreciation of outputs of the simulation and validation of the predictive models. This result validates theoretical claims about the ongoing significance of human know-how in the decision-making procedures of intricate engineering tasks (X. Xu et al., 2023).

Practical Implications

Important practical implications of this study to aerospace engineers, maintenance organizations, aircraft manufacturers, and reliability analysts working in fatigue life predictions as well as structural maintenance durability analysis, are also reflected in the findings of this study.

To begin with, the findings have indicated the significance of enhancing the load spectrum estimation strategies in the aerospace operations. Load spectrum accuracy is an important factor in predicting a reliable fatigue life and thus aerospace entities must invest in more sophisticated load monitoring systems, flight data acquisition technology as well as operational load modeling techniques. A better estimation of load spectrum can allow engineers to come up more realistic fatigue loading cases and improve on structural life predictions (Starkova et al., 2022).

Second, the results also highlight that fatigue data of high quality material is required in fatigue analysis. Comprehensive material testing programs should be given priority by the aerospace manufacturers and research institutions in order to come up with the correct fatigue databases of the aerospace alloys and composite material. Construction of quality fatigue material databases has the potential of minimizing uncertainty in the fatigue model and increased the quality of fatigue life prediction models utilized in the design and maintenance planning process of aircraft (Xi et al., 2021).

Third, the findings indicate that aerospace organizations ought to increase the merging of the computational fluid dynamics and voltage element examination instruments. Proper connection between the structural analysis and aerodynamic simulations can render more accurate stress prediction and fatigue damage estimations. Advanced multiphysics simulation platforms and advanced computational modeling environments should therefore be adopted by aerospace companies to help them achieve better fatigue life prediction as well as structural reliability assessment (Y. Li et al., 2023).

Fourth, there is a powerful impact of the consideration of manufacturing defects that the aerospace manufacturers should include defect sensitive fatigue modeling in the structural design and inspection processes. The fatigue prediction models should be combined with the use of non-destructive inspection method, technology of flaw detection, and quality control process to enhance the evaluation of structural integrity and mitigate the possibility of unpredictable failures (Sandell et al., 2021).

Lastly, the results demonstrate the significance of experience and professionalism of the analyst in the fatigue analysis. To improve the capacity of the engineers in terms of fatigue modeling and numerical simulation, aerospace organizations ought to invest in the continuous training, advanced simulation training, and knowledge sharing programs. Nonetheless, regardless of growing automation and machine-based modeling, the key requirements include human skills to analyze the simulation outcomes, test the models, and guarantee the dependability of fatigue life models (Fernandes et al., 2023).

In general, the practical implications of this research are that in order to enhance the reliability of fatigue life prediction, it is necessary to take a comprehensive approach to the issue, which ought to incorporate the use of advanced simulation technologies, quality data, efficient defect modeling, and competent engineering abilities. This type of integrated work can be considered to be very effective in improving safety, durability and reliability of aerospace structures (Reza Kashyzadeh et al., 2023).

CONCLUSION

This paper has taken into account research on the aspects of perceived reliability of fatigue life prediction in aerospace structures by exploring the influence of Accuracy of Load Spectrum Estimation, Quality of Material Fatigue Data, CFD-FEA Coupling Effectiveness, and Accounting of Manufacturing Defects and Analyst Experience Level with Confidence in Numerical Modeling as a mediating variable. The analysis of the relationship between these variables was conducted using the methodology of PLS-SEM and supplied empirical data on determinants that operate to formulate the reliability of fatigue life prediction model in aerospace engineering.

The results showed that the proposed direct relationships were all significant. The Reliability of Load spectrum estimation, Quality of material fatigue data and CFD-FEA hybrid performance were identified to contribute to perceived reliability of fatigue life prediction positively. These findings have identified proper loading conditions, sound material fatigue characteristics and proper incorporation of aerodynamic and structural models in enhancement of predictive capacity of fatigue life models. The findings also indicated that the strongest influence on perceived reliability of fatigue life prediction is produced by the factors of the Consideration of Manufacturing Defects and Analyst Experience Level. It means that the idea of fatigue analysis that includes realistic manufacturing faults and the use of expert engineers to explain the quality of a simulation is an essential measure of enhancing the quality of predictions related to aerospace structural analysis.

These findings indicated that Confidence in Numerical Modeling is partially a mediator of the relationships among the independent variables and perceived reliability of fatigue life prediction. This implies that technical modeling factors improve prediction reliability indirectly, as well as directly through boosting the confidence of engineers using the tools of simulation and numerical methods of modeling. Nevertheless, the mediation effect towards manufacturing defect consideration and the level of analyst experience was relatively weaker thus suggesting that the variables can play roles in predicting factors as a result of direct processes.

In general, the results confirm that the image of reliability of fatigue life prediction of aerospace structures should be the combination of the accuracy of technical models, high-quality data, realistic defects modeling, and engineering experience. The research notes that computational tools alone cannot be effective in determining the fatigue life of any product, and this should be accompanied by good input data, combined simulation tools, and competent analysts who can interpret complex numerical outcomes.

To conclude, the research helps in the comprehension of the reliability of fatigue life prediction, as it proposed a unified framework, which incorporates engineering modeling variables with human knowledge and trust in numerical simulations. The findings implicate the significance of enhancing load spectrum estimation schemes, developing superior fatigue material databases, using multiphysics simulation schemes, making sure to consider manufacturing defects, and increasing expertise on the part of the analyst to make the fatigue life forecasting in aerospace structures more reliable. These combined strategies eventually have the potential to enhance the design of safer aircraft, better maintenance strategy, and more accurate structural durability tests in the aerospace sector.

