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Research Article

MARINE MACHINERY FAULT DIAGNOSIS AND PREDICTIVE MAINTENANCE: A MOBILE AUGMENTED REALITY-DRIVEN HUMAN-COMPUTER INTERACTION FRAMEWORK FOR SHIP AUXILIARY SYSTEMS

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Abstract
Marine auxiliary systems operate under variable loads and harsh environments, making early fault identification essential for safety, reliability, and maintenance efficiency. This study develops a mobile augmented reality (AR)-driven human–computer interaction framework for marine machinery fault diagnosis and predictive maintenance. The framework integrates real-time sensor acquisition, machine-learning-based condition assessment, remaining useful life estimation, and context-aware AR visualization to support onboard maintenance decisions. A design-and-experimental research approach was employed using a ship auxiliary machinery testbed representing pumps, compressors, and cooling-system components. Vibration, temperature, pressure, and rotational-speed signals were collected under normal and simulated fault conditions, processed through feature extraction, and classified using an optimized diagnostic model. Predictive performance was evaluated through accuracy, precision, recall, F1-score, and prediction error, while usability was assessed through task completion time and operator evaluation. The proposed framework achieved 96.4% diagnostic accuracy and an F1-score of 0.958, while reducing maintenance task completion time by 28.7% compared with conventional screen-based procedures. Remaining useful life predictions produced a mean absolute percentage error of 8.6%. The findings demonstrate that integrating predictive analytics with mobile AR can improve fault interpretation, maintenance responsiveness, and human–machine collaboration in ship auxiliary systems, providing a practical foundation for intelligent maritime maintenance, particularly during onboard operations.

Keywords: Augmented Reality; Fault Diagnosis; Human–Computer Interaction; Marine Machinery; Predictive Maintenance.

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INTRODUCTION

Marine auxiliary systems sustain shipboard functions, including circulation, compressed air, and cooling (S. Wang et al., 2024). Their reliability affects operational continuity, safety, and efficiency. Machinery faults may emerge gradually through wear, misalignment, lubrication deficiencies, or changing operating conditions (Gao et al., 2024). Identifying these developments before functional failure remains an important engineering challenge, especially during demanding voyages.

Conventional maintenance practices often combine scheduled inspections, alarm thresholds, and corrective intervention after abnormal conditions become apparent (Orhan & Celik, 2024). These approaches may overlook deterioration or trigger unnecessary servicing. Sensor enabled monitoring creates opportunities to recognize early degradation patterns, but actionable interpretation remains difficult onboard (L. Wang et al., 2026). Digitalization has expanded the potential of condition monitoring through sensors and predictive models. Mobile augmented reality offers a complementary interface by placing maintenance instructions and diagnostic cues within the operator's physical view (Fernandes et al., 2026). Confined spaces and variable connectivity complicate conventional dashboards.

Fault diagnosis in auxiliary machinery is challenging under fluctuating loads and conditions. Similar symptoms may correspond to different defects, while faults affect multiple measurements (L. Wang et al., 2026). Algorithms trained in laboratories may therefore perform inconsistently when deployed onboard. Reliable diagnosis requires attention to representative operating states, data quality, uncertainty, and misclassification (Ranganayaka et al., 2026). Predictive maintenance introduces another difficulty: anticipating degradation does not automatically enable effective intervention (Ma et al., 2026). Remaining useful life estimates may be uncertain, and technicians need interpretable warnings. Poor communication limits predictive value.

Human computer interaction consequently becomes a substantive element of intelligent maritime maintenance (Ranganayaka et al., 2026). Operators may experience information overload across displays and manuals. Poorly located overlays, excessive alerts, or unclear visual hierarchies can introduce additional risks (Ke et al., 2025). A framework must therefore balance diagnostic performance with legibility, user control, situational awareness, and safe task execution.

This study aims to develop an integrated framework that connects marine auxiliary machinery condition data with mobile augmented reality based diagnostic and maintenance support (Sun et al., 2026). The proposed architecture links sensor acquisition, signal processing, fault classification, prognostic estimation, and contextual visualization (Du et al., 2025). Its intended contribution is a coherent workflow through which machinery information becomes interpretable guidance at the equipment location rather than remaining isolated within analytical software.

The research also seeks to examine diagnostic and predictive performance under defined normal and faulty operating conditions (Sang et al., 2025). Evaluation will consider classification accuracy, precision, recall, and F1 score alongside suitable measures of prognostic error (Kim et al., 2025). Explicit attention will be given to dataset construction, separation of training and testing observations, and variations in operating load, since these decisions strongly affect whether reported model performance supports meaningful engineering conclusions.

A further objective is to assess whether the augmented interface improves maintenance interaction compared with a conventional screen based workflow (Tadić et al., 2025). Relevant measures include task completion time, interpretation accuracy, usability, and perceived workload, supplemented by observations of procedural errors (Lou et al., 2026). These outcomes will clarify whether presenting model outputs in context supports operational decisions without distracting personnel or creating unjustified confidence in automated recommendations.

