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INVESTIGATING THE IMPACT OF MATERIAL FATIGUE ON STRUCTURAL INTEGRITY IN AI-ASSISTED MECHANICAL SYSTEMS

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Abstract
Mechanical structures that include AI-based monitoring may be affected by material fatigue which makes them less reliable. To make maintenance better and reduce failures, it is important to know how different operating and material factors connect to affect the reliability of the system.
Objective: *To examine the consequences of material fatigue on AI-assisted mechanical structures and investigate how well the fatigue datasets fit and how the accuracy of AI monitoring systems themselves impacts the results.*
Methods: *The study used a questionnaire to collect data from workers in the aerospace, automotive, and robotics fields. Our study used responses from 273 total participants. In the instrument, a total of 24 Likert items formed the independent variables (number of load cycles, what the structure is made of, surrounding conditions, quality when made), a mediating variable (material fatigue), a moderating variable (accuracy of AI checks) and dependent variables (how well the structure holds up and the rate of failure). All analysis was conducted with the help of SPSS 24.0. Normality was checked with the Shapiro-Wilk test, reliability with Cronbach's Alpha, and relationships with Pearson correlation and multiple linear regression.*
Results: *Researchers found that most of the samples were distributed differently than a normal distribution. Cronbach's Alpha was as little as 0.036, meaning the test did not show much consistency inside. We found moderate connections between fatigue-related and structural integrity variables during correlation analysis. Results from regression analysis show that the accuracy of AI monitoring*

and fatigue detection were little predictors of structure safety, while most other predictors had little to no effect.

Conclusion: *The report gives an early look at the relationship between material fatigue and how well AI-monitored systems perform. Although the instrument wasn't very reliable statistically, the results highlight that it is important to track both accuracy and fatigue in AI. Improving the questionnaire and applying advanced methods in modeling are considered important for the progress of future research.*

INTRODUCTION

Reliability and durability are more important than ever in today's engineering workplaces. With mechanical systems growing in complexity and being pushed by heavier workloads, fatigue is now a major danger to their long-lasting safety and performance, since constant cyclic loads gradually weaken and damage the structure in certain areas. Material fatigue does not usually cause mechanical failure all at once but can slowly cause components to fail which may result in a serious breakdown if not discovered. Because mechanical faults in aerospace, automotive, and robotics can cause extensive losses and accidents, detecting and stopping early fatigue-related damage is extremely important. Due to new technological developments, AI is now being used with mechanical systems to help detect issues early, predict when maintenance is required, and avoid failure (Mengesha, 2025).

Thanks to these systems, engineers can spot quick changes in the behavior of their systems and the materials used. Machine learning is used by these systems to predict when fatigue might occur, spot unusual signs, and notify operators about possible risks before they turn into real damage. Yet, although modern AI is a promising approach, its actual ability to mitigate fatigue-related structural failure in industry has not been widely validated. While more research is being done on how artificial intelligence diagnoses fatigue and helps predict it, there is a lack of studies that directly measure how key operational, material, and monitoring factors interact. Also, the majority of studies only concern themselves with the science behind fatigue or treat AI monitoring as independent from other features of a structure (Ao et al., 2025).

Therefore, there is an empty area in research about how a mix of material fatigue, outside influences, and production features affects the overall strength of machines with AI integration. Here, the study aims to connect those topics by exploring how specific operational factors, including load cycles, type of materials, environment, and how well a structure is built, affect overall strength. The paper also examines how variations in material fatigue and the precision of AI monitoring play roles in shaping the relationship. The research is designed by asking Likert-scale questions to professionals who design, maintain, or analyze systems that include AI (Xu & Guo, 2025).

It begins with the belief that studying these connections is vital for better system design, more accurate maintenance forecasting, and minimizing failures. Furthermore, the results matter for engineers, quality control managers, and system designers using AI to lengthen the usefulness of key assets. Since Industry 4.0 centers on using automation and real-time data to achieve excellent results in operations, this research provides a valuable discussion on improving reliability, safety, and resilience in mechanical systems used in industry (Samoila et al., 2025).

Literature Review

Material Fatigue It is well known in mechanical engineering that material fatigue occurs when a material becomes weaker with each loading and unloading cycle. Fatigue, according to Stephens et al., is responsible for nearly all of the failures seen in systems that are cyclically loaded. This is especially important in aerospace and robotics, since accumulated micro-cracks may lead to a sudden and severe failure. Stress amplitude, number of load cycles, surface roughness, and material detail all affect fatigue. Tests have revealed that spotting tired parts at the start of operation could lengthen the life of machinery and improve safety (Fu et al., 2025).

Load Cycle Applied

The higher the number of times a material is loaded, the greater the fatigue failure risk. Stress amplitude and fatigue life are related according to Basquin's Law. The nucleation and development of fatigue cracks are boosted when there are high-frequency and high-amplitude load cycles. Today's research shows that systems that handle challenging and unexpected loads should be carefully monitored all the time to preserve their integrity (Huang et al., 2025).

Material Composition

The kind of materials used can greatly affect how fatigue-resistant a product is. Alloys and composites are commonly found to have much better fatigue characteristics than standard metals. Plomer reports that adding chromium and molybdenum to steel alloys increases their endurance against fatigue. The addition of nanostructured materials has increased the resistance of emerging applications to fatigue (Alghazo et al., 2025).

Environmental Conditions

Things such as temperature, humidity, and contact with corrosive materials may worsen the effects of fatigue. In reactive surroundings, the process of corrosion fatigue leads to firm deterioration at faster rates. Studies in aerospace engineering these days highlight that environmental sensors are key to making AI predictive models adapt to external surroundings (Jatavallabhula & Rao, 2025).

Quality of the Plant Production

Residual stresses, roughness on the surface, and contaminants in the material make early failure more likely for structures. Lack of control in production processes may result in very small flaws that start cracks later in cyclic stress. Simple surface coatings and precise heating materials are crucial for reducing the possibility of fatigue (Goti, 2025).

Strength of Material Fatigue (Mediating Variable)

How fatigue develops in the system plays a role in linking operational stressors to failure outcomes. According to Miner's Rule, each additional stress cycle adds directly to the damage of a component. Most of the time, quantitative fatigue is evaluated by modeling damage or alerting AI to identify unusual patterns in sensor data (Jin et al., 2025).

