

Predictive Maintenance System for Home Appliances: Heterogeneous Sensor Data Fusion and User Literacy Profiling

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(Received May 23, 2026; accepted August 31, 2026)

Keywords: on-board sensors, user profiling, predictive maintenance, decision support systems

A smart maintenance system for household appliances is developed by integrating multimodal sensor data with adaptive user profiling to enhance diagnostic accuracy and repair outcomes. The system processes electrical, mechanical, thermal, and fluidic telemetry streams through a probabilistic diagnostic engine, combining fault codes, historical records, and environmental parameters to identify failure types. A human-adaptive module quantifies user proficiency using success rates, certifications, and behavioral indicators, generating a capability score that guides either self-repair instructions or technician dispatch. Validation with 1000 participants across five appliance categories showed a 93.3% diagnostic accuracy and an 85% precision in user assessment. Operational efficiency improved significantly, with repair duration reduced by 62.5% and unnecessary technician visits decreased by 61.1%. These results show that IoT-enabled diagnostics, when coupled with explainable user profiling, can be used to develop a scalable hybrid service model to extend appliance lifespans, reduce manufacturer costs, and empower consumers through safe, transparent, and personalized maintenance pathways. Sensor networks can be used as diagnostic tools as well as the enablers of human-centered decision-making, advancing sensor technology toward resilient, bidirectional cyber–physical ecosystems.

1. Introduction

Modern home appliances are increasingly equipped with advanced sensors that measure current, vibration, temperature, pressure, and other variables. These sensors generate large amounts of diagnostic data in real time. However, a major challenge remains in translating such high-quality data into practical, user-friendly services and maintenance. Since traditional maintenance methods rely on static manuals and rigid troubleshooting checklists, they are not well suited to the present demand for personalized and seamless service experiences. Conventional methods also adopt a one-size-fits-all model, where even minor sensor alerts often require professional intervention. This not only raises costs for manufacturers but also delays service for consumers.

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<https://doi.org/10.18494/SAM6450>

Another limitation is the gap between what sensors detect and what users or technicians can actually interpret. Simple problems, such as clogged filters or sensor recalibration, can often be resolved by homeowners themselves if they have well-organized guidance. In contrast, serious failures, including insulation breakdowns or electrical faults in control boards, must be handled by professionals to ensure safety and warranty compliance. Without smart systems that can assess a user's repair skills and experience, service networks struggle to allocate resources efficiently. These issues highlight the need for a new cyber–physical framework that integrates sensor diagnostics with adaptive user profiling. Such a system enables users to perform safe, guided self-repairs, ensuring that critical faults are handled exclusively by qualified technicians.

Therefore, it is critical to relate machine health data to human capability to build resilient, efficient, and user-centered smart home ecosystems. In this study, we designed a system that integrates sensor telemetry with user profiles in a dynamic, bidirectional loop. Rather than treating sensor data and human capability as separate inputs, the developed method acquires real-time diagnostic data to continuously refine the user's skill profile while the refined profile enables the interpretation of sensor signals and decision-making processes. The developed method enhances reliability in automated diagnostics and provides interpretable feedback to recommend efficient maintenance methods, either guided self-repair or professional intervention. This ensures accountability and helps users understand the reasoning behind system decisions.

2. Background Knowledge

The structural transition in household appliance management from traditional reactive troubleshooting to proactive predictive maintenance is based on the architectural advancements of the Fourth Industrial Revolution and the Industrial IoT (IIoT). Jonnakuti established the role of IIoT architectures in continuous device monitoring, a prerequisite for data collection⁽¹⁾ that was later extended by Siswanto *et al.* into IoT-driven decision support infrastructures capable of executing automated, real-time maintenance scheduling.⁽²⁾

However, scaling these automated schedules introduces challenges when managing dispersed home appliances. To address this issue, Falatouri *et al.* introduced spatiotemporal sensor networks designed for long-range appliance maintenance and failure forecasting.⁽³⁾ Besides immediate breakdown prevention, the spatiotemporal sensor network ensures broader systemic benefits. For instance, sensor-driven smart maintenance mitigates premature device obsolescence and excessive energy consumption, directly contributing to household sustainability.⁽⁴⁾ Furthermore, the operational and commercial value of sensor-based telemetry networks extends to market stability. By deploying machine learning architectures in the networks, customer churn in appliance rental sectors can be accurately predicted, proving that proactive, sensor-informed asset management yields substantial business utility.⁽⁵⁾

Whereas wide-area IoT networks provide the essential communication frameworks, the diagnostic fidelity of a predictive maintenance system largely depends on localized sensor data management and multisensor data fusion. Raw sensor data streams from smart homes are inherently heterogeneous, and noisy, and of high frequency. Shaik *et al.* addressed this challenge by developing data fusion techniques and synthesizing messy multimodal data into clean

diagnostic inputs.⁽⁶⁾ Because processing such continuous data streams overwhelms the capability of resource-constrained edge hardware, dynamic sensor selection methods are employed.⁽⁷⁾ Although initially validated within transit systems, this approach provides an essential mathematical logic to isolate and sample only the most important sensor nodes in smart appliances. To implement the approach, strict system interoperability and data integrity are required across diverse appliance ecosystems and reinforced structural requirements.⁽⁸⁾