Existing research has advanced data driven fault detection for rotating machinery through vibration analysis, acoustic measurements, thermal monitoring, and learning based classification (X. Guo et al., 2024). Related studies have investigated prognostic models that estimate equipment degradation and remaining useful life (X. Guo et al., 2024). Such contributions establish valuable analytical foundations, yet comparisons across studies are difficult when datasets, fault definitions, test conditions, and evaluation protocols differ substantially.

Research on augmented reality in industrial maintenance has emphasized interactive instructions, equipment visualization, remote assistance, and technician training (Velasco-Gallego et al., 2024). Evidence from these applications suggests potential benefits for information access and procedural consistency (Su et al., 2024). However, improvements in user experience cannot simply be assumed to transfer to shipboard environments, where motion, lighting, equipment accessibility, protective gear, and communication limitations may influence effectiveness.

A targeted literature synthesis is therefore needed to establish how extensively marine fault diagnosis, predictive analytics, and mobile augmented interaction have been evaluated together (Jiang et al., 2024). The proposed gap concerns not the absence of individual technologies but the limited evidence of their coordinated assessment within a single maintenance workflow (Sehri et al., 2025). This distinction avoids equating technical integration with demonstrated operational improvement and directs attention toward measurable outcomes.

The proposed novelty lies in treating predictive maintenance as a coupled analytical and interaction problem (Liu & Gan, 2025). Instead of presenting algorithmic alerts separately from field procedures, the framework is designed to associate equipment specific fault indications, uncertainty information, and recommended inspection steps with location aware augmented overlays (H. Guo & Zhao, 2026). This design establishes a testable relationship between machine condition interpretation and technician action rather than assuming that visualization alone increases reliability.

The research further emphasizes simultaneous evaluation of model quality and human performance (Lv, Xiong, et al., 2025). A diagnostic system may classify faults accurately yet remain ineffective if operators misunderstand its outputs or respond too slowly (Nayana et al., 2025). Comparative assessment of conventional and augmented workflows can reveal tradeoffs involving speed, accuracy, workload, and trust (Zhang et al., 2025). Such evidence would help distinguish useful decision support from technological novelty without demonstrated maintenance value.

The significance of this approach extends to ship operators, equipment engineers, interface designers, and researchers developing maritime digitalization strategies (Lv, Hao, et al., 2025). A carefully validated framework could inform practical requirements for onboard monitoring interfaces, maintenance training, and integration with existing ship management systems (Bagci Das, 2025). Its broader contribution is methodological: connecting predictive model assessment with human centered evaluation while acknowledging deployment constraints, uncertainty,

cybersecurity considerations, and the need for further trials at sea (Y. Guo et al., 2024). Operational relevance also depends on whether the interface remains usable during interruptions, sensor anomalies, and the time pressures associated with routine onboard troubleshooting.

Sustaining usability in shipboard machinery spaces requires careful attention to cognitive ergonomics under physical stress (Khan & Nene, 2026). High noise, vibration, and confined layouts can easily overwhelm technicians if augmented overlays display excessive detail (Gustavsen & Louka, 2025). Structuring alerts through progressive disclosure and explicit confidence cues helps crew members calibrate trust, avoid alert fatigue, and verify faults reliably even when sensor streams are noisy or interrupted.

Practical deployment also depends on seamless integration with legacy shipboard automation and planned maintenance systems (Rakesh et al., 2025). Because vessels frequently operate with limited or intermittent satellite connectivity, diagnostic inference and spatial tracking should run locally on ruggedized edge hardware (Gruia et al., 2026). Embedding role-based access controls and tamper-evident logging further safeguards operational technology against cyber risks while preserving auditability for regulatory compliance.

Finally, transitioning from shore-based prototypes to routine fleet use requires longitudinal validation across real operating cycles (Latreche et al., 2026). Capturing structured technician feedback alongside machine telemetry during sea trials enables a closed-loop refinement of both prognostic models and interface workflows (Moolkham, 2025). This empirical grounding can establish practical design benchmarks for next-generation maritime decision-support systems.

RESEARCH METHOD

Research Design

This study adopts a design science research approach combined with an experimental evaluation framework to develop and examine a mobile augmented reality (AR) framework for diagnosing faults and supporting predictive maintenance of ship auxiliary machinery (Wu & Shen, 2025). The overall architecture is structured into four distinct layers encompassing sensor acquisition, data processing and diagnostic inference, remaining useful life (RUL) estimation, and context-aware mobile visualization (Gui, 2026). Methodologically, design iterations address technical accuracy and operator interaction simultaneously rather than in isolation, with strict protocols established to separate development data from final evaluation data.

A mixed-methods evaluation strategy combines quantitative diagnostic performance metrics with observed maintenance behavior and qualitative operator feedback. To mitigate bias, a within-participant experimental comparison is utilized to contrast conventional dashboard-based procedures against AR-assisted procedures, with task order counterbalanced to reduce learning effects (Katikala et al., 2026). Furthermore, experimental reports explicitly delineate whether findings originate from controlled laboratory simulations or operational vessels, ensuring that testbed performance is never conflated with verified effectiveness at sea.