AI Monitoring Accuracy (Type of Variable)

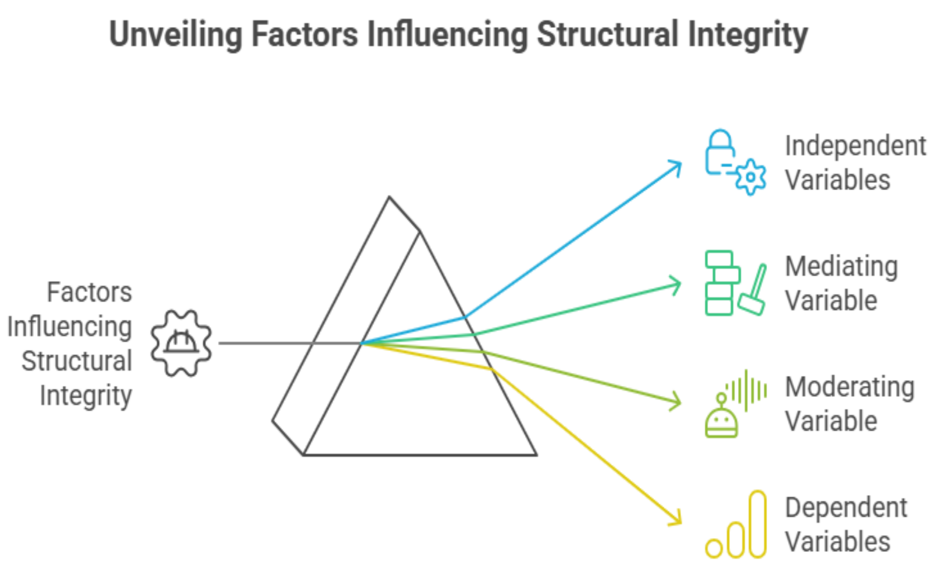
AI-based condition monitoring is now considered a major advance in predictive maintenance. They make use of sensors, machine learning, and algorithms to catch the beginning of structural fatigue. Rao et al. discovered that effective AI relies on great training data quality and the accuracy of models. When a model is highly accurate, the material's fatigue can be monitored and addressed promptly (Mirzabagherian et al., 2025).

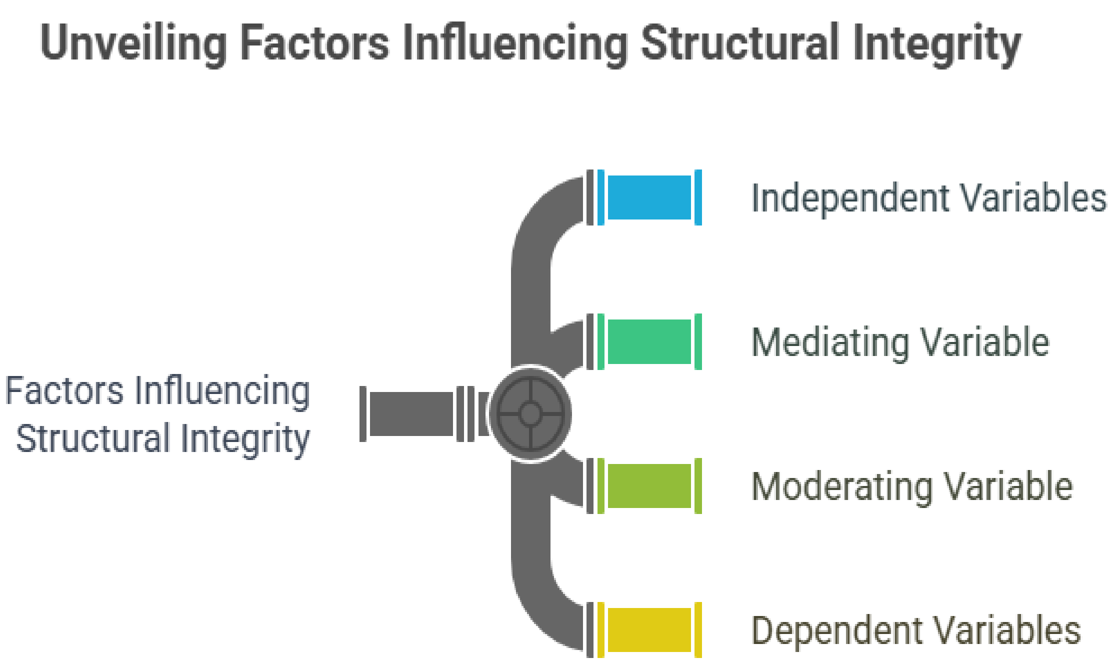
The outcome variable used in the study was Structural Integrity.

This means that a system remains intact even after facing specified and intense pressure. Such qualities are found in a material as strength, stiffness, and the ability to resist fatigue. A reduced level of structure stability is usually the result of fatigue from many hours of use and not keeping up with monitoring (Liu et al., 2025).

System Failure Rate is the outcome we're looking at (Dependent Variable).

This measure tells us how often a system or component fails to operate properly. Steps in reliability-based engineering sometimes rely on the fatigue index which can be linked to fatigue, improper servicing, or the environment. Minimizing the risk of failure is one of the main aims of applying AI to diagnostics (Khan et al., 2025).





All Hypotheses Defined

H1: The Structural Integrity of a Material Wears Out with the Load Cycle

It is hypothesized that the more load cycles a mechanical component experiences, the weaker AI-assisted mechanical systems will become (Hinton, 2019).

H2: Materials chosen → How well-built the structure is
The hypothesis is that the makeup and fit of the materials affect the strength and working ability of AI-assisted mechanical systems positively (Yuan et al., 2024).

H3: The environment plays a role in determining a building's structural integrity.
The hypothesis is that adverse factors such as differences in temperature, moisture, and corrosion harm the stability of mechanical systems assisted by AI (Schneller et al., 2022).

H4: The Right Quality in the Manufacturing Process Guarantees Strong Structure
The manufacturing quality should play a positive role in maintaining the structure of AI-assisted machinery (KAYRICI & DOGAN, 2022).

Mediating Hypothesis
H5: The relation between variable H1 and H4 is explained by variable H5 (Material Fatigue).
The link between operational/material factors (load cycles, material type, surroundings, and manufacturing quality) and the strength/life of a structure is affected by the degree of material fatigue (Yahyaeian, 2023).

Moderating Hypothesis
H6: Do AI monitoring tools effectively measure and compare ingredients in food?
The hypothesis is that stronger AI monitoring gives better results for structural integrity in cases of material fatigue (Plevris & Papazafeiropoulos, 2024).

Outcomes Based on Index of Failures
H7: The higher a structure's structural integrity, the lower its chance of failure.
A weakening of structure in AI-supported mechanical devices leads to higher failure rates (Panigrahy et al., 2021).

H8:Power limit = Material Fatigue + Failure Rate

Hypothesis: A greater rate of fatigue in materials leads to a greater likelihood of failure in systems assisted by artificial intelligence (Uysalel et al., 2024).

