Health-Cost Trade-Offs in Medical Device Reuse using Markov Decision Processes

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Abstract

With increasing healthcare expenditures worldwide, medical providers and community leaders seek alternative strategies aimed at reducing overall medical costs. One recently discussed approach is to reuse medical devices, originally designated for single-use. In this paper, we aim to explore the economic risks and benefits associated with the practice of medical device reuse via a Markov decision process (MDP) model. Inspired by Thomas Sloan's study on this practice, we implement an MDP model and use value iteration to predict the best action (use of a new or a reprocessed device) under different scenarios. Ultimately we find that preferred actions are scenario dependent based on the parameters for a given device. Our approach primarily aims to minimize expected cost along with a thoughtful discussion of the ethical implications of machine-based decisions.

1 Introduction

Healthcare expenditures in the United States reached $4,300 billion in 2021 (centers for Medicare and Services). These expenditures, as seen in Figure 1, have rapidly increased over the past decade. This trend has encouraged healthcare providers and community leaders to seek alternative strategies aimed at reducing overall costs. A recent approach taken by hospitals and medical care facilities to combat these extraneous costs has been to reuse medical devices, originally designed for single-use. Examples of such devices include external devices such as compression sleeves (Sloan 2007) in addition to internal devices such as catheters and surgical tools (Bayrak and Soylu 2021). Advocates of medical device reuse around the world suggest that such a practice would decrease medical costs by preventing the frequent need for new devices (typical cost difference of about 80%) while also decreasing waste from single-use devices (Hailey et al. 2008). In practicing reuse of these traditionally single-use devices (SUDs), healthcare facilities send used devices to third-party companies that sterilize the devices and test their functionality. In recent years, these sterilization processes in the United States have been regulated by the US FDA (U.S. Food and Drug Administration). Primary concerns with this practice revolve around the safety of reuse due to potential device failure or contamination and the ethical and economic implications of such adverse effects.

Medical devise reuse, and the aforementioned concerns, have been explored in terms of the associated philosophical, administrative and technical issues. Objective research related to these topics is limited, and tends to be high-level, resulting either in general ethical discussions or overall regulations for reprocessing (cleaning, testing and reusing devices) programs (Sloan 2007). Little work has been done to offer objective determinations of when device reuse is advisable, in terms of safety and cost efficiency, for a given device in a given scenario. In this context, there is a clear need to study the reprocessing and reuse of medical devices, in a systematic and objective manner. Ideally, such an exploration would guide future ethical and economic discussions regarding this evolving practice, eventually offering a path for medical providers and members of associated fields to follow.

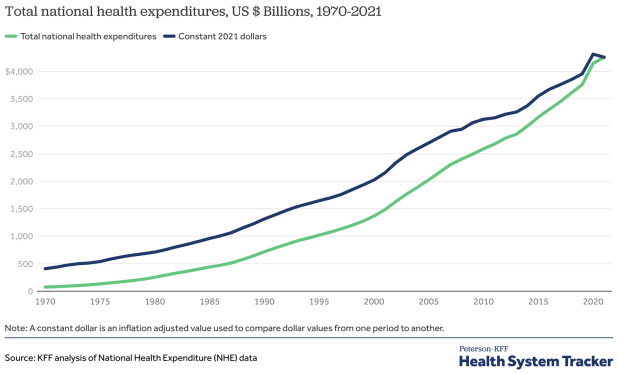

Figure 1: Total health expenditures, United States. Adapted from Peterson-KFF Health (Peterson-Kaiser Health System Tracker).

Markov Decision Processes (MDPs) are mathematical frameworks that enable decision-makers to determine the best sequence of actions to maximize cumulative rewards over time (Garcia and Rachelson 2013). They aid in designing optimal strategies for sequential decision-making in dynamic and uncertain environments. Previously, MDPs have been utilized to analyze a range of problems including applications in natural resource management (Williams 2009), endangered species conservation (Tomberlin 2010) and eco-

nomics (Lave 1966). Recently, MDPs have been applied to analyze challenges in healthcare, including medical device reuse. Several studies have explored the economical impacts and adverse effects of contaminated device reuse (Liao, Cade, and Behdad 2021).

