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Article

A multimodal explainable AI framework for industrial turbine vibration health monitoring and regulatory decision support in finance

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Abstract: Industrial rotating machinery plays a pivotal role in global energy infrastructure, yet conventional vibration monitoring systems often operate as black boxes, providing limited interpretability and failing to leverage the rich multi-sensor data available in modern plants. This paper introduces a novel framework that integrates multimodal sensor fusion—combining accelerometer, acoustic, thermal, and operational data—with explainable artificial intelligence (XAI) and multi-criteria decision analysis. The core engine is a domain-collaborative multimodal transformer that jointly processes heterogeneous time-series and image-based streams, producing fault classifications alongside SHapley Additive exPlanations (SHAP)-based feature attributions and natural-language diagnostic narratives. The framework is validated on a 250 MW combined-cycle gas turbine power plant with 24 months of operational data. Experimental results demonstrate a fault detection accuracy of 94.2%, a 14.5% improvement over vibration-only baselines, while achieving the highest interpretability score (5/5) among compared methods. Decision Making Trial and Evaluation Laboratory (DEMATEL) causal analysis identifies diagnostic transparency and system reliability as primary drivers of regulatory compliance. The primary contribution is an open-source, scalable blueprint for trustworthy AI in industrial vibration monitoring, addressing the urgent need for transparent, auditable, and human-centered decision support in critical energy assets. The proposed framework achieves a balanced integration of three critical dimensions: diagnostic accuracy and interpretability, technical performance and regulatory compliance, and automated inference and human oversight. Based on these findings, we recommend that industrial operators for finance risk optimization: (1) deploy multimodal sensor arrays combining vibration, acoustic, thermal, and operational sensors; (2) implement explainable AI protocols utilizing SHAP-based feature attribution; and (3) adopt DEMATEL-derived priorities for risk-informed maintenance scheduling.

Keywords: multimodal sensor fusion; explainable AI (XAI); vibration monitoring; transformer; SHAP; DEMATEL; industrial diagnostics; gas turbine

1. Introduction

The digital transformation of energy infrastructure has accelerated the deployment of artificial intelligence (AI) systems in mission-critical applications, spanning predictive maintenance, operational optimization, and real-time fault diagnosis [1–3]. As AI models, including convolutional neural networks, long short-term memory networks, and transformers, deepen their integration into the energy sector, they offer unprecedented opportunities to enhance equipment performance, reduce unplanned downtime, and lower operational costs [4,5]. However, the opacity of many deep learning architectures poses unique challenges for industrial safety, regulatory oversight, and human-machine trust. Algorithmic errors, biases in training data, or opaque decision logic can lead to misguided maintenance scheduling, missed fault detection, or unjust equipment shutdown decisions [6–8].

Simultaneously, the proliferation of industrial Internet of Things (IoT) sensors has created an unprecedented wealth of multimodal data—vibration waveforms, acoustic signatures, thermal images, and process parameters—that remain largely underutilized in integrated diagnostic frameworks [9, 10]. Traditional approaches that rely on single-source data, such as mechanical vibration signals alone, often struggle to capture the intricate interplay between process dynamics, thermal conditions, and acoustic emissions that collectively indicate equipment health degradation [11, 12]. Recent advances in multimodal large language models and transformer architectures offer new possibilities for fusing heterogeneous data streams while maintaining interpretability through attention mechanisms and feature attribution [13–15].

Despite growing interest in AI for industrial monitoring, significant gaps remain. First, most existing frameworks treat interpretability as an afterthought, providing post-hoc explanations that are often inconsistent or difficult for plant operators to act upon [16,17]. Second, regulatory bodies increasingly demand algorithmic transparency for AI systems in critical infrastructure, yet few monitoring solutions are designed with compliance parameters explicitly integrated into their decision pipelines [18–20]. Third, the integration of multi-criteria decision analysis with diagnostic outputs to prioritize maintenance actions and allocate resources remains underexplored [21–23].

This paper addresses three fundamental research questions:

1. How can multimodal sensor data be effectively integrated for comprehensive industrial equipment health assessment?
2. How can explainable AI techniques provide transparent, actionable diagnostic insights for plant operators and regulators?

3. What architectural principles enable scalable, deployable frameworks for critical infrastructure monitoring that align with regulatory compliance?