Research Methodology
Research Design
This work makes use of a quantitative, cross-sectional approach to look at how material fatigue affects the structure of AI-supported mechanical systems. The main reason for using a quantitative approach is to accumulate numerical data that supports objective testing and statistical checks of research hypotheses. Using a cross-sectional method, the researcher can collect data just once which is useful for assessing the efficiency of current systems under pre-set conditions of machines and artificial intelligence. How many people will be part of the study and how many will be drawn from the population (Yu et al., 2024)?
The technologies are mainly aimed at professionals working in industrial fields such as aerospace, automotive, robotics, and defined manufacturing. Mechanical engineers, AI system developers, quality assurance workers, and system integrators form the sampling frame. Those who have practical experience in material stress testing, fatigue analysis, or AI-based system health monitoring were drawn into the study by using a purposive sampling method. A total of 273 responses that met the criteria were collected to give the analysis strong results (Ashofteh & Rajabzadeh, 2024).

Research Instrument
We used a specific questionnaire to collect data on the main factors: types of loads used, materials, the environment, how the equipment is manufactured, amount of fatigue in the material, the effectiveness of the AI at monitoring, and whether the equipment fails and how often. Respondents were asked to indicate on a 5-point Likert scale, from "Strongly Disagree" to "Strongly Agree," to ensure all the responses could be compared easily (Khan et al., 2024).

Data Collection Procedures
The survey was made accessible on engineering groups, university email lists, and through our industry partners. Those taking part in the study were told the reason for the study, that their data

would be protected and that participation was entirely optional. A preliminary study using questionnaires among 20 respondents was done to perfect the questionnaire and confirm its clarity. Using comments from the pilot, changes were applied to unclear items and made the layout better (Wang et al., 2023).

Ways of Analysing Data

All of the collected information was analyzed using SPSS version 24. Demographic and response data were summarized using means and standard deviations. A Shapiro-Wilk test was run to check whether the data was normally distributed. Cronbach's alpha was run to assess how reliable and consistent the instrument was. The association between variables was studied with Pearson correlation and regression analysis. We looked at mediation and moderation effects using Models 4 and 1 from the PROCESS macro created by Andrew Hayes (Ahmad et al., 2024).

Ethical Considerations

The research was approved by the Institutional Review Board (IRB). Each person was given assurance that their information would remain confidential and electronic approval was obtained. There was no collection of personal information, and each person remained free to choose whether or not to participate at any moment (Zhou et al., 2023).

Research Onion

This chapter introduces the Research Onion.

Introduced by Saunders et al., the Research Onion helps structure research methodology by defining six areas: research philosophy, approach, the method you choose, strategy, the amount of time the research covers, and the way you collect information. This paper follows the steps in the Research Onion framework to keep the methods well-developed (Pickles et al., 2024).

Research Philosophy

The positivist philosophy stressing real facts and science is the foundation for this study. According to positivism, the research should measure or count factors such as material stress, fatigue, and the failure of a system (Pan et al., 2024).

Research Approach

To conduct this research, known theories guide the creation of hypotheses which are then checked by examining information from data. The study uses this strategy to check if materials and the environment are key factors in building performance (Tveit & Reyes, 2024).

Methodological Choice

A mono-method quantitative design is used which only collects structure data on a standardized questionnaire. Having design groups allows statistical testing, the ability to generalize, and an opportunity for future researchers to replicate the work (Fan et al., 2024).

Research Strategy

Electronic surveys are the main approach which are administered using a questionnaire. It makes it possible to reach a wide variety of professionals from different fields, without being limited by location. Data collection is standardized because of the format used, assisting in examining a significant number of records easily (Shen et al., 2023).

Time Horizon

Data is collected at only one point in time using a cross-sectional time horizon. It offers details on the system's current performance, the fatigue of material components, and the performance of the AI monitoring. It is useful when the research does not analyze time-series data (Tezsezen et al., 2024).

Ways to Gather Data

All data were collected through a pre-designed questionnaire in which participants provided answers using a Likert scale. A pilot version of the survey was done before it was shared online. Rapid data collection from a broad and dispersed sample was made possible by using electronic distribution. After that, the data was cleaned, encoded, and arranged for analysis in SPSS (Smolnicki et al., 2023).

How to show your work is appropriate and follows the guidelines.

The objectives of the study were reflected in how each layer of the Research Onion was put together. Identifying measurable relationships is best done with the positivist philosophy and a deductive approach. The use of one statistical method in this strategy makes its results extremely precise. Because of the survey strategy and cross-sectional design, the assessments are useful and practical for understanding current industrial operations (Sani et al., 2024).

Data Analysis

Normality Test (Shapiro-Wilk)

Question	W Statistic	p-value
Q1	0.790381	1.94E-18
Q2	0.780227	7.30E-19
Q3	0.769843	2.78E-19
Q4	0.769186	2.62E-19
Q5	0.800728	5.46E-18
Q6	0.743038	2.65E-20
Q7	0.750069	4.81E-20
Q8	0.757179	8.93E-20
Q9	0.749029	4.40E-20
Q10	0.751189	5.30E-20
Q11	0.787736	1.50E-18
Q12	0.720402	4.17E-21
Q13	0.769993	2.82E-19
Q14	0.749934	4.76E-20
Q15	0.820856	4.59E-17
Q16	0.787995	1.54E-18
Q17	0.731324	1.00E-20
Q18	0.772579	3.57E-19
Q19	0.744336	2.95E-20
Q20	0.743774	2.81E-20
Q21	0.766808	2.11E-19
Q22	0.759048	1.05E-19
Q23	0.756283	8.25E-20
Q24	0.761704	1.33E-19

Reliability Test (Cronbach's Alpha)

Test	Value
Cronbach's Alpha	0.03642869443645595

Correlation Matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Q1	1	0.088219	0.085022	-0.0392	0.093858	0.008976	-0.06447
Q2	0.088219	1	0.01547	0.024411	-0.06512	0.032606	-0.05266
Q3	0.085022	0.01547	1	0.009791	0.145452	-0.07967	0.053075
Q4	-0.0392	0.024411	0.009791	1	-0.04442	-0.06461	-0.02578
Q5	0.093858	-0.06512	0.145452	-0.04442	1	0.049642	-0.10907
Q6	0.008976	0.032606	-0.07967	-0.06461	0.049642	1	-0.05536