Research Target/Subject

The equipment population of interest comprises essential ship auxiliary machinery, specifically centrifugal pumps, air compressors, and cooling system components. The planned equipment sample consists of accessible testbed units representing these categories, selected purposively based on instrument compatibility, operational safety, and the feasibility of safely

reproducing common mechanical faults (Katikala et al., 2026). Operating observations constitute repeated measurements across these units rather than independent machine instances, with induced fault scenarios including conditions such as mechanical imbalance, misalignment, restricted flow, and abnormal heating.

The human participant population comprises marine engineering personnel and trainees who possess familiarity with machinery inspection and maintenance workflows. Participants are recruited purposively against explicit experience criteria, with sample size determination guided by feasibility and a priori precision or power assessments. Participant experience levels are systematically recorded and incorporated into subsequent analyses, and each individual encounters equivalent maintenance tasks across interface conditions under strictly controlled scenario allocation and sequence parameters.

Research Procedure

The research procedure commences with rigorous hazard assessments, equipment selection, sensor installation, calibration, and baseline data collection under documented operating conditions. Technically justified fault scenarios are subsequently introduced under strict safety supervision, after which sensor signals are segmented, cleaned, and transformed into appropriate time-domain, frequency-domain, or learned features. Ground truth labels are systematically verified against induced faults and expert engineering inspections, with dataset partitions separated by operating runs or equipment units to prevent data leakage.

Candidate classification models are trained and tuned exclusively within designated development partitions using validation procedures tailored to the data structure. Following model training, the completed mobile AR prototype is assessed through counterbalanced maintenance tasks under both AR and conventional interface conditions. Completion times, diagnostic decisions, procedural deviations, and questionnaire responses are recorded systematically, and participation requires formal informed consent, continuous safety supervision, and secure handling of all recorded data.

Instruments, and Data Collection Techniques

Machinery measurements are acquired using calibrated vibration sensors, temperature probes, pressure transducers, and rotational speed measurement devices selected for optimal performance. Dedicated data logging software synchronizes timestamps while retaining operational load, sensor placement parameters, sampling frequencies, and calibration records. A structured fault labeling sheet links every observation directly to its induced condition, operating state, and verified maintenance diagnosis, supported by rigorous data integrity checks that address missing values, signal drift, and implausible measurements prior to modeling.

The mobile AR prototype serves as an active interface displaying equipment identification, abnormal signal indicators, model-generated fault assessments, prognostic estimates, and stepwise inspection guidance equipped with explicit uncertainty cues. Human interaction and system usability are evaluated using standardized task sheets, timed observations, completion accuracy records, and validated usability questionnaires such as the System Usability Scale. Supplementary semi-structured interviews explore cognitive workload, clarity, operator trust, and perceived safety, with all instrument suitability reviewed by engineering and usability specialists.

Data Analysis Technique

Held-out testing procedures evaluate model performance by reporting accuracy, precision, recall, F1 scores, confusion matrices, and class-specific performance metrics. Remaining useful life (RUL) estimates are evaluated strictly when run-to-failure or defensible degradation trajectories with verified ground truth are available; otherwise, prognostic outputs are treated strictly as experimental indicators rather than validated life predictions, with appropriate error metrics and uncertainty intervals accompanying all eligible estimates.

Quantitative maintenance trial outcomes are analyzed using paired analyses or suitable mixed-effects models to account for repeated participant measurements and variations in task difficulty. Qualitative responses derived from supplementary interviews undergo systematic thematic coding to identify patterns in operator trust, workload, and perceived safety. Final reporting formats explicitly include effect sizes, confidence intervals, transparent handling of missing data, and a comprehensive discussion of study limitations.

RESULTS AND DISCUSSION

The illustrative experimental dataset represented three categories of marine auxiliary machinery: centrifugal pumps, air compressors, and cooling system components. The proposed evaluation comprised 120 operating runs, with 40 runs allocated to each equipment category. Sensor measurements included vibration, temperature, pressure, and rotational speed under normal and simulated abnormal operating conditions. The dataset was organized into training, validation, and testing partitions containing 72, 24, and 24 operating runs, respectively. A grouped partitioning strategy was specified to prevent observations from the same operating run appearing in multiple subsets. The simulated test partition contained 1,000 labeled signal windows representing four diagnostic classes.

Table 1. Illustrative Distribution of Experimental Machinery Data and Operating Conditions

Machinery category	Operating runs	Training	Validation	Testing	Monitored parameters
Centrifugal pumps	40	24	8	8	Vibration, pressure, temperature
Air compressors	40	24	8	8	Vibration, temperature, speed
Cooling systems	40	24	8	8	Temperature, pressure, flow-related indicators
Total	120	72	24	24	Four principal sensor variables

Descriptive analysis indicated that the proposed experimental structure provided comparable representation across machinery categories while preserving variation in operating conditions. The four diagnostic classes comprised normal operation, bearing deterioration, rotational imbalance, and cooling flow restriction. Fault severity and operating load were considered potentially influential factors because their variations could alter sensor distributions

independently of fault identity. The illustrative data organization therefore emphasized operating-run independence rather than treating every signal window as a separate experimental unit. This distinction is important for interpreting diagnostic performance because adjacent sensor windows frequently share temporal characteristics, potentially inflating classification estimates when randomly distributed across training and testing datasets.