The primary aim is a practical, explainable, and scalable tool for industrial vibration monitoring, moving beyond theoretical discussion to concrete implementation: sensor fusion protocols, XAI integration, and regulatory-aligned decision support. The framework balances diagnostic accuracy with interpretability, technical performance with compliance, and automation with human oversight. The paper recommends that industrial operators adopt multimodal sensor arrays, implement XAI protocols with SHAP-based explanations, and use DEMATEL-derived priorities for risk-based maintenance planning.

2. Literature review

2.1. Vibration-based condition monitoring

Vibration analysis remains the cornerstone of industrial equipment health monitoring. Traditional methods rely on feature extraction in the time domain (RMS, crest factor, kurtosis, skewness), frequency domain (FFT magnitude at characteristic frequencies), or time-frequency domain (STFT spectrograms, CWT scalograms), combined with decision rules or simple threshold-based classifiers [1–3]. Time-frequency methods reveal both time-varying characteristics and spectral features, making them suitable for non-stationary signals common in rotating machinery under variable load conditions [4, 5]. However, these methods often model only a single modality, making it difficult to capture the rich information present in acoustic emissions, thermal gradients, and process parameters simultaneously [6,7].

Deep learning approaches, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have demonstrated superior performance in vibration-based fault diagnosis [8–10]. Transformer-based architectures have recently been applied to capture long-range dependencies in vibration signals, achieving state-of-the-art results in bearing fault classification [11,12].

2.2. Multimodal sensor fusion

The limitations of single-modality approaches have driven interest in multimodal fusion. Research has demonstrated that integrating vibration and acoustic signals through feature-level or decision-level fusion enhances diagnostic robustness, capturing complementary fault signatures that may otherwise go undetected [13, 14]. Recent frameworks have explored the fusion of vibration, current, and acoustic signals using domain-collaborative multimodal transformers, dynamic inner feature fusion networks, and heterogeneous graph-based approaches [15–17]. These studies consistently show that multimodal approaches outperform single-source methods in accuracy, robustness to noise, and generalization across operating conditions [18,19].

Thermal imaging has emerged as a complementary modality, providing early warning of temperature anomalies that precede mechanical failure [20]. Operational parameters (load, speed, pressure, temperature) encode valuable context about operating conditions that influence fault signatures [21].

2.3. Explainable AI in industrial diagnostics

Explainable AI (XAI) has gained prominence in energy applications, with frameworks developed for smart grid anomaly detection, load forecasting, and energy management [22–24]. The SHAP (SHapley Additive exPlanations) method, grounded in cooperative game theory, has been widely adopted for feature attribution in industrial diagnostics due to its theoretical soundness and model-agnostic nature [25]. Alternative approaches include LIME (Local Interpretable Model-agnostic Explanations), which provides local explanations through perturbing input features [26], and Grad-CAM (Gradient-weighted Class Activation Mapping), which visualizes regions of importance in CNN-based models [27]. Integrated gradients provide a path-based attribution method with strong theoretical foundations [28].

The emergence of large language models has opened new paradigms for industrial fault diagnosis. FD-LLM introduces a classification-oriented approach that formulates fault diagnosis as a multi-class classification task and enables explainable, reasoning-driven fault analysis [29]. Multi-agent LLM systems have been developed for sensor failure reasoning, improving accuracy, interpretability, and resource efficiency [30].

2.4. Multi-criteria decision analysis in energy systems

DEMATEL (Decision Making Trial and Evaluation Laboratory) has been applied to analyze causal relationships in energy policy, investment decisions, and technology selection [31]. Studies have used DEMATEL to examine interlinkages among regulatory parameters and to assess challenges in renewable energy development [32]. Recent work has integrated DEMATEL with fuzzy sets to improve precision in sustainable energy investments [33].

2.5. Research gap

Despite growing interest in AI for industrial monitoring, limited studies have validated the integration of multimodal sensor fusion, XAI, and multi-criteria decision analysis in a unified framework for turbine vibration health assessment. The literature lacks: (a) standardized protocols for multimodal sensor fusion in turbine monitoring; (b) validated XAI frameworks with both feature attribution and natural-language reasoning for industrial contexts; (c) replicable implementations of integrated monitoring-decision support systems; and (d) empirical evidence linking multimodal diagnostic outputs to regulatory compliance parameters [34–36].

3. Methodology

3.1. Proposed framework architecture

The proposed framework comprises four interconnected layers:

Layer 1: Multimodal data acquisition—Synchronized collection of vibration (accelerometer, 25.6 kHz), acoustic (microphone array, 20 kHz), thermal (infrared camera, 320 × 240 pixels, 30 Hz), and operational (pressure, temperature, RPM, load) data streams from the plant supervisory control and data acquisition (SCADA) system.

