Yuzuncu Yil University Journal of the Institute of Natural & Applied Sciences, Volume 28, Issue 3 (December), 993-1001, 2023

Yuzuncu Yil University
Journal of the Institute of Natural & Applied Sciences

https://dergipark.org.tr/en/pub/yyufbed

Research Article

A Clustering-based Approach for Maintenance Prioritization of Medical Devices in a New Hospital

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Article Info

Received: 08.05.2023
Accepted: 24.07.2023
Online December 2023

DOI:10.53433/yyufbed.1294093

Keywords
Analytical hierarchy process,
Data clustering,
Maintenance prioritization,
Medical devices

Abstract: Medical devices are fundamental to preventing, diagnosing and treating disease and high availability of them is vital for the uninterrupted operation of a hospital. That is why hospitals should plan and carry out maintenance activities to keep their medical devices in a healthy operating condition. The effectiveness of these activities can be increased by determining the maintenance priorities of devices. On the other hand, setting individual priorities for each device becomes complicated when a hospital has hundreds of medical devices. In this concern, grouping medical devices and determining group-based maintenance priorities will be more advantageous for maintenance planning. In this study, a novel approach is proposed for the maintenance prioritization of medical devices in a new hospital. In the proposed approach, first prioritization attributes are defined and weighted using the analytical hierarchy process (AHP). Then, medical devices are grouped based on the predetermined attributes by using data clustering. Finally, maintenance priorities of medical device clusters are determined based on the weighted sum of cluster centers.

Yeni bir Hastaneye Ait Medikal Cihazların Bakım Önceliklendirmesine Yönelik Kümeleme Tabanlı bir Yaklaşım

Makale Bilgileri

Geliş: 08.05.2023
Kabul: 24.07.2023
Online Aralık 2023

DOI:10.53433/yyufbed.1294093

Anahtar Kelimeler
Analitik hiyerarşi süreci,
Bakım önceliklendirmesi,
Medikal cihazlar,
Veri kümeleme

Öz: Medikal cihazlar hastalıkların önlenmesi, teşhisi ve tedavisinde oldukça önemli olup, bu cihazların ihtiyaç halinde kullanılabilir durumda olması bir hastanenin operasyonlarının sürekliliği için hayati önem teşkil etmektedir. Bu nedenle, hastaneler mevcut medikal cihazları çalışır durumda tutmak için bakım planları oluşturmalı ve uygulamalıdır. Bakım planlarının etkinliğinin artırılmasında ise cihazların bakım önceliklerinin belirlenmesi oldukça önemlidir. Öte yandan, bir hastanede yüzlerce medikal cihaz olduğu bir durumda her bir cihaz için ayrı bir bakım önceliği tayin etmek oldukça zordur. Bu anlamda, medikal cihazları gruplandırmak ve grup bazlı bakım öncelikleri oluşturmak bakım planlaması açısından daha faydalı olacaktır. Bu çalışmada yeni bir hastaneye ait medikal cihazların bakım önceliklendirmesine ilişkin yeni bir yaklaşım önerilmiştir. Bu kapsamda ilk olarak bakım önceliklendirmesinde kullanılacak nitelikler tanımlanmış ve analitik hiyerarşi süreci (AHS) ile ağırlıklandırılmıştır. Daha sonra, medikal cihazlar nitelikleri baz alınarak veri kümeleme ile gruplandırılmıştır. Son olarak, medikal cihaz kümelerine ilişkin bakım öncelikleri küme merkezlerinin ağırlıklı toplamı alınarak belirlenmiştir.

1. Introduction

The effectiveness of hospitals largely depends on the uninterrupted operation of medical devices. Breakdowns of medical devices may result in life-threatening complications and may lead to high repair costs. Hence maintenance activities must be planned and carried out for these devices. Since medical devices' characteristics and criticality levels are different, prioritization of medical devices for maintenance activities increases the effectiveness of maintenance activities and decreases the cost of maintenance operations.

There are several studies on the maintenance prioritization of medical devices. Multi-attribute-decision-making techniques are employed in some of these studies. Taghipour et al. (2011) and Hutagalung & Hasibuan (2019) use analytical hierarchy process (AHP) for maintenance prioritization of medical devices. Tawfik et al. (2013) develop a fuzzy inference model to classify medical devices into risk categories. Mahfoud et al. (2016) propose a two-step approach. First, the attribute weights are determined using AHP. Then, PROMETHEE multi-attribute-decision-making technique is used to prioritize medical devices for maintenance activities. Houria et al. (2016) first determine the ranking of maintenance strategies using AHP and TOPSIS. Then, the optimum maintenance strategy for each medical device is determined by using a mixed integer linear programming model.