In our work, we focus on the study described by Thomas W. Sloan in his paper "Safety-cost trade-offs in medical device reuse: a Markov decision process model", which analyzes the reuse of medical devices via a MDP model, from the perspective of healthcare providers (Sloan 2007). The model considers new vs. reprocessed device costs, failure probabilities and the penalty cost for a given device failure. It then considers, given a scenario unique to a device and corresponding parameters, if it is better to use a new or reprocessed device. The author reports details of the model and then tests it on a series of device examples with known data, to guide decisions regarding device reuse.

Inspired by this work, we aim to replicate the MDP model described by Sloan and solve it by a value-iteration method to derive the minimum expected costs achievable from using reprocessed compared to new devices. Sloan highlights four devices: orthopedic blades, cardiac catheters, compression sleeves and trocars. For each of these devices and the given parameters, we compare our value-iteration informed policy (reprocessed vs. new device) in the initial state to that derived in Sloan's work. We then sweep the parameter space of the MDP model for one device, compression sleeves, elucidating the impact of device costs, failure probabilities and failure costs on the economic outcome of medical device reuse. Ultimately, we offer insight into the ethical implications of the aforementioned algorithmic informed decisions.

2 Background

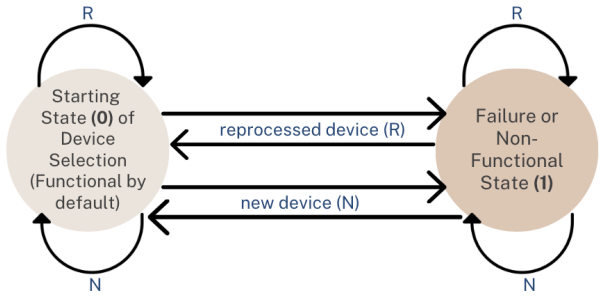

Figure 2: Diagram of the MDP model utilized here, inspired by Sloan.

In the light of the problem defined in the previous section, we aim to examine the practice of reprocessing medical devices and the scenarios in which reprocessing is a viable option through an MDP model that is a detailed interpretation of the MDP discussed by Sloan. According to our model, a healthcare provider can use a new device or a reprocessed device to perform a medical procedure. Regardless of the type of device used, there is a failure probability which means that the device malfunctions or causes some harm to the patient. The failure probabilities guide the formation of our transition probabilities between states. The state transition diagram of the MDP shown in Figure 2 provides an overview of the MDP model where a medical device can be in two states: state 0 which denotes the type of device we will start with in the medical procedure and state 1 which indicates a non-functional state of the device failing in the medical procedure. The different components of our MDP along with specific notations are defined as follows:

I. States: A medical device can be in the following two states:
   i. *State 0* which denotes the type of device we will start with in the medical procedure.
   ii. *State 1* which indicates a non-functional state of the device failing in the medical procedure.

II. Actions: In each state, the healthcare provider has two possible actions:
   i. A_n denotes the use of a new device.
   ii. A_r denotes the use of a reprocessed device.

III. Policies: Since there are two states and two actions, we have four possible policies that are as follows:
   i. $[r, n]$: This policy specifies that the healthcare provider can start by using a reprocessed device in the initial functional state but when a failure occurs and we transition to the non-functional state, then a new device should be used.
   ii. $[n, r]$: Similarly, we can start with a new device and use a reprocessed device if a failure occurs.
   iii. $[r, r]$: This policy continues using a reprocessed device even when a failure occurs (another "fresh" reprocessed device and not the same one).
   iv. $[n, n]$: Similarly, we continue opting for a new device even when a failure occurs.

   It is important to note that while we do have four distinct policies, for the sake of simplicity and understanding, we specifically focus on the device we start with and whether we transition to a different type based on its performance. We are, therefore, only interested in the first action suggested by any of the above policies, essentially just r or n.

IV. Transition Probabilities: Each action has an associated probability of failure which results in the transition from the initial functional state (0) to the non-functional state (1). Additionally, an action could also result in the device being in the same state which is indicated by the self-directed loops in Figure 2. According to Sloan's work, the probabilities of failure are defined as follows:
   i. P_n: Probability that a new device fails.
   ii. P_r: Probability that a reprocessed device fails.

   Based on the above probabilities, we can then infer the following:
   i. $1 - P_n$: Probability that a new device does not fail which is indicated by the device remaining in the starting functional state.

ii. $1 - P_r$: Probability that a reprocessed device does not fail which is indicated by the device remaining in the starting functional state.