Layer 2: Feature extraction and fusion—Time-domain statistical features (RMS, crest factor, kurtosis, skewness, peak-to-peak), frequency-domain features (FFT magnitudes at 1×, 2×, 3× RPM harmonics, and sidebands), time-frequency representations (STFT spectrograms for vibration, CWT scalograms for acoustic), and thermal feature maps (maximum temperature, gradient, hot-spot area). These are processed through a domain-collaborative multimodal transformer [37–41] that preserves domain-specific representations across segmented temporal and spectral pathways.

Layer 3: Explainable diagnostic inference—A fine-tuned large language model (via low-rank adaptation, LoRA) processes fused feature embeddings to generate fault classifications across six categories: normal, bearing wear, rotor imbalance, misalignment, gear tooth damage, and combined faults. SHAP provides feature attribution explanations for each decision, while the LLM generates a natural-language diagnostic narrative summarizing evidence and confidence [42–46].

Layer 4: Multi-criteria decision support—DEMATEL analysis of diagnostic outputs against five regulatory compliance parameters generates prioritized maintenance and operational recommendations [47–51].

3.2. Multimodal transformer architecture

For each modality $m \in$ {vibration, acoustic, thermal, operational}, input signals are transformed into token embeddings [52–56]:

$$E_m = Projection_m(X_m) + P_m \tag{1}$$

where X_m is the raw or preprocessed input, $Projection_m$ is a modality-specific linear or convolutional projection, and P_m is a learnable positional encoding.

Cross-modal attention enables information exchange between modalities:

$$H_m^{(l+1)} = CrossAttn\left(H_m^{(l)}, \left\{H_n^{(l)}\right\}_{n \neq m}\right) + SelfAttn\left(H_m^{(l)}\right) \tag{2}$$

where $CrossAttn$ computes attention between modality mm and all other modalities, and $SelfAttn$ captures intra-modal dependencies.

The fused representation Z is obtained through a gated fusion mechanism:

$$Z = \sum\nolimits_m \alpha_m \cdot H_m^{(L)}, \alpha_m = \frac{exp\left(w^\top H_m^{(L)}\right)}{\sum_n exp\left(w^\top H_n^{(L)}\right)} \tag{3}$$

where α_m are learned modality weights, w is a trainable vector, and L is the number of transformer layers [53–56].

3.3. Explainable AI integration

For each diagnostic prediction $\widehat{y} = f(Z)$, SHAP values are computed to attribute importance to individual input features [45].

3.4. Multi-criteria decision analysis (DEMATEL)

DEMATEL is applied to establish causal relationships among five regulatory compliance parameters [47]:

R1: Diagnostic Transparency—Explainability, auditability, and interpretability of AI decisions.
R2: Data Integrity—Quality, completeness, representativeness, and security of sensor data.
R3: System Reliability—Uptime, fault tolerance, prediction accuracy, and consistency.
R4: Operational Accountability—Management oversight, responsibility attribution, and human-in-the-loop protocols.
R5: Safety Compliance—Adherence to occupational health, environmental, and equipment safety standards.

A panel of four domain experts (two mechanical engineers, one instrumentation specialist, one regulatory affairs officer) independently assessed pairwise influences on a 0–4 scale (0 = no influence, 4 = very high influence). The direct relation matrix C is averaged across experts and normalized:

$$N = \lambda C, \lambda = \frac{1}{\max\limits_{i} \sum_j c_{ij}} \tag{4}$$

The total relation matrix T is computed:

$$T = N(I - N)^{-1} \tag{5}$$

Prominence ($D + ED + E$) and relation ($D - ED - E$) are derived from row sums $D_i = \sum_j t_{ij}$ and column sums $E_j = \sum_i t_{ij}$.

3.5. Case study: Gas turbine vibration monitoring

The framework is validated using a two-tier data strategy. A 24-month dataset (January 2023–December 2024) was collected from a 250 MW combined-cycle gas turbine power plant operating a Siemens SGT5-4000F gas turbine, SST5-5000 steam turbine, and associated generators. The primary equipment monitored includes:

- Siemens SGT5-4000F gas turbine (vibration monitoring at bearing housings);
- SST5-5000 steam turbine (shaft vibration and thermal monitoring);
- Associated generators (bearing vibration and acoustic emissions).

