Proceedings of the ASME 2025 20th International Manufacturing Science and Engineering Conference
MSEC2025
June 23-27, 2025, Greenville, South Carolina

MSEC2025-155833

ARTIFICIAL INTELLIGENCE-BASED PRODUCT DURABILITY ASSESSMENT

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ABSTRACT

This study provides an AI-based product durability assessment framework for estimating the longevity of products based on historical repair logs. It uses a repair and maintenance dataset of medical equipment to develop a scoring model that assesses product longevity and failure trends despite limited data attributes. The dataset includes work order numbers, asset identifiers, equipment descriptions, manufacturers, models, serial numbers, service dates, and repair determinations. The study applies machine learning techniques to analyze patterns in failure frequency, time between failures, equipment types, and manufacturer-specific issues to develop a durability score that aids in optimizing maintenance scheduling and resource allocation. To improve the model, feature engineering is used on categorical fields, such as equipment type, manufacturer, and model, to change these into predictive features that demonstrate failure likelihood and product lifespan trends. Moreover, temporal analysis on repair dates shows the long-term reliability of specific models over time and further improves the durability score. The study correlates repair outcomes (determination descriptions) with failure frequency and time to failure to identify high-risk equipment and provide recommendations for preventive maintenance. The analyses demonstrate that, despite limited data attributes, it is possible to generate practical information about product longevity using AI models trained on categorical and temporal data.

Keywords: Durability Score, AI, Repairability, Medical Equipment

1. INTRODUCTION

Repairability and durability are essential in sustainable design and circular economy practices, as they extend the lifespan of products and minimize waste [1]. In response to growing environmental challenges and increasing consumer interest in longer-lasting goods, the development of durability and repairability scores has gained attention among manufacturers, policymakers, and researchers. These scores guide organizations in optimizing maintenance decisions, resource allocation, and replacement strategies. Despite the existence of indices for repairability such as the French Repairability Index [2], iFixit score [3], and methodologies such as the Product Repairability Index (PRI) [4], existing frameworks are often limited by static assessments as they mainly use design attributes, such as disassembly complexity [5], modularity [6], and spare part availability [7], while underemphasizing product longevity, failure rates, and durability over the lifecycle.

This paper addresses these gaps by introducing a data-driven approach to analyzing product durability using machine learning and historical repair data. The objective is to develop a machine learning-based framework for estimating durability scores using a dataset of medical equipment repair logs. The study analyzes failure frequency, the time between failures, maintenance duration, and manufacturer-specific patterns toward predictive durability assessment. The approach includes feature engineering on categorical data and temporal analysis to improve model accuracy. Moreover, the study uses root cause analysis, anomaly detection, and clustering techniques to uncover trends in failure and repair patterns and provide actionable recommendations for optimizing maintenance strategies that extend product lifespan.

The remainder of this paper is organized as follows: Section 2 reviews the literature. Section 3 describes the dataset used in this study. Section 4 outlines the proposed framework for developing durability scores, including root cause analysis and predictive modeling. Section 5 presents the results of clustering and anomaly detection analyses, and Section 6 concludes with recommendations for future research.

2. BACKGROUND

Repairability and durability are the basis for sustainable design and circular economy as they extend product lifespans and reduce resource depletion. As consumer demand for long-lasting and repairable products grows, policymakers and manufacturers focus on durability and repairability to mitigate environmental impacts. Cordella et al. showed the environmental and economic trade-offs between reliability and repairability by emphasizing modular designs and durable components [8]. Similarly, Cavillot and Swaen pointed out policy-driven initiatives, such as the French Repairability Index, to make repairability transparent for consumers [2].

Despite these efforts, studies such as Makov and Fitzpatrick revealed that repairability alone may not extend product lifespans due to perceived obsolescence [9]. However, repairability could facilitate recovery operations for recyclers and remanufacturers. Physical durability may delay functional obsolescence [10].

Repairability assessment frameworks vary widely in their scope and criteria. Ruiz-Pastor and Mesa introduced the Product Repairability Index (PRI), which incorporates disassembly complexity, spare part availability, and functional importance to prioritize design changes [4]. Similarly, Bracquené et al. applied the Assessment Matrix for ease of Repair (AsMeR) and the Repair Scoring System (RSS) methods by emphasizing the influence of priority parts in repairability scoring [11]. Barros and Dimla showed how industrial design features and service quality affect repairability indices [12]. De Fazio et al. proposed the Disassembly Map method to guide design for repairability but relied on manual processes [13]. These approaches exclude behavioral factors such as consumer willingness to repair and product longevity considerations, as identified by Bigerna et al. [14] and Makov and Fitzpatrick [9]. Furthermore, Cordier et al. expanded the theoretical basis by introducing self-healability by linking diagnosability and repairability but did not address durability as a factor in long-term functionality [15].

