Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

TOWARDS USING SIMULATION TO EVALUATE THE CIRCULAR ECONOMY OF SMALL MEDICAL DEVICES

Mohd Shoaib[1], Antuela Tako [1], Ramzi Fayad[2], and Armando Vargas-Palacios[2]

[1]Nottingham Business School, Nottingham Trent University, Nottingham, UK
[2]Academic Unit of Health Economics, School of Medicine, University of Leeds, Leeds, UK

ABSTRACT

A linear economy (LE)-based take-make-use-waste model is environmentally unsustainable and other care settings for medical devices. A significant proportion of UK's National Health Service (NHS) emissions is derived from medical devices. The alternative, a circular economy (CE) system, has the potential to mitigate the environmental impacts associated with LE. This paper evaluates the effect of introducing CE in the healthcare supply chain in the context of small medical devices (SMDs). We develop simulation models that quantify the environmental, operational, and financial impact of circular interventions in the value chain of SMDs. Two complementary simulation models that evaluate the impact of CE for a surgical instrument, laparoscopic scissors, as an example, representing the whole-system perspective and cost-effectiveness from the hospital setting perspective, are presented. Our preliminary findings suggest that the introduction of CE leads to reduced overall environmental emissions, and to improved cost-effectiveness from a hospital setting perspective.

1 BACKGROUND AND INTRODUCTION

The UK's National Health Service (NHS) is responsible for more than 4% of the country's total greenhouse gas emissions (NHS England 2022; Tennison et al. 2021). A significant proportion (nearly 10%) of these emissions are derived from the use of medical devices (NHS England 2022). A majority of medical devices used in the NHS are single-use devices based on the take-make-use-dispose model characterizing a linear economy (LE) system. The LE model is inherently unsustainable and results in unnecessary resource depletion, end-of-life (EOL) waste, and ecosystem degradation (Ellen MacArthur Foundation 2013; Michelini et al. 2017). Against this backdrop, the prospect of transitioning to a circular economy (CE) is gaining considerable attention in the healthcare sector. The CE aims to minimize waste and maximize resource utilization, thereby promoting a more sustainable and efficient use of resources within the healthcare system.

A CE can be achieved through the introduction of innovative business models that aim to reduce excessive resource consumption, eliminate waste and pollution, and simultaneously create value for both society and the environment Moving to a CE often involves redesigning products, changing materials, and rethinking EOL device management. These changes have an impact on the overall performance of the supply chain, affecting financial, environmental, and operational indicators. Evaluating these performance indicators is necessary how system performance is impacted and to help identify potential improvement opportunities. However, the complex and interconnected structure of the healthcare supply chain, which consists the supply of medical devices by manufacturers, their use and options for circular re-routing after their end of life, leads to a dynamic environment, which makes the tracking of these performance indicators a challenging task. It requires computational tools that can handle these characteristics effectively.

Existing work assessing the economic and environmental impact of the transition to a CE has used techniques such as life cycle assessment (LCA) and life cycle cost analysis (LCCA) (Keil et al. 2023; Lieder et al. 2017; Meister et al. 2023. These techniques map the flow of materials while considering the product life cycle from raw material extraction to EOL disposal stages. In doing so, the amount of material utilized,

energy consumed, and emissions released to air, water, and land are measured and quantified at each stage. However, they have several limitations; for instance, the LCAs are generally based on a set of assumptions, and any deviation from those invalidates the models. Furthermore, these techniques offer limited support for predicting the overall supply chain's operational performance for decision-making, particularly when substantial changes in product pathways, business models, and supply chain network configurations are trialed.

Simulation modeling can be useful in representing complex systems and evaluating the systemic impact of an intervention or change in the pathway of product flows and waste management (Abe et al. 2016; Brailsford et al. 2016). This is also relevant for assessing the impact of CE adoption. Simulation can represent the dynamic changes in system characteristics over time and enables a risk-free exploration of various scenarios and their impact on system performance, which has been used in a range of domains, including healthcare and supply chain modeling (Katsaliaki and Mustafee 2011; Tako and Robinson 2012). Equally, the simulation would be suitable in the context of supply chains of circular economy for small medical devices to model the flow of products and identify optimal strategies for integrating future scenarios of new CE practices. Few studies have recently used simulation modeling approaches to investigate the effect of a CE transition on system behavior (Charnley et al. 2019; Guzzo et al. 2019; Huster et al. 2022; Lieder et al. 2017). These studies utilize key performance measures, including carbon dioxide emission, product disposal volume, and long-term demand for new products.

For instance, (Lieder et al. 2017) constructed a simulation model to analyze the lifecycle costs and carbon dioxide emissions linked with the implementation of different circular business models using washing machines as an example case. Similarly, (Huster et al. 2022) modeled electric vehicle battery remanufacturing using simulation to explore the impact on the demand for new batteries. Simulation has also been used to support decisions for the remanufacturing of electric vehicle batteries (Charnley et al. 2019). Regarding CE in healthcare, simulation has been successfully used to analyze the long-term impacts associated with adopting a sharing platform (a CE strategy) for low-utilization consumables, mostly single-use products such as sutures, syringes, and gloves, and durables (electromedical machines like MRI, Computed Tomography, X-ray, etc.) products (Guzzo et al. 2019). The authors argue that these products, when on a sharing platform, can be utilized by other hospitals who may not have access to such products otherwise. The results of the study showed an overall decrease in the total unmet demand.