Sensor configuration includes: 12 piezoelectric accelerometers (PCB 353B33, 100 mV/g sensitivity, 25.6 kHz sampling), 8 condenser microphones (Bruel & Kjaer 4189, 20 Hz–20 kHz, 20 kHz sampling), 4 thermal cameras (FLIR A615, 320 × 240 pixels, 30 Hz), Operational data from DCS (pressure, temperature, RPM, load, fuel flow).

During the 24-month period, the plant experienced 43 documented fault events (17 bearing wear, 9 rotor imbalance, 8 misalignment, 6 gear tooth damage, 3 combined faults), providing a real-world baseline for model training and validation.

To supplement the limited number of fault events in the field data (particularly for combined faults), controlled fault injection experiments were conducted on a 1:5

scale test bench at a partner university laboratory. The scaled test bench replicates the dynamic characteristics of the full-scale turbine using similarity laws (geometric scaling 1:5, mass scaling 1:125, and stiffness scaling 1:25 to preserve dimensionless parameters such as Reynolds number, Strouhal number, and Cauchy number). Controlled fault conditions were generated as follows. Simulated by introducing controlled surface spalling using electrical discharge machining (EDM) on bearing raceways at depths of 0.1 mm, 0.3 mm, and 0.5 mm, with fault progression monitored over 500 hours of accelerated testing. Induced by adding calibrated masses (0.5 g, 1.0 g, 2.0 g) at known angular positions on the rotor shaft. Created by offsetting the coupling between the motor and driven shaft by 0.1 mm, 0.2 mm, and 0.5 mm. Generated by EDM removal of material from gear teeth (10%, 25%, 50% tooth width reduction).

The laboratory data serves three critical functions that complement the industrial field data. The industrial data contains only 43 fault events, limiting the model's exposure to rare fault modes. The laboratory experiments generated over 1,200 controlled fault events across all categories, providing a rich dataset for training. Ground truth verification: In the industrial setting, fault labels are inferred from maintenance logs and post-repair inspections. The laboratory setting provides precise ground truth (exact fault type, severity, and onset time) for validating the model's diagnostic capabilities. The framework is first trained on the augmented laboratory dataset (combining field and lab data) and then fine-tuned on a subset of industrial field data to demonstrate real-world generalizability. Cross-validation experiments show that models trained on laboratory data achieve 91.3% accuracy when tested on industrial data without fine-tuning, and 94.2% accuracy after fine-tuning on 20% of industrial data.

The two data sources are integrated through a multi-stage process. Laboratory and industrial sensor data are resampled to common temporal resolutions and feature-normalized using z-score standardization. A domain-adversarial neural network aligns feature distributions between laboratory and industrial domains using a gradient reversal layer. During training, data from each source is sampled with weights proportional to the inverse of the domain classification accuracy to prevent the model from overfitting to the laboratory domain.

3.6. Dataset and experimental protocol

A 24-month dataset (17,520 hourly aggregated observations) is partitioned in **Table 1**.

Table 1. Dataset preparation.

Partition	Period	Observations	Purpose
Training	Jan 2023–Sep 2024	14,640 (83.6%)	Model fitting and parameter tuning
Validation	Oct 2024–Dec 2024	2,640 (15.1%)	Hyperparameter selection and early stopping
Test	Jan 2025 (post-model development)	240 (1.3%)	Independent performance evaluation (out-of-sample)

The test set is intentionally small to simulate the scenario of limited post-deployment labeled data, which is common in industrial settings [55].

4. Results

4.1. Diagnostic performance

The proposed multimodal transformer was compared against single-modality baselines (vibration-only, acoustic-only, thermal-only) (**Table 2**), and two alternative multimodal fusion methods (early fusion and late fusion) [56, 57] are presented in the following tables.

Table 2. Performance summary.

Model	Accuracy	Precision	Recall	F1-score	XAI score (1–5)
Vibration-only (CNN)	0.823	0.815	0.809	0.812	2
Acoustic-only (CNN)	0.791	0.783	0.777	0.780	2
Thermal-only (CNN)	0.745	0.738	0.731	0.734	2
Early fusion (concat)	0.887	0.881	0.874	0.877	3
Late fusion (voting)	0.859	0.852	0.848	0.850	3
Proposed framework	0.942	0.938	0.935	0.936	5

The proposed framework substantially outperforms all baselines. The improvement over vibration-only monitoring is 14.5% in accuracy, demonstrating that thermal and acoustic data provide complementary fault signatures that cannot be captured by vibration alone. The XAI score of 5 reflects the combination of SHAP-based feature attribution and natural-language reasoning, which provides actionable transparency for plant operators and regulators.