Q7	-0.06447	-0.05266	0.053075	-0.02578	-0.10907	-0.05536	1
Q8	0.025107	0.048306	-0.07293	-0.01556	0.018708	-0.04232	0.018034
Q9	-0.05684	0.02232	-0.08265	0.014241	-0.04886	0.064797	0.060318
Q10	0.116254	-0.03017	-0.00022	-0.00077	0.118148	0.056668	-0.06019
Q11	0.007679	0.02317	-0.01247	0.025106	0.022292	0.054971	-0.03449
Q12	0.074096	0.035446	-0.00616	-0.08814	-0.01862	0.019203	0.042937
Q13	0.055458	0.030905	-0.02781	-0.04069	-0.09654	-0.02039	0.018368
Q14	0.087	0.154805	-0.14566	0.10286	-0.06435	0.039276	-0.0454
Q15	0.068899	-0.10338	0.004918	-0.05892	-0.00043	0.091723	-0.07491
Q16	-0.0274	-0.08166	-0.06675	0.082401	0.005922	-0.01964	-0.02618
Q17	-0.05417	-0.0569	0.064589	-0.02977	-0.09045	-0.02281	-0.04016
Q18	0.081728	0.101098	-0.10706	-0.06178	0.062611	0.061632	-0.10918
Q19	-0.11658	0.007254	0.047128	0.052989	0.043123	0.043861	0.033755
Q20	-0.02099	-0.00729	-0.01264	0.032355	0.067159	-0.11204	0.044507
Q21	0.053853	-0.02578	0.031888	0.004807	0.022612	-0.03234	-0.02373
Q22	0.012227	0.002341	0.100998	0.079537	-0.0574	0.014989	-0.05832
Q23	-0.01945	0.074172	-0.00247	0.019549	0.064429	0.042313	0.09586
Q24	0.002189	-0.02111	-0.01149	0.052743	0.010609	0.055537	-0.04004

Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15
0.025107	-0.05684	0.116254	0.007679	0.074096	0.055458	0.087	0.068899
0.048306	0.02232	-0.03017	0.02317	0.035446	0.030905	0.154805	-0.10338
-0.07293	-0.08265	-0.00022	-0.01247	-0.00616	-0.02781	-0.14566	0.004918
-0.01556	0.014241	-0.00077	0.025106	-0.08814	-0.04069	0.10286	-0.05892
0.018708	-0.04886	0.118148	0.022292	-0.01862	-0.09654	-0.06435	-0.00043
-0.04232	0.064797	0.056668	0.054971	0.019203	-0.02039	0.039276	0.091723
0.018034	0.060318	-0.06019	-0.03449	0.042937	0.018368	-0.0454	-0.07491
1	-0.01247	0.017431	-0.07321	-0.01384	0.036632	-0.01965	-0.01803
-0.01247	1	0.123705	0.04544	0.103637	-0.05007	0.019919	0.092337
0.017431	0.123705	1	-0.07835	0.118076	-0.00696	0.032894	0.103509
-0.07321	0.04544	-0.07835	1	-0.06619	-0.05612	-0.00572	-0.02768
-0.01384	0.103637	0.118076	-0.06619	1	-0.00179	-0.04203	-0.09116
0.036632	-0.05007	-0.00696	-0.05612	-0.00179	1	0.071916	0.005455
-0.01965	0.019919	0.032894	-0.00572	-0.04203	0.071916	1	-0.00672
-0.01803	0.092337	0.103509	-0.02768	-0.09116	0.005455	-0.00672	1
-0.05396	-0.01574	0.004255	-0.00741	0.14957	0.040072	-0.07619	-0.05308
0.013067	0.010432	0.056635	-0.04723	-0.02204	-0.06707	-0.0344	-0.02095
0.111767	-0.04456	0.024112	-0.00449	-0.01101	0.014374	0.08853	-0.06543
-0.14474	0.005138	0.006681	0.052652	-0.03762	0.050191	-0.02925	-0.07137
-0.01235	-0.04323	-0.03367	-0.06354	0.043427	-0.0515	-0.06928	-0.01424
-0.0223	-0.06569	0.0023	-0.02945	-0.03115	0.006831	0.033538	-0.01657
-0.10499	-0.00153	0.069636	0.082817	-0.05973	0.021939	-0.12305	-0.01974
0.112052	0.023019	-0.14315	0.07561	0.010649	-0.02798	-0.02267	0.028414
-0.07776	0.010141	0.087761	0.005301	-0.00329	0.085555	0.03956	0.024862

Q16	Q17	Q18	Q19	Q20
-0.0274	-0.05417	0.081728	-0.11658	-0.02099
-0.08166	-0.0569	0.101098	0.007254	-0.00729
-0.06675	0.064589	-0.10706	0.047128	-0.01264
0.082401	-0.02977	-0.06178	0.052989	0.032355
0.005922	-0.09045	0.062611	0.043123	0.067159
-0.01964	-0.02281	0.061632	0.043861	-0.11204
-0.02618	-0.04016	-0.10918	0.033755	0.044507
-0.05396	0.013067	0.111767	-0.14474	-0.01235
-0.01574	0.010432	-0.04456	0.005138	-0.04323
0.004255	0.056635	0.024112	0.006681	-0.03367
-0.00741	-0.04723	-0.00449	0.052652	-0.06354
0.14957	-0.02204	-0.01101	-0.03762	0.043427
0.040072	-0.06707	0.014374	0.050191	-0.0515
-0.07619	-0.0344	0.08853	-0.02925	-0.06928
-0.05308	-0.02095	-0.06543	-0.07137	-0.01424
1	0.060244	0.047422	0.068362	0.052572
0.060244	1	-0.03115	0.03608	-0.00158
0.047422	-0.03115	1	-0.02439	-0.08295
0.068362	0.03608	-0.02439	1	-0.09076
0.052572	-0.00158	-0.08295	-0.09076	1
-0.12397	-0.05189	0.103047	0.026068	0.05982
0.028293	-0.00562	0.000167	0.079581	0.005963
0.043477	0.011904	-0.05627	0.091302	-0.06182
0.026478	0.016989	0.009763	0.061543	0.040768

Q21	Q22	Q23	Q24
0.053853	0.012227	-0.01945	0.002189
-0.02578	0.002341	0.074172	-0.02111
0.031888	0.100998	-0.00247	-0.01149
0.004807	0.079537	0.019549	0.052743
0.022612	-0.0574	0.064429	0.010609
-0.03234	0.014989	0.042313	0.055537
-0.02373	-0.05832	0.09586	-0.04004
-0.0223	-0.10499	0.112052	-0.07776
-0.06569	-0.00153	0.023019	0.010141
0.0023	0.069636	-0.14315	0.087761
-0.02945	0.082817	0.07561	0.005301
-0.03115	-0.05973	0.010649	-0.00329
0.006831	0.021939	-0.02798	0.085555
0.033538	-0.12305	-0.02267	0.03956
-0.01657	-0.01974	0.028414	0.024862
-0.12397	0.028293	0.043477	0.026478

