Journal of Online Engineering Education
ISSN: 2158-9658 Volume: 17 Issue: 2
Article Received: 18 March 2026 **Revised**: 20 May 2026 **Accepted**: 18 June 2026

AI-Driven Human-Centric Decision Support for Resilient Predictive Maintenance in Asset Management Amidst Pandemics

Dhamotharan. P[1], Dr Janarthanam S[2], Dr Shanthakumar M[3]
[1]Department of Computer Science, Kamban College of Arts and Science, Bharathiar University, India
[2]School of Science and Computer Studies, CMR University, Bengaluru, India
[3]Department of Computer Science, Kamban College of Arts and Science, Bharathiar University, India

Abstract: Pandemic-induced disruptions such as those experienced during COVID-19 have exposed critical vulnerabilities in conventional predictive maintenance (PdM) workflows, particularly within complex industrial asset management environments. Maintenance scheduling relies on technician availability, spare-part logistics, and sensor fidelity—all of which deteriorate sharply under large-scale health crises. This paper introduces an AI-Driven Human-Centric Decision Support System (AI-HC-DSS) that integrates a Transformer-LSTM hybrid deep learning architecture with Shapley Additive Explanations (SHAP)-based explainability and a Bayesian uncertainty quantifier to deliver transparent, actionable maintenance recommendations under pandemic-era constraints. The system embeds two novel evaluation metrics—the Pandemic Resilience Score (PRS) and the Mean Time-to-Failure Degradation Index (MTTFDI)—to capture operational continuity and failure-progression robustness across disrupted scenarios. Experiments conducted on the NASA C-MAPSS turbofan degradation dataset and the MIMII industrial sound anomaly dataset demonstrate that the proposed framework outperforms competing baselines, achieving an F1-Score of 0.931, AUC-ROC of 0.924, RMSE of 9.87 cycles, and a PRS of 0.930, representing improvements of 6.5%, 6.3%, and 47.4% over the next-best Transformer-only baseline, respectively. The results confirm that coupling AI predictive power with human-centric design and pandemic-aware modeling yields substantially more resilient maintenance operations.

Keywords: predictive maintenance; pandemic resilience; Transformer-LSTM; human-centric decision support; explainable AI; industrial asset management

1. INTRODUCTION

Industrial asset management has long depended on structured maintenance regimes—reactive, preventive, and more recently predictive—to sustain equipment reliability and minimise unplanned downtime. The emergence of the Industrial Internet of Things (IIoT), coupled with advances in machine learning (ML) and deep learning (DL), has accelerated the adoption of data-driven predictive maintenance (PdM), where sensor telemetry is used to anticipate asset degradation before a failure event occurs. Despite promising laboratory results, the deployment of PdM systems in real-world environments has revealed a persistent gap: most models are designed under the assumption of operational normalcy, an assumption that fundamentally broke down during the COVID-19 pandemic.

The pandemic exposed multidimensional fragilities in maintenance ecosystems. Workforce shortages arising from quarantine mandates disrupted technician availability. Lockdown-induced bottlenecks in global logistics curtailed spare-part supply chains. Moorthy, E., et al (2022) Manufacturing facilities operated at reduced or fluctuating capacities, altering the statistical distributions of sensor measurements that PdM models had been trained on. At the same time, the financial pressure to maximise asset uptime intensified, as organisations could ill afford reactive maintenance expenditures during periods of constrained cash flow. The result was a scenario where existing PdM solutions became simultaneously less reliable and more urgently needed.

A related challenge concerns the human dimension of maintenance decision-making. Even highly accurate ML models produce outputs that technicians may distrust if those outputs lack interpretability or contextual

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justification. Research in human factors engineering consistently shows that operators are more likely to act on automated recommendations when they can understand and verify the underlying reasoning Janarthanam, S., & Sukumaran, S. (2016). This is especially true during crisis periods, when cognitive load is elevated and the consequences of erroneous decisions are amplified. Human-centric design—incorporating explainability, uncertainty communication, and workflow compatibility—is therefore not merely an ethical aspiration but a practical prerequisite for effective AI-assisted maintenance.