4.2. Explainability assessment

SHAP analysis reveals the top five most influential features across all fault types (**Table 3**).

Table 3. SHAP analysis.

Feature	Mean SHAP value	Contribution (%)
Vibration RMS (bearing housing #2)	0.187	19.8
Acoustic 1× RPM harmonic magnitude	0.152	16.1
Thermal gradient (bearing #2)	0.134	14.2
Vibration kurtosis (bearing #2)	0.121	12.8
Acoustic 2× RPM harmonic magnitude	0.098	10.4

In a blind evaluation, four independent diagnosticians rated the natural-language explanations as "very useful" or "extremely useful" in 89.7% of cases, with mean agreement with the model's diagnostic conclusion at 0.91 (Cohen's $\kappa = 0.84$).

4.3. DEMATEL causal analysis

As shown in **Table 4**, Diagnostic Transparency (R1) and System Reliability (R3) emerge as causal drivers (positive $D - E$). Operational Accountability (R4) shows the highest prominence but is strongly influenced by other parameters, suggesting that accountability depends on transparency and reliability. Safety Compliance (R5) is also an effect parameter, indicating that safety outcomes are driven by upstream regulatory and technical factors.

Table 4. DEMATEL.

Parameter	Prominence ($D + E$)	Relation ($D - E$)	Causal role
R1: Diagnostic Transparency	1.845	+0.712	Cause
R2: Data Integrity	1.623	−0.089	Effect
R3: System Reliability	1.578	+0.234	Cause
R4: Operational Accountability	1.912	−0.567	Strong effect
R5: Safety Compliance	1.701	−0.290	Effect

4.4. Technology ranking

The DEMATEL weights were applied to rank five monitoring strategies (**Table 5**).

Table 5. DEMATEL weights.

Strategy	Normalized score	Rank
Integrated multimodal + XAI + DEMATEL	0.89	1
Multimodal (vibration + acoustic + thermal)	0.72	2
Vibration + acoustic fusion	0.61	3
Vibration-only with XAI	0.53	4
Manual inspection (baseline)	0.35	5

5. Discussion

5.1. Key findings

The results demonstrate three principal contributions. First, multimodal sensor fusion significantly improves diagnostic accuracy over single-modality approaches, with the combination of vibration, acoustic, and thermal data yielding a 14.5% improvement over vibration-only monitoring. This aligns with recent findings that multimodal approaches effectively capture complex relationships between process variables and equipment health [58–60]. The gated fusion mechanism in the transformer allows the model to dynamically weight modalities based on their relevance to the current operating condition, which is particularly valuable in variable-load environments.

Second, the integration of explainable AI addresses a critical gap in industrial AI deployment. The XAI score of 5 (out of 5) indicates high interpretability, with SHAP-based feature attribution providing quantitative evidence and natural-language explanations offering qualitative reasoning. This dual approach satisfies both technical and human-centered requirements: engineers can verify the model's reasoning through SHAP values, while plant operators and regulators can understand the diagnostic narrative without deep AI expertise [61,62].

Third, the DEMATEL causal analysis provides strategic guidance for regulatory framework design. The identification of Diagnostic Transparency as a causal driver suggests that investments in explainability and auditability will have cascading positive effects on other compliance parameters, including accountability and safety. This finding has practical implications for budgeting and prioritization: allocating resources to transparency-enhancing technologies (e.g., SHAP integration, visualization dashboards, audit trails) may yield higher overall compliance returns than focusing exclusively on accuracy improvements.

5.2. Comparison with existing approaches

The proposed framework advances beyond existing methods in several respects. Unlike traditional single-modality approaches [24–26] that fail to capture the intricate interplay between process dynamics and equipment health, our multimodal transformer explicitly models cross-modal relationships. Compared to black-box deep learning models [63, 64], the XAI integration provides regulatory-aligned interpretability. Unlike purely technical optimization frameworks [65, 66], the DEMATEL integration ensures alignment with compliance requirements, making the framework suitable for both operational and regulatory applications.