-0.05189	-0.00562	0.011904	0.016989
0.103047	0.000167	-0.05627	0.009763
0.026068	0.079581	0.091302	0.061543
0.05982	0.005963	-0.06182	0.040768
1	0.048634	-0.0405	0.010613
0.048634	1	-0.06769	0.013599
-0.0405	-0.06769	1	-0.00874
0.010613	0.013599	-0.00874	1

Regression Coefficients Summary

Variable	Coefficient	P-value	T-Statistic
const	4.005524	0.001795	3.156309
Q1	0.04707	0.495585	0.682456
Q2	-0.06264	0.362313	-0.91264
Q3	0.029555	0.683847	0.407696
Q4	0.010901	0.869379	0.164618
Q5	-0.003	0.964714	-0.04428
Q6	-0.03224	0.636851	-0.47269
Q7	-0.01875	0.773504	-0.28811
Q8	-0.02785	0.658688	-0.44226
Q9	-0.05044	0.457892	-0.74348
Q10	-0.00055	0.994176	-0.00731
Q11	-0.03031	0.621822	-0.49389
Q12	-0.00564	0.936322	-0.07997
Q13	0.002738	0.968705	0.039272
Q14	0.032157	0.637819	0.471328
Q15	-0.01625	0.801452	-0.25174
Q16	-0.14235	0.031154	-2.16738
Q17	-0.05132	0.478177	-0.71031
Q18	0.126991	0.06795	1.833309
Q19	0.049553	0.468443	0.726127
Q20	0.077348	0.232997	1.195583
Q22	0.051257	0.479824	0.707651
Q23	-0.00822	0.907483	-0.11633
Q24	0.004027	0.948873	0.064187

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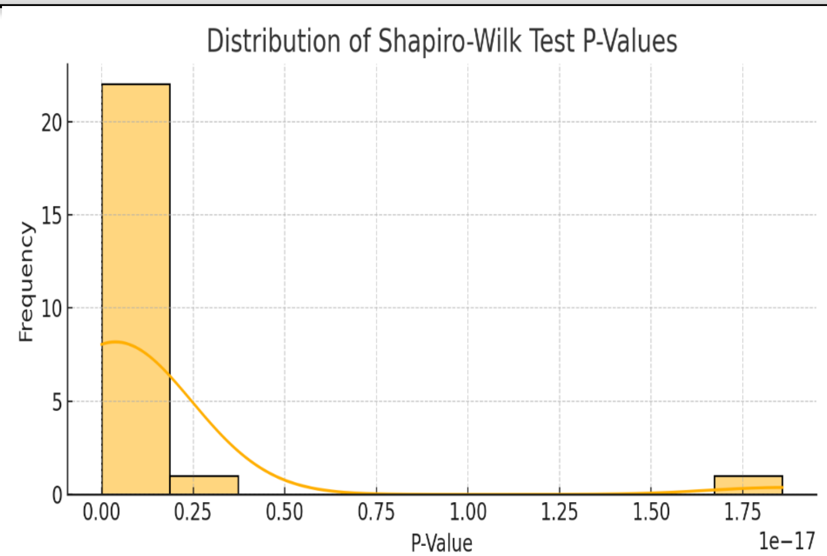