Moreover, some studies determine the risk classes of medical devices and determine the maintenance prioritization based on risk class. The majority of these studies employ failure mode and effects analysis (FMEA). Jamshidi et al. (2015) develop a fuzzy FMEA-based approach for the prioritization of medical device maintenance activities and the determination of the most suitable maintenance strategy for these devices. Azadi Parand et al. (2021) calculate fuzzy risk priority numbers for medical device risk assessment. An ordered weighted averaging aggregation operator is employed to aggregate the opinions of experts. Tavakoli et al. (2022) develop a weighted FMEA approach for the risk assessment of medical devices. They use fuzzy DEMATEL and the fuzzy best-worst method to determine attribute weights.

From another point of view, device age (Taghipour et al., 2011; Jamshidi et al., 2015; Houria et al., 2016; Hutagalung & Hasibuan, 2019; Zamzam et al., 2021), device cost (Taghipour et al., 2011; Hutagalung & Hasibuan, 2019; Zamzam et al., 2021), device function (Taghipour et al., 2011; Jamshidi et al., 2015; Houria et al., 2016; Hutagalung & Hasibuan, 2019; Zamzam et al., 2021), risk class (Taghipour et al., 2011; Houria et al., 2016; Hutagalung & Hasibuan, 2019), maintenance complexity (Houria et al., 2016; Hutagalung & Hasibuan, 2019; Zamzam et al., 2021), maintenance requirements (Taghipour et al., 2011; Jamshidi et al., 2015; Zamzam et al., 2021) and the number of available identical devices (Taghipour et al., 2011; Houria et al., 2016; Hutagalung & Hasibuan, 2019; Zamzam et al., 2021) are the most common attributes used in the literature for the maintenance prioritization of medical devices.

In the above studies, the maintenance priority level is determined for each medical device individually. This device-based approach to maintenance prioritization may be very time-consuming considering the high number of medical devices in a hospital. Hence, the determination of maintenance priority levels for device groups instead of individual devices is a more cost-effective approach. In the literature, only Zamzam et al. (2021) use cluster analysis in the maintenance prioritization of medical devices and they cluster devices based on device characteristics. They consider multiple devices from the same category in their study. However, grouping device categories is more important for maintenance prioritization. Therefore, we cluster device categories based on device characteristics and then determine the maintenance priorities of the obtained clusters in our study. On the other hand, Zamzam et al. (2021) present only cluster profiles and do not provide information on the determination of cluster priorities. To fill this gap, we employ AHP in our study to determine the cluster priorities. In addition, while Zamzam et al. (2021) present a case-specific approach, our proposed approach is more generic and can be applied to the maintenance prioritization problem of any hospital.

The remainder of this study is structured as follows. Brief information on the proposed medical device maintenance prioritization approach, AHP, and Ward's hierarchical clustering method is presented in Section 2. Device attributes that are used to cluster the medical devices are also explained in the same section. In Section 3, AHP and clustering analysis are applied to the medical device maintenance prioritization problem of a new hospital. Finally, conclusions and future research directions are presented in Section 4.

2. Material and Methods

The proposed approach for the maintenance prioritization of medical devices is presented in Figure 1. In the first stage of the proposed approach, attributes to be used in the clustering analysis are identified. Their measurement units and scales are also defined. In the following stage, attribute weights are determined. In this study, AHP is used for this purpose. Then, medical devices are grouped based on predetermined attributes by using clustering algorithms. We used Wards' method as a clustering technique in our study. Finally, maintenance priorities of medical device clusters are determined based on the weighted sum of cluster centers.