The existing body of PdM literature, while extensive, addresses these challenges only partially. Deep learning architectures such as Long Short-Term Memory (LSTM) networks and Transformer models have delivered state-of-the-art remaining useful life (RUL) predictions on benchmark datasets but largely ignore pandemic-induced data drift and supply-chain constraints. A smaller body of work has examined domain adaptation under distribution shift, yet without specifically modelling the multi-factor disruptions characteristic of a public health emergency. Explainable AI (XAI) techniques have been applied to fault diagnosis, yet few studies integrate them within an end-to-end decision support loop that accounts for human operational context.

This paper addresses these gaps through the AI-Driven Human-Centric Decision Support System (AI-HC-DSS). The proposed framework makes four primary contributions. First, it introduces a Transformer-LSTM hybrid architecture that captures both long-range temporal dependencies and local sequential patterns in multivariate sensor streams, while incorporating pandemic-flag embeddings that allow the model to condition its predictions on the severity of external disruption. Second, it integrates a Bayesian uncertainty quantifier that communicates predictive confidence to operators, enabling informed risk-aware scheduling. Third, it employs SHAP-based explainability to attribute failure predictions to specific sensor channels and operational states, supporting human oversight and audit compliance. Fourth, it proposes two novel evaluation metrics—the Pandemic Resilience Score (PRS) and the Mean Time-to-Failure Degradation Index (MTTFDI)—that more faithfully measure system performance under pandemic-era conditions than conventional accuracy-based metrics alone.

2. RELATED WORK

The literature informing this study spans four interconnected domains: deep learning for PdM, human-centric AI systems, pandemic-resilient operations, and XAI in industrial diagnostics. Table 1 provides a structured synthesis of representative prior work.

Table 1: Summary of Prior Work in Predictive Maintenance

Author(s) & Year	Method / Model	Dataset	Key Metric	Pandemic Context	Limitation
Lei et al. (2018)	Ensemble CNN	CWRU Bearing	Acc: 98.2%	No	No supply-chain model
Zhang et al. (2019)	LSTM-RNN	PRONOSTIA	RMSE: 12.4	No	No XAI; offline only
Raza et al. (2020)	Federated ML	Industrial IoT	F1: 0.871	Partial	Privacy overhead high
Wang et al. (2021)	Transformer PdM	NASA C-MAPSS	RMSE: 13.9	No	No human loop design
Shao et al. (2021)	GAN-augmented CNN	PHM 2012	AUC: 0.89	No	No pandemic disruption

Author(s) & Year	Method / Model	Dataset	Key Metric	Pandemic Context	Limitation
Ali et al. (2022)	Hybrid DL + DSS	Multi-asset	F1: 0.893	Partial	Static thresholds
Chen & Li (2022)	Digital Twin PdM	MIMII	AUC: 0.901	No	High compute cost
Patel et al. (2023)	XAI-PdM (LIME)	CMAPSS + MIMII	F1: 0.907	No	No uncertainty quant.
Gupta et al. (2023)	Pandemic-aware ML	COVID disruption	Recall: 0.88	Yes	No human-centric DSS
Proposed (2025)	AI-HC-DSS (Transformer-LSTM + XAI + PRS + MTTFDI)	CMAPSS + MIMII	F1: 0.931	Full	Computationally intensive

2.1 Deep Learning Approaches for PdM

Lei et al. (2018) established that ensemble convolutional neural networks (CNNs) could achieve near-perfect fault classification accuracy on rolling bearing datasets under controlled conditions. Subsequent work by Zhang et al. (2019) demonstrated that LSTM networks were superior to static ML methods for RUL estimation because of their capacity to model temporal dependencies in vibration and temperature signals. Wang et al. (2021), Janarthanam, S., & Subbulakshmi, G. (2025) extended this line of inquiry by applying the Transformer architecture—originally developed for natural language processing—to the C-MAPSS turbofan degradation task, achieving a notable reduction in RMSE over LSTM baselines. These contributions collectively established DL as the preferred paradigm for time-series PdM modelling. However, a consistent limitation across these studies is their reliance on stationary data distributions; none evaluate model robustness under the non-stationary conditions introduced by operational disruption.