Although these methods contribute to repairability evaluation, they lack integration with lifecycle data, failure prediction models, and predictive analytics that could assess durability over time.

Recent advances in data analytics provide opportunities to advance durability and repairability assessments. Liao et al. utilized AI-based approaches by developing supervised learning to evaluate teardown images and unsupervised clustering to group products by design features [16]. This automated framework demonstrates scalability but is limited by its reliance on static image data. Bracquené et al. [11] and Rodríguez et al. [17] also discussed the need for consistent methodologies to maintain reliability between product categories. They suggested the potential for machine learning to address these gaps.

Although some existing metrics assess repairability, they are mainly qualitative and design-based, considering factors such as disassembly complexity and spare part availability. There is a lack of standardized, data-driven metrics for quantifying repairability, and no established durability metric considers product longevity and failure trends.

Data-driven studies on repair, such as the one by Huang et al., have analyzed user-reported repair experiences [18]; however, their approach utilized user behavior data rather than product-specific or lifecycle information. Current models fail to utilize lifecycle data, such as time between failures, failure modes, and maintenance history, to predict durability. The current study aims to address this gap by developing a data-driven framework that incorporates product lifecycle data and predictive modeling to provide durability assessments.

3. REPAIR AND MAINTENANCE DATASET

The dataset used in this study is a repair and maintenance log for medical equipment, including 536,597 records. It contains numeric and categorical data, including unique work order numbers, asset identifiers, equipment descriptions, manufacturers, models, serial numbers, and service-related information such as repair determination descriptions, date work order created, and date work order completed.

The dataset consists of 536,597 records of medical device maintenance and repair history. The dataset features equipment from 1,336 unique manufacturers. Among the asset descriptions, “Infusion Pumps, Multitherapy” is the most common. The Determination Description column includes 34 unique failure types, with “Random Failure” being the most frequent cause, recorded in 240,944 cases. In addition, the First Asset Serial Number includes 87,170 unique identifiers, with some serial numbers appearing multiple times, indicating repeated maintenance for certain devices.

Figure 1 presents the number of work orders recorded annually from 2004 to 2018. Figure 2 shows the average turnaround time for each repair and the duration of maintenance processes.

Table 1 lists the Top 10 Frequent Asset Failures, which reflects the frequency of records associated with each asset type.