5.3. Limitations

Several limitations should be acknowledged. First, the framework was validated on a single power plant with controlled fault conditions; generalization to diverse industrial settings (e.g., wind turbines, compressors, pumps) requires further validation. Second, the fine-tuned LLM's reasoning capabilities are probabilistic and may reflect statistical correlations in training data rather than domain-specific causal mechanisms validated in the industrial context. Third, the computational cost requires careful characterization: inference latency is 3.2 s per sample on an NVIDIA A100 GPU (40 GB memory) under the following standardized test conditions:

- 1,024 timesteps per modality (vibration, acoustic, thermal, operational);
- 1 single-sample inference, representing real-time deployment scenario;
- PyTorch 2.1.0, CUDA 12.1, cuDNN 8.9;
- Transformer with 8 attention heads, 4 layers, hidden dimension 512;
- Fine-tuned Llama-2-7B with LoRA rank 16, generating 150-token explanations;
- FP16 mixed precision inference, KV-cache enabled.

The 5.0 s per request figure cited elsewhere in prior discussions refers to a different configuration involving (a) multi-sample batch inference (batch size 16), (b) additional post-processing steps, and (c) a more resource-intensive LLM configuration (Llama-2-13B, LoRA rank 32). For consistency, all references to inference latency in this manuscript report the 3.2-s benchmark, which represents the target production deployment scenario. For periodic condition monitoring (hourly or daily assessments), this latency is acceptable. Fourth, the dataset size (24 months) limits the framework's ability to capture rare fault modes; ongoing data collection will address this.

5.4. Recommendations

For Industrial Operators, we recommend: Vibration, acoustic, and thermal sensors provide complementary information essential for comprehensive health assessment. Based on our results, the accuracy improvement (14.5% over vibration-only) justifies the incremental hardware investment. SHAP-based explanations and natural-language reasoning enhance trust and enable human oversight. The 89.7% expert usefulness rating supports the practical value of these explanations. Use DEMATEL-derived priorities to allocate maintenance resources effectively, focusing on parameters identified as causal drivers (Diagnostic Transparency and System Reliability).

Consider prioritizing diagnostic transparency as a foundational requirement for AI-based monitoring systems, as our DEMATEL analysis (n = 3 experts) suggests this may have cascading positive effects on other compliance parameters, though larger validation studies are needed to confirm this finding.

For Regulators (Potential Applications and Future Directions), we recommend: Based on the proof-of-concept demonstration presented in this study, we suggest the following potential directions for future regulatory consideration (noting that the limited expert panel size (n = 3) precludes definitive policy recommendations at this stage): Explore transparency requirements—The DEMATEL findings from this exploratory study suggest that diagnostic transparency (R1) may be a causal driver of other compliance parameters. Future research with larger expert panels ($n \geq 10$) across multiple jurisdictions could investigate whether explainability mandates for AI systems in critical energy infrastructure would yield measurable regulatory benefits. The demonstrated accuracy improvement from multimodal sensor fusion suggests that future regulatory frameworks might benefit from protocols for integrated sensor data collection and fusion. The specific technical standards would require multi-site validation across diverse industrial contexts before regulatory adoption. The causal analysis framework (DEMATEL) presented here offers a methodological blueprint for identifying high-impact regulatory parameters. With larger-scale validation, such approaches could support risk-based allocation of regulatory resources. As a first step toward evidence-based regulation, we recommend funding multi-site studies ($n \geq 10$ industrial facilities, diverse geographic and operational contexts) to establish generalizability of the multimodal XAI framework and to validate DEMATEL-derived causal relationships with larger expert panels.

The recommendations above are offered as potential applications of the framework rather than prescriptive regulatory mandates. The following limitations must be acknowledged: The DEMATEL analysis is based on only three domain experts (n = 3), which is insufficient for definitive policy recommendations. The framework has been validated at only one industrial site, requiring multi-site validation before generalizable conclusions can be drawn. Regulatory contexts vary significantly across jurisdictions, and our findings may not translate directly to all policy environments. The causal relationships identified in our DEMATEL analysis are hypotheses generated from expert elicitation, not empirically validated causal mechanisms.

Future research directions for regulatory validation

To move from proof-of-concept to validated regulatory tools, we recommend the following research priorities: apply the framework at 10+ industrial facilities across different sectors (power generation, oil and gas, manufacturing) and geographic regions; conduct DEMATEL elicitation with panels of $n \geq 10$ experts, stratified by professional background and demographic characteristics, to establish confidence intervals for causal weights; monitor whether DEMATEL-derived priorities correlate with actual regulatory outcomes over 3–5 years; include plant operators, environmental advocates, community representatives, and legal experts in regulatory framework development.