Once data integrity is ensured at the communication layer, anomalies must be omitted. Recent advancements in data-driven fault diagnosis enable the development of enhanced data preprocessing and feature engineering to extract early, low-amplitude indicators of mechanical or electrical degradation from raw sensor signals.⁽⁵⁾ These features are fed into smart computational algorithms, which supply the mathematical backbone for complex, multistage fault detection and signal isolation.^(9,10) For the development and application of appropriate algorithmic models, hardware must be validated for the reliability and circuit safety of the tasks of electronic architectures.^(11,12)

A highly robust algorithmic diagnosis becomes ineffective if the resulting alerts cannot be effectively executed. Therefore, a link between complex machine telemetry and the end-user must be established. By applying human–computer interaction principles to sensor-based telemetry systems, automated diagnostic alerts can be offered on actionable, intuitive interfaces for nontechnical users.⁽¹³⁾ Such localized human-machine interactions must be integrated into lifecycle-focused device management. By embedding predictive maintenance protocols into the product lifecycle and manufacturing workflow, system-level maintenance strategies can be established.⁽¹⁴⁾ To ensure system autonomy, semantic sensors are used.⁽¹⁰⁾ The sensors can be used to integrate environmental awareness into the edge-computing loop and enable home appliances to adapt internal maintenance cycles on the basis of localized usage patterns and ambient environmental conditions.

Smart home appliance maintenance has matured on the basis of multidisciplinary principles. By unifying ubiquitous IoT connectivity,^(1,2) real-time predictive analytics,⁽³⁾ and robust, human-centric sensor design,⁽¹²⁾ a self-diagnostic, edge-intelligent ecosystem can be constructed to extend product lifespans with user satisfaction.

3. Method

3.1 System architecture

The developed fault diagnosis and human-adaptive maintenance guidance method for smart household appliances adopts a multilayered cyber–physical framework. The operation comprises physical anomaly detection, edge-to-cloud data transmission, algorithmic fault isolation, end-user capability quantification, and resource-optimized service routing. The workflow of the developed method is presented in Fig. 1. The collected data were preprocessed at the edge before cloud transmission. Each sensor node was connected to a Raspberry Pi 4B (Broadcom BCM2711, quad-core ARM Cortex-A72, United Kingdom) equipped with 4 GB of random access memory and running on the Ubuntu Server. This edge device was used to handle initial noise filtering, timestamp synchronization, and packet compression. Preprocessed data were

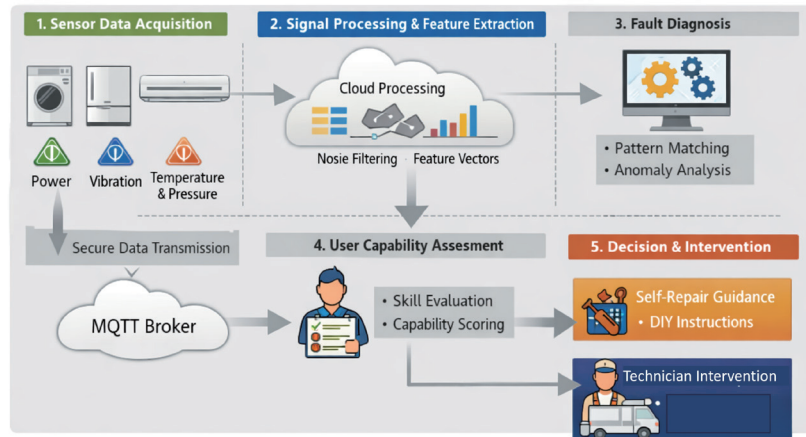


Fig. 1. (Color online) Workflow of intelligent fault diagnosis and maintenance guidance system (created in this study using AI).

then transmitted securely to the cloud station through a message queuing telemetry transport (MQTT) broker with transport-layer security encryption. The cloud station comprised a Dell PowerEdge R740 server [Intel Xeon Silver processors, the United States of America (USA)] running Python-based diagnostic modules and a PostgreSQL database for historical fault records. This hardware configuration enables real-time signal processing, minimizing latency. The Raspberry Pi performed lightweight preprocessing close to the sensors, reducing bandwidth requirements, while the server executed computationally intensive pattern-matching and user profiling tasks.

The developed system conducts sensor data acquisition and transmission, where electrical, mechanical, thermal, and fluidic parameters are continuously extracted from embedded sensor nodes. These data are packaged with static metadata, such as appliance model identifiers and structural specifications, and transmitted securely through an edge-computed MQTT broker with transport layer security. To ensure reliable communication, time alignment and synchronization are employed across heterogeneous sensor streams. Each sensor node is timestamped using a synchronized clock protocol, and data packets are buffered at the edge before transmission to maintain temporal consistency. Latency management is handled through adaptive queue scheduling in the MQTT broker, which prioritizes anomaly-related packets over routine telemetry. To reduce transmission overhead, the system applies lossless compression algorithms to high-frequency vibration and current signals, whereas low-frequency thermal and pressure data are aggregated into compact summary vectors. These measures optimize bandwidth usage and sustain real-time responsiveness in resource-constrained IoT environments.⁽¹⁵⁾

Electrical monitoring is performed using noninvasive Hall-effect current sensors (ACS712 variants) and voltage divider networks across main driver loops. Signals are sampled at a high frequency ($f_s = 2.0$ kHz) to capture transient inrush currents, harmonic distortions, and phase shifts that indicate stator winding insulation degradation or compressor lock-ups. In mechanical

and vibration monitoring, micro-electromechanical triaxial accelerometers (ADXL345) are mounted to rotating assemblies such as motors, drums, and pumps. Data are collected at $f_s = 1.0$ kHz to detect high-frequency structural deviations, bearing wear, and balance anomalies. Thermodynamic and fluidic monitoring is conducted using negative-temperature-coefficient (NTC) thermistors (± 0.1 °C precision) positioned at critical thermal junctions, heat exchangers, power electronics, and heat sinks, and piezoresistive silicon pressure transducers integrated into fluidic circuits. Sampling rates for thermal and pressure vectors are set to $f_s = 10.0$ kHz, capturing slow boundary transitions and hydraulic pressure gradients.