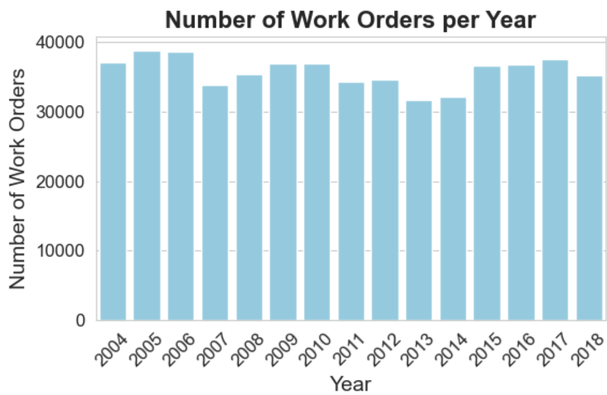

Figure 1. The number of work orders per year

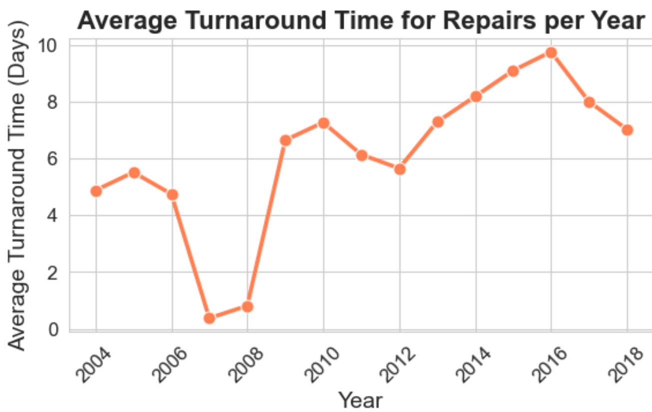

Figure 2. The average repair completion time per year

Table 1. The top 10 asset categories with the most frequent failures

	Asset Description	Frequency
1	Infusion Pumps, Multitherapy	54,154
2	Controllers, Infusion Pump Systems, Programmable	22,404
3	Monitors, Physiologic, Vital Signs	14,934
4	Circulatory Assist Units, Peripheral Compression	13,596
5	Monitors, Physiologic, Multipurpose, Telemetric	13,490
6	Hospital Communication Systems, Nurse Call	12,198
7	Thermometers, Electronic, Thermistor/Thermocou	8,286
8	Monitors, Physiologic, Central Station	7,761
9	Oximeters, Pulse	7,469

Although the dataset is extensive, some limitations may affect the analysis results. Certain manufacturers are overrepresented, which may potentially skew predictions. The dataset also spans from 2004 to 2018, where older devices may show higher failure rates simply due to wear, which may lead to possible overestimation of failures. Also, the lack of usage history and workload data makes it difficult to assess actual product durability, as differences in operational stress are not considered.

4. DURABILITY SCORE FRAMEWORK

This section describes the proposed framework for developing a data-driven durability score. The framework includes two key steps. (1) first, we identify the most important features related to durability, and then (2) we build a predictive model for the durability score to predict the durability score for each device based on its historical data and most important features.

4.1. Root Cause Analysis and Feature Importance

The first step of the framework is to identify the features that are important in predicting the repair needs of a device. We used a decision tree classifier to predict the likelihood of “frequent maintenance” for medical equipment based on historical repair and maintenance data to perform this step.

Decision trees help us understand which equipment attributes and maintenance characteristics are most influential in predicting frequent maintenance needs. The target variable, “Frequent Maintenance,” was defined based on a threshold of maintenance frequency by specifying assets that had undergone maintenance more than five times as frequent maintenance items. Four main features have been used as predictors: (1) First Asset Model Number, The specific model of the asset; (2) First Asset Manufacturer Name: The manufacturer of the equipment, and (3) Turnaround Time (Days): The time taken to complete each maintenance event, calculated as the difference between the “Date Created” and “Completed Date” fields. Categorical features such as “First Asset Model Number” and “First Asset Manufacturer Name” were encoded numerically using label encoding. The dataset was then split into training and testing sets (70% for training and 30% for testing).

The decision tree achieved an accuracy of 84% on the test dataset, with a precision of 88% and recall of 91% for predicting frequent maintenance. This performance shows that the model is relatively reliable in identifying assets that require frequent maintenance. The classification report further shows an F1-score of 0.89 for the frequent maintenance class. The feature importance analysis highlighted that “First Asset Model Number” was the most influential feature, contributing to 52.6% of the model’s predictive power. “First Asset Manufacturer Name” was the second most important feature (34.8%), followed by “Turnaround Time (Days)” (12.6%).

4.2. Data-Driven Durability Score

In this section, a durability score model was developed to assess medical equipment’s durability quantitatively. The scoring model uses several factors, including failure frequency, turnaround time, manufacturer and model-specific characteristics, and failure type. A simplified numerical score is developed using a weighted combination of main quantitative factors to establish an initial measure of durability. This approach offers an interpretable baseline for assessing durability. However, this manually defined score serves as a preliminary estimate and does not capture all potential factors that affect durability. To modify this metric, we later introduce a data-driven machine learning approach that determines factor importance.

Feature engineering was applied using label encoding to manage categorical fields such as manufacturer and model. The numerical fields (failure frequency, turnaround time) were scaled to provide uniform weighting in the model. A custom scoring function was initially used to assign weighted values based on factor importance. Then, a Random Forest Regressor was used to predict durability scores. The model outputs a durability score, where lower values show assets more prone to failure.

The score incorporates several quantitative factors to assess the product longevity, including Failure Frequency, Turnaround Time, and Time Between Failures. Failure Frequency is a significant indicator, with higher frequencies suggesting lower longevity and increased maintenance needs. This was quantified by counting each asset's total repair records. Turnaround Time, the duration from repair request to completion, reflects service complexity. Time Between Failures provides information about reliability over time, as shorter intervals between repairs imply frequent breakdowns.