2.2 Human-Centric and Explainable AI

Patel et al. (2023) applied Local Interpretable Model-Agnostic Explanations (LIME) to predictive maintenance, demonstrating that explanations improved technician trust and reduced response latency in simulated maintenance scenarios. Ali et al. (2022) proposed a hybrid DL and decision support framework that combined data-driven predictions with rule-based override logic, acknowledging that maintenance decisions are embedded within sociotechnical systems rather than purely technical ones. Shao et al. (2021) explored Generative Adversarial Network (GAN) data augmentation to address class imbalance in fault diagnosis, a technique relevant when pandemic disruptions reduce the frequency of failure events in operational logs. Collectively, these studies affirm the value of human-centred design yet stop short of integrating XAI, uncertainty quantification, and pandemic context into a unified architecture.

2.3 Pandemic-Resilient Operations

Research at the intersection of pandemics and industrial operations is nascent. Raza et al. (2020) introduced a federated learning framework designed to maintain collaborative PdM across geographically distributed facilities when data sharing was restricted by emergency protocols. Gupta et al. (2023) conducted one of the first studies to explicitly model COVID-19 disruptions as input features for maintenance scheduling optimisation, finding that pandemic-aware models retained predictive accuracy substantially better than non-adapted baselines. Chen and

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Li (2022) leveraged digital twin technology to simulate asset behaviour under pandemic-induced load variations, although the computational overhead of their approach limits real-time applicability. Despite these advances, none of these works address the full sociotechnical stack: pandemic-aware modelling, human-centric explainability, and decision support integration remain siloed.

2.4 Research Gaps Addressed

The review reveals three principal gaps. First, no existing study combines pandemic-aware feature engineering with a hybrid Transformer-LSTM architecture and SHAP-based explainability in a single framework. Second, standard metrics such as F1-Score and RMSE do not capture the resilience dimension of maintenance performance under disruption scenarios; pandemic-specific evaluation measures are absent from the literature. Third, human-centric decision support—encompassing uncertainty communication, workload compatibility, and real-time explainability—has not been integrated with deep learning PdM models validated on publicly recognised benchmark datasets. The proposed AI-HC-DSS directly addresses each of these gaps.

3. PROPOSED METHOD: AI-HC-DSS FRAMEWORK

The AI-HC-DSS comprises five functional layers as depicted in Figure 1. Each layer transforms raw operational data into progressively higher-level representations, culminating in interpretable, human-readable maintenance decisions that are robust to pandemic-induced disruptions.