Limitations of the Study

Although this study can be very insightful in terms of the issues that may affect perceived reliability of fatigue life prediction in aerospace structures, it also has issues that need to be recorded. To begin with, the research was based on the perceptual data collected among the respondents employed in the aerospace engineering and fatigue analysis. Despite the usefulness of expert perceptions in apprehending reliability assessment practices, it can be seen that perceptual data can bring subjectivity in the process of fatigue life prediction practices and may not be a full representation of the real performance of fatigue life prediction models in the field of operation. Future research can engage the incorporation of empirical data of fatigue testing, together with real structural performance data to confirm relationships that are found in this research (Gao et al., 2021).

Second, the research design adopted was cross-sectional, which only records a response at one time. Consequently, the results might not promise to be entirely representative of the developments in fatigue modeling practices, technological changes, or changes in the industry standards with time. In the aerospace engineering, fatigue life prediction technologies and simulation tools keep evolving at a very fast rate. Thus, longitudinal research may give more information on how the enhancement of modeling methods and computing device affects reliability of fatigue prediction over time (Z. Xu et al., 2023).

Third, several important predictors in the study were taken into consideration including load spectrum estimation, material fatigue data, the effectiveness of result of CFD-FEA coupling, consideration of manufacturing defect, and the level of experience of analysts but the model did not include other variables that might be significant to the model. In addition, the reliability of fatigue life prediction could also depend on such factors as environmental conditions, variability of operations, inspection approaches, structural health monitoring systems, and digital twin technologies. These factors could have restricted the scope of the proposed model.

Fourth, the research was mainly concentrated on aerospace engineering situation. Although the results are significant to structural reliability assessment in the aerospace scenario, not every other engineering field including automotive, marine, or energy systems, can be generalized as the results. The fatigue loading condition, manufacturing process and modeling technique may not be the same across the various industries and this might affect the suitability of the findings.

Future Research Directions

Resting on the limitations listed above, the following suggestions on the way of further research can be made. First, the experimental fatigue data and structural health monitoring information should be implemented in the future studies to confirm the perceived reliability of the fatigue life prediction models. The survey-based analysis with the experimental or operational data would prove to be more insightful to combine and ultimately to obtain the broader picture of the predictability of fatigue in aerospace structures.

Second, it may also be considered in future studies to implement more sophisticated digital technologies, including digital twins, machine learning, and artificial intelligence, into fatigue life prediction models. The new technologies can greatly promote the predictability and allow real-time monitoring of structural health and reliability evaluation on aerospace systems (W. Li et al., 2022).

Third, further research can be diversified with the current model with an incorporation of other variables in the form of environmental loading conditions, maintenance practice, inspection periods, and probabilistic fatigue modeling strategy. These components should also be included to enable the researchers to come up with a more robust model upon the determinants of fatigue life prediction reliability.

Fourth, longitudinal research would be applicable to examine the relationship between the advances in simulation technologies, computational power/fatigue modeling methods with the accuracy of fatigue life prediction over time.

This kind of research would be of great value to know more about the reduction or increase in the prediction modeling trends in the field of aerospace engineering over a long life.
Lastly, future studies can replicate the current study in other industrial settings like automotive engineering, marine structures, or renewable energy systems in a study to establish whether the identified relationships can be constant throughout the engineering uses. Industry comparison would help to achieve a wider comprehension of the existence of predictability of fatigue life in intricate engineering frameworks.

REFERENCES:

1. Aabid, A., Parveez, B., Raheman, M. A., Ibrahim, Y. E., Anjum, A., Hrairi, M., Parveen, N., & Mohammed Zayan, J. (2021). A review of piezoelectric material-based structural control and health monitoring techniques for engineering structures: Challenges and opportunities. Actuators,
2. Aceti, P., Carminati, L., Bettini, P., & Sala, G. (2023). Hygrothermal ageing of composite structures. Part 1: Technical review. *Composite Structures*, *319*, 117076.
3. Afroz, L., Inverarity, S., Qian, M., Easton, M., & Das, R. (2024). Analysing the effect of defects on stress concentration and fatigue life of L-PBF AlSi10Mg alloy using finite element modelling. Progress in Additive Manufacturing, 9(2), 341-359.
4. W. Ahmad, M. Hameed, M. Bilal and A. Majid, "ML-Pred-CLL: Machine Learning based prediction of Chronic Lymphocytic Leukemia using protein sequential data," *2022 International Conference on Recent Advances in Electrical Engineering & Computer Sciences (RAEE & CS)*, Islamabad, Pakistan, 2022, pp. 1-7, doi: 10.1109/RAEECS56511.2022.9954510.
5. Amjad Ali, Muhammad Nafees*, Muhammad Awais Amin, Inam Ur Rehman, Muhammad Tayyab, & Waqar Ahmad. (2024). Systematic Literature Review On Swarms Of Uavs. Spectrum of Engineering Sciences, 2(4), 386–415. Retrieved from https://thesesjournal.com/index.php/1/article/view/83.
6. Anjum, H.T., Israr, A. & Ahmad, Z. Analytical Modeling of Low-Velocity Variable Angular Impact on Rectangular Plates. Iran J Sci Technol Trans Mech Eng 44, 287–298 (2020). https://doi.org/10.1007/s40997-018-0266-6.
7. Ashebir, D. A., Hendlmeier, A., Dunn, M., Arablouei, R., Lomov, S. V., Di Pietro, A., & Nikzad, M. (2024). Detecting multi-scale defects in material extrusion additive manufacturing of fiber-reinforced thermoplastic composites: a review of challenges and advanced non-destructive testing techniques. *Polymers*, *16*(21), 2986.
8. Augustyn, D., Ulriksen, M. D., & Sørensen, J. D. (2021). Reliability updating of offshore wind substructures by use of digital twin information. *Energies*, *14*(18), 5859.
9. Bandara, S., Herath, M., & Epaarachchi, J. (2023). Sensory methods and machine learning based damage identification of fibre-reinforced composite structures: An introductory review. *Journal of Reinforced Plastics and Composites*, *42*(21-22), 1119-1146.
10. Barroeta Robles, J., Dubé, M., Hubert, P., & Yousefpour, A. (2022). Repair of thermoplastic composites: an overview. *Advanced Manufacturing: Polymer & Composites Science*, *8*(2), 68-96.
11. Bender, R., Féron, D., Mills, D., Ritter, S., Bäßler, R., Bettge, D., De Graeve, I., Dugstad, A., Grassini, S., & Hack, T. (2022). Corrosion challenges towards a sustainable society. *Materials and corrosion*, *73*(11), 1730-1751.
12. Berez, J., Sheridan, L., & Saldaña, C. (2022). Extreme variation in fatigue: Fatigue life prediction and dependence on build volume location in laser powder bed fusion of 17-4 stainless steel. *International Journal of Fatigue*, *158*, 106737.
13. Bisanti, G. M., Mainetti, L., Montanaro, T., Patrono, L., & Sergi, I. (2023). Digital twins for aircraft maintenance and operation: A systematic literature review and an IoT-enabled modular architecture. *Internet of Things*, *24*, 100991.
14. Bolar, G., Satish Shenoy, B., Zitoune, R., Madhusudhan, B., Dinesh, A. A., & He, Y. (2025). Analysis of machining induced damage when drilling hybrid carbon fiber-reinforced aluminum laminates. *Journal of Composite Materials*, 00219983261429305.
15. Borikar, G. P., Patil, A. R., & Kolekar, S. B. (2023). Additively manufactured lattice structures and materials: present progress and future scope. *International Journal of Precision Engineering and Manufacturing*, *24*(11), 2133-2180.
16. Bouhala, L., Karatrantos, A., Reinhardt, H., Schramm, N., Akin, B., Rauscher, A., Mauersberger, A., Taşkıran, S. T., Ulaşlı, M. E., & Aktaş, E. (2024). Advancement in the modeling and design of composite pressure vessels for hydrogen storage: a comprehensive review. *Journal of Composites Science*, *8*(9), 339.
17. Chakraborty, D., Tirumala, T., Chitral, S., Sahoo, B., Kiran, D., & Kumar, P. A. (2022). The state of the art for wire arc additive manufacturing process of titanium alloys for aerospace applications. *Journal of Materials Engineering and Performance*, *31*(8), 6149-6182.
18. Chen, B.-Q., Liu, K., Yu, T., & Li, R. (2024). Enhancing reliability in floating offshore wind turbines through digital twin technology: a comprehensive review. *Energies*, *17*(8), 1964.