To make sure that numerical features contributed proportionately, each was scaled to a uniform range using min-max scaling. This transformation makes each feature range from 0 to 1, to provide direct comparison and weighting. $\acute{x} = \frac{x - x_{min}}{x_{max} - x_{min}}$. Each scaled feature was then assigned a weight based on its relative importance. The weighting values (e.g., 0.4 for failure frequency, 0.3 for turnaround time, and 0.3 for time between failures) were assigned based on commonly accepted maintenance principles, where frequent failures, long service times, and short failure intervals imply lower durability. These weights provide an initial approximation. However, we acknowledge that these values should be empirically optimized and may vary among equipment types. Future work could incorporate expert validation from reliability engineers and maintenance professionals to better reflect real-world conditions. The weighted scoring formula for the durability score D was defined as:

$$D = 1 - (w_{freq} . \acute{x}_{freq} + w_{turn} . \acute{x}_{turn} + w_{TimeFail} . \acute{x}_{TimeFail})$$

To improve the score calculation with more data-driven intuitions, we developed a predictive model that uses both quantitative and qualitative data as features to predict the repairability score more precisely. Although the initial numerical score provides a simplified way to assess durability, it is based on fixed weightings and does not account for more complex relationships between factors.

To overcome this gap, we have used a Random Forest Regressor and trained the model to learn from historical repair data, where it identifies patterns from all relevant features. Random Forest Regressor was selected due to its strength in handling tabular data with mixed categorical and numerical variables, which is suitable for our dataset. It also provides feature importance rankings for better interpretability in identifying the factors influencing durability scores. Also, Random Forest models are less sensitive to missing data and outliers.

In addition to quantitative features, qualitative features such as manufacturer, model, and failure types were also included in the predictive model through encoding techniques. Manufacturer and model fields were transformed into numerical values using label encoding. The failure types (from the Determination Description) were represented through one-hot encoding, where a binary feature was created for each unique failure type. This encoding helps each failure type contribute individually to the score.

Combining quantitative features with encoded qualitative data helps the predictive model consider a broad picture of durability and repairability. We should acknowledge that label encoding can impose an unintended ordinal structure on non-ordered categories. Future work could explore alternative encoding techniques and embedding-based methods to preserve categorical relationships better while minimizing biases.

Devices with high failure frequency, long turnaround times, short intervals between failures, or recurrent failure types are predicted to have lower durability scores. The score for each device is predicted by:

$$D = Model\begin{pmatrix} Failure\ Frequency, \text{Turnaround Time, Time Between Failures,} \\ \text{Manufacturer, Model, Failure Type} \end{pmatrix}$$

We should note that the durability score is derived from historical repair data, which means that devices with higher recorded failures may receive lower scores. However, frequent servicing does not always imply poor durability; it may also reflect widespread use, preventive maintenance policies, or manufacturer service strategies. Future modifications could normalize scores based on market share, device utilization levels, or expected service intervals to address this potential bias. Also, considering failure rates per operational time rather than raw repair frequency could increase fairness when comparing manufacturers and device types.

To show the application of the model, Table 2 provides a summary of features and predicted score for device 26256. Multiple features were evaluated to provide a detailed assessment of its repair history, typical turnaround time, failure frequency, and predicted durability score.

Table 2. Summary of Repair and Predictive Metrics for Device 26256

Metric	Value
Failure Frequency	50
Average Turnaround Time (days)	1.16
Average Time Between Failures (days)	86.80
Manufacturer Code	702
Model Code	7666
Predicted Repairability Score	0.728

In addition to the features in Table 2, we included failure type code in the prediction model. For device 26256, various failure types are observed in multiple repair records. Table 3 provides an overview of the identified failure type codes and their occurrence rates.

Table 3. Failure Type Codes and Their Occurrence Rates for Device 26256

Failure Type Code	Occurrence Rate
Battery Related	0.08
No Problem Found	0.16
PM Passed	0.02
PM Related	0.12
Physical Damage	0.24
Random Failure	0.26
Random Software Failure	0.02
Use Error	0.10

The most frequently observed failure type for device 26256 was Random Failure, with an occurrence rate of 26%, followed by Physical Damage (24%), No Problem Found (16%), and Use Error (10%). Other failure types, such as Battery Related, PM Passed, PM Related, and Random Software Failure, were observed at lower frequencies.

5. DATA-DRIVEN ANALYSES

This section discusses the importance of product lifecycle data and extends the data analytics beyond the durability score. It shows the value of the lifecycle data of individual devices and examines the use of machine-learning approaches for understanding recurring patterns and trends.