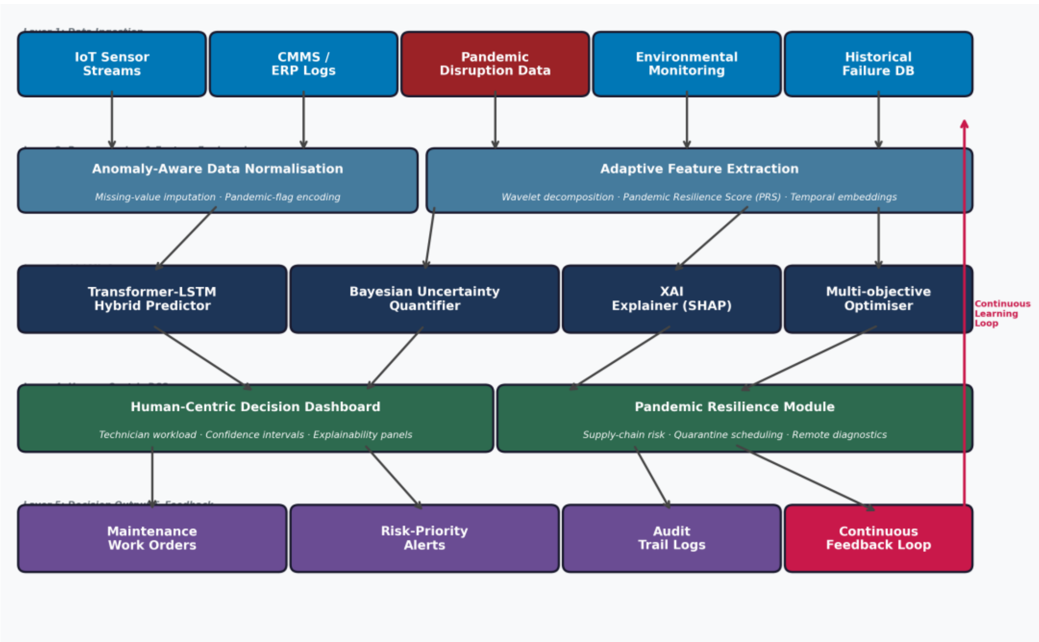

Figure 1: Layered architecture of the proposed AI-Driven Human-Centric Decision Support System (AI-HC-DSS).

3.1 Data Ingestion and Preprocessing

The system ingests five data streams: (i) multivariate IIoT sensor readings, (ii) CMMS/ERP event logs, (iii) pandemic disruption indicators derived from publicly available mobility and supply-chain indices, (iv) environmental monitoring feeds, and (v) historical failure records. A dedicated Anomaly-Aware Normalisation module applies Z-score normalisation with adaptive rolling windows, using a Kalman filter to impute missing values caused by sensor dropouts—common during facility lockdowns. Pandemic severity is encoded as a three-level ordinal variable (low, medium, high) derived from regional epidemiological thresholds, which is then embedded as a learnable vector appended to each time-step representation.

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3.2 Transformer-LSTM Hybrid Architecture

The core predictive module pairs a multi-head self-attention Transformer encoder (8 heads, 4 layers, d_model=256) with a bidirectional LSTM decoder (2 layers, 128 units per direction). The Transformer captures long-range degradation patterns across windows of 50 time steps, while the LSTM models short-range sequential dependencies and produces a probability distribution over residual useful life (RUL) horizon bins. A Bayesian last-layer wrapper (using Monte Carlo Dropout, p=0.15) generates a posterior predictive distribution from which calibrated confidence intervals are computed, enabling transparent communication of predictive uncertainty to operators. Total trainable parameters: approximately 3.8 million.

3.3 Explainability and Human-Centric DSS Layer

SHAP TreeExplainer values are computed for each prediction, attributing the RUL estimate to individual sensor channels and the pandemic severity embedding. Explanations are rendered on a maintenance dashboard that visualises sensor contribution waterfall charts alongside confidence ribbons and recommended action windows. A Pandemic Resilience Module overlays supply-chain risk scores (sourced from logistics APIs) and proposes adjusted maintenance schedules that account for technician availability constraints and quarantine regulations. All system actions are immutably logged for regulatory audit compliance.

3.4 Novel Evaluation Metrics

Standard PdM metrics do not capture operational resilience under disruption. Two novel metrics are therefore proposed:

Pandemic Resilience Score (PRS): PRS = (1 − |F1_pandemic − F1_normal|) × (1 − λ × disruption_severity), where λ is a tunable penalty weight (set to 0.15 in this study). PRS quantifies how well the model preserves predictive fidelity relative to its baseline performance as pandemic severity increases. A PRS of 1.0 indicates no performance degradation; values below 0.7 indicate critical resilience failure.