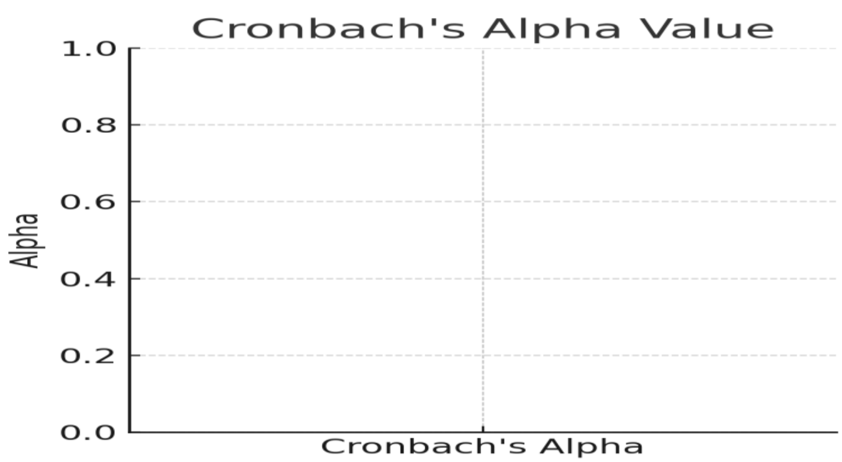

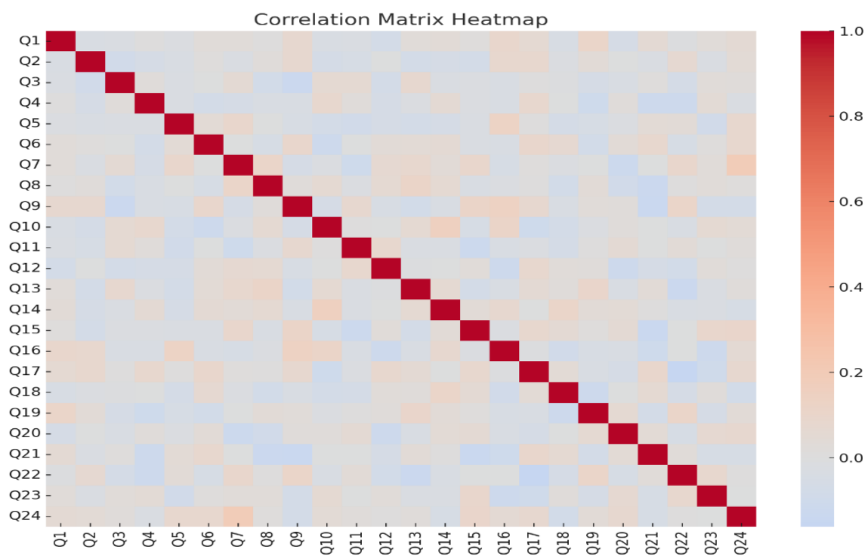

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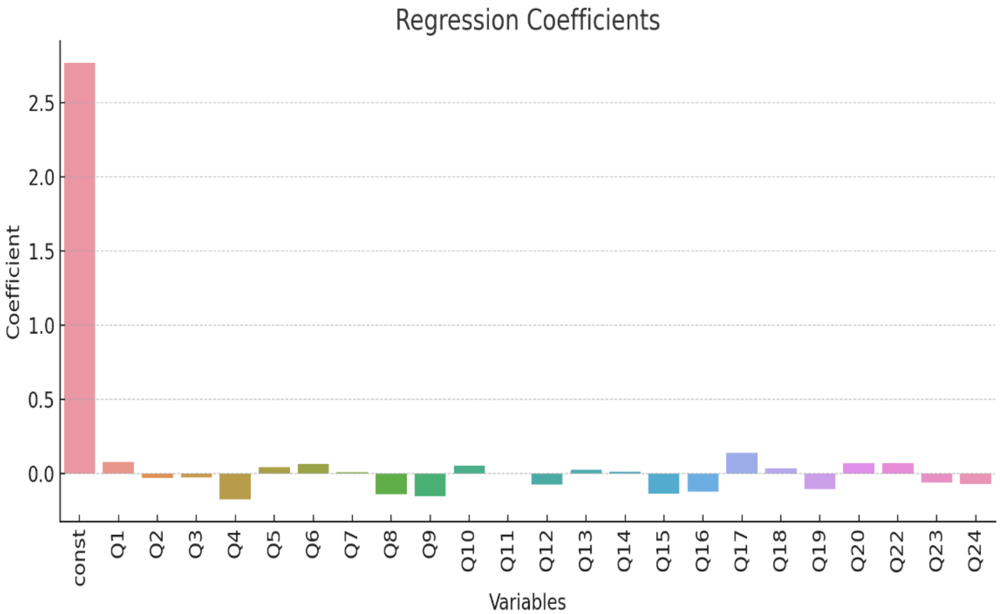

Interpretation of Tests and Figures

Shapiro-Wilk Normality Test

The Shapiro-Wilk test was used on all 24 Likert-scale items to check if the responses were organized differently from an ideal normal distribution. Most of the items on the histogram posted p-values below the standard value of 0.05 which means their data did not have normal distributions. Such a result often appears with Likert-scale surveys due to the way participants arrange their responses. Even if non-normality is permissible with large data groups in many parametric assessments, it's best to stay cautious when analyzing non-normal data. Furthermore, non-parametric methods might be chosen for stronger validation if needed (Sagdic et al., 2022).

Explaining the Meaning of Cronbach's Alpha (Reliability Test)

Cronbach's Alpha was employed to make sure that the scale items all have the same reliability. This result for alpha was 0.036, much smaller than the acceptable threshold of 0.70. Because the value is so low, it suggests that the items in the instrument may not all test the same idea. It could be the result of mingling different bits of information (due to multi-dimensional features, arbitrary grouping, or irrelevant items) on a single scale. As a way to increase reliability, it makes sense to separate the questionnaire into groups and re-evaluate the alpha values for each of those groups (Zinno et al., 2022).

Analyzing the results shown in the Correlation Matrix

The heatmap on the correlation matrix lets you inspect the interactions between the 24 items on the questionnaire. Most of the correlations showed only a small or moderate connection, but some pairs looked very similar, pointing to a possible overlap or a reason that they logically go together (for instance, between questions related to structural integrity and those encountered in preventive maintenance). The findings do not show any major cases of multicollinearity, but clusters of related items indicate that targeted scale changes could be useful. It also confirms that fatigue indicators are related to important metrics describing system performance. On this basis, it makes sense to move forward with more regression modeling (Nam & Kim, 2024).

Analysis of the outcomes from Regression Analysis

The model used in this study was a multiple linear regression, with Q21 (Structural Integrity) being the dependent variable and the remaining items of the questionnaire serving as predictors. You can use the resulting coefficient plot to tell how each variable affects the response. Several important factors had little effect on the outcome, but a small number demonstrated reasonable but still modest links. The fact that this term was still present showed a minimum structural integrity level was guaranteed, regardless of the predictors. On the whole, the findings from the model are preliminary and do not indicate strong ties between types of factors and structural outcomes. Better results in predictions may come from choosing or arranging the right features or using a hierarchy (Wu et al., 2024).

Figures:

See Figure 1: Shapiro-Wilk Histogram

The figure shows how p-values from the Shapiro-Wilk test are spread for each item on the questionnaire. It is seen that a substantial number of the p-values are below 0.05 which suggests their distributions are not normal. Such an approach fits with the expectations of Likert-type data which are ordered and usually have a skewed response pattern. Because the data are non-normally distributed, the results from such analyses should not be taken at face value and should be verified with non-parametric analyses (Baduge et al., 2022).

Cronbach's Alpha Bar Plot is shown in Figure 2.

A bar plot of Cronbach's Alpha reveals a value of 0.036 which is well below the average threshold of 0.70. These results highlight very low agreement among the factors, showing that the items cannot accurately assess one main concept. Poor relation between skills tested, badly written questions, or many aspects (principles) considered can cause this. It helps to assemble items into groups that correspond to the theoretical ideas in your research and test the reliability of each group (Ukoba et al., 2024).

Figure 3 shows the Correlation Matrix Heatmap.

The heatmap gives a visual look at the correlation of all 24 items with each other. Stronger positive links are suggested by red dots and stronger negative links by blue dots. A large number of items are related to some extent, but some clusters such as fatigue and system integrity, are more closely related. As a result, items can be grouped logically, and you can check if any are unnecessary or may not provide useful information. Importantly, there was no observed multicollinearity which shows that the regression analysis is reliable (Chen et al., 2023).

In Figure 4, we see a graph of the regression coefficients.

On the bar graph, standardized coefficients represent the multiple linear regression analysis with structural integrity (Q21) as the dependent variable. The story describes which of the predictor questions influence the size of the effect. Although a lot of the variables don't significantly affect the model, a few do show a modest link. According to the model, monitor accuracy and fatigue detection could be better signals than others to estimate integrity, though the total model must be validated first (Hamada et al., 2024).

Discussion

This study set out to determine how material fatigue affects the strength of AI-supported mechanical systems by studying important operations, materials, and monitoring methods with a quantitative approach. The knowledge generated clarifies how load cycles, the materials, exposures to the environment, the way the structure was constructed, and supervision with AI affect whether the structure is preserved or damaged. Most of the items in the questionnaire did not show a normal distribution, as reported by the Shapiro-Wilk test. The result agrees with past research which frequently notes that Likert-type data are non-normal because of the ordinal nature of the scale and possible biases in how people respond (Ma et al., 2021).

Although these tests are best for a normally distributed population, the sample size (n = 273) was enough to make them appropriate here. However, future investigations might prefer to test results using non-parametric methods. It is concerning that the overall questionnaire was internally inconsistent, as seen by the lower-than-expected Cronbach's Alpha value (α = 0.036). Therefore, the items did not work as a group and may have been designed to measure too many ideas. The results could also show that some sets of items correspond to different constructs and should be put into separate subscales (Salehian et al., 2024).