5.1. Lifecycle Data Analysis of Individual Devices

The dataset provides unique serial numbers for each device to facilitate tracking of the repair and maintenance history of individual assets over time.

Figure 3 illustrates the distribution of devices that have undergone fewer than 100 repair events, and Figure 4 presents an analysis of a specific device with serial number 26251. It shows the time intervals between successive failures and the types of failures experienced. Also, Figure 5 shows Random Failure and No Problem Found as the main reasons for the recalls of device 26251.

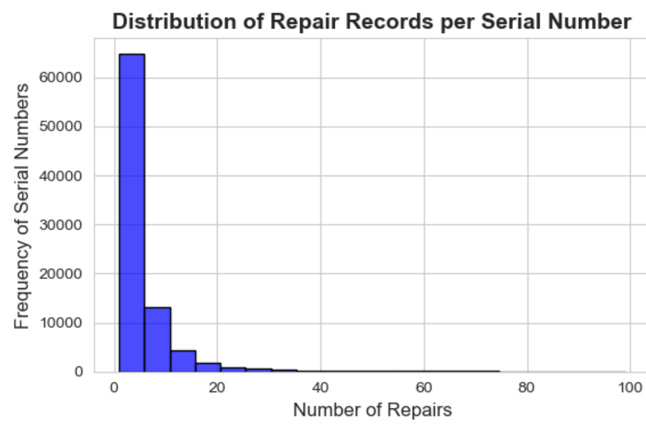

Figure 3. The distribution of serial numbers with fewer than 100 repair records.

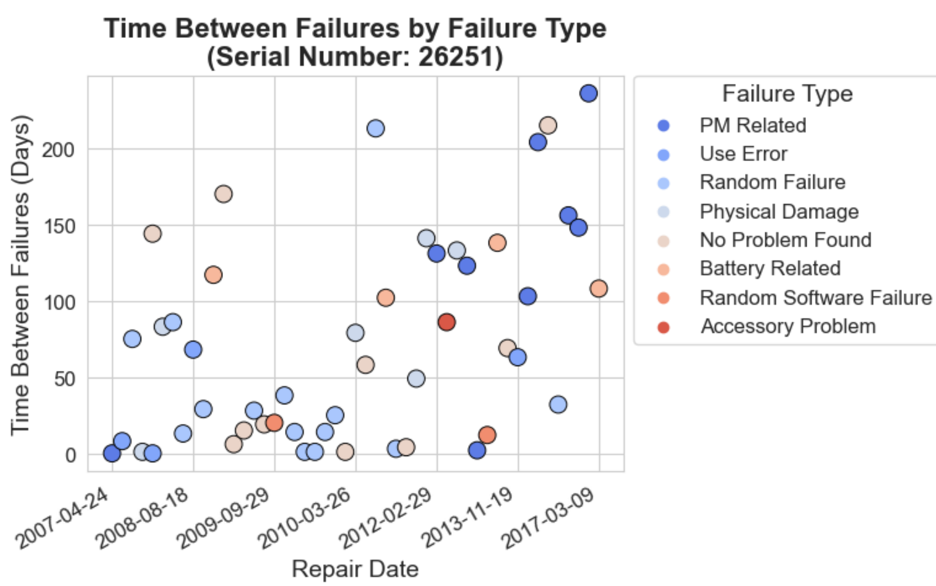

Figure 4. The time between failure and the type of failure for the device with serial number 26251

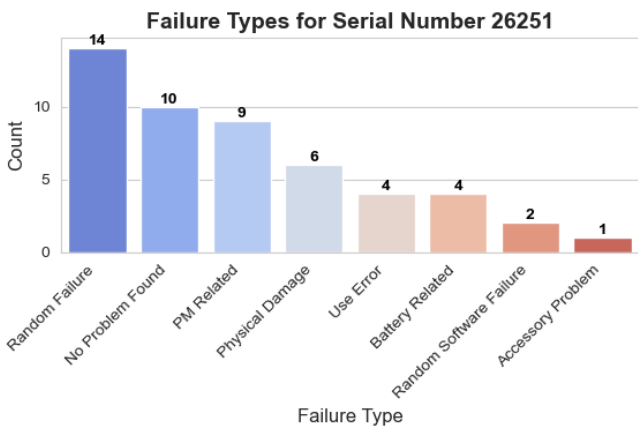

Figure 5. The count of failure type for device 26251

5.2. Predictive Maintenance Classification for Failure Types

This analysis aims to develop a predictive maintenance framework that forecasts the next likely failure type for individual devices based on their historical repair data. This model provides a proactive planning tool to maintenance teams for anticipating repair needs and allocating resources accordingly.