Based on these probabilities, for a given policy $\theta = [A_0, A_1]$ where A_0 and A_1 is any possible action used in state 0 and state 1 respectively, we define our transition probability in the following way:

$$[P_{01}^{a_i}] = \begin{bmatrix} 1 - P_{A_0} & P_{A_0} \\ 1 - P_{A_1} & p_{A_1} \end{bmatrix}$$

Each element of the matrix indicates the probability of a transition from state 0 to state 1 when action A_i is taken.

V. Costs: The model has different costs associated with each action since the main objective of the healthcare provider is to determine a new/reprocessed policy that minimizes the long-run expected costs. The costs are defined as following:

i. C_n: Cost of using a new device.

ii. C_r: Cost of using a reprocessed device.

iii. C_f: Penalty cost incurred due to device failure regardless of the type

VI. Discount Factor (γ): While Sloan's work does not specify the discount factor used for the MDP, we chose a discount factor of 0.97 based on the value generally used in other literature resources focusing on healthcare applications of MDP.

VII. Epsilon Value (ϵ): For our value iteration method, we used $\epsilon = 1 \times 10^{-8}$ to ensure sufficient iterations to achieve convergence.

Using the specific parameters defined above, we solve our MDP using the value-iteration method where we compute the Bellman equation iteratively to find the minimum expected costs in each state. Our value iteration varies from the traditional approach as we aim to minimize costs whereas typically one is trying to maximize rewards. Based on the results of value iteration, we then derive the optimal policy for a given medical device and associated parameters. In this paper, we also derive thresholds for each parameter which can be defined as a cut-off point that leads to a change in the type of device (new or reprocessed) being used.

3 Experiments

For each of the four devices highlighted by Sloan, we implemented our MDP model under the given parameters and compared the resulting policy for the preferred device type in the initial state (state 0) to that reported in (Sloan 2007). The policy was informed by value iteration performed for each device, which calculated the minimum expected cost for each action (using a reprocessed vs. new device) in the initial state. The action resulting in the lowest minimum cost was therefore selected as the preferred type. For each device analyzed, a threshold value for a different parameter was identified. We compared the threshold values that we calculated to those reported by Sloan. The four devices and their outlined parameters have been included in Figure 3.

Device		Orthopedic Blades	Cardiac Catheter	Compression Sleeve	Trocar
C_n		30	280	120	115
C_r		15	60	119.09	30
C_f		1.0E+06	2.4E+04	1.0E+06	1.0E+04
P_n		1.0E-06	1.0E-03	1.0E-07	1.0E-03
P_r		1.6E-05	1.0E-02	1.0E-06	1.0E-02
Preferred Type in State 0	Rep.	R	R	R	N
	Calc.	R	R	R	N
Threshold	Rep.	P_r = 0.000016	C_f = 24,444	C_r = 119.10	NA
	Calc.	P_r = 0.0000165	C_f = 25,201	C_r = 119.13	NA

Figure 3: Parameters used for each device & comparison of our results (Calc.) to results reported by Sloan (Rep.). Threshold values for different variables were given for each device.

To further analyze the influence of parameters, we swept the parameter space of the MDP model to calculate threshold values for each parameter under a single device, compression sleeve. This was done by varying a single parameter at a time, and keeping the remaining parameters constant with the given assignments for compression sleeves outlined in Figure 3. We identified threshold values to be the point denoting the cross over point for action choice. This absolute difference was then collected as our final dependent variable of interest, with the scanning parameter of interest as the independent variable.

4 Results

Comparison of MDP Performance on Devices

We first compared the performance of our MDP to that described by Sloan, by analyzing our calculated policies and thresholds for each of the four highlighted devices and their prescribed parameters. These results have been included in Figure 3, where "R" denotes a reprocessed device and "N" denotes a new device. For all four devices, our calculated preferred device types for state 0 were consistent with Sloan's reported values i.e. our model generated the same optimal policy as identified in Sloan's study for each device. This consistency supports that our MDP and value iteration algorithm were implemented as intended to align with Sloan's results. Sloan also identifies a threshold parameter for each highlighted device, denoting when a change in device type is favored. Threshold values for P_r, C_f, and C_r were identified for orthopedic blades, cardiac catheters and compression sleeves, respectively. In this case, all three of the identified threshold variables indicate a point after which new devices are favored over reprocessed devices. For all devices, our calculated threshold values were fairly consistent with those reported by Sloan, as seen in the last two rows of Figure 3, varying at most by 3%. Slight differences may be attributed to the expected cost calculations used to derive these values. We utilize value iteration to calculate the minimum expected cost associated with each action, using a discount factor of 0.97 to promote convergence. Sloan does not report a discount factor, creating a possible source of discrepancy between our values. Overall, any variations are minor, further supporting the robust algorithm and that

our MDP operates as intended to accurately replicate Sloan's findings.