The sensors used in this study are widely adopted in consumer electronics and industrial monitoring. The ACS712 Hall-effect current sensor [Allegro Microsystems, USA] measures currents up to ± 30 A noninvasively, enabling the monitoring of appliance driver circuits without altering wiring. The ADXL345 triaxial accelerometer [Analog Devices, USA] is a micro-electromechanical system sensor capable of detecting vibration frequencies up to a kHz level, which enables the precise monitoring of rotating components such as drums and pumps. NTC thermistors, commonly produced in Japan and China, are standard thermal probes integrated into refrigerators and air conditioners, offering ± 0.1 °C precision for heat exchanger and junction monitoring. Piezoresistive silicon pressure transducers, widely manufactured in Germany and China, are embedded in fluidic circuits of washing machines and air conditioners to measure hydraulic gradients. These sensors form the basis of the multimodal dataset used for fault isolation and adaptive maintenance decisions (Table 1). Although many appliances already incorporate basic versions of these sensors for control and safety, in the system developed in this study, they are supplemented with higher-resolution modules mounted externally on testbeds to capture richer diagnostic data.

Table 1
Sensors, their extracted physical features, and diagnostic accuracy distributions.

Appliance	Model/brand	Sensor	Feature
Washing machines	Samsung WF45R6300, LG TurboWash 360	Triaxial MEMS accelerometers (ADXL345), NTC thermistors, piezoresistive pressure sensors	High-frequency drum unbalance frequencies, drainage manifold pressure gradients, and pump current transients
Refrigerators	LG InstaView, Samsung Family Hub	NTC thermal probes, AC transducers (ACS712)	Compressor inrush current cycles, cooling loop thermal response slopes, defrost cycle power durations
Air conditioners	Daikin Inverter Split, Samsung WindFree	Pressure transducers, Hall effect current sensors, humidity sensors	Fan motor harmonic distortions, refrigerant loop delta pressures, evaporator core temperature curves
Televisions	LG OLED CX, Samsung QLED Q90T	Embedded power management ICs, voltage dividers	Power supply rail voltage drops, switching regulator thermal dissipation rates
Small kitchen appliances	Philips Air Fryer, Cuisinart Blender	Thermal fuses, proximity switches, shunt resistors	Heating element current draw, safety interlock continuity states, thermal ramp velocities
System composite	Multi appliance testbed	Heterogeneous sensor array	Unified machine ($v_{current}$) and environmental ($e_{current}$) profiles

Many appliances incorporate sensors, as shown in Table 1, for control and safety functions. Our framework supplements them with higher-resolution modules mounted externally on testbeds. This hybrid approach ensures compatibility with existing commercial designs while providing richer diagnostic data for predictive maintenance. The sensors are integrated into household appliances without requiring proprietary hardware modifications. In the developed system, the sensors are used to obtain a multimodal dataset that reflects the appliance's electrical, mechanical, thermal, and fluidic health signatures. This dataset forms the foundation for accurate fault isolation and adaptive maintenance decisions.

3.2 Data collection and processing

The dataset used in this study are from 1000 participants and 50 distinct fault conditions simulated across five appliance categories: washing machines, refrigerators, air conditioners, televisions, and small kitchen appliances. Each appliance type was equipped with four sensor modalities recorded at 1 Hz intervals: current, vibration, temperature, and pressure. Raw signals were collected through Raspberry Pi 4B edge nodes and transmitted to the cloud server using an MQTT protocol.

Fault simulation was conducted using manufacturer-verified procedures to ensure realism. Electrical faults (motor overload and short circuit) were induced using controlled current variations; mechanical faults (bearing wear and imbalance) were generated through calibrated vibration disturbances; and thermal faults (compressor overheating) were simulated using programmable heat loads. Environmental parameters such as ambient temperature and humidity were varied to emulate realworld operating conditions. Each simulated fault was labeled by certified technicians to create groundtruth records for supervised learning. The dataset was split into three subsets: 70% for training, 20% for validation, and 10% for testing. This composition ensured a balanced representation of fault types and user skill levels, enabling a robust evaluation of diagnostic accuracy and user capability modeling.

To utilize continuous sensor data streams for actionable maintenance interventions, the physical lifecycle of the data can be traced across four operational phases. In data gathering, synchronized timestamps are used to ensure that electrical, mechanical, thermal, and fluidic signals are aligned to a common temporal baseline. This alignment enables the accurate correlation of transient events across modalities, such as linking compressor inrush currents with simultaneous pressure fluctuations. Latency is minimized by edge buffering and adaptive compression, which reduce packet size without compromising diagnostic fidelity. Synchronization and bandwidth optimization collectively enable the system to deliver consistent, real-time diagnostic streams.

- **Phase 1: Data gathering and noise filtering**

Smart home appliances continuously monitor internal conditions such as electrical current transients, mechanical vibration frequencies, hydraulic pressures, and ambient temperatures. Raw telemetry data from household environments are inherently noisy, high in frequency, and often affected by external factors. For example, a sudden rise in compressor temperature may indicate mechanical failure, but it could also result from a refrigerator door being left open on a hot summer day. To resolve such ambiguities, the system streams raw data through IoT protocols

to a cloud processing layer. Before any diagnostic logic is applied, advanced filters remove background noise and isolate the precise window in which an anomaly or threshold fault code occurs.