The inputs of the model include sequential repair records for each device. Each sequence contains features such as Repair Frequency, which counts the total number of repairs for each device; Turnaround Time, which captures the duration of each repair event; Time Since the Last Repair, which measures the interval between consecutive repairs; and Previous Failure Type that records the most recent failure type encountered for each device. These inputs are structured as sequences to provide the model with the order and timing of past events. The output is the predicted failure type for the next maintenance event, represented as a categorical label.

We use a Long Short-Term Memory (LSTM) architecture [19] for time-series data and sequence-based prediction tasks. First, the data for each device is sorted by repair date and organized into sequences of fixed length (e.g., five prior repair events). The LSTM model consists of a masking layer that handles varying sequence lengths and focuses only on actual repair events, followed by an LSTM layer with 128 units, which learns temporal patterns within each device's repair history. A dense output layer with a softmax activation function outputs probabilities for multiple failure types.

The model is trained with categorical cross-entropy as the loss function, and accuracy is used as the primary evaluation metric. We also use F1-score, precision, and recall to address any class imbalances in the dataset.

LSTMs were used to analyze how sequential dependencies in failure events could be used for predictive maintenance. The LSTM model achieved an overall test accuracy of 45% for device serial number 2625. This result suggests that the model has learned some patterns but faces challenges in accurately predicting the next failure type due to high variability in failure patterns and overlapping characteristics among failure types. For device 26251 specifically, the model predicted "Accessory Problem" as the next likely failure type.

Several modifications could be considered to improve predictive accuracy. Addressing class disparity in the dataset and introducing additional features, such as device age or cumulative repair costs, may tackle the issue if possible. Also, alternative models, such as Transformers or ensemble approaches, could increase prediction accuracy.

5.3. Cluster Analysis of Device Types for General Repair Trends

This section describes how clustering can identify groups of devices with similar repair patterns. For example, clusters may represent devices that frequently experience battery-related issues or have extended repair durations.

We applied clustering to examine repair trends among the top 10 most frequently repaired devices from a specific manufacturer, anonymized with a Manufacturer Code. The focus was on battery-related failures. We computed two primary metrics for each device type: (1) the frequency of battery-related failures and (2) the average repair time.

We applied hierarchical clustering with Ward's method on the normalized repair metrics to group devices. This approach organizes devices into clusters by minimizing the variance within each group.

The resulting dendrogram (Figure 6) visually represents these clusters. For example, specific clusters emerged with devices exhibiting frequent but relatively short repair times, which shows quick, high-frequency battery maintenance. Other clusters included devices with less frequent battery failures but longer repair durations. Hierarchical clustering does not require a predefined number of clusters but rather forms clusters based on distance thresholds.

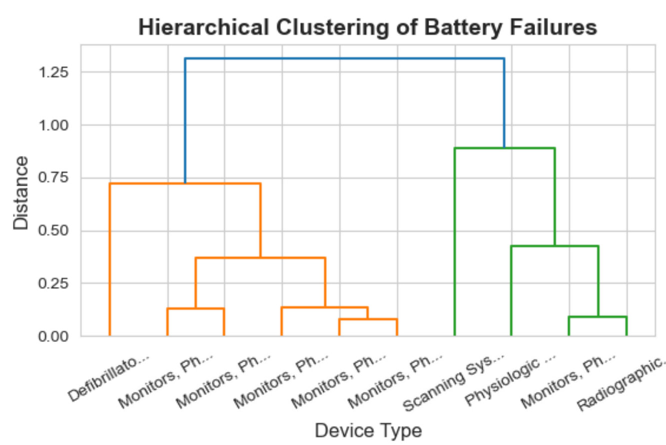

Figure 6. Hierarchical clustering dendrogram of top devices by Battery-Related repair characteristics