Additionally, we were motivated to apply this model to other medical devices to expand on Sloan's work. We explored market prices of new and reprocessed devices such as endoscopes and surgical forceps. While we were able to find the current market costs of these devices, it was hard to determine a reliable failure probability for using a new and a reprocessed device. However, if healthcare providers have that data available to them, we believe that this model's scope can be expanded to guide the decision-making of various other devices used in medical procedures.

Impact of Parameters on MDP Policy

We further aimed to explore the impact of different parameters on the policy generated by the MDP and its calculated preferred device type. We selected one of the aforementioned device types, the compression sleeve, to focus on. We investigated how changing each of the following parameters with all other factors consistent with the values reported by Sloan affected the decision-making process.

C_n: With all parameters consistent, when the cost of a new compression sleeve was increased starting from \$110, we notice that a new device was preferred by the model until \$119.97 and then a reprocessed sleeve was preferred after that mark. This trend is highlighted in Figure 4. We therefore derive the threshold to consider a reprocessed device, under the aforementioned conditions, to be when the cost of new sleeve is \$119.97. This trend seems reasonable with the general idea of an increase in cost of a device leading to a preference of a different device that has a lower cost.

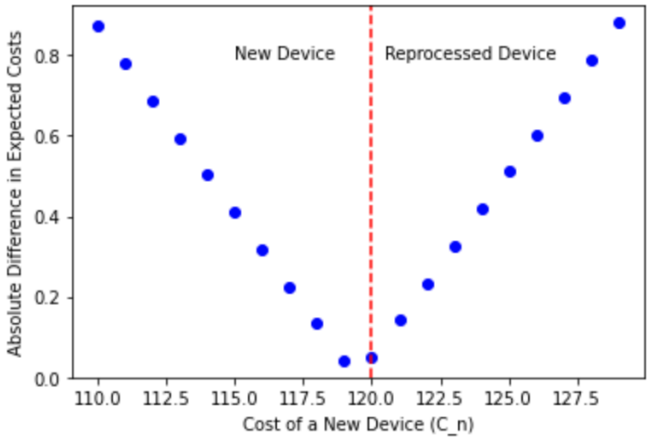

Figure 4: Scanning of parameter C_n. Threshold C_n = \$119.97, after which a reprocessed device is favored.

C_r: With all parameters consistent, when the cost of a reprocessed compression sleeve increases starting from \$110, we notice that a reprocessed device was preferred until \$119.13 and then a new sleeve was preferred after that mark. This trend is displayed in Figure 5. We derive the threshold to consider a new device to be when the cost of a reprocessed sleeve is \$119.13. This result is reasonable, as the C_r threshold should be slightly lower than the C_n threshold because our P_r is higher under the default parameters which implies that a reprocessed device has a lower cost, considering it is more likely to fail.

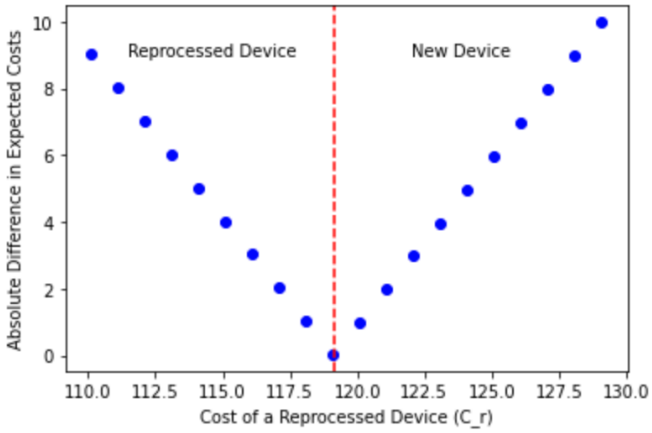

Figure 5: Scanning of parameter C_r. Threshold C_r = \$119.13, after which a new device is favored.