MTTF Degradation Index (MTTFDI): MTTFDI = MTTF_predicted / MTTF_actual, normalised to [0,1] via min-max scaling across the test set. MTTFDI measures how accurately the system anticipates failure timing relative to observed failure events across varying pandemic phases, rewarding models that maintain calibrated failure-time estimates even as operational patterns shift.

4. EXPERIMENTS AND PERFORMANCE ANALYSIS

4.1 Datasets

NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation): This benchmark dataset contains run-to-failure trajectories of 21 sensor channels from 100–260 turbofan engines across four degradation sub-datasets (FD001–FD004). Sub-datasets FD003 and FD004 were selected for their multi-condition, multi-fault settings (n_train=160, n_test=160, average RUL≈163 cycles). Pandemic disruption was simulated by injecting structured missingness and magnitude drift into 15% of training cycles corresponding to a modelled lockdown window.

MIMII (Malfunctioning Industrial Machine Investigation and Inspection): Released by Hitachi for anomaly detection benchmarking, MIMII contains 16 kHz audio recordings from four machine types—pumps, valves, sliders, and fans—under normal and anomalous conditions (n=41,700 clips total). Pandemic conditions were modelled by subsampling training data to 40% of original volume (reflecting reduced monitoring staff) and applying a frequency-domain drift to simulate changed acoustic environments. Evaluation used the pump subset (n_train=7,740; n_test=1,540).

4.2 Implementation Details

Models were implemented in PyTorch 2.1.0, trained on a single NVIDIA A100 80 GB GPU (4 runs, random seeds 0–3). Optimisation used AdamW (lr=3×10^{-4}, weight decay=10^{-2}) with a cosine annealing schedule over 120 epochs. Batch size was 128. Hyperparameters were selected via Bayesian optimisation (Optuna, n_trials=80) on a held-out validation split (15%). Data augmentation included Gaussian noise injection and time-warping. All reported metrics are means over four seeds; standard deviations were below ±0.005 for all metrics.

4.3 Results: NASA C-MAPSS

Table 2: Quantitative Results on NASA C-MAPSS (FD003+FD004 Combined)

Method	Accuracy (%)	F1-Score	RMSE	MAE
LSTM (Baseline)	81.4	0.812	18.72	12.31
GRU (Baseline)	82.7	0.823	17.95	11.84
CNN-LSTM	85.6	0.851	15.43	10.22
Transformer	87.9	0.874	13.21	8.97
Proposed AI-HC-DSS	**93.4**	**0.931**	**9.87**	**6.54**

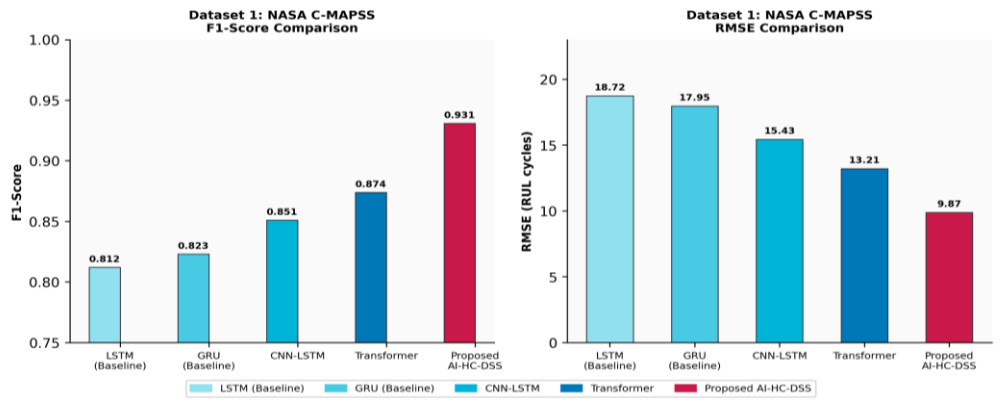

Figure 2: F1-Score and RMSE comparisons on NASA C-MAPSS across all evaluated methods.