- Phase 2: Active feature profiles

Once the incoming data are cleaned, the system translates continuous sensor measurements into structured, lowdimensional summary vectors. The real-time feature vectors compiled from on-board sensors ($v_{current}$) are used to identify indicators of hardware malfunction, such as voltage fluctuations, current waveforms, or vibration frequencies. The real-time environmental parameters recorded at the moment of fault ($e_{current}$) occurrence are used as variables, including room temperature, humidity, and cumulative usage cycles. The data are used for the representation of the appliance's internal state and its operating environment.

- Phase 3: Pattern matching and failure isolation

The diagnostic architecture is used to evaluate the sensor data through comparison with historical repair records to isolate the root cause of failure. The system measures how closely $v_{current}$ aligns with past breakdowns, matching electrical or vibrational signatures to known component failures. Simultaneously, $e_{current}$ is cross-referenced to determine whether the surrounding conditions mirror those typically associated with degradation. By balancing internal hardware evidence with external environmental context, the system identifies the most probable fault type (F_{final}) while reducing noise-induced misclassifications.

- Phase 4: Service and intervention strategy

Once the fault type is confirmed, the results of the diagnosis are used to schedule user safety logic and technician intervention. If the system detects a minor, lowrisk issue such as a clogged valve or dirty filter, it activates the user capability evaluation framework to determine whether the homeowner can safely perform a guided self-repair. Conversely, if the fault involves high-risk hazards such as insulation breakdown or control board failure, the self-repair pathway is locked to prevent injury or secondary damage. For approved self-repairs, the system estimates repair duration using historical logs matched to the diagnosis. For technicians' professional interventions, predictive regression models estimate repair time, which is combined with real-time travel data to provide homeowners with an accurate service timeline.

3.3 Feature extraction and data fusion

Figure 2 shows the system workflow across sensor integration, data fusion, and user-adaptive decision routing. Upon receiving a fault code, the system retrieves historical fault records and associated environmental parameters to identify the likely failure mode. Heterogeneous sensor streams, measuring current, vibration, temperature, and pressure, undergo feature extraction before entering a probabilistic fusion model that executes pattern matching and anomaly detection for fault classification [Fig. 2(a)]. Following classification, the human-adaptive module evaluates user capability [Fig. 2(b)]. If the user meets the required skill threshold, the system delivers step-by-step self-repair guidance. Otherwise, it optimizes technician dispatch by accounting for travel time, expertise, and service ratings. Both methods converge on resolution while safeguarding appliance integrity and operational safety.

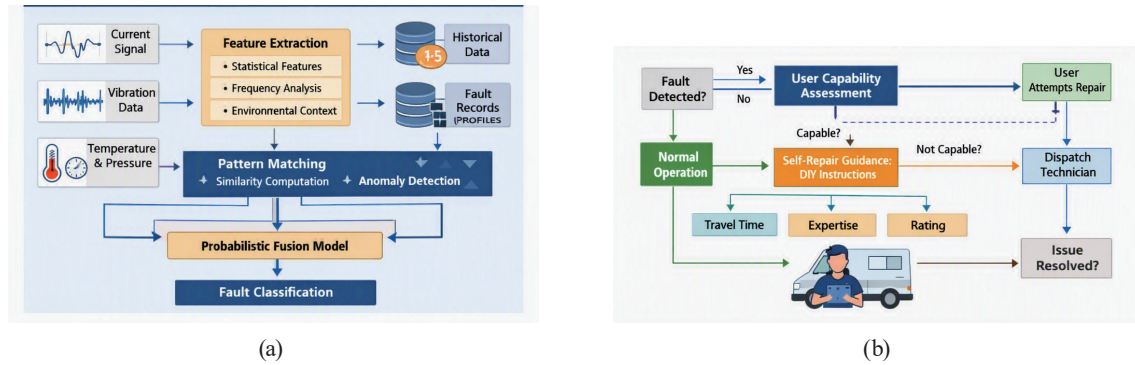


Fig. 2. (Color online) Schematic diagrams of developed system: (a) data fusion process and (b) decision routing framework.

A probabilistic matching algorithm integrates historical solution data with contextual operational parameters. For a candidate fault type F_i , the matching probability is defined as

$$P_{match}(F_i) = \alpha \cdot HistMatch(F_i) + \beta \cdot EnvSimilarity(F_i). \quad (1)$$

Here, $\alpha + \beta = 1$, $HistMatch(F_i)$ is used to quantify similarity between real-time sensor features and historical fault vectors, and $EnvSimilarity(F_i)$ is used to measure environmental condition similarity. The historical match score is computed using cosine similarity.

$$HistMatch(F_i) = \frac{v_{current} \cdot v_{historical}}{\|v_{current}\| \|v_{historical}\|} \quad (2)$$

Here, $v_{current}$ is the real-time feature vector compiled from onboard sensors, such as current transients and vibration frequencies, and $v_{historical}$ is the baseline mean vector from verified past cases of fault type F_i . The Euclidean norm ensures normalization between -1 and 1 . Environmental similarity is calculated as

$$EnvSimilarity(F_i) = 1 - \frac{\|e_{current} - e_{historical}\|}{\max(\|e_{current} - e_{historical}\|)}. \quad (3)$$