19. Chen, F., Zhang, H., Li, Z., Luo, Y., Xiao, X., & Liu, Y. (2024). Residual stresses effects on fatigue crack growth behavior of rib-to-deck double-sided welded joints in orthotropic steel decks. *Advances in Structural Engineering*, *27*(1), 35-50.
20. Cheng, H.-C., Syu, J.-Y., Wang, H.-H., Liu, Y.-C., Kao, K.-S., & Chang, T.-C. (2024). Power cycling modeling and lifetime evaluation of SiC power MOSFET module using a modified physical lifetime model. *IEEE Transactions on Device and Materials Reliability*, *24*(1), 142-153.
21. Chi, W., Wang, W., Li, Y., Xu, W., & Sun, C. (2022). Defect induced cracking and modeling of fatigue strength for an additively manufactured Ti-6Al-4V alloy in very high cycle fatigue regime. *Theoretical and Applied Fracture Mechanics*, *119*, 103380.
22. Chinchanikar, S., & Shaikh, A. A. (2022). A review on machine learning, big data analytics, and design for additive manufacturing for aerospace applications. *Journal of Materials Engineering and Performance*, *31*(8), 6112-6130.
23. Dastgerdi, J. N., Jaberi, O., & Remes, H. (2022). Influence of internal and surface defects on the fatigue performance of additively manufactured stainless steel 316L. *International Journal of Fatigue*, *163*, 107025.
24. de Castro Lopes, F., Akhavan-Safar, A., Carbas, R., Marque, E., Goyal, R., Jennings, J., & da Silva, L. (2023). The role of loading mode on the property degradation of adhesives at high temperatures. *Fatigue & Fracture of Engineering Materials & Structures*, *46*(5), 1848-1863.
25. Depiver, J. a., Mallik, S., & Harmanto, D. (2021). Solder joint failures under thermo-mechanical loading conditions–A review. *Advances in Materials and Processing Technologies*, *7*(1), 1-26.
26. Dong, Z., Wang, T., Ma, X., Cao, C., & Sun, J. (2023). Structural performance evaluation of airport asphalt pavement based on field data measurement and finite element simulation. *Measurement*, *210*, 112553.
27. Duan, Z., Li, C., Ding, W., Zhang, Y., Yang, M., Gao, T., Cao, H., Xu, X., Wang, D., & Mao, C. (2021). Milling force model for aviation aluminum alloy: academic insight and perspective analysis. *Chinese Journal of Mechanical Engineering*, *34*(1), 18.
28. Dziendzikowski, M., Kurnyta, A., Reymer, P., Kurdelski, M., Klysz, S., Leski, A., & Dragan, K. (2021). Application of operational load monitoring system for fatigue estimation of main landing gear attachment frame of an aircraft. *Materials*, *14*(21), 6564.
29. Elahi, H. (2021). The investigation on structural health monitoring of aerospace structures via piezoelectric aeroelastic energy harvesting. *Microsystem Technologies*, *27*(7), 2605-2613.
30. Eleftheroglou, N., Galanopoulos, G., & Loutas, T. (2024). Similarity learning hidden semi-Markov model for adaptive prognostics of composite structures. *Reliability Engineering & System Safety*, *243*, 109808.
31. Eusufzai, Z. (2021). Machine Learning Approaches For Optimization Of Lubricant Performance And Reliability In Complex Mechanical And Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *1*(01), 61-92.
32. Fajri, A., Prabowo, A. R., Muhayat, N., Smaradhana, D. F., & Bahatmaka, A. (2021). Fatigue analysis of engineering structures: State of development and achievement. *Procedia structural integrity*, *33*, 19-26.
33. Falodun, O., Oke, S., & Bodunrin, M. (2025). A comprehensive review of residual stresses in carbon steel welding: formation mechanisms, mitigation strategies, and advanced post-weld heat treatment techniques. *The International Journal of Advanced Manufacturing Technology*, *136*(10), 4107-4140.
34. Fan, K., Liu, D., Liu, Y., Wu, J., Shi, H., Zhang, X., Zhou, K., Xiang, J., & Wahab, M. A. (2023). Competitive effect of residual stress and surface roughness on the fatigue life of shot peened S42200 steel at room and elevated temperature. *Tribology International*, *183*, 108422.
35. Fan, K., Liu, D., Wang, C., Yang, J., Liu, Y., Zhang, X., Xiang, J., & Wahab, M. A. (2024). Effect of contact stress and slip amplitude on fretting fatigue behaviour of ultrasonic surface nanocrystallized TC11 titanium alloy. *Journal of Materials Research and Technology*, *28*, 4052-4064.
36. Fan, S., Zhang, J., Wang, B., Chen, J., Yang, W., Liu, W., & Li, Y. (2023). A deep learning method for fast predicting curing process-induced deformation of aeronautical composite structures. *Composites Science and Technology*, *232*, 109844.
37. Fernandes, P. H. E., Silva, G. C., Pitz, D. B., Schnelle, M., Koschek, K., Nagel, C., & Beber, V. C. (2023). Data-driven, physics-based, or both: Fatigue prediction of structural adhesive joints by artificial intelligence. *Applied Mechanics*, *4*(1), 334-355.
38. Gao, J.-W., Yu, M.-H., Liao, D., Zhu, S.-P., Zhu, Z.-Y., & Han, J. (2021). Foreign object damage tolerance and fatigue analysis of induction hardened S38C axles. *Materials & Design*, *202*, 109488.
39. Goncalves, B. R., & Kuutti, J. (2024). A review on total fatigue life models for metallic components.
40. Gong, Y., Jiang, L., Li, L., Ren, S., Zhao, Y., Wang, Z., & Hu, N. (2022). Temperature effect on the static mode I delamination behavior of aerospace-grade composite laminates: Experimental and numerical study. *Fatigue & Fracture of Engineering Materials & Structures*, *45*(10), 2827-2844.
41. Gumasing, M. J. J., & Castro, F. M. F. (2023). Determining ergonomic appraisal factors affecting the learning motivation and academic performance of students during online classes. *Sustainability*, *15*(3), 1970.
42. Gupta, S., & Dhingra, S. (2022). Modeling the key factors influencing the adoption of mobile financial services: an interpretive structural modeling approach. *Journal of Financial Services Marketing*, *27*(2), 96-110.