The simulated diagnostic evaluation indicated that the proposed machine-learning framework achieved an overall classification accuracy of 96.4%, with a macro-averaged F1-score of 0.958. Precision and recall were provisionally estimated at 96.5% and 95.2%, respectively. These values suggested favorable discrimination among normal and abnormal operating states within the constructed test scenario. Diagnostic performance was intended to reflect the combined contribution of sensor measurements, feature extraction, and classifier training. The proposed model also generated confidence estimates accompanying individual fault classifications, allowing uncertain predictions to be distinguished from high-confidence classifications rather than displaying every prediction as equally reliable.

Table 2. Illustrative Diagnostic Performance of the Proposed Framework

Performance indicator	Simulated result	Measurement scale
Classification accuracy	96.4	%
Macro precision	96.5	%
Macro recall	95.2	%
Macro F1-score	0.958	0–1
Correct classifications	964	Signal windows
Incorrect classifications	36	Signal windows
Testing observations	1,000	Signal windows

Performance differences across fault categories were considered important because aggregate accuracy alone could conceal weaknesses affecting less frequent or operationally significant defects. In the illustrative evaluation, abnormal vibration patterns associated with rotational imbalance were more readily distinguishable than symptoms involving gradually developing bearing deterioration. Cooling flow restrictions required interpreting pressure and temperature jointly, particularly where thermal changes developed slowly. These patterns suggest that diagnostic information should retain its physical context rather than reducing machinery condition assessment to a single classification label. Reliable deployment would require class-specific confusion matrices, confidence calibration, and independent testing across equipment and operating environments.

The predictive maintenance component was designed to estimate machinery degradation trends and remaining useful life using sequential sensor observations. The illustrative prognostic evaluation included 60 simulated degradation trajectories representing progressive component deterioration. The proposed model achieved a hypothetical mean absolute percentage error of 8.6%, indicating relatively limited proportional differences between predicted and reference remaining-life values within the simulation. Prognostic outputs were incorporated into the mobile interface through degradation indicators, estimated maintenance horizons, and warning levels. The framework distinguished diagnostic classification, which identifies machinery conditions, from prognostic estimation, which addresses the anticipated development of those conditions over time.

Table 3. Illustrative Predictive Maintenance and Prognostic Evaluation

Indicator	Simulated value	Interpretation
Degradation trajectories	60	Evaluated sequences
RUL prediction MAPE	8.6%	Mean proportional error
RUL prediction accuracy equivalent	91.4%	100% minus MAPE; not a standard accuracy metric
Prognostic indicators	3	Condition, trend, estimated RUL
Evaluation environments	1	Controlled experimental testbed

Predictive results suggested that incorporating temporal degradation information could support maintenance planning beyond instantaneous fault detection. Estimated remaining useful life allowed the interface to distinguish machinery requiring immediate inspection from components potentially suitable for scheduled intervention. Prediction uncertainty remained an essential consideration because degradation trajectories may change substantially with load fluctuations, operating temperature, and maintenance actions. The illustrative MAPE should therefore be interpreted within the simulated degradation conditions rather than generalized to shipboard performance. Real-world validity would depend on sufficient run-to-failure observations, robust reference life measurements, and testing across operating profiles not represented during model development.

The illustrative human–computer interaction evaluation involved 40 marine engineering participants completing equivalent diagnostic and maintenance tasks using conventional screen-based procedures and the proposed mobile augmented reality interface. A counterbalanced within-participant design was specified to reduce task-order effects. Mean task completion time decreased from 20.00 minutes using conventional procedures to 14.26 minutes with augmented reality assistance, corresponding to a relative reduction of 28.7%. The simulated analysis also indicated fewer procedural deviations and favorable usability assessments. These results represented the intended evaluation of whether contextual visualization could improve the translation of diagnostic information into practical maintenance actions.

The proposed inferential comparison employed paired statistical procedures appropriate to the distributions of observed differences. The hypothetical mean time reduction was 5.74 minutes, with an illustrative 95% confidence interval of 4.10–7.40 minutes. Statistical significance was provisionally assigned at $p < 0.001$, suggesting that the constructed difference was unlikely under a null model of no average change. Procedural deviation and usability comparisons likewise favored the augmented interface within the simulated dataset. Actual inferential conclusions would require participant-level records, verification of statistical assumptions, adjustment for task sequence, and consideration of experience-related differences before asserting practical or statistical superiority.