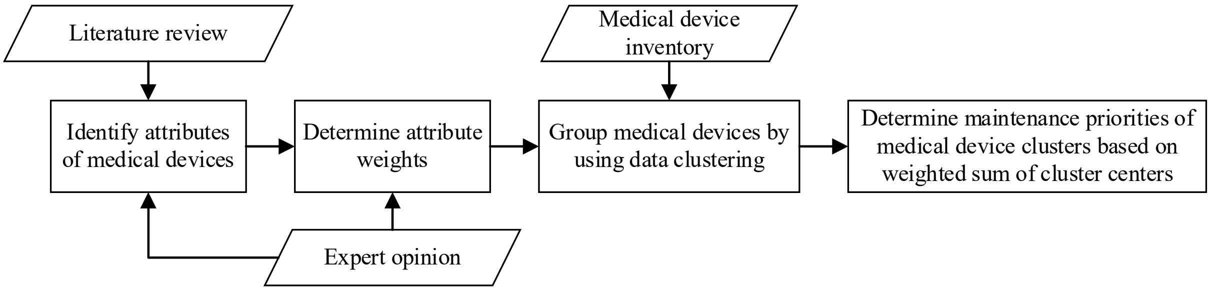

Figure 1. Proposed medical device maintenance prioritization approach.

2.1. Medical device attributes

In this section, six attributes that are used to cluster the medical devices are identified. Attributes related to device usage rate or age are not included in this study as we deal with the medical devices of a newly established hospital.

- ***Function* (*F1*):** This attribute refers to the intended use of medical devices and can be evaluated in five grades (Taghipour et al., 2011). In the following grading, a higher value indicates higher maintenance priority.
  1: Other
  2: Analytical
  3: Diagnostic
  4: Therapeutic
  5: Life support
- ***Risk class* (*F2*):** This attribute shows the risk level of medical equipment. According to the European Union, a piece of medical equipment falls into one of the following four risk classes depending on the level of harm it may pose to users or patients (Aronson et al., 2020). The risk class of medical equipment is determined based on the rules that consider various issues such as duration of use, degree of invasiveness, potential toxicity, part of the body affected, and energy transmission (Medical Device Coordination Group, 2021). For instance, class I covers equipment that is non-invasive and does not penetrate the human body (i.e. manual wheelchair, bandages, hospital beds, stethoscopes). If equipment is short-term invasive or causes energy transfer with the patient, then it is classified as class IIa. Equipment in this class is usually used for monitoring and diagnostics (i.e. suction equipment, centrifuge, ultrasound machine, magnetic resonance imaging machine). Class IIb refers to the most invasive equipment that is partially or completely introduced into the human body (i.e. ventilator, defibrillator, surgical laser). Finally, class III refers to implantable and long-term invasive equipment that are important to sustaining a patient's life (i.e. pacemaker, intra-aortic balloon pump, breast implants). As the risk level of medical equipment increases, the maintenance priority also increases.
  1: Class I (low risk)
  2: Class IIa (low to moderate risk)
  3: Class IIb (moderate to high risk)
  4: Class III (high risk)

- ***Device cost* (*F3*):** This attribute indicates the cost of the medical device in Turkish Lira. In this study, cost values are obtained from the website of the State Supply Office (DMO) of Turkey. It is obvious that, the device cost directly affects the repair cost of the device. Expensive medical devices have expensive spare parts and usually require extensive maintenance. Therefore, keeping those devices in healthy operating condition is very important for the hospitals in terms of time, money and effort. In this concern, the maintenance priority of a medical device increases, as its cost increases.
- ***Maintenance complexity* (*F4*):** Maintenance complexity defines the level of complexity of the maintenance operations required by a medical device. Fennigkoh & Smith (1989) classified the complexity level of medical device maintenance into three grades such as low, moderate, and high. Low-level maintenance usually includes visual inspection, cleaning, basic performance checks and battery replacement. Mid-level maintenance usually includes performance and safety tests, filter replacement and lubrication. High-level maintenance is carried out, especially for the mechanical, pneumatic, or hydraulic devices and it usually includes performance and safety tests, calibration, and spare part replacement. Complex maintenance operations require special tools, and specialized worker(s) and take longer time. Therefore, medical devices with high levels of maintenance complexity should be prioritized in maintenance plans.
  1: Low
  2: Moderate
  3: High
- ***The number of available identical devices* (*F5*):** This attribute shows the number of identical devices in the hospital and consists of two grades as the following. In case of failure of insufficient devices, negative consequences such as patient death may occur. Therefore, we should give higher priority to devices that have no alternative in our maintenance plans.
  0: There are multiple identical devices
  1: There is only one device
- ***Maintenance staff* (*F6*):** Maintenance staff refers to whether the maintenance operations are performed by the internal staff or external staff. Maintenance of some medical devices must be carried out by authorized service providers. In this case, we have to make an appointment with the service provider. However, appointment availability may change during some peak periods and this can cause longer waiting time for maintenance. On the other hand, if the maintenance staff is inside the hospital (i.e. technician, biomedical engineer) maintenance operations are carried out in a short time. Therefore, a medical device that requires external maintenance staff should have a higher priority in maintenance plans.
  0: Internal
  1: External