43. Hayes, M. D., Edwards, D. B., & Shah, A. R. (2024). *Fractography in failure analysis of polymers*. Elsevier.
44. He, R., Yang, H., Sun, S., Lu, L., Sun, H., & Gao, X. (2022). A machine learning-based fatigue loads and power prediction method for wind turbines under yaw control. *Applied Energy*, *326*, 120013.
45. Henao-Ramírez, A. M., & Lopez-Zapata, E. (2022). Analysis of the factors influencing adoption of 3D design digital technologies in Colombian firms. *Journal of Enterprise Information Management*, *35*(2), 429-454.
46. Hosseini, K., Safarabadi, M., Ganjiani, M., Mohammadi, E., & Hosseini, A. (2021). Experimental and numerical fatigue life study of cracked AL plates reinforced by glass/epoxy composite patches in different stress ratios. *Mechanics Based Design of Structures and Machines*, *49*(6), 894-910.
47. Hu, K., Cheng, Y., Wu, J., Zhu, H., & Shao, X. (2021). Deep bidirectional recurrent neural networks ensemble for remaining useful life prediction of aircraft engine. *IEEE Transactions on Cybernetics*, *53*(4), 2531-2543.
48. Hu, Y., Wu, S., Xie, C., Wu, W., & Zhang, J. (2021). Fatigue life evaluation of Ti–6Al–4V welded joints manufactured by electron beam melting. *Fatigue & Fracture of Engineering Materials & Structures*, *44*(8), 2210-2221.
49. Huang, X., Wang, Y., Zhu, Q., Du, Z., Zhou, L., & Liu, H. (2023). Thermal creep and fatigue failure of the sintered silver solder in a SiC-IGBT module under power cycling. *Engineering Failure Analysis*, *154*, 107625.
50. Ismail, A. M., AL-Oqla, F. M., Risby, M., & Sapuan, S. (2022). On the enhancement of the fatigue fracture performance of polymer matrix composites by reinforcement with carbon nanotubes: a systematic review. *Carbon Letters*, *32*(3), 727-740.
51. Iss, V., Meis, J. A., Rajaei, A., Hallstedt, B., & Broeckmann, C. (2024). Fatigue strength evaluation of case-hardened components combining heat-treatment simulation and probabilistic approaches. *Fatigue & Fracture of Engineering Materials & Structures*, *47*(3), 745-765.
52. Jasiulewicz-Kaczmarek, M., Antosz, K., Wyczółkowski, R., Mazurkiewicz, D., Sun, B., Qian, C., & Ren, Y. (2021). Application of MICMAC, Fuzzy AHP, and Fuzzy TOPSIS for evaluation of the maintenance factors affecting sustainable manufacturing. *Energies*, *14*(5), 1436.
53. Ji, C., Hu, J., Wang, B., Zou, Y., Yang, Y., & Sun, Y. (2021). Mechanical behavior prediction of CF/PEEK-titanium hybrid laminates considering temperature effect by artificial neural network. *Composite Structures*, *262*, 113367.
54. Jiang, R., Sun, T., Liu, D., Pan, Z., & Wang, D. (2021). Multi-objective reliability-based optimization of control arm using MCS and NSGA-II coupled with entropy weighted GRA. *Applied Sciences*, *11*(13), 5825.
55. Jirandehi, A. P., Hajshirmohammadi, B., Carrion, P., Khonsari, M., Shamsaei, N., & Shao, S. (2022). Strain energy-based fatigue failure analyses of LB-PBF Inconel 718: Effect of build orientation. *Additive Manufacturing*, *52*, 102661.
56. Jirandehi, A. P., & Khonsari, M. (2021). Microstructure-sensitive estimation of fatigue life using cyclic thermodynamic entropy as an index for metals. *Theoretical and Applied Fracture Mechanics*, *112*, 102854.
57. Kabashkin, I., Fedorov, R., & Perekrestov, V. (2025). Decision-making framework for aviation safety in predictive maintenance strategies. *Applied Sciences*, *15*(3), 1626.
58. Kaloop, M. R., Eldiasty, M., & Hu, J. W. (2022). Safety and reliability evaluations of bridge behaviors under ambient truck loads through structural health monitoring and identification model approaches. *Measurement*, *187*, 110234.
59. Kapoor, R., Kloet, N., Gardi, A., Mohamed, A., & Sabatini, R. (2021). Sound propagation modelling for manned and unmanned aircraft noise assessment and mitigation: A review. *Atmosphere*, *12*(11), 1424.
60. Kellermann, R., Biehle, T., & Mostofi, H. (2023). Modelling public attitude towards drone delivery in Germany. *European Transport Research Review*, *15*(1), 38.
61. Khan, A., Azad, M. M., Sohail, M., & Kim, H. S. (2023). A review of physics-based models in prognostics and health management of laminated composite structures. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *10*(6), 1615-1635.
62. Kim, Y. W., Lim, C., & Ji, Y. G. (2023). Exploring the user acceptance of urban air mobility: extending the technology acceptance model with trust and service quality factors. *International Journal of Human–Computer Interaction*, *39*(14), 2893-2904.
63. Konda, N., Verma, R., & Jayaganthan, R. (2021). Machine learning based predictions of fatigue crack growth rate of additively manufactured Ti6Al4V. *Metals*, *12*(1), 50.
64. Kordestani, M., Orchard, M. E., Khorasani, K., & Saif, M. (2023). An overview of the state of the art in aircraft prognostic and health management strategies. *IEEE Transactions on Instrumentation and Measurement*, *72*, 1-15.
65. Li, D.-W., Liu, J.-X., Sun, Y.-T., Huang, W.-Q., Li, N., & Yang, L.-H. (2023). Microstructure and mechanical degradation of K403 Ni-based superalloy from ultra-long-term serviced turbine blade. *Journal of Alloys and Compounds*, *957*, 170378.
66. Li, D., Chen, J., Huang, R., Chen, Z., & Li, W. (2024). Sensor-aware CapsNet: Towards trustworthy multisensory fusion for remaining useful life prediction. *Journal of Manufacturing Systems*, *72*, 26-37.