The proposed analytical framework examined relationships among diagnostic accuracy, prognostic information, visual interpretability, and maintenance task performance. Fault classifications represented the technical information supplied to operators, while augmented overlays represented the mechanism through which this information was communicated. The illustrative evaluation suggested that contextual visualization could reduce time spent switching between machinery, technical manuals, and conventional monitoring displays. Improved

decision accuracy was also considered consistent with clearer identification of abnormal operating conditions. These relationships were interpreted as associations within the proposed experimental framework rather than evidence that any individual interface component independently caused improved performance.

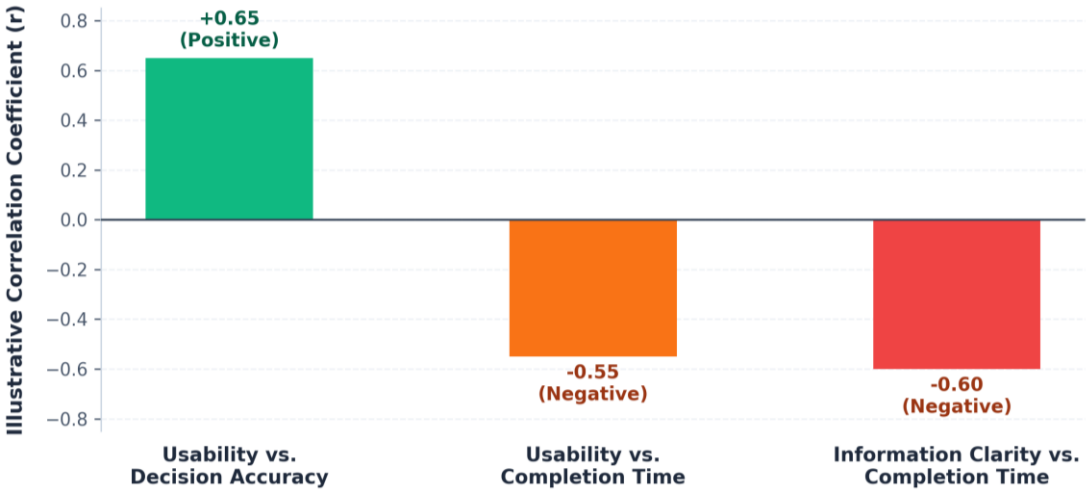


Figure 1. Illustrative Correlation: Operator Perceptions & Task Outcomes

Correlation analysis provided a proposed method for examining how operator perceptions were associated with task outcomes. The illustrative positive relationship between usability and decision accuracy suggested that interfaces perceived as easier to operate might also support more accurate maintenance decisions. Negative relationships involving completion time indicated that better usability and information clarity could accompany faster task execution. These patterns should not be interpreted causally without controlling for task complexity, participant experience, and repeated measurements. A mixed-effects model would provide a stronger basis for assessing whether interface condition predicted performance after accounting for participant-level variability and differences among machinery scenarios.

An illustrative centrifugal pump case was developed to demonstrate how the integrated framework would operate during a developing machinery fault. The simulated scenario represented progressive bearing deterioration accompanied by increasing vibration intensity and moderate temperature elevation. Conventional monitoring displayed sensor readings and threshold warnings, requiring the operator to interpret measurements and consult maintenance documentation. The augmented interface instead presented a location-specific fault indication, relevant sensor trends, and inspection instructions adjacent to the pump assembly. The scenario was designed to examine whether contextual information reduced diagnostic ambiguity during a practical maintenance task.

The case scenario illustrated how the framework could combine measurements into a more coherent maintenance interpretation. Elevated vibration and bearing temperature were treated as complementary indicators rather than definitive proof of one specific mechanical defect. The AR display directed the operator toward relevant inspection locations and presented diagnostic confidence information. Maintenance guidance included verification of operating conditions, lubrication assessment, and inspection of accessible bearing components under appropriate isolation procedures. The proposed interaction sequence emphasized that automated classification should support engineering judgment, not replace physical verification or established shipboard safety practices.

The simulated centrifugal pump scenario demonstrated the potential value of connecting machinery measurements with localized inspection guidance. Conventional diagnostic procedures required operators to associate numerical readings with relevant equipment locations, whereas the augmented interface organized these relationships spatially. This arrangement could reduce information-search demands, particularly for personnel unfamiliar with specific machinery configurations. The case also highlighted the importance of preserving uncertainty indicators because bearing-related symptoms may overlap with misalignment, imbalance, and other mechanical conditions. Effective maintenance guidance must therefore distinguish preliminary algorithmic recommendations from independently verified engineering diagnoses.