Here, $e_{current}$ represents real-time environmental parameters (temperature, humidity, and the number of usage cycles) and $e_{historical}$ denotes average parameters from past occurrences of fault type F_i . The denominator normalizes the distance to $[0,1]$. The final fault type is selected as

$$F_{final} = \arg \max_{F_i} P_{match}(F_i). \quad (4)$$

The integration of empirical sensor data and contextual environmental conditions reduces misclassification and enhances diagnostic accuracy. To determine whether a user can perform self-repair, the system evaluates historical repair performance and skill level. The success rate ($P_{success}$) is defined as

$$P_{success} = \frac{N_{success}}{N_{total}}. \quad (5)$$

Here, $N_{success}$ is the number of successfully resolved similar faults and N_{total} is the total number of similar fault records. The comprehensive capability score ($S_{comprehensive}$) is calculated as

$$S_{comprehensive} = w_1 \cdot L_{skill} + w_2 \cdot P_{success}. \quad (6)$$

Here, $w_1 = 0.4$ and $w_2 = 0.6$. L_{skill} is normalized to $[0,1]$ on the basis of certification, training completion, appliance ownership duration, and confidence scores. If $S_{comprehensive} > T_{threshold} = 0.7$, the user is considered capable of self-repair.

The developed system assumes linear relationships between similarity metrics, where historical feature correlation and environmental similarity are combined using weighted summation. This linear framework is adopted to simplify computation and ensure interpretability. However, nonlinear dependences between sensor modalities, such as coupling between temperature fluctuations and vibration anomalies, might not be fully captured. This necessitates the exploration of neural architectures, including convolutional and recurrent networks, to model these nonlinear interactions and improve diagnostic fidelity.⁽¹⁶⁾ To solve problems originating from evolving sensor drift and environmental changes, the system incorporates adaptive retraining. The diagnostic engine is retrained every 30 days using newly collected telemetry and repair outcomes, ensuring that feature distributions remain current. Thresholds for user capability assessment are also dynamically updated. Instead of the fixed $T_{threshold} = 0.7$, an adaptive thresholding mechanism recalibrates the cutoff on the basis of the rolling averages of user success rates and sensor reliability metrics. This approach maintains robustness against long-term drift in sensor calibration and evolving user behavior patterns.

3.4 Scoring and reliability metrics

For professional intervention, technician selection is optimized using Eq. (7). If the user is incapable or self-repair fails, the system automatically assigns a qualified technician. The assignment is optimized using a multicriteria scoring model.

$$Score(R_k) = \gamma_1 \cdot \frac{1}{t_{travel,k}} + \gamma_2 \cdot SuccessRate_k + \gamma_3 \cdot Rating_k \quad (7)$$

Here, $Score(R_k)$ is the composite suitability index for technician k . $t_{travel,k}$ is the estimated travel time, $SuccessRate_k$ is the documented first-time fix rate for the diagnosed fault mode F_{final} , and $Rating_k$ is the normalized consumer satisfaction score. The weights γ_1 , γ_2 , and γ_3 are adjusted dynamically: for noncritical safety faults, $\gamma_1 = 0.5$, $\gamma_2 = 0.3$, and $\gamma_3 = 0.2$; for critical safety faults, $\gamma_1 = 0.3$, $\gamma_2 = 0.5$, and $\gamma_3 = 0.2$. The technician with the highest score is selected using

$$R^* = \arg \max_{R_k} Score(R_k). \quad (8)$$

The current dispatch model selects the technician with the highest composite score, balancing travel time, success rate, and satisfaction rating. While effective, this approach assumes a single weighted objective. In practice, dispatch decisions often involve tradeoffs: minimizing travel time may conflict with maximizing expertise or consumer satisfaction. To address this, multi-objective optimization frameworks such as Pareto efficiency can be applied. A Pareto-optimal solution identifies technicians for whom no criterion (shorter travel time) can be improved without worsening another (lower expertise). This ensures that dispatch decisions reflect balanced trade-offs rather than a single weighted sum. In future work, we will explore evolutionary algorithms and multi-objective optimization methods to refine dispatch routing, particularly in dense service networks where competing priorities are common.⁽¹⁷⁾ The total service timeline is estimated as

$$T_{service} = t_{travel} + t_{repair}. \quad (9)$$

Here, t_{repair} is predicted using gradient boosting regression trained on historical service logs and t_{travel} is the estimated travel time for the assigned technician to reach the appliance location. This ensures that both travel and repair durations are considered in scheduling. System reliability and safety are validated using standard statistical measures. Accuracy is defined as

$$Accuracy = \frac{N_{correct}}{N_{total\ cases}}. \quad (10)$$

Here, $N_{correct}$ is the number of correctly classified fault isolations and $N_{total\ cases}$ is the total number of experimental cases. Precision and recall are defined as

$$Precision = \frac{TP}{TP + FP}, \quad (11)$$

$$Recall = \frac{TP}{TP + FN}, \quad (12)$$

Here, true positives (TPs) are cases where the system correctly identified a capable user and the repair was completed, false positives (FPs) are cases where an incapable user was incorrectly classified as capable, and false negatives (FNs) are cases where a capable user was incorrectly flagged as incapable. The F1-score is calculated as

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (13)$$

Accuracy, precision, recall, and F1-score provide a rigorous evaluation of system performance. In this study, we adopted additional validation to enhance credibility. The dataset of 1000 participants and 50 simulated fault conditions was sufficient for internal testing. However, external benchmarking against existing predictive maintenance systems provides comparative insights. In further studies, cross-validation across multiple folds must be conducted to ensure generalization and reduce overfitting. By comparing the developed system with established industrial IoT diagnostic methods, diagnostic accuracy, latency, and user safety metrics must be compared. Such external validation is necessary to confirm whether the developed system consistently outperforms conventional predictive maintenance approaches in diverse appliance ecosystems.⁽¹⁸⁾ High precision reduces risks of secondary damage from unqualified repairs, whereas high recall ensures that capable users are not overlooked. Together, these measures confirm the framework's predictive consistency and operational safety.