2.2. AHP

AHP developed by Saaty (1980) is a commonly used multi-attribute-decision-making technique. It uses a hierarchical decision structure. The goal of the multi-attribute decision problem is located at the top of the decision hierarchy while the attributes are placed at the levels below the goal. Based on this hierarchy, pairwise comparison matrices are constructed using the scale provided in Table 1, and attribute weights are determined by using an appropriate technique. Among these techniques, the most used one is the eigenvalue method.

Table 1. Saaty's nine-point scale

Scale value	**Short definition**
1	Equal importance
3	Medium superiority
5	High superiority
7	Very high superiority
9	Absolute superiority
2,4,6,8	In-between judgment values

The eigenvalue method obtains the principal eigenvalue of a pairwise comparison matrix by solving the following system of equations (Lipuščeк et al., 2010):

$$(A - \lambda_{max} I)w = 0 \tag{1}$$

where A is the pairwise comparison matrix, I is the identity matrix, λ_{max} is the principal eigenvalue of A and w is the principal eigenvector of A (i.e., the vector of priorities).

Consistency of human judgments plays an important role in AHP. Therefore, a consistency ratio (CR) must be calculated for each pairwise comparison matrix to measure the consistency level. The formula of CR can be presented as follows:

$$CR = \frac{(\lambda_{max} - n)}{(n-1)RI} \tag{2}$$

where n is the size of the pairwise comparison matrix, $\lambda_{\max}$ is the principal eigenvalue of the matrix and RI is the random index value. Table 2 presents RI values for each value of n. The comparisons in a pairwise comparison matrix are said to be consistent if the CR value of the matrix is less than or equal to 0.1.

Table 2. *RI* values for different matrix sizes

n	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.90	1.12	1.24	0.32	1.41	1.45	1.49

2.3. Ward's hierarchical clustering method

Data clustering is a data mining technique that is used to divide a heterogeneous data set into more homogeneous groups. In this grouping, similarities between objects based on the selected attributes are taken into account and it is aimed to form clusters so that objects within the same cluster are similar and objects from different clusters are dissimilar.

Data clustering methods can be categorized as partitioning methods, hierarchical methods, density-based methods and grid-based methods (Han et al., 2022). Partitioning methods decompose data set into a predetermined number of clusters to achieve low inter-cluster and high intra-cluster variance. Those methods usually change the centers of clusters until the distance between the objects and the center of the cluster they belong to is minimized. Hierarchical methods build clusters based on hierarchy and can be divided into two categories namely agglomerative and divisive. In agglomerative methods, each object is initially treated as a single cluster, and then the most similar clusters are successively merged until the final clusters are formed. In divisive methods, all objects are initially in the same cluster and then the most dissimilar clusters are split recursively. Density-based methods consider object densities rather than the distance between objects and define a region with high object density as a cluster. Finally, grid-based methods create a grid structure by splitting the object space into a finite number of cells and performing clustering based on this grid structure.

In this study, we used Ward's method which is an agglomerative hierarchical clustering algorithm proposed by Ward, 1963. This method handles data clustering as an ANOVA problem and generates clusters in a way that minimizes inter-cluster variance. Apart from other agglomerative methods, it uses a sum of squares instead of distance metrics. In agglomerative hierarchical clustering, the sum of squares is initially zero since each object forms its cluster and then this value grows as clusters are merged. Ward's method tries to keep this growth as small as possible by merging two clusters with the smallest merging cost in each step (Vijaya et al., 2019). The cost of merging two clusters is calculated by using the formula given in Equation 3.

$$\Delta(A,B) = \frac{n_A n_B}{n_A + n_B} \|\overrightarrow{m_A} - \overrightarrow{m_B}\|^2 \tag{3}$$

where $\Delta(A, B)$ is the merging cost of clusters A and B. $\overrightarrow{m_A}$ and $\overrightarrow{m_B}$ are the centroids of clusters A and B, n_A and n_B are the number of objects in clusters A and B respectively. Cluster centroids are the vector mean of objects in each cluster. The norm of the difference between two vectors $\vec{p}$ and $\vec{q}$ also equals the Euclidean distance between those vectors and it is computed by using Equation 4 as follows:

$$||\vec{p} - \vec{q}|| = \sqrt{\sum_{i=1}^{N} (p_i - q_i)^2} \tag{4}$$

where N is the dimension of vector space or in other words number of attributes.