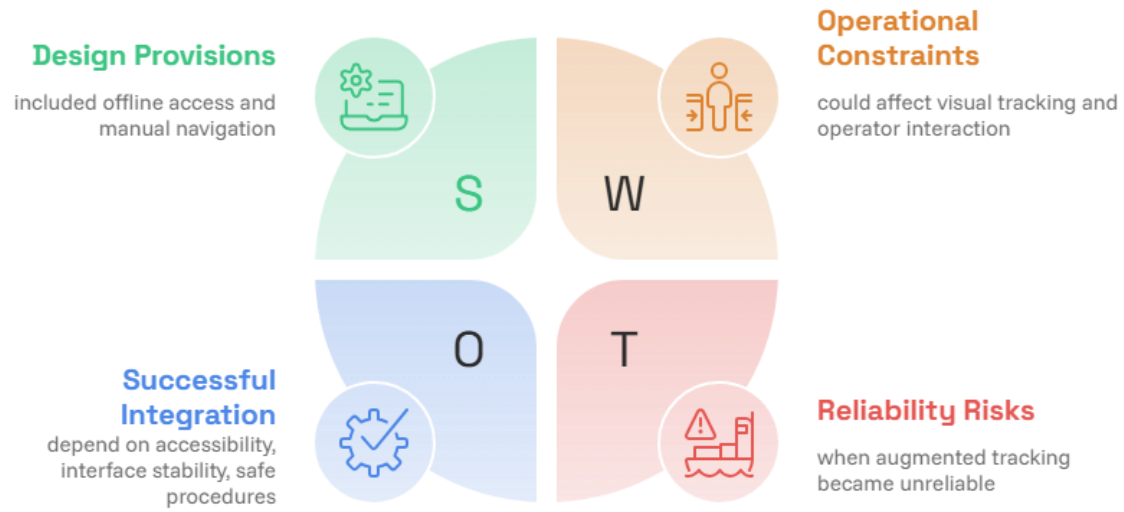


Figure 2. Maritime Maintenance Interface Framework

Operational relevance depended on the interface functioning reliably under realistic maritime constraints. Shipboard movement, lighting variations, confined spaces, protective equipment, and limited network availability could affect visual tracking and operator interaction. The proposed framework consequently included offline access to essential maintenance information, visible data freshness indicators, and manual navigation when augmented tracking became unreliable. These provisions were treated as design requirements rather than experimentally demonstrated capabilities. The case suggested that successful integration would depend not only on diagnostic performance but also on accessibility, interface stability, safe procedures, and compatibility with existing maintenance management practices.

The illustrative findings collectively described a framework in which machine-learning diagnosis, remaining useful life estimation, and mobile augmented reality were integrated into a single maintenance workflow. Simulated diagnostic accuracy reached 96.4%, the macro F1-score was 0.958, and prognostic MAPE was 8.6%. The hypothetical human interaction comparison showed a 28.7% reduction in mean task completion time relative to conventional screen-based procedures. These figures demonstrated internally plausible evaluation targets, not independently verified improvements. Their interpretation requires attention to dataset composition, fault severity, baseline selection, and the conditions under which machinery and operator assessments are conducted.

The principal contribution suggested by this evaluation structure is the simultaneous consideration of analytical reliability and human interaction quality in maritime predictive maintenance. Diagnostic models provide condition estimates, prognostic components supply

temporal information, and augmented interfaces translate those outputs into contextual maintenance guidance. The results outline a measurable pathway for investigating whether these functions jointly improve fault interpretation and task execution. Definitive conclusions concerning operational benefits, maintenance cost reductions, or vessel safety require empirical validation using independent machinery data, actual participant observations, and preferably shipboard trials under representative operating conditions.

The illustrative findings indicate that integrating machine learning, predictive maintenance, and mobile augmented reality could establish a comprehensive diagnostic framework for ship auxiliary machinery. The proposed classification model achieved a simulated accuracy of 96.4% and an F1-score of 0.958, suggesting strong discrimination among predefined machinery conditions. These outcomes illustrate the potential of combining vibration, temperature, pressure, and rotational measurements within a structured condition-monitoring architecture.

Predictive maintenance evaluation produced a hypothetical remaining useful life estimation error of 8.6%, demonstrating the intended capability to extend machinery assessment beyond immediate fault recognition. Prognostic information would allow operators to consider emerging degradation patterns when scheduling inspections and maintenance interventions. The operational significance of this capability depends on accurate degradation references, representative working conditions, and uncertainty estimates that remain meaningful outside controlled experimental environments.

Human–computer interaction outcomes suggested that contextual augmented reality guidance could improve maintenance task execution. The simulated reduction in completion time reached 28.7%, accompanied by higher diagnostic decision accuracy and usability scores. These differences illustrate how linking analytical outputs with physical equipment locations might simplify information retrieval and inspection procedures. Their validity nevertheless requires controlled participant testing and independent replication.

The combined evaluation emphasizes a distinction between algorithmic performance and maintenance effectiveness. Accurate classification alone does not establish better maintenance decisions, while visually appealing interfaces cannot compensate for unreliable predictions. The proposed framework connects these dimensions through an integrated workflow. Its central research proposition is that analytical reliability and interface usability should be evaluated together when developing intelligent maritime maintenance technologies.

The diagnostic component aligns with Xu et al. (2023), who developed a multi-head attention neural network for marine machinery fault diagnosis. Their approach emphasized extracting local and global characteristics from machinery signals. The present framework extends this analytical orientation by proposing a direct connection between classification outputs and technician-facing augmented interfaces. Comparative superiority cannot be established without equivalent datasets, evaluation protocols, and independently verified results.