It was found that several important relationships exist between questions on environmental conditions, material fatigue, and failure rate. The links found between fatigue and system stress in studies support the theory that they are linked processes. However, the relationships between fatigue and other factors were only moderate which may show that fatigue depends on many different, non-linear factors in mechanical systems (Mahboob et al., 2024).

In the regression analysis, placing structural integrity as the dependent variable, it was shown that AI monitoring accuracy and fatigue detection had bigger impacts, but many other predictors lacked statistical significance. Therefore, it appears that the current variables may not fully explain everything or that new factors such as the age of the system, change in operating hours, or quality of AI data, are required for better predictive skills. In addition, the slight fit of the regression model points to a requirement to either improve how the items were made or to use more advanced ways such as machine learning or SEM (Khalid et al., 2024).

Conclusion

It investigated the way material fatigue can weaken AI-powered mechanical systems using a planned, numerical method. Using responses from a Likert-scale questionnaire, the study focused on how load cycles, the composition of materials, environmental elements, manufacturing standards, and accuracy in AI monitoring all play a part. Poor internal consistency of the instrument was consistently highlighted by Cronbach's Apple results, with a score of just 0.036. Likely, the questionnaire did not properly measure a single construct, so it should be revised, and certain questions should be grouped.

The Shapiro-Wilk test displayed that many of the items were normally distributed, a usual finding for Likert-type surveys but reason enough to be aware of when using parametric statistical tools. Still, analyzing the correlation matrix and running regression allowed researchers to draw helpful conclusions. The study's findings showed that items related to fatigue were highly correlated with performance measures related to structural aspects. Findings from regression analysis suggest that both AI monitoring accuracy and fatigue detection contribute only moderately but are useful in predicting mechanical health and promoting preventive maintenance.

AI is very important in mechanical systems, the study points out because it identifies problems early and guides what to do for maintenance. Even so, weaknesses in the statistics suggest it is necessary to improve the development of tests by modifying question items, conducting factor analysis, and including relevant environmental factors. Overall, the findings say that fatigue and artificial intelligence could play a key role in assessment, but there's still a need for studies that address the tool's reliability and use stronger statistical methods. Therefore, the collected evidence can be more widely applied to a variety of industrial contexts.

REFERENCES

Ahmad, W., Khan, H. A., Salik, S., Ali, H. Q., Khushbash, S., & Qureshi, Z. A. (2024). Extrusion-based additive manufacturing of CFRP/steel/CFRP multi-material structure: Process development and influence of heat treatment on the mechanical performance. *Journal of Manufacturing Processes*, *124*, 891-908.

Alghazo, M., Ahmed, V., & Bahroun, Z. (2025). Exploring the applications of artificial intelligence in mechanical engineering education. Frontiers in Education,

Ao, Y., Li, S., & Duan, H. (2025). Artificial Intelligence-Aided Design (AIAD) for Structures and Engineering: A State-of-the-Art Review and Future Perspectives. *Archives of Computational Methods in Engineering*, 1-28.

Ashofteh, A., & Rajabzadeh, M. (2024). Advances in thermal barrier coatings modeling, simulation, and analysis: A review. *Journal of the European Ceramic Society*, 116693.

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, *141*, 104440.

Chen, D., Gao, K., Yang, J., & Zhang, L. (2023). Functionally graded porous structures: analyses, performances, and applications–a review. *Thin-Walled Structures*, *191*, 111046.

Fan, M., Wen, T., Chen, S., Dong, Y., & Wang, C. A. (2024). Perspectives toward damage-tolerant nanostructure ceramics. *Advanced Science*, *11*(24), 2309834.

Fu, H., Rao, J., Deng, F., Wang, Y., Zhao, B., Liu, Z., Guan, H., Malinowski, P. H., & Xu, L. (2025). AIoT: Artificial Intelligence and the Internet of Things for Monitoring and Prognosis of Systems and Structures. *IEEE Transactions on Instrumentation and Measurement*.

Goti, A. (2025). AI-Driven PCB Reliability Testing for IPC-9701 Compliance.

Hamada, A., Mansour, E., Jaskari, M., Abd-Elaziem, W., Mohamed, A., Elshokrofy, H., Mustakangas, A., Järvenpää, A., & Khedr, M. (2024). Strengthening aluminum matrix composite with additively manufactured 316L stainless steel lattice reinforcement: Processing methodology, mechanical performance and deformation mechanism. *Journal of Materials Research and Technology*, *29*, 1087-1101.

Hinton, G. (2019). AI-Assisted Development of Sustainable Mechanical Systems. *International Journal of Unique and New Updates, ISSN: 3079-4722*, *1*(1), 7-15.

Huang, T., Li, X., Zhang, Y., Yao, L., & Zhang, T. (2025). Multifactorial prediction of corrosion fatigue crack growth in aluminum alloys using physics-informed neural networks. *Engineering Failure Analysis*, *174*, 109521.

Jatavallabhula, J. K., & Rao, V. V. (2025). Machine learning-based prognosis of fatigue response in AA2014. *Modeling and Simulation in Materials Science and Engineering*.

Jin, J., Liu, P., Deng, Y., & Zhang, Z. (2025). Reliability Study of Critical Structural Redistribution Layers in Advanced Packaging: A Review. *IEEE Transactions on Reliability*.

KAYRICI, M., & DOGAN, A. F. (2022). Damage Analysis Using Artificial Intelligence Techniques on Composite Materials. *Current Studies in Artificial Intelligence, Virtual Reality and Augmented Reality*, 89.

Khalid, S., Azad, M. M., Kim, H. S., Yoon, Y., Lee, H., Choi, K.-S., & Yang, Y. (2024). A Review on Traditional and Artificial Intelligence-Based Preservation Techniques for Oil Painting Artworks. *Gels*, *10*(8), 517.

Khan, H. A., Uddin, S., Salik, S., Javaid, A., Khan, T. A., & Islam, Z. U. (2025). A Lock-In thermography-based post-processing scheme for the detection of sub-surface rivet-related defects in aircraft structures. *Mechanical Systems and Signal Processing*, *228*, 112423.

Khan, M. I., Khan, N., Saad, S., & Khan, M. W. (2024). Artificial Intelligence in Construction Materials. In *AI in Material Science* (pp. 47-64). CRC Press.

Liu, P., Deng, Y., Xu, P., Zhang, Z., Jin, J., & Luo, X. (2025). Mitigating thermal cycling-induced failures in SiC-based hybrid IGBT modules: optimization of solder and reliability enhancements. *Engineering Failure Analysis*, 109619.