3. Results

This section consists of two subsections. In the first subsection, importance weights of the device attributes are determined using AHP. In the second subsection, medical devices are clustered based on the identified attributes and then maintenance priorities of the obtained clusters are determined.

3.1. Attribute weights

The weights of medical device maintenance prioritization attributes are determined using AHP. First, the pairwise comparison matrix presented in Table 3 is constructed based on the consensus of the experts working in the different departments of the hospital. Then, the attribute weights presented in Table 4 are obtained by applying the eigenvalue method to the pairwise comparison matrix which has an acceptable level of consistency (i.e., CR = 0.0313 < 0.1). When the results given in Table 4 are evaluated, it can be concluded that the most important attribute is *F1* (function) with a weight of 0.328 while the least important one is *F6* (maintenance staff) with a weight of 0.07.

Table 3. Pair-wise comparison matrix for the attributes

Attribute	*F1*	*F2*	*F3*	*F4*	*F5*	*F6*
F1	1	2	3	4	2	3
F2	0.50	1	2	3	1	3
F3	0.33	0.50	1	2	0.50	3
F4	0.25	0.33	0.50	1	0.50	2
F5	0.50	1	2	2	1	2
F6	0.33	0.33	0.33	0.50	0.50	1

0 Table 4. Importance weights of the attributes

Attribute	Importance weight
F1	0.328
F2	0.205
F3	0.131
F4	0.087
F5	0.179
F6	0.070

3.2. Clustering results

In this section, 53 medical devices of a new hospital are clustered by using Ward's hierarchical clustering algorithm to determine the maintenance priorities. Data normalization is applied before clustering to ensure that all attributes contribute equally to the result and Ward's algorithm is terminated when the number of clusters reaches three. Cluster assignments are presented in Table 5 and cluster profiles are illustrated in Figure 2. From the total number of 53 devices, the number of devices assigned to clusters is as follows: 20 devices assigned to Cluster 1, 26 devices assigned to Cluster 2 and 7 devices assigned to Cluster 3. As a result of this grouping, inter-cluster variance which is also known as within cluster sum of squares value is obtained as 17.327. We have also used the well-known clustering algorithm k-means, and obtained this value as 19.590. Since smaller inter-cluster variance indicates better clustering, we presented the results of Ward's method in this section.

Table 5. Cluster assignments

Cluster 1 (C1)	Cluster 2 (C2)	Cluster 3 (C3)
Infant incubator	Ventilator	Infant radiant warmer
Defibrillator	Intra-aortic balloon pump	Pulmonary function testing machine
Syringe pump	Anesthesia machine	Holter system
Infusion pump	Surgical microscope	Autoclave
Patient monitor	Heart & lung machine	Laminar flow cabinet
Phototherapy unit	Treadmill test machine	X-ray machine
Blood & fluid warmer	Pacemaker	Echocardiography machine
Humidifier	Hematology analyzer	
Pulse oximeter	Urine analyzer	
Operating table	Microplate reader	
Operating light	Biochemistry analyzer	
Electrosurgical unit	Microscope	
Suction machine	Immunoassay analyzer	
Automatic tourniquet system	Incubator	
Electrocardiogram machine	Blood gas analyzer	
Centrifuge	Biosafety cabinet	
Ultrasound machine	CT scanner	
Fetal monitor	MRI scanner	
Blood pressure monitoring device	Cath lab system	
Nebulizer	Mammography unit	
	Electromyogram machine	
	Electroencephalogram machine	
	Bone densitometer	
	Lithotripsy machine	
	Hemodialysis machine	
	Endoscopic devices	