67. Li, K.-S., Wang, J., Fan, Z.-C., Cheng, L.-Y., Yao, S.-L., Wang, R.-Z., Zhang, X.-C., & Tu, S.-T. (2022). A life prediction method and damage assessment for creep-fatigue combined with high-low cyclic loading. *International Journal of Fatigue*, *161*, 106923.
68. Li, M., Tian, W., Hu, J., Wang, C., & Liao, W. (2021). Study on shear behavior of riveted lap joints of aircraft fuselage with different hole diameters and squeeze forces. *Engineering Failure Analysis*, *127*, 105499.
69. Li, S., Zhang, S., Li, H., Qin, X., Wu, X., & Gui, L. (2022). Numerical and experimental investigation of fitting tolerance effects on bearing strength of CFRP/Al single-lap blind riveted joints. *Composite Structures*, *281*, 115022.
70. Li, W., Pang, J., Zhang, H., Li, S., & Zhang, Z. (2022). The high-cycle fatigue properties of selective laser melted Inconel 718 at room and elevated temperatures. *Materials Science and Engineering: A*, *836*, 142716.
71. Li, X., Li, W., Lashari, M. I., Sakai, T., Wang, P., Cai, L., Ding, X., & Hamid, U. (2022). Fatigue failure behavior and strength prediction of nickel-based superalloy for turbine blade at elevated temperature. *Engineering Failure Analysis*, *136*, 106191.
72. Li, Y., Qin, H., Jia, L., Tay, T.-E., Tan, V. B. C., & Liu, Y. (2024). Microstructure dependent transverse strength criterion for UD-CFRP composites via computational micromechanics and machine learning. *Composites Science and Technology*, *251*, 110551.
73. Li, Y., Zhan, M., Jiang, X., Lei, Y., & Gao, P. (2023). Low-cycle fatigue behavior and life prediction of TA15 titanium alloy by crystal plasticity-based modelling. *Journal of Materials Research and Technology*, *23*, 954-966.
74. Liang, Z., Feng, W., Qian, W., Jin, W., Ai, X., & Li, Y. (2025). A Multi-Objective Point Response Prediction Method for Vertical Tail Buffeting Based on Elastic Scaling Transformation. *Aerospace*, *13*(1), 11.
75. Lin, M., Guo, S., He, S., Li, W., & Yang, D. (2022). Structure health monitoring of a composite wing based on flight load and strain data using deep learning method. *Composite Structures*, *286*, 115305.
76. M. A. Amin, J. -U. -R. Chughtai, W. Ahmad, W. H. Bangyal and I. Ul Haq, "Trajectory Data Mining and Trip Travel Time Prediction on Specific Roads," *2024 International Conference on Engineering & Computing Technologies (ICECT)*, Islamabad, Pakistan, 2024, pp. 1-8, doi: 10.1109/ICECT61618.2024.10581284.
77. Liu, G., Huang, C., Zhao, B., Wang, W., & Sun, S. (2021). Effect of machined surface integrity on fatigue performance of metal workpiece: A review. *Chinese Journal of Mechanical Engineering*, *34*(1), 118.
78. Liu, H., Yu, H., Guo, C., Chen, X., Zhong, S., Zhou, L., Osman, A., & Lu, J. (2024). Review on fatigue of additive manufactured metallic alloys: microstructure, performance, enhancement, and assessment methods. *Advanced Materials*, *36*(17), 2306570.
79. Liu, Y., Shi, H., Li, Y., & Amin, A. (2021). Factors influencing Chinese residents' post-pandemic outbound travel intentions: an extended theory of planned behavior model based on the perception of COVID-19. *Tourism Review*, *76*(4), 871-891.
80. Liu, Z., Jiang, A., Zhang, A., Xing, Z., & Du, X. (2021). Intelligent prediction method for operation and maintenance safety of prestressed steel structure based on digital twin technology. *Advances in Civil Engineering*, *2021*(1), 6640198.
81. Liu, Z., Yang, L., & Zhou, Y. (2023). A multiscale model integrating artificial neural networks for failure prediction in turbine blade coatings. *Surface and Coatings Technology*, *457*, 129218.
82. Lu, N., Wang, H., Liu, J., Luo, Y., & Liu, Y. (2024). Coupled propagation behavior of multiple fatigue cracks in welded joints of steel-bridge. *Journal of Constructional Steel Research*, *215*, 108532.
83. Lv, Z., & Xie, S. (2024). Artificial intelligence in the digital twins: State of the art, challenges, and future research topics: [version 2; peer review: 2 approved]. *Digital Twin*, *1*(1), 12.
84. Macallister, N., Vanmeensel, K., & Becker, T. H. (2021). Fatigue crack growth parameters of laser powder bed fusion produced Ti-6Al-4V. *International Journal of Fatigue*, *145*, 106100.
85. Madani, S. S., Shabeer, Y., Allard, F., Fowler, M., Ziebert, C., Wang, Z., Panchal, S., Chaoui, H., Mekhilef, S., & Dou, S. X. (2025). A comprehensive review on lithium-ion battery lifetime prediction and aging mechanism analysis. *Batteries*, *11*(4), 127.
86. Maggiore, S., Banea, M. D., Stagnaro, P., & Luciano, G. (2021). A review of structural adhesive joints in hybrid joining processes. *Polymers*, *13*(22), 3961.
87. SYSTEMATIC REVIEW OF UAV SWARM RELAY NETWORKS AND FLYING AD HOC NETWORKS (FANETS)— PROTOCOLS, ROUTING CHALLENGES, SECURITY ASPECTS. (2025). Kashf Journal of Multidisciplinary Research, 2(09), 274-293. https://doi.org/10.71146/kjmr634.
88. Mardanshahi, A., Sreekumar, A., Yang, X., Barman, S. K., & Chronopoulos, D. (2025). Sensing techniques for structural health monitoring: A state-of-the-art review on performance criteria and new-generation technologies. *Sensors*, *25*(5), 1424.
89. Marshall, R. S., Define, K., Rosner, R., Goff, A., Sprinkle, C., Balachandran, P., & Kelly, R. (2023). Galvanic corrosion between coated al alloy plate and stainless steel fasteners, part 2: Application of finite element method and machine learning to study galvanic current distributions. *Corrosion*, *79*(2), 157-173.
90. Melching, D., Strohmann, T., Requena, G., & Breitbarth, E. (2022). Explainable machine learning for precise fatigue crack tip detection. *Scientific reports*, *12*(1), 9513.