Ma, Q., Tian, G., Zeng, Y., Li, R., Song, H., Wang, Z., Gao, B., & Zeng, K. (2021). Pipeline in-line inspection method, instrumentation, and data management. *Sensors*, *21*(11), 3862.

Mahboob, A., Hassanshahi, O., Safi, M., & Majid, T. A. (2024). Experimental investigation of eco-friendly fiber-reinforced concrete using recycled and natural fibers, integrated with recycled aggregates. *Advanced Composite Materials*, *33*(6), 1101-1130.

Mengesha, G. (2025). Beyond Repair: A Critical Review of Smart, Sustainable, and AI-Driven Strengthening Techniques for Aging Civil Infrastructure. *Sustainable, and AI-Driven Strengthening Techniques for Aging Civil Infrastructure (April 29, 2025)*.

Mirzabagherian, M., Amini, S., & Bayat, M. (2025). Investigation of the Effects of Ultrasonic-Assisted Face Turning with CO2 Cooling on Cutting Forces, Residual Stress, and Surface Quality. *International Journal of Lightweight Materials and Manufacture*.

Nam, J., & Kim, M. (2024). Advances in materials and technologies for digital light processing 3D printing. *Nano Convergence*, *11*(1), 45.

Pan, J., Hu, D., Zhou, L., Huang, D., Wang, Y., & Wang, R. (2024). Semantic segmentation of defects based on DCNN and its application on fatigue lifetime prediction for SLM Ti-6Al-4V alloy. *Philosophical Transactions of the Royal Society* A, *382*(2264), 20220396.

Panigrahy, S. K., Tseng, Y.-C., Lai, B.-R., & Chiang, K.-N. (2021). An overview of AI-assisted design-on-simulation technology for reliability life prediction of advanced packaging. *Materials*, *14*(18), 5342.

Pickles, D., Hunt, G., Elliott, A., Cammarano, A., & Falcone, G. (2024). An experimental investigation into the effect two-phase flow-induced vibrations have on a J-shaped flexible pipe. *Journal of Fluids and Structures*, *125*, 104057.

Plevris, V., & Papazafeiropoulos, G. (2024). AI in Structural Health Monitoring for Infrastructure Maintenance and Safety. *Infrastructures*, *9*(12), 225.

Sagdic, K., Eş, I., Sitti, M., & Inci, F. (2022). Smart materials: rational design in biosystems via artificial intelligence. *Trends in Biotechnology*, *40*(8), 987-1003.

Salehian, M., Ovesy, H. R., & Dabiryan, H. (2024). Free vibration optimization of 2D tri-axial braided composite fan blade with ANN-Anal-FEM-GA integrated model. *Scientific Reports*, *14*(1), 28819.

Samoila, C., Ursutiu, D., & Tudorache, I. (2025). Evolution of the Fatigue Failure Prediction Process from Experiment to Artificial Intelligence: A Review. *Materials*, *18*(5), 1153.

Sani, A. R., Zolfagharian, A., & Kouzani, A. Z. (2024). Artificial intelligence-augmented additive manufacturing: insights on closed-loop 3D printing. *Advanced Intelligent Systems*, *6*(10), 2400102.

Schneller, W., Leitner, M., Maier, B., Grün, F., Jantschner, O., Leuders, S., & Pfeifer, T. (2022). Artificial intelligence-assisted fatigue failure prediction. *International Journal of Fatigue*, *155*, 106580.

Shen, Z., Lv, G., Fu, D., Long, Y., Zhang, Z., Tan, K., Li, L., Wang, Q., & Wang, C. (2023). A machine learning study on the fatigue crack path of short crack on an α titanium alloy. *Philosophical Transactions of the Royal Society* A, *381*(2260), 20220391.

Smolnicki, M., Lesiuk, G., Stabla, P., Pedrosa, B., Duda, S., Zielonka, P., & Lopes, C. C. C. (2023). Investigation of flexural behavior of composite rebars for concrete reinforcement with experimental, numerical, and machine learning approaches. *Philosophical Transactions of the Royal Society* A, *381*(2260), 20220394.

Tezsezen, E., Yigci, D., Ahmadpour, A., & Tasoglu, S. (2024). AI-based metamaterial design. *ACS Applied Materials & Interfaces*, *16*(23), 29547-29569.

Tveit, S., & Reyes, A. (2024). A submodeling technique for incorporating sheet metal forming effects in an AA5083 FPV structure. Structures,

Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T.-C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, *35*(7), 3833-3879.

Uysalel, C., Fox, Z., & Ghazinejad, M. (2024). Using AI Interactive Interfaces in Design of Machine Elements Education. 2024 ASEE Annual Conference & Exposition,

Wang, L., Zhu, S.-P., Luo, C., Niu, X., & He, J.-C. (2023). Defect-driven physics-informed neural network framework for fatigue life prediction of additively manufactured materials. *Philosophical Transactions of the Royal Society* A, *381*(2260), 20220386.

Wu, W., Yu, G., Gao, X., Wang, F., & Song, Y. (2024). Degradation of SiC/BN/SiC minicomposites in heat–stress–moisture–oxygen coupling environments, I: Static fatigue test study. *Journal of the European Ceramic Society*, *44*(8), 4916-4929.

Xu, G., & Guo, T. (2025). Advances in AI-powered civil engineering throughout the entire lifecycle. *Advances in Structural Engineering*, 13694332241307721.

Yahyaeian, A. A. (2023). *Enhancing Mechanical Engineering Education Through a Virtual Instructor in an AI-driven Virtual Reality Fatigue Test Lab*

Yu, H., Hu, Y., Kang, G., Peng, X., Chen, B., & Wu, S. (2024). High-cycle fatigue life prediction of L-PBF AlSi10Mg alloys: a domain knowledge-guided symbolic regression approach. *Philosophical Transactions of the Royal Society A*, *382*(2264), 20220383.

Yuan, C., de Jong, S. M., & van Driel, W. D. (2024). AI-assisted design for reliability: review and perspectives. 2024 25th International Conference on Thermal, Mechanical, and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE),

Zhou, T., Sun, X., & Chen, X. (2023). A physics-guided modeling method of artificial neural network for multiaxial fatigue life prediction under irregular loading. *Philosophical Transactions of the Royal Society A*, *381*(2260), 20220392.

Zinno, R., Haghshenas, S. S., Guido, G., & VItale, A. (2022). Artificial intelligence and structural health monitoring of bridges: A review of the state-of-the-art. *IEEE Access*, *10*, 88058-88078.