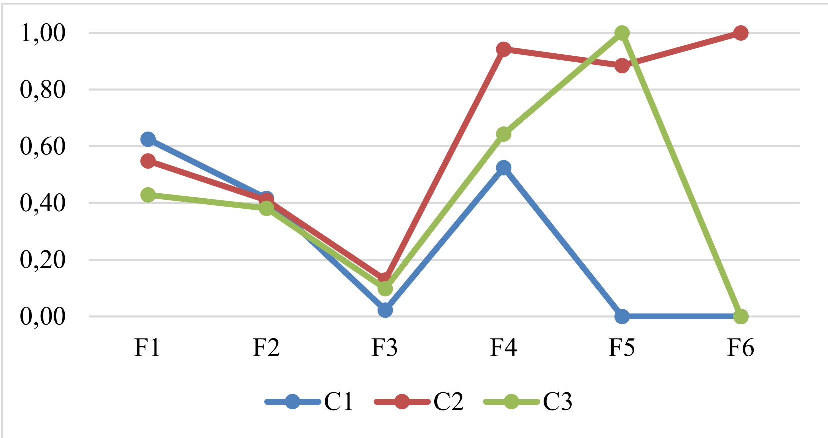

Figure 2. Cluster profiles.

Figure 2 displays the centers of three clusters. Cluster center is a *N*-dimensional vector where *N* is the number of attributes and it is obtained by computing the mean of each object over the attributes in a cluster. When we evaluate the results given in Figure 2, we can conclude that cluster C1 contains mostly class IIb or class III devices that used for therapeutic or life support purposes. Therefore, cluster C1 has the highest priority in maintenance with respect to attributes *F1* and *F2*. Devices in cluster C2 are high-cost devices that require complex maintenance operations carried out by the service providers. That is why cluster C2 has the highest priority in maintenance with respect to attributes *F3*, *F4* and *F6*. On the other hand, devices in cluster C3 have no alternatives and this makes cluster C3 the most important cluster with respect to attribute *F5*. These results indicate that there is no cluster that has the highest maintenance priority for all attributes. Therefore, the obtained clusters are sorted as A, B and C in descending order of priority in maintenance by considering attribute weights and cluster centroids. Since we have designed our attributes as the maximum is better, larger values of weighted sum imply higher priority in maintenance.

As it is shown in Table 6, cluster C2 has the highest and cluster C1 has the lowest priority in maintenance. Cluster C2 contains medical devices that are quite expensive and usually used for therapeutic or life support purposes. In addition, most of these devices are unique in the hospital and fall into moderate or high-risk categories. From a maintenance perspective, we can see that these devices require complex maintenance operations which can only be performed by external staff. On the other hand, cluster C1 contains low-cost devices which require non-complex maintenance operations that can be performed by internal staff. Although these devices are commonly used for therapeutic or life support purposes, maintenance priority of them is low as there are many identical alternatives to these devices in the hospital.

Table 6. Cluster centers and maintenance priorities

Cluster	*F1*	*F2*	*F3*	*F4*	*F5*	*F6*	weighted sum	maintenance priority
C1	0.625	0.417	0.022	0.525	0.000	0.000	0.339	3 (low)
C2	0.548	0.410	0.129	0.942	0.885	1.000	0.591	1 (high)
C3	0.429	0.381	0.098	0.643	1.000	0.000	0.467	2 (medium)

4. Discussion and Conclusion

Maintenance management in the healthcare industry has an increasing importance considering the number and variety of medical devices in today's hospitals. Costly and life-threatening medical device breakdowns can only be prevented by planning and carrying out maintenance operations based on device criticality. In this study, we developed a novel approach for the maintenance prioritization of medical devices. The proposed approach divides the medical devices into clusters based on device characteristics and then determines the maintenance priorities of clusters using AHP.

It is believed that the proposed approach will be more advantageous especially for hospitals with high number of medical devices. It will also provide information for maintenance budget allocation across the devices. On the other hand, the success of the proposed approach highly depends on the recording of data about the devices and the quality of the data set.

One of the limitation of this study is that, device age, which is an important issue in maintenance planning, was not considered since we dealt with a new hospital in our research. However, this attribute directly affects the maintenance requirements and reliability of a device. Therefore, it should be included in the future studies on medical device maintenance prioritization. Other issues for consideration by future researchers include that different device attributes, clustering algorithms and multi-attribute-decision-making methods can be used to determine the maintenance priorities of medical devices. Further, the development of maintenance schedules based on cluster-based maintenance priorities is another interesting future research direction.

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