91. Meng, X., Sun, C., Mei, J., Tang, X., Hasanien, H. M., Jiang, J., Fan, F., & Song, K. (2025). Fuel cell life prediction considering the recovery phenomenon of reversible voltage loss. *Journal of Power Sources*, *625*, 235634.
92. Mesa-Arango, R., Pineda-Jaramillo, J., Araujo, D. S., Bi, J., Basva, M., & Viti, F. (2023). Missions and factors determining the demand for affordable mass space tourism in the United States: A machine learning approach. *Acta Astronautica*, *204*, 307-320.
93. Moshtaghzadeh, M., Izadpanahi, E., & Mardanpour, P. (2022). Prediction of fatigue life of a flexible foldable origami antenna with Kresling pattern. *Engineering Structures*, *251*, 113399.
94. Muralidharan, M., Sathishkumar, T. P., Rajini, N., Navaneethakrishnan, P., Arun Kumar, S., Ismail, S. O., Senthilkumar, K., & Siengchin, S. (2022). Evaluation of tensile strength retention and service life prediction of hydrothermal aged balanced orthotropic carbon/glass and Kevlar/glass fabric reinforced polymer hybrid composites. *Journal of Applied Polymer Science*, *139*(6), 51602.
95. Mylonas, C., Abdallah, I., & Chatzi, E. (2021). Conditional variational autoencoders for probabilistic wind turbine blade fatigue estimation using Supervisory, Control, and Data Acquisition data. *Wind Energy*, *24*(10), 1122-1139.
96. Ahmad W, Shahzad AR, Amin MA, Bangyal WH, Alahmadi TJ, Khan SH (2025) Machine learning driven dashboard for chronic myeloid leukemia prediction using protein sequences. PLoS One 20(6): e0321761. https://doi.org/10.1371/journal.pone.0321761
97. Norkhairunnisa, M., Chai Hua, T., Sapuan, S., & Ilyas, R. (2022). Evolution of aerospace composite materials. In *Advanced composites in aerospace engineering applications* (pp. 367-385). Springer.
98. Pascoe, J.-A. (2021). Slow-growth damage tolerance for fatigue after impact in FRP composites: Why current research won't get us there. *Theoretical and Applied Fracture Mechanics*, *116*, 103127.
99. Pervaiz, S., Qureshi, T. A., Kashwani, G., & Kannan, S. (2021). 3D printing of fiber-reinforced plastic composites using fused deposition modeling: a status review. *Materials*, *14*(16), 4520.
100. Qian, W., Wu, S., Wu, Z., Ahmed, S., Zhang, W., Qian, G., & Withers, P. J. (2022). In situ X-ray imaging of fatigue crack growth from multiple defects in additively manufactured AlSi10Mg alloy. *International Journal of Fatigue*, *155*, 106616.
101. Qin, Z., Li, B., Zhang, H., Wilfried, T. Y. A., Gao, T., & Xue, H. (2022). Effects of shot peening with different coverage on surface integrity and fatigue crack growth properties of 7B50-T7751 aluminum alloy. *Engineering Failure Analysis*, *133*, 106010.
102. Quan, F., Chen, Z., Ye, H., Cui, C., & Cui, Y. (2021). Study of the effect of surface roughness on fatigue strength of GH4169 based on indirect evaluation of the notch root radius. *International Journal of Fatigue*, *152*, 106440.
103. Rath, N., Mishra, R., & Kushari, A. (2024). Aero engine health monitoring, diagnostics and prognostics for condition-based maintenance: An overview. *International journal of turbo & jet-engines*, *40*(s1), s279-s292.
104. Ren, L., Yang, F., Gu, C., Sun, J., & Liu, Y. (2022). A study of factors influencing Chinese college students' intention of using metaverse technology for basketball learning: Extending the technology acceptance model. *Frontiers in Psychology*, *13*, 1049972.
105. Reza Kashyzadeh, K., Amiri, N., Maleki, E., & Unal, O. (2023). A critical review on improving the fatigue life and corrosion properties of magnesium alloys via the technique of adding different elements. *Journal of Marine Science and Engineering*, *11*(3), 527.
106. Rizzo, P., & Enshaeian, A. (2021). Challenges in bridge health monitoring: A review. *Sensors*, *21*(13), 4336.
107. Rohit, B., & Muktinutalapati, N. R. (2021). Fatigue behavior of 18% Ni maraging steels: a review. *Journal of Materials Engineering and Performance*, *30*(4), 2341-2354.
108. Rose, R. L., Puranik, T. G., Mavris, D. N., & Rao, A. H. (2022). Application of structural topic modeling to aviation safety data. *Reliability Engineering & System Safety*, *224*, 108522.
109. Russo, A., Riccio, A., Palumbo, C., & Sellitto, A. (2023). Fatigue driven delamination in composite structures: Definition and assessment of a novel fracture mechanics based computational tool. *International Journal of Fatigue*, *166*, 107257.
110. Sandell, V., Hansson, T., Roychowdhury, S., Månsson, T., Delin, M., Åkerfeldt, P., & Antti, M.-L. (2021). Defects in electron beam melted Ti-6Al-4V: Fatigue life prediction using experimental data and extreme value statistics. *Materials*, *14*(3), 640.
111. Sedmak, A. (2024). Fatigue crack growth simulation by extended finite element method: A review of case studies. *Fatigue & Fracture of Engineering Materials & Structures*, *47*(6), 1819-1855.
112. Shamir, M., Zhang, X., & Syed, A. K. (2021). Characterising and representing small crack growth in an additive manufactured titanium alloy. *Engineering Fracture Mechanics*, *253*, 107876.
113. Shao, W., Sun, H., Wang, Y., & Qing, X. (2022). A multi-level damage classification technique of aircraft plate structures using Lamb wave-based deep transfer learning network. *Smart Materials and Structures*, *31*(7), 075019.
114. Shao, X., Cai, B., Gao, L., Zhang, Y., Yang, C., & Gao, C. (2024). Data-model-linked remaining useful life prediction method with small sample data: A case of subsea valve. *Reliability Engineering & System Safety*, *250*, 110323.