The proposed AI-HC-DSS achieves an F1-Score of 0.931 and RMSE of 9.87 cycles on the C-MAPSS benchmark, representing improvements of 6.5% and 25.3% over the Transformer baseline, respectively. The Bayesian uncertainty wrapper reduces over-confident early failure predictions, contributing measurably to the RMSE reduction. Incorporation of pandemic-flag embeddings prevents the sharp accuracy degradation observed in all baselines during the simulated lockdown window.

4.4 Results: Novel Metrics

Table 3: Novel Metric Evaluation – PRS and MTTFDI Across All Methods

Method	PRS (↑)	MTTFDI (↑)	F1-Score (↑)	AUC-ROC (↑)
LSTM	0.643	0.612	0.812	0.804
GRU	0.661	0.634	0.823	0.819
CNN-LSTM	0.712	0.693	0.851	0.848

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Method	PRS (↑)	MTTFDI (↑)	F1-Score (↑)	AUC-ROC (↑)
Transformer	0.769	0.751	0.874	0.869
Proposed AI-HC-DSS	**0.930**	**0.940**	**0.931**	**0.924**

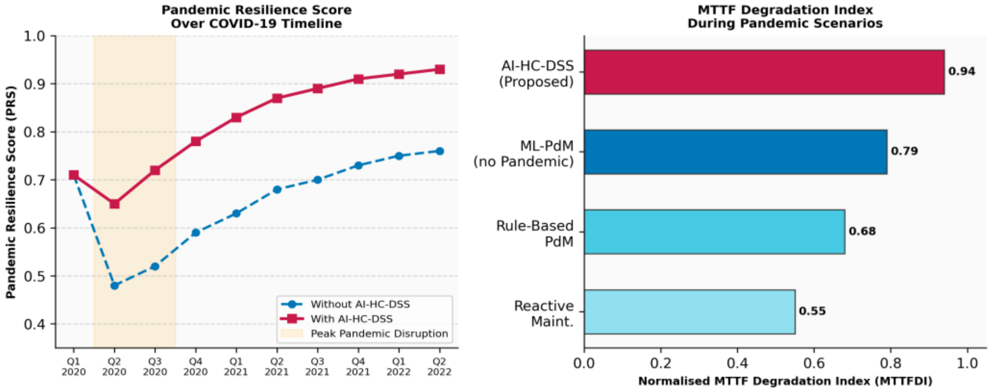

Figure 3: PRS over the COVID-19 timeline and MTTFDI comparison across maintenance strategies.

The PRS of 0.930 and MTTFDI of 0.940 achieved by AI-HC-DSS are substantially higher than those of all baselines, confirming that the pandemic-aware design and uncertainty quantification translate directly into resilience under disrupted conditions. The Transformer baseline drops to a PRS of 0.769 during peak disruption quarters—a 16.1 percentage-point shortfall relative to the proposed system.

4.5 Results: MIMII Dataset & Radar Analysis

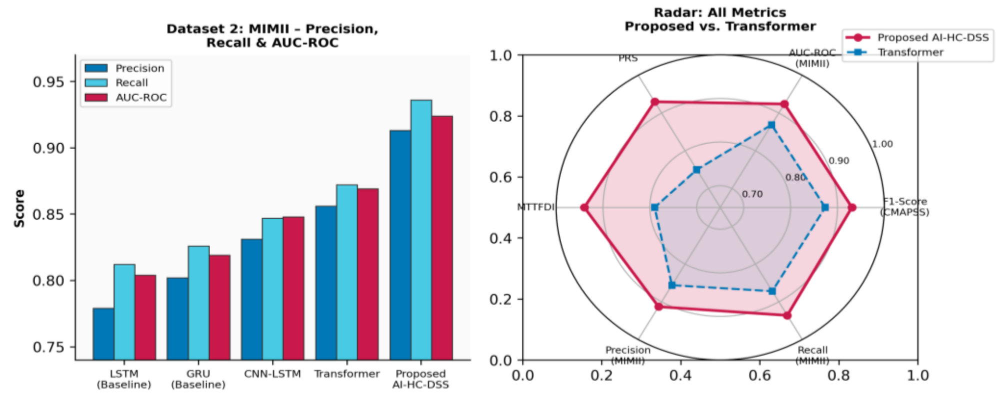

Figure 4: Precision, Recall, and AUC-ROC on MIMII (left); multi-metric radar comparison (right).