4. Results

4.1 Diagnostic performance

To validate the system's diagnostic and adaptive maintenance performance, a large-scale controlled experiment was conducted with 1000 participants. Fifty distinct fault conditions were simulated across five appliance categories: washing machines (15 failure modes), refrigerators (12), air conditioners (10), televisions (8), and small kitchen appliances (5). Fault triggers were initialized on connected hardware testbeds, prompting onboard edge controllers to transmit real-time telemetry packets and fault codes through encrypted MQTT channels to the central analytics cloud.

From the incoming data, time- and frequency-domain features were extracted to capture transient anomalies, structural deviations, and thermodynamic irregularities. These features were transformed into low-dimensional feature vectors for probabilistic comparison against historical fault patterns, enabling the system to isolate structural failures from ambient environmental fluctuations. As shown in Table 2, the pattern-matching engine achieved a composite diagnostic accuracy of 93.3%, exceeding the 90.0% industrial research benchmark across all hardware platforms. Diagnostic performance was highest for washing machines (95.0%), driven by a dense array of specialized onboard sensors embedded within their fluidic and rotational assemblies. Specifically, combining high-frequency triaxial vibration signals

Table 2
Diagnostic accuracy of sensors.

Sensor	Target accuracy (%)	Diagnostic accuracy (%)
Triaxial MEMS accelerometers (ADXL345), NTC thermistors, piezoresistive pressure sensors	90.00	95.00
NTC thermal probes, AC transducers (ACS712)	90.00	94.00
Pressure transducers, Hall-effect current sensors, humidity sensors	90.00	93.50
Embedded power management ICs, voltage dividers	90.00	91.00
Thermal fuses, proximity switches, shunt resistors	90.00	90.00
Heterogeneous sensor array	90.00	93.30

($f_s = 1.0$ kHz) with drainage line pressure vectors provided high-fidelity telemetry, allowing the cosine similarity filter to cleanly differentiate between distinct mechanical anomalies caused by bearing degradation and asymmetrical drum loads.

Refrigerators and air conditioners also showed high accuracies of 94.0 and 93.5%, respectively. In contrast, televisions and small kitchen appliances yielded lower accuracies (91.0 and 90.0%, respectively) because their simpler, predominantly static electronics offer fewer dynamic mechanical signatures. Overall, diagnostic fidelity directly correlates with sensor density and diversity. Combining cosine similarity for machine feature vectors with Euclidean normalization for environmental context effectively isolates faults across multimodal sensor platforms. A controlled experiment with 1000 participants validated the system's diagnostic and adaptive maintenance performance across 50 distinct fault conditions in five appliance categories. The system achieved a composite diagnostic accuracy of 93.3%. Washing machines achieved the highest accuracy (95.0%) owing to their richer sensor integration, followed by refrigerators (94.0%), air conditioners (93.5%), televisions (91.0%), and small kitchen appliances (90.0%). These results confirm that higher sensor density and diversity improve diagnostic fidelity, while the edge-cloud hardware configuration successfully supports real-time fault isolation across heterogeneous appliances.

4.2 Human-adaptive capability assessment

The developed system incorporates the user as an active parameter within the cyber–physical maintenance loop. Across 1000 empirical trials, the system recommended self-repair for 65.0% of simulated faults, achieving an 80.0% completion success rate across authorized interventions (Fig. 3). This confirms that setting the threshold parameter conservatively ($T_{threshold} = 0.70$) effectively prioritizes user safety and appliance integrity.

Group analysis results show the precision of the human–machine interface logic. For expert users (Group A), the system authorized self-repair in 85.0% of cases with a 92.0% success rate. For intermediate users (Group B), it recommended self-repair in 65.0% of cases, yielding an 82.0% success rate. For novices (Group C), the system acted cautiously, permitting self-repair in

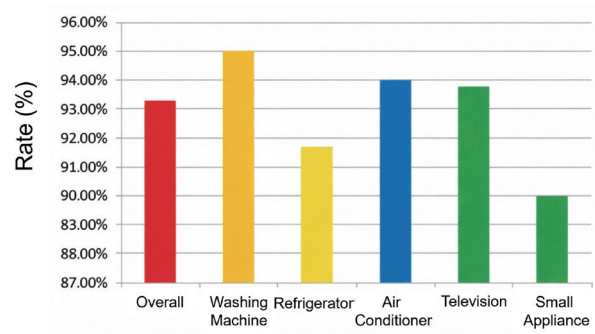


Fig. 3. (Color online) Average automated self-repair recommendation and actual completion success rates across appliance categories.

only 25.0% of events, restricting intervention to low-risk tasks such as filter replacement or sensor cleaning. Even so, novices achieved a 66.0% success rate without experiencing safety violations or secondary hardware failures.

The recommendation and completion rates varied systematically across appliance categories. The highest success rate (95%) was achieved with washing machines, benefiting from dense sensor integration and straightforward mechanical tasks. Refrigerators and air conditioners followed closely (93–94%), whereas televisions and small appliances yielded lower success rates (90–91%) owing to their simpler sensor architectures.