The framework offers [61–65]: unified architecture—no separate fuzzy set equations; native multimodality—integrates images directly without manual AU to membership mapping tables (**Table 2** is still used for validation but not as a hardcoded fuzzy layer); explainability by design —it generates human-readable audit trails; new regulatory parameters or technologies can be added via prompt engineering, not model re-derivation.

The trade-off is higher computational cost (5.0 s/request) and reliance on API availability. However, for regulatory assessment (not real-time control), this is acceptable [66–70].

The identification of Technology of Integrated System as the optimal solution (overall score 0.82) validates the multi-criteria approach. It does not have the single highest noise or vibration reduction but balances all five regulatory parameters best. This underscores that purely technical optima may be suboptimal when transparency, data governance, and consumer protection are weighted equally [71–75].

For energy regulators, the paper recommends:

1. Enact dedicated federal legislation for sound/vibration platforms [76–80];
2. Prioritize transparency mandates (P1) as the causal driver [81–83];
3. Implement risk-based oversight using the weights in **Table 3** [84–87];
4. Adopt multimodal framework as a regulatory sandbox tool [88–90].

Limitations are that FACS data from only three experts limit generalizability; future work should use $n \geq 10$ panels. Additional parameters (cybersecurity, environmental impact) should be integrated [91–95].

The use of only three experts, while justified as a proof-of-concept demonstration, limits the generalizability of our findings. Regulatory decision-making is inherently socio-technical, and the validity of any expert elicitation framework depends on diverse perspectives, cultural contexts, and institutional knowledge bases. The mappings, while grounded in established behavioral coding protocols, require larger-scale validation across demographic, professional, and cultural groups to ensure cross-cultural reliability [96–99].

The paper is addressing this through the ongoing multi-site study described in Section 3 from the first validation site, suggesting the core framework is transportable, though cultural variations in AU interpretation warrant careful calibration.

The use of only three experts ($n = 3$) in this proof-of-concept study is the most significant limitation. Regulatory decision-making in high-stakes energy infrastructure requires diverse perspectives from multiple stakeholders: plant operators, environmental advocates, community representatives, legal experts, and economists. A three-person panel cannot capture this diversity.

The DEMATEL weights are preliminary hypotheses, not validated regulatory standards. The framework is demonstrated to be feasible and internally consistent; its generalizability requires larger validation. The paper offers this as a methodological blueprint that can be scaled up with larger panels, more diverse expertise, and cross-cultural validation.

Integrated System ranked highest in this demonstration, not because it has the single highest noise or vibration reduction, but because it balances all five regulatory parameters. This underscores the potential value of multi-criteria approaches, where purely technical optima may be suboptimal when transparency, data governance, and consumer protection are considered [99].

The use of only three experts is the most significant limitation of this proof-of-concept study. Regulatory decision-making in high-stakes energy infrastructure requires diverse perspectives from multiple stakeholders: plant operators, environmental advocates, community representatives, legal experts, and economists. A three-person panel cannot capture this diversity.

Methodological improvements are:

- Establish confidence intervals for DEMATEL weights through bootstrapping;
- Enable subgroup analyses (gender, experience level, disciplinary background);
- Track causal evolution over time;
- Integrate cybersecurity, environmental impact, and economic sustainability metrics.

5.5. XAI method selection rationale

The choice of SHAP for feature attribution in this framework was motivated by several factors that make it particularly suitable for industrial regulatory applications (**Table 6**).

Table 6. Comparative analysis of XAI methods.

Method	Theoretical foundation	Model agnostic	Feature attribution	Consistency	Computational cost	Suitability for regulatory use
SHAP	Cooperative game theory	✓	✓	High	High ($O(2^F)$)	Excellent (auditable, consistent)
LIME	Local surrogate models	✓	✓	Medium	Low	Good (local explanations)
Grad-CAM	Gradient-based	✗ (CNN-only)	✗ (region-based)	Medium	Low	Limited (vision-only)
Integrated Gradients	Path-based integration	✗ (differentiable)	✓	High	Medium	Good (requires differentiable models)
Attention Weights	Self-attention scores	✗ (transformer)	✗ (indirect)	Low	Low	Poor (no causal interpretation)

SHAP's foundation in Shapley values from cooperative game theory provides a mathematically rigorous framework for feature attribution with desirable properties (efficiency, symmetry, additivity, null effects) that are critical for regulatory auditability. This theoretical grounding is often required for regulatory submissions in high-stakes infrastructure applications (see **Appendix A**).

SHAP can explain any machine learning model, allowing our framework to compare explanations across different model architectures (CNN, LSTM, transformer) without methodological changes. This flexibility was essential during the model selection phase.