Table 4. Clustering Result Based on Battery-Related Failures

	First Asset Description	Repair Time (Days)	Battery Failure Count	Cluster
0	Defibrillator/Pacemakers, External	0.752	206	2
1	Monitors, Physiologic, Central Station	2.932	74	1
2	Monitors, Physiologic, Fetal	2.291	24	3
3	Monitors, Physiologic, Multipurpose, Bedside	5.804	82	1
4	Monitors, Physiologic, Multipurpose, Telemetric	1.659	88	1
5	Monitors, Physiologic, Patient Transport	8.190	126	1
6	Monitors, Physiologic, Vital Signs	3.984	128	1
7	Physiologic Monitor Modules, Multiparameter	13.714	7	3
8	Radiographic/Fluoroscopic Systems, Cardiovascular	3.750	8	3
9	Scanning Systems, Ultrasonic, Cardiac	28.000	2	4

Table 4 presents the clustering results of devices based on battery-related failures by showing each device's description and average repair time (in days).

5.4. Anomaly Detection for Identifying At-Risk Devices

In this section, we used an anomaly detection analysis to identify devices that show unusual maintenance patterns that may require further investigation. The anomaly detection process was conducted using an Isolation Forest algorithm, which flagged devices deviating from typical behavior based on key metrics: failure frequency, average repair time, and failure type characteristics. These metrics were normalized to provide comparability between devices. Isolation Forest was selected for its performance in detecting outliers in high-dimensional data and its ability to handle varied distributions of repair metrics [20].

The results identified 4.99% of the devices as anomalies, including units with atypical repair frequency or repair durations and/or failure types not commonly seen within the dataset. For example, the device with serial number 1285 was flagged as an anomaly.

Table 5 lists a few samples of devices identified as anomalies based on their maintenance patterns. Each device's First Asset Serial Number is shown alongside key metrics: Repair Frequency, Average Repair Time, and Failure Type Encoded.

Table 5. Sample of Anomaly Detection Results

First Asset Serial Number	Repair Frequency	Average Repair Time	Failure Type Encoded
1285	0.078231	0.004814	0.696395
000000-Beta	0.033163	0.004804	0.698529
us37890284	0.002551	0.021202	0.764706

Future work could improve the interpretability of the results by using dimensionality reduction techniques (e.g., PCA, t-SNE) for visual clustering and incorporating expert validation.

6. CONCLUSION

This study proposed a data-driven framework for estimating product durability using historical repair and maintenance data. Machine learning techniques have been used to analyze failure frequency, maintenance durations, and failure patterns in medical equipment. The study utilizes categorical and temporal data to demonstrate how feature engineering and predictive modeling can facilitate durability analysis. Furthermore, clustering and anomaly detection techniques revealed repair trends and identified high-risk devices to help with proper repair planning.

The study applies the machine learning framework to medical equipment; however, the methodology applies to other product categories, including automotive, consumer electronics, and industrial machinery. The framework's main components, including failure prediction, maintenance trend analysis, and durability scoring, can be modified based on industry-specific failure patterns and operational data. Future work could validate the framework for different industries by incorporating relevant product-specific factors such as mileage in automotive settings, software failures in electronics, or wear-and-tear cycles in heavy machinery.

The study has some limitations, mainly due to data sparsity in certain failure types and manufacturers, which may affect how well the model generalizes between different devices. Some products have significantly fewer repair records. This makes obtaining consistent failure patterns challenging. Also, the dataset does not include detailed failure-specific attributes and operational activity data. Since the model depends on historical repair logs, it cannot incorporate real-time data or be fit for changing maintenance conditions.

The study can be extended in several ways. Advanced temporal modeling techniques, such as transformers, could improve prediction accuracy by better capturing temporal dependencies and long-term repair trends. Also, the work can be extended to include richer datasets and broader product domains and improve its generalizability. Although no durability metrics are available in the literature, future work could evaluate and integrate existing repairability scoring systems, such as the iFixit score, French Repairability Index, and PRI, to create a hybrid framework. Combining design-specific attributes, such as disassembly complexity and modularity, with operational factors, such as repair frequency and failure intervals, could provide a more complete scoring methodology. Expanding the scope to analyze behavioral data, including consumer repair behavior and willingness to repair, would further improve the scoring framework and move it beyond product longevity to repairability. Future work could also incorporate expert validation from maintenance engineers, reliability analysts, and manufacturers, who can assess whether the predicted durability scores align with real-world product performance.

ACKNOWLEDGEMENT

The National Science Foundation – USA has provided financial support for the conduct of the research under grant grants # CCF 2324950 and CMMI 2412471 for Sara Behdad. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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