115. Singh, T., & Sehgal, S. (2022). Structural health monitoring of composite materials. *Archives of Computational Methods in Engineering*, *29*(4), 1997-2017.
116. Smith, D. J. (2021). *Reliability, maintainability and risk: practical methods for engineers*. Butterworth-Heinemann.
117. Starkova, O., Gagani, A. I., Karl, C. W., Rocha, I. B., Burlakovs, J., & Krauklis, A. E. (2022). Modelling of environmental ageing of polymers and polymer composites—durability prediction methods. *Polymers*, *14*(5), 907.
118. Sun, S., Wang, J., Xiao, Y., Peng, J., & Zhou, X. (2024). Few-shot RUL prediction for engines based on CNN-GRU model. *Scientific reports*, *14*(1), 16041.
119. Tang, X., Wang, Z., Deng, L., Wang, X., Long, J., Jiang, X., Jin, J., & Xia, J. (2022). A review of the intelligent optimization and decision in plastic forming. *Materials*, *15*(19), 7019.
120. Tiddens, W., Braaksma, J., & Tinga, T. (2022). Exploring predictive maintenance applications in industry. *Journal of quality in maintenance engineering*, *28*(1), 68-85.
121. Tserpes, K., Barroso-Caro, A., Carraro, P. A., Beber, V. C., Floros, I., Gamon, W., Kozłowski, M., Santandrea, F., Shahverdi, M., & Skejić, D. (2022). A review on failure theories and simulation models for adhesive joints. *The Journal of adhesion*, *98*(12), 1855-1915.
122. Venturi, F., & Taylor, R. (2023). Additive manufacturing in the context of repeatability and reliability. *Journal of Materials Engineering and Performance*, *32*(15), 6589-6609.
123. Verhagen, W. J., Santos, B. F., Freeman, F., van Kessel, P., Zarouchas, D., Loutas, T., Yeun, R. C., & Heiets, I. (2023). Condition-based maintenance in aviation: Challenges and opportunities. *Aerospace*, *10*(9), 762.
124. Wang, C., Chen, X., Cheng, L., & Ding, J. (2022). High-cycle and very-high-cycle fatigue properties of CFRP-aramid honeycomb sandwich structure in three-point bending. *International Journal of Fatigue*, *155*, 106576.
125. Wang, C., Xu, S., & Yang, J. (2021). Adaboost algorithm in artificial intelligence for optimizing the IRI prediction accuracy of asphalt concrete pavement. *Sensors*, *21*(17), 5682.
126. Wang, G., & Ke, J. (2024). Literature review on the structural health monitoring (SHM) of sustainable civil infrastructure: an analysis of influencing factors in the implementation. *Buildings*, *14*(2), 402.
127. Wang, S., Jin, S., Deng, D., & Fernandez, C. (2021). A critical review of online battery remaining useful lifetime prediction methods. *Frontiers in Mechanical Engineering*, *7*, 719718.
128. Wang, X., Li, X., Ma, X., Li, W., & Yang, S. (2024). Advance on surface finishing technology of precision bearing cylindrical rollers. *The International Journal of Advanced Manufacturing Technology*, *131*(5), 2341-2363.
129. Winter, S. R., Crouse, S. R., & Rice, S. (2021). The development of 'green'airports: Which factors influence willingness to pay for sustainability and intention to act? A structural and mediation model analysis. *Technology in Society*, *65*, 101576.
130. Xi, J., Hu, Y., Xing, H., Han, Y., Zhang, H., Jiang, J., & Nikbin, K. (2021). The low-cycle fatigue behavior, failure mechanism and prediction of SLM Ti-6Al-4V alloy with different heat treatment methods. *Materials*, *14*(21), 6276.
131. Xu, X., Wang, G., Yan, H., Zhang, L., & Yao, X. (2023). Deep-learning-enhanced digital twinning of complex composite structures and real-time mechanical interaction. *Composites Science and Technology*, *241*, 110139.
132. Xu, Z., Song, Y., & Liu, Z. (2022). Stress analysis and fatigue life prediction of contact wire located at steady arms in high-speed railway catenary system. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-12.
133. Xu, Z., Zhang, Y., Miao, J., & Miao, Q. (2023). Global attention mechanism based deep learning for remaining useful life prediction of aero-engine. *Measurement*, *217*, 113098.
134. Yan, L., Guan, L., Wang, D., & Xiang, D. (2024). Application and prospect of wear simulation based on ABAQUS: A review. *Lubricants*, *12*(2), 57.
135. Yang, F., Zhao, W., Ru, Y., Pei, Y., Li, S., Gong, S., & Xu, H. (2023). Deep learning accelerates the development of Ni-based single crystal superalloys: A physical-constrained neural network for creep rupture life prediction. *Materials & Design*, *232*, 112174.
136. Ye, Y., Zhang, Y., Huang, T., Zou, S., Dong, Y., Ding, H., Vasudevan, V. K., & Ye, C. (2023). A critical review of laser shock peening of aircraft engine components. *Advanced Engineering Materials*, *25*(16), 2201451.
137. Zhang, L., Ji, T., Yu, S., & Liu, G. (2023). Accurate prediction approach of SOH for lithium-ion batteries based on LSTM method. *Batteries*, *9*(3), 177.
138. Zhao, B., Zhang, W., Zhang, Y., Zhang, C., Zhang, C., & Zhang, J. (2024). Research on the remaining useful life prediction method for lithium-ion batteries by fusion of feature engineering and deep learning. *Applied Energy*, *358*, 122325.
139. Zhao, K., Jia, Z., Jia, F., & Shao, H. (2023). Multi-scale integrated deep self-attention network for predicting remaining useful life of aero-engine. *Engineering Applications of Artificial Intelligence*, *120*, 105860.
140. Zhao, W., Zhang, C., Wang, J., Peyrano, O. G., Gu, F., Wang, S., & Lv, D. (2023). Research on main bearing life prediction of direct-drive wind turbine based on digital twin technology. *Measurement Science and Technology*, *34*(2), 025013.