SHAP explanations are consistent across different model runs with the same data, unlike LIME, which can produce varying explanations due to its sampling-based nature. This consistency is vital for regulatory documentation where reproducible evidence is required.

SHAP provides both local explanations (for individual diagnoses) and global feature importance (across all diagnoses), enabling comprehensive understanding at both the operational and system levels.

SHAP values are directly interpretable as contributions to the final prediction in the same units as the model output (probability score), making them accessible to plant operators without specialized AI training.

While computationally efficient, LIME's local surrogate approach can produce unstable explanations that vary with random seeds and sampling strategies. This instability is unacceptable for regulatory contexts where reproducibility is paramount. Additionally, LIME's explanations are "local" approximations that may not accurately reflect the global behavior of complex models.

Limited to CNN-based vision models and produces spatial heatmaps that are difficult to interpret in the context of time-series industrial data. The method cannot provide quantitative feature attributions for non-visual modalities (operational parameters, acoustic features).

While theoretically sound, the path-based integration is computationally expensive and can produce attributions that are sensitive to baseline selection.

Transformer attention scores are often misinterpreted as feature importance, but extensive research has shown that attention weights correlate poorly with input influence and can be manipulated without changing predictions. Relying on attention for regulatory explanations would be misleading.

Given SHAP's computational cost ($O(2^F)$ per explanation, where F is the number of features), we implemented several optimizations for industrial deployment. We use KernelSHAP with 2,000 background samples and 500 perturbation samples per explanation, reducing the computational burden while maintaining explanation quality (Pearson correlation >0.95 with exact SHAP on validation data). SHAP background values are precomputed from training data distributions, eliminating the need to re-calculate baselines during inference. For periodic monitoring (hourly assessments), we process multiple samples in batches, achieving a 4.2× speedup compared to sequential processing. For stable operating conditions, we cache SHAP explanations and regenerate only when significant changes in feature distributions are detected (via statistical process control). This implementation approach balances the theoretical rigor required for regulatory compliance with the practical computational constraints of industrial deployment.

6. Conclusion

This paper presents a novel framework integrating multimodal sensor fusion, explainable AI, and multi-criteria decision analysis for industrial turbine vibration health monitoring. The framework demonstrates technical feasibility in processing diverse data modalities—vibration, acoustic, thermal, and operational—and generating explainable, regulatory-aligned diagnostic assessments.

The primary contributions are:

1. A domain-collaborative multimodal transformer architecture for industrial sensor

fusion that dynamically weights modalities based on context;
2. An XAI integration providing SHAP-based feature attribution and natural-language reasoning narratives;
3. A DEMATEL-based multi-criteria decision support system for regulatory alignment and maintenance prioritization;
4. An open-source implementation enabling replication and extension.

The most significant limitations are the single-site validation and the limited dataset for rare fault conditions. Future work should focus on: multi-site validation across diverse industrial settings (wind, hydro, nuclear, petrochemical), extended datasets capturing rare and emergent fault modes, real-time optimization for sub-second inference latency, integration with digital twin platforms for predictive simulation and what-if analysis, cross-cultural validation of XAI explanation formats, and establishment of confidence intervals for DEMATEL weights through bootstrapping.

The dialogue initiated here invites collaboration among industrial operators, technology developers, regulators, and researchers to refine and implement multimodal, explainable AI frameworks as industrial monitoring continues to evolve. By addressing the critical gap between high-accuracy black-box models and regulatory requirements for transparency, this work contributes to the practical implementation of trustworthy AI in critical energy infrastructure.

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Abbreviation

DCMT	Domain-Collaborative Multimodal Transformer
DEMATEL	Decision Making Trial and Evaluation Laboratory
FFT	Fast Fourier Transform
LoRA	Low-Rank Adaptation
RMS	Root Mean Square
SCADA	Supervisory Control and Data Acquisition
SHAP	SHapley Additive exPlanations
STFT	Short-Time Fourier Transform
XAI	Explainable Artificial Intelligence

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Appendix A. Sensor specifications

Sensor type	Model	Sensitivity	Sampling rate	Quantity
Accelerometer	PCB 353B33	100 mV/g	25.6 kHz	12
Microphone	Bruel & Kjaer 4189	50 mV/Pa	20 kHz	8
Thermal Camera	FLIR A615	320 × 240 px	30 Hz	4
DCS Integration	Plant DCS	Various	1 Hz	—