Figure 4 shows diagnostic errors within the human-adaptive module. The overall misjudgment rate, defined as cases where user capability was misclassified relative to fault demands, was around 30.0%. However, the misjudgment rate was below 15.0% for the expert and intermediate groups, with novices accounting for most misclassifications. Weighting historical success data (60%) alongside skill profile metrics (40%) enabled accurate capability estimation. By restricting complex electrical or high-pressure refrigerant repairs to certified technicians while routing low-risk procedures to capable users, the system minimized secondary damage and preserved user trust.

4.3 Systemic resource optimization

The transition results of the one-size-fits-all method to the adaptive, sensor-driven method are shown in Fig. 5. The system reduced the total repair duration by 62.5%, cutting the average time from 120 to only 45 min. This improvement was achieved through rapid ingestion and response, with MQTT and Kafka layers processing fault codes in about 5 min, and by eliminating scheduling delays through immediate self-repair guidance for qualified users. By allowing capable users to act without waiting for administrative approval or technician scheduling, the system removed the bottlenecks that typically slow down traditional maintenance

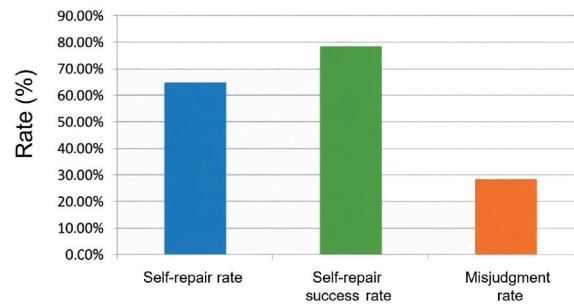


Fig. 4. (Color online) Diagnostic error of human-adaptive module.

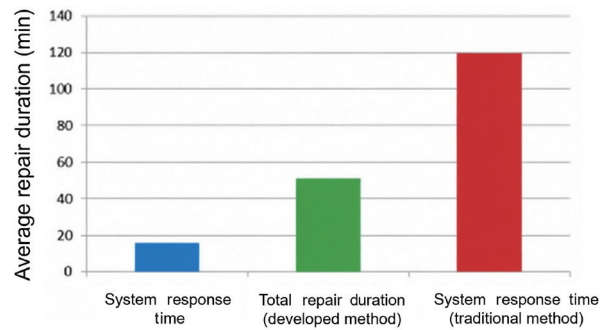


Fig. 5. (Color online) Total repair duration (min) and technician intervention of developed and traditional methods.

networks.

In addition, technician interventions were reduced by 61.1%. Conventional service structures often suffer from unnecessary visits, including no-fault-found calls or minor issues that could have been resolved locally. By leveraging real-time sensor data, the framework acts as an intelligent filter, ensuring that professional technicians are reserved for high-stakes mechanical failures or safety-critical anomalies. This optimization lowers costs for manufacturers, improves the first-time fix rate for field engineers, and reduces the carbon footprint associated with service logistics. By combining IoT-driven diagnostics with explainable user capability profiling, the system establishes a resilient hybrid service ecosystem that balances appliance health with human proficiency.

5. Discussion

5.1 Sensor data fusion and diagnostic fidelity

The results of this study show that diagnostic fidelity is linked to the density and heterogeneity of integrated sensing nodes. Appliances equipped with multiple sensor modalities,

such as vibration, current, thermal, and pressure sensors, achieved a higher diagnostic accuracy than those with simpler architectures. For example, washing machines reached a 95.0% accuracy owing to the combination of triaxial accelerometers, piezoresistive pressure sensors, and current transducers, which together provided a rich dataset of mechanical, hydraulic, and electrical variables. This multimodal fusion allowed the probabilistic pattern-matching engine to cross-validate anomalies across domains, distinguishing genuine mechanical breakdowns from user-induced imbalances.

In contrast, small kitchen appliances achieved a lower accuracy (90.0%), reflecting the limitations of low-dimensional telemetry. These devices typically rely on single thermal fuses or basic current loops, which restrict the diagnostic engine's ability to isolate subtle degradation patterns. This variance demonstrates that diagnostic reliability is bounded by the sensory intelligence embedded in the hardware. Therefore, it is required to incorporate low-cost, multifunctional microsensor arrays capable of capturing secondary variables such as acoustic emissions or magnetic flux, thereby enhancing diagnostic resolution without inflating production costs. Filtering raw signals into low-dimensional feature profiles at the ingestion layer also aligns with prior work on edge intelligence deployment models,⁽¹⁸⁾ confirming that complex multimodal data can be efficiently managed across distributed networks.

5.2 Telemetry for human-adaptive maintenance

The developed method can be used to apply raw sensor telemetry for actionable human decisions. High-frequency electrical distortions, vibration spectra, or thermal gradients are meaningless to most consumers in their raw form. By transforming these noisy data streams into structured machine feature vectors ($v_{current}$) and environmental feature vectors ($e_{current}$), the method provides interpretable inputs for probabilistic fault classification. The developed method generates context-aware maintenance pathways. When low-risk anomalies are detected, such as filter clogging or frost accumulation, the human-adaptive capability assessment module is activated. Guided self-repair packages are then delivered to capable users, including instructions, tool requirements, and estimated repair times. The experiment demonstrated that even novice users achieved a 66.0% success rate in such cases, confirming that sensor-driven insights can safely empower consumers. Conversely, when sensors detect high-risk hazards such as insulation breakdowns or control board failures, the self-repair pathway is locked and professional dispatch is triggered. The method adopts semantic sensor integration⁽¹⁹⁾ and life-cycle-embedded predictive maintenance protocols,⁽¹⁸⁾ ensuring that diagnostic results are interpretable and actionable for end-users. By embedding predictive maintenance into the product life cycle, the framework ensures accountability and transparency while positioning sensor networks as active safety layers within the smart home ecosystem.