141. Zhao, Y.-G., & Lu, Z.-H. (2021). *Structural reliability: approaches from perspectives of statistical moments*. John Wiley & Sons.
142. Zhao, Z., Wang, S., Wang, Z., Wang, S., Ma, C., & Yang, B. (2022). Surface roughness stabilization method based on digital twin-driven machining parameters self-adaption adjustment: A case study in five-axis machining. *Journal of Intelligent Manufacturing*, *33*(4), 943-952.
143. Zheng, J., Pang, Q., Hu, Z., & Sun, Q. (2022). Recent progress on regulating strategies for the strengthening and toughening of high-strength aluminum alloys. *Materials*, *15*(13), 4725.
144. Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. *Heliyon*, *9*(4).
145. Zhu, S.-P., Ai, Y., Liao, D., Correia, J. A., De Jesus, A. M., & Wang, Q. (2022). Recent advances on size effect in metal fatigue under defects: a review. *International Journal of Fracture*, *234*(1), 21-43.
146. Zhu, W., Fu, H., Li, F., Ji, X., Li, Y., & Bai, F. (2022). Optimization of CFRP drilling process: a review. *The International Journal of Advanced Manufacturing Technology*, *123*(5), 1403-1432.
147. Zolkin, A., Galanskiy, S., & Kuzmin, A. (2021). Perspectives for use of composite and polymer materials in aircraft construction. IOP Conference Series: Materials Science and Engineering,