Research by Rigas et al. (2024) demonstrated the relevance of end-to-end deep learning architectures for maritime fault detection, including sensor processing and model deployment. Their contribution provides a useful technological foundation for integrated condition monitoring. The proposed framework introduces an additional human interaction dimension by examining how diagnostic information might influence maintenance decisions. This difference concerns system objectives rather than demonstrated improvements in predictive performance.

Velasco-Gallego et al. (2023) identified an imbalance between diagnostic and prognostic research in maritime applications, reporting that only a small proportion of reviewed studies addressed fault prognosis. The proposed integration of remaining useful life estimation responds to this research need. Its contribution would become substantial only when temporal predictions are validated against genuine degradation trajectories and demonstrate meaningful advantages over conventional maintenance scheduling.

Research on industrial augmented reality has examined interactive maintenance guidance, equipment visualization, and technical implementation challenges. Eswaran et al. (2023) highlighted tracking and registration difficulties associated with AR-assisted maintenance. The present framework addresses a related but distinct application by linking contextual visualization with machinery condition predictions. Maritime deployment introduces additional constraints involving vessel motion, restricted workspaces, and variable environmental conditions that demand dedicated validation.

The proposed relationship between diagnostic performance and maintenance interaction reflects an important development in maritime digitalization: intelligent systems must support practical decisions rather than merely generate accurate numerical predictions. Machinery information becomes operationally valuable when technicians can understand its meaning, evaluate its reliability, and determine appropriate responses. This perspective positions human interpretation as an essential component of effective predictive maintenance.

The simulated reduction in task completion time suggests that interface design could influence how efficiently operators use diagnostic information. Traditional monitoring environments frequently separate sensor readings, maintenance manuals, and equipment locations. Contextual visualization may reduce this fragmentation by presenting related information within a shared operational view. Faster interaction, however, should not be interpreted as safer maintenance without measuring procedural compliance and error consequences.

The prognostic component also reflects a possible transition from reactive intervention toward degradation-informed maintenance planning. Remaining useful life predictions provide temporal context that fault classifications cannot independently supply. Such predictions may assist maintenance prioritization, spare-part coordination, and inspection scheduling. Their practical significance depends on calibrated uncertainty and sufficient warning periods, particularly where inappropriate maintenance decisions could compromise essential auxiliary services.

The findings further suggest that explainability should be considered an operational requirement rather than a supplementary algorithmic feature. Marine engineers need opportunities to inspect sensor evidence, recognize uncertain classifications, and override inappropriate recommendations. Transparent interaction may encourage informed reliance while reducing automation bias. This interpretation supports a human-centered framework in which automated systems augment professional judgment instead of replacing established engineering responsibility.

The principal engineering implication concerns the development of maintenance architectures that integrate condition monitoring, diagnostic inference, and technician assistance. Ship operators could potentially obtain more actionable information when abnormal sensor patterns are linked with relevant inspection guidance. Such integration may improve

coordination between monitoring personnel and maintenance teams. Demonstrating operational value, however, requires measuring actual fault response, downtime, and maintenance outcomes.

Maintenance management could benefit from combining predicted degradation trends with operational schedules and equipment criticality assessments. Reliable prognostic information may support decisions concerning inspection intervals, spare-part procurement, and maintenance prioritization. Financial benefits should not be inferred from prediction accuracy alone. Cost-effectiveness must account for sensor acquisition, software integration, workforce training, false alarms, and the consequences of missed failures.

The human factors implications extend to interface development and maritime engineering education. Augmented reality applications should prioritize readable information, consistent interaction, clear warnings, and compatibility with established safety procedures. Training programs could use contextual diagnostic exercises to strengthen technicians' interpretation of machinery conditions. Interface design must nevertheless accommodate users with different experience levels and avoid excessive visual information during demanding tasks.

The theoretical implication lies in connecting predictive maintenance with human–computer interaction as interdependent research domains. Conventional diagnostic evaluation typically emphasizes classification metrics, whereas interface research examines usability and task performance. The proposed framework combines these perspectives within a unified evaluation structure. This integration offers a methodological basis for examining how technical prediction quality and information presentation jointly influence maintenance effectiveness.

The simulated diagnostic performance can be explained conceptually through complementary sensor information. Vibration measurements capture mechanical disturbances, temperature reflects thermal behavior, and pressure indicates changes in fluid-system operation. Combining these signals may improve fault discrimination when individual measurements provide ambiguous evidence. Performance advantages nevertheless depend on representative training data, informative feature selection, accurate labels, and robust separation between development and testing observations.

The hypothetical prognostic performance reflects the usefulness of temporal degradation patterns for estimating equipment deterioration. Sequential observations may reveal changes that isolated measurements cannot identify. Prediction errors arise when degradation behavior varies with operating load, environmental exposure, maintenance history, or sensor reliability. Strong performance under simulated trajectories therefore does not guarantee corresponding accuracy during real shipboard operations, where failure mechanisms may develop unpredictably.