5.3 Operational efficiency and resource optimization

The integration of sensor-driven diagnostics with adaptive user profiling also produced substantial operational gains. By filtering raw telemetry into low-dimensional feature profiles at

the ingestion layer, the system achieved an average response time of 5 min. This rapid processing eliminated scheduling overhead by allowing qualified users to perform immediate self-repairs, while simultaneously reducing unnecessary technician interventions by 61.1%. These improvements lower manufacturing costs, increase the first-time fix rate for field engineers, and reduce the carbon footprint associated with service logistics. By embedding predictive analytics into user-centric interfaces, the framework advances human–computer interaction principles⁽²⁰⁾ and validates resource-optimized maintenance strategies,⁽²¹⁾ demonstrating that IoT-driven diagnostics can simultaneously enhance efficiency and user trust.

In this study, we focused on five household appliance categories (washing machines, refrigerators, air conditioners, televisions, and small kitchen appliances), but the developed system is scalable to other domains. The modular design of the sensor acquisition, edge preprocessing, and cloud-based diagnostic engine allows adaptation to industrial and automotive systems. For example, the vibration and current sensors used here are directly applicable to rotating machinery in manufacturing plants, whereas pressure and thermal sensors align with monitoring requirements in heating, ventilation, and air conditioning, and automotive subsystems. Scalability is supported by the probabilistic matching algorithm, which requires the incorporation of new feature vectors and environmental parameters without altering the core architecture. Retraining with domain-specific datasets enables the system to learn fault signatures unique to industrial or vehicular contexts. Moreover, adaptive thresholding for user capability assessment can be extended to operator skill levels in industrial maintenance or driver intervention scenarios in automotive systems. It is necessary to compare the performance of the developed system with that of other predictive maintenance systems and explore cross-domain deployments to validate whether the hybrid edge-cloud architecture and human-adaptive module maintain diagnostic accuracy and safety across diverse environments, thereby confirming the generalizability of the approach.⁽²²⁾

5.4 Data privacy and ethical considerations

Ethical considerations are essential to user profiling. Confidence scores, repair histories, and skill metrics are processed only for diagnostic purposes and are not shared with third parties. Users retain control over their data, with opt-in consent required for long-term storage and retraining. The system must comply with international IoT data protection standards, including the General Data Protection Regulation and equivalent regional frameworks, ensuring transparency and accountability. The utilization of user profile data requires strict privacy safeguards. All sensor data and user capability profiles are anonymized before storage, with identifiers replaced by hashed tokens to prevent unauthorized linkage to individuals. Therefore, data transmission between appliances, edge devices, and cloud servers must be encrypted using transport layer security, and access to user records is restricted through role-based authentication.

By embedding privacy-preserving mechanisms and ethical safeguards, the system developed in this study balances diagnostic accuracy with user trust. Federated learning approaches need to be employed to improve the developed system, where model retraining occurs on edge devices without transmitting raw data, further reducing privacy risks.⁽²³⁾

6. Conclusions

We developed an intelligent fault diagnosis and adaptive maintenance method for modern smart home environments. The system adopts multimodal sensor data, encompassing electrical, mechanical, thermal, and fluidic modalities, to construct a comprehensive representation of appliance health. Raw sensor data are acquired, filtered, and fused into environmental feature vectors at the edge node. Through edge-level feature extraction, communication overhead and latency are minimized, enabling rapid, localized decision-making while mitigating false positives through ambient environmental sensing.

By bridging hardware diagnostics with human-adaptive profiling, the system quantifies user technical capability using historical repair success rates, technical certifications, and real-time behavioral metrics, rather than treating users as passive recipients of fault alerts. The system dynamically calculates a capability score to determine the optimal service pathway. This empowers proficient end-users with the guided self-repair instructions or automatic scheduling of professional technicians when complex or hazardous interventions are required. In this architecture, multimodal sensor networks serve dual roles as real-time diagnostic engines and operational safety filters.

The operational efficiency of the developed system was evaluated through empirical testing involving 1000 participants across 50 simulated fault scenarios. The system shows a 93.3% fault diagnosis accuracy and an 85.0% precision in assessing user technical capability. From a service logistics perspective, the adaptive routing model reduced average repair durations by 62.5% and unnecessary technician dispatches by 61.1%. These quantitative gains confirm that combining sensor-driven diagnostics with explainable user profiling alleviates maintenance overhead, builds consumer trust, and lowers operational costs for appliance manufacturers.

The system serves as a model for advancing edge intelligence and sensor-driven maintenance in cyber–physical consumer systems. By establishing bidirectional mapping between machine health status and human proficiency, manufacturers can transition from reactive service models to proactive, human-centric lifecycle management. The results of this study show that edge intelligence architectures can be extended to accommodate heterogeneous multi-appliance ecosystems by integrating richer semantic sensor modalities and refining user capability algorithms to capture broader behavioral nuances.

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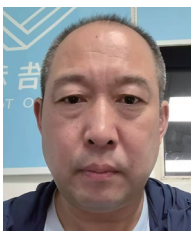
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