C_f: With all parameters consistent, when the penalty cost incurred due to any type of device failure increases starting from no penalty to \$2 million, we notice that a reprocessed device was preferred until \$1.04 million and then a new sleeve was preferred after that mark. This trend is displayed in Figure 6. We derive the threshold to consider a new device when the penalty cost is \$1.04 million. It is reasonable that as the C_f increases, a reprocessed device would no longer be favored. Under the studied conditions, the P_r is greater than the P_n meaning that reprocessed devices fail more frequently and thus the failure penalty has a greater effect on the expected cost of reprocessed devices than that of new devices.

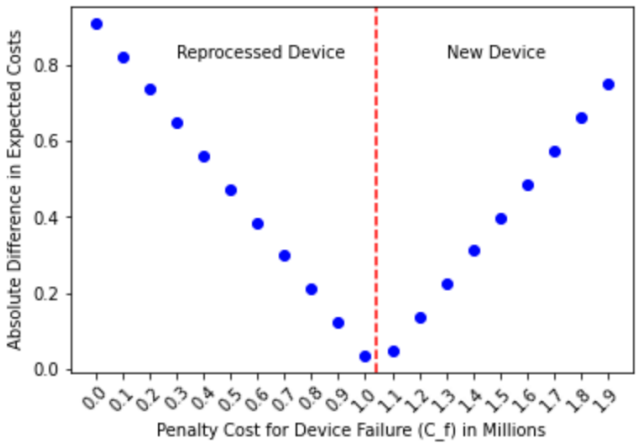

Figure 6: Scanning of parameter C_f. Threshold C_f = \$1,042,382, after which a new device is favored.

P_n: With all parameters consistent, when the probability

of a new device failing increases from none to 1×10^{-7}, we notice that a new device was preferred until the probability was 6.18×10^{-8} and then a reprocessed sleeve was preferred after that mark. This is shown in Figure 7. We derive the threshold to consider a reprocessed device when the probability of a new device failing is 6.18×10^{-8}. It is implied that as the new device becomes more likely to fail, and considering that $C_n > C_r$ under the studied conditions, a reprocessed device could be more preferred.

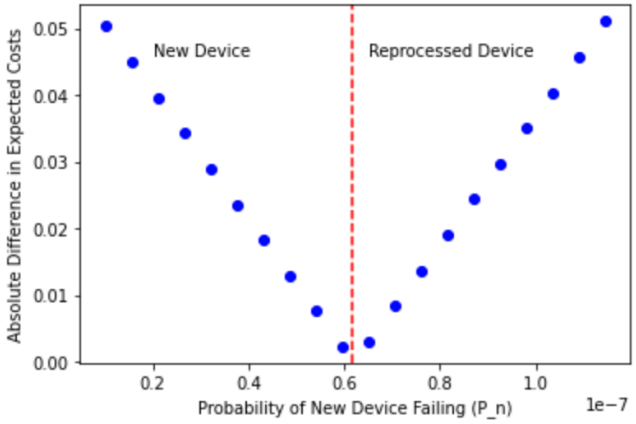

Figure 7: Scanning of parameter P_n. Threshold $P_n = 6.18 \times 10^{-8}$, after which a reprocessed device is favored.

P_r: With all parameters consistent, when the probability of a reprocessed device failing increases from none to 2×10^{-6}, we notice that a reprocessed device was preferred until the probability was 1.04×10^{-6} and then a new sleeve was preferred after that mark. These results are shown in Figure 8. We derive the threshold to consider a new device when the probability of a reprocessed device failing is 1.04×10^{-6}. It is implied that as the reprocessed device becomes more likely to fail, the new could be more preferred. Additionally, it is reasonable that the P_r would be higher than the P_n threshold because the C_r is lower than the C_n; the lower cost of using a reprocessed device balances more frequent failure in the overall expected cost computation.

Overall, we find that adjusting different parameters informs threshold values which ultimately can help guide decisions for using reprocessed or new devices. While we only performed a threshold-parameter analysis for a compression sleeve device, a similar analysis may be applied to any device and its current market parameters to provide a rough-cut threshold of when the use of reprocessed devices may be beneficial. Our findings, and their consistency with Sloan's reports, support the use of this model as an additional tool for assessing the cost-benefits of utilizing reprocessed vs. new medical devices under given scenarios.