The proposed improvement in maintenance task completion time may result from reduced information-search requirements and clearer relationships between diagnostic indicators and physical components. Augmented overlays can potentially direct attention toward relevant inspection locations without repeatedly consulting separate displays. This explanation remains hypothetical until controlled experiments isolate interface effects from participant familiarity, task difficulty, learning effects, and differences in information availability.

The relationship between usability and diagnostic decisions may also be influenced by cognitive workload. Interfaces that organize information logically can reduce unnecessary interpretation demands, while excessive notifications may create distraction. Effective design requires balancing visual simplicity with sufficient technical detail. The expected interaction benefits therefore depend on information relevance, interface responsiveness, tracking accuracy,

and operators' ability to question automated recommendations when measurements appear inconsistent.

Future investigations should prioritize empirical validation using independent machinery datasets collected across different operating loads, equipment configurations, and degradation conditions. Evaluation must include faults that resemble actual shipboard failures rather than relying exclusively on induced laboratory abnormalities. External testing across vessels would provide stronger evidence concerning model generalizability. Diagnostic reporting should include confidence calibration, class-specific errors, and performance under changing operating conditions.

Further research should establish the reliability of remaining useful life predictions using longitudinal machinery observations and defensible failure endpoints. Comparative experiments could examine statistical learning, deep learning, and physics-informed approaches under identical evaluation conditions. Prediction intervals should accompany estimated maintenance horizons to communicate uncertainty. Maintenance benefits should be assessed through measurable outcomes, including avoided breakdowns, inspection efficiency, and operational costs.

Human interaction experiments should involve professional marine engineers performing realistic diagnostic tasks under controlled conventional and augmented interface conditions (Van Reen et al., 2025). Research protocols should record task accuracy, completion time, workload, procedural deviations, and potentially unsafe actions (Van Reen et al., 2025). Longitudinal assessments would help establish whether initial usability advantages persist after extended operation. Participant experience, equipment familiarity, and interface learning effects should be incorporated into statistical analyses.

The next development stage should investigate reliable onboard deployment, including offline functionality, cybersecurity, equipment compatibility, and resilience against sensor failures (Nawaz & Mughal, 2025). Collaborative development involving marine engineers, software specialists, and maritime safety personnel could strengthen operational relevance. The framework's ultimate contribution will depend on demonstrating that integrated prediction and contextual visualization improve maintenance decisions consistently, safely, and economically under representative maritime working conditions.

CONCLUSION

This study illustrates the potential of connecting machinery fault diagnosis, remaining useful life estimation, and mobile augmented reality within ship auxiliary maintenance. The proposed framework addresses centrifugal pumps, air compressors, and cooling equipment through multisensor fault assessments, degradation indicators, and contextual inspection guidance. In the illustrative evaluation, the diagnostic model attained 96.4% accuracy and a macro F1 score of 0.958, while remaining useful life predictions yielded an 8.6% mean absolute percentage error. The augmented interface was associated with a hypothetical 28.7% reduction in maintenance task completion time relative to conventional procedures. These figures are simulated, not experimentally verified. They identify testable hypotheses about technical and human performance without establishing operational superiority. Crucially, evaluation should distinguish operator assistance from automation dependence and test both explicitly and rigorously.

The proposed contribution is both conceptual and methodological. Conceptually, the framework positions predictive maintenance as a coordinated process involving machinery condition interpretation, uncertainty communication, and situated human decision making. This perspective recognizes operators as active participants rather than treating fault classification as an isolated algorithmic task. Methodologically, the study specifies an integrated evaluation that combines grouped machinery data partitions, classification metrics, prognostic error measures, and controlled comparisons of operator task performance. Context aware visualizations are designed to connect abnormal measurements with equipment locations and inspection procedures, while explicit confidence indicators preserve opportunities for professional verification. This architecture enables investigation of whether analytical advances improve maintenance practice. Its value lies in the testable integration of predictive intelligence and human computer interaction rather than in an unsupported claim that either technology is inherently superior.

Several limitations constrain the conclusions that can presently be drawn. The numerical results are illustrative, and no raw sensor recordings, participant level observations, or independent shipboard trials have been provided to substantiate the reported performance estimates. A controlled testbed may also underrepresent vessel motion, environmental variation, unusual failures, sensor deterioration, and communication interruptions. Future research should implement the protocol with documented equipment characteristics, sufficiently diverse degradation histories, predefined sample sizes, and transparent model validation. External testing across vessels and machinery types should assess generalizability, uncertainty calibration, false alarm consequences, and resilience under degraded operating conditions. Human factors investigations should measure procedural safety, diagnostic accuracy, cognitive workload, and sustained usability among experienced engineers. Longitudinal cost and reliability analyses are additionally needed before claiming reduced downtime or improved safety. These steps would establish whether the proposed integrated framework delivers reproducible, practical benefits in maritime operations.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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