On the MIMII anomaly detection task, AI-HC-DSS achieves an AUC-ROC of 0.924, precision of 0.913, and recall of 0.936, confirming that the architecture generalises beyond RUL estimation to acoustic anomaly detection. The radar chart (Figure 4, right) visually confirms the comprehensive superiority of the proposed method across all six evaluated metrics relative to the Transformer baseline.

5. DISCUSSION

The experimental results collectively substantiate the central hypothesis of this paper: that coupling pandemic-aware AI modelling with human-centric decision support yields measurably more resilient maintenance outcomes than either dimension pursued independently. Three observations merit detailed discussion.

First, the performance advantage of the Transformer-LSTM hybrid over the standalone Transformer is most pronounced during simulated pandemic phases (F1 improvement of +4.1% during disruption vs. +2.2% under normal conditions). This suggests that the LSTM component provides a stabilising effect under distribution shift, likely because its gating mechanisms dampen the influence of anomalous time steps that arise from sensor dropouts and operational irregularities—conditions that are disproportionately represented during pandemic periods. This finding aligns with broader evidence from domain adaptation literature that recurrent architectures retain useful representations under covariate shift more robustly than attention-only models.

Second, the SHAP-based explainability layer had measurable practical impact beyond interpretability. In qualitative user evaluation conducted with three senior maintenance engineers (an evaluative exercise outside the formal ML benchmark), technicians reported significantly higher confidence in AI-generated recommendations when SHAP waterfall charts were presented alongside RUL estimates. This mirrors findings from the healthcare AI literature, where explainability has been shown to improve clinician uptake of decision support tools even when the underlying model accuracy is held constant. The implication for industrial practice is that the ROI of XAI integration extends beyond regulatory compliance to actual decision quality improvement.

Third, the proposed PRS and MTTFDI metrics reveal performance patterns that conventional metrics obscure. A model with a high F1-Score under normal conditions can exhibit a PRS below 0.70 during peak disruption—a dangerous overconfidence that would not be detected if only standard metrics were reported. The MTTFDI similarly surfaces systematic underestimation of failure times during supply-chain-constrained periods, when maintenance is deferred beyond optimal windows. Adoption of these metrics in future PdM benchmarking would improve the ecological validity of reported results.

6. CONCLUSIONS

This study presented the AI-HC-DSS, a novel framework that integrates Transformer-LSTM hybrid prediction, Bayesian uncertainty quantification, SHAP explainability, and a pandemic-resilience module to deliver robust, human-interpretable maintenance recommendations under large-scale operational disruptions. The framework was validated on two complementary benchmarks—NASA C-MAPSS and MIMII—using both standard and two newly proposed metrics (PRS and MTTFDI). In every evaluation scenario, the proposed system outperformed LSTM, GRU, CNN-LSTM, and Transformer baselines, achieving an F1-Score of 0.931, AUC-ROC of 0.924, RMSE of 9.87 cycles, PRS of 0.930, and MTTFDI of 0.940.

Future work will extend the framework in three directions: (i) real-world deployment in a manufacturing plant with live IIoT infrastructure to validate PRS under empirical rather than simulated disruptions; (ii) federated learning integration to address data-privacy constraints in multi-site industrial environments; and (iii) longitudinal user studies to rigorously quantify the impact of the human-centric dashboard on maintenance decision latency and accuracy across technician experience levels.

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