Broader Impacts

The implemented model, as inspired by Sloan's work, offers an objective cost-based analysis of medical device reuse - which was lacking in previous literature. Strengths of this model include this objective analysis and the beneficial

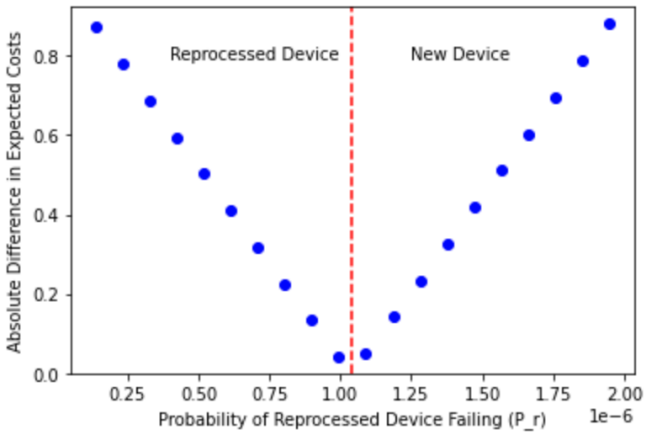

Figure 8: Scanning of parameter P_r. Threshold $P_r = 1.04 \times 10^{-6}$, after which a new device is favored.

implications associated with using reprocessed devices, when appropriate. Health care costs in the United States, and across the world, are high, implying that communities could benefit from lower cost options offered by device reprocessing. Additionally, a rise in use of reprocessed devices would help the economy by creating more business for third-party firms involved in device sterilization. More importantly, reprocessing of medical devices could positively impact the environment by reducing medical waste. Individuals of lower socio-economic status may benefit from the option of utilizing a reprocessed device in comparison to a new one, if it were to reduce the overall cost of the medical procedure. Such an option would be particularly beneficial if the decision was between being able to afford a procedure in the first place, or not have it at all. Naturally, this may also be a drawback as individuals of lower socio-economic status are potentially serving as human subjects for the practice, leading to further inequities. However, with the reprocessing of devices becoming more common, the FDA has placed regulations on these practices which leads to a more legitimate and supervised process. The use of our discussed model appears to favor the reprocessing of devices under many parameters which further enables these benefits.

We also acknowledge the limitations of this work, particularly in regards to the ethics of machine-guided decisions. This analysis only takes into account the economic costs associated with reprocessed vs. medical devices, when ethical and legal factors should be considered, as well. The implemented model should not be followed blindly, and the medical history of particular patients or populations should be noted prior to deployment of this model. For example, under many parameters the overall effective cost appeared to be minimized by using a reprocessed device, however such a practice may not be advised for an immunocompromised patient, who is at a greater risk for contamination. One improvement that could be made in our model to more accurately replicate such scenarios would be to have different

failure penalties for new and reprocessed devices. Currently, our model uses a single failure penalty, regardless of device type which could be deemed unrealistic. We suggest that a higher penalty cost should be incurred from a failed reprocessed device as such a failure may cause contamination and other related risks. Overall, we suggest that the described model should be combined with patient history and previous research on the efficacy of medical device research, to offer a holistic view for parameter-specific scenarios.

5 Conclusions

In this paper, we described an implementation of the MDP model outlined by Sloan in his paper "Safety-cost trade-offs in medical device reuse: a Markov decision process model". We found that our model performed similarly to that designed by Sloan as our resulting medical-devise reprocessing policies and threshold values were consistent with reported values for a set of four devices under prescribed parameters. We expanded our work and analyzed the impact of different parameters on the new vs. reprocessed use policy for a given medical device (compression sleeves). It was found that the resulting policies were parameter dependent, therefore supporting the use of this MDP as a tool when market-prices, the probability of failure and failure penalty costs for a specific device are known. While our model mainly considers economic factors, we advocate for its use in conjunction with prior efficacy studies to to guide scenario-specific decisions regarding medical devise reprocessing. By offering further insights into the use of MDP in this study, we hope to empower decision-makers to adapt policies based on varying conditions to foster more sustainable and economically viable approach to medical device management.

6 Contributions

All code was written collaboratively between M.K. and M.F. M.F. primarily wrote the introduction and experiments sections. M.K. primarily wrote the background section. M.K. made most of the graphs. Both M.K. and M.F. worked together on the results and conclusions.

7 Acknowledgements

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