Much of the existing work on the evaluation of the impact of introducing a CE for medical devices in healthcare concentrates on the use of LCAs and LCCAs to assess the environmental and financial impacts of specific medical instruments or products, or procedures (Hibbs et al. 2024; John et al. 2024; Rizan 2024). However, to evaluate the potential benefits and drawbacks of transitioning to a CE, it is necessary to consider the integrated impact across environmental, economic (cost), and operational dimensions over time. Furthermore, these studies do not assess the value of CE adoption at patient level or from an operational perspective to help understand the economic value for members of the supply chain, including healthcare providers. To the best of our knowledge, there are limited studies that use simulation to evaluate the impact of CE from a business and operations perspective.

To address these limitations and explore the potential of introducing CE, specifically in small medical devices (SMDs), this paper adopts DES modeling to assess the impact of adopting a CE in the healthcare supply chain system both within and outside hospital. Through the analysis, this paper contributes to the existing literature by presenting a novel study on the implications of circularity in SMDs that considers the environmental financial implications as well as operational implications in the overall system. These indicators include carbon dioxide emissions, and patient-level costs among others. Considering these performance indicators has the potential to offer a comprehensive understanding of the impact of adopting the CE in healthcare supply chains from a sustainability and efficiency point of view in healthcare delivery.

We adopt laparoscopic scissors as a case example of SMDs. The majority of laparoscopic scissors are designed for single-use in a LE setting. We consider future scenarios wherein these instruments are reprocessed for reuse over multiple cycles in a CE setting. It is assumed that the reprocessed instruments

meet all the regulatory requirements and are CE marked post reprocessing. Note that throughout this paper, the term refitted instruments is used to refer to reprocessed instruments as well, and these terms are used interchangeably. We present two complementary Discrete Event Simulation (DES) models, a) a high-level model representing the flow of SMDs in the supply chain, and b) a detailed hospital setting model of the usage of SMDs at the care facility level. The first model provides a high-level assessment of the overall system performance using operational, financial, and environmental indicators, whereas the second model reports per-patient cost analysis under different scenarios of transition from LE to CE. The two models offer a complementary view at overall supply chain and hospital level on the adoption of CE initiatives.

The remainder of the paper is organized as follows. First, we explain the approach adopted in developing our DES models to evaluate the impact of the transition from LE to CE. Next, we provide a case study of two complementary simulation models developed, applied for surgical instruments, laparoscopic scissors, as an illustrative example. Subsequently, we present our preliminary findings and conclude with a discussion of the key outcomes and potential directions for future research.

2 APPROACH AND METHODS

This study presents DES models of the flow of small medical devices throughout the supply, use, and recovery beyond their EOL. DES is suitable due to its stochastic approach to modeling events over time in the system, which is capable of capturing the inherent variability and uncertainty in the occurrence of activities. By tracking the flow of individual entities, laparoscopic instruments, throughout their lifecycle, this technique allows for a detailed analysis of system outcomes (Robinson 2014; Tako and Robinson 2012)

Our analysis takes two different perspectives of the healthcare supply chain system. At one end, we take a high-level view of the overall flow of SMDs in the supply chain system, representing the flow of small medical devices including manufacturing, distribution, usage within a healthcare facility, and finally, disposal and recovery, the latter applicable in CE scenario. We refer to this as the high-level supply chain (SC) model. At the other end, we adopt a micro-level view of the use of SMDs at the care facility level (point-of-use), to consider specific processes and pathways the instrument goes through in the hospital settings. This is referred to as the healthcare settings model. A schematic representation of the flow of instruments in the system is depicted in Figure 1. The high-level flow of the SMDs in the supply and recovery chain (SRC) is enclosed in a dashed box on the left, while the hospital settings model, is depicted within a solid box on the right side.

The two models offer a complementary perspective in representing the impact of CE adoption in the system. The SC model presents a holistic high-level view to examine the impact of the transition to CE in SMDs. The model represents the flow of SMDs across the key members of the SRC, including manufacturer, distributor, hospital, and reprocessor. The model takes as input the costs and carbon dioxide emissions occurring across the different SC members along with other operational variables such as patient arrival pattern, ordering policy, and processing and transport times. It then generates outcomes based on the operational, economic, and environmental system performance of the overall healthcare supply chain.
The hospital setting model represents the SMD pathways within the hospital environment. It considers various costs alongside resource implications (e.g., nurses and other support staff) required to manage the instrument storage, usage, transportation, and waste disposal. This model is adopted to report the economic impact of implementing a CE approach at healthcare setting level. The main focus is on estimating the per-patient cost in healthcare settings under different scenarios of transition to CE using five cost components. These include supply chain costs, recovery chain costs, transportation costs from the local warehouse to the NHS hospital, repackaging costs for used instruments to be sent for reprocessing, personnel costs associated with preparing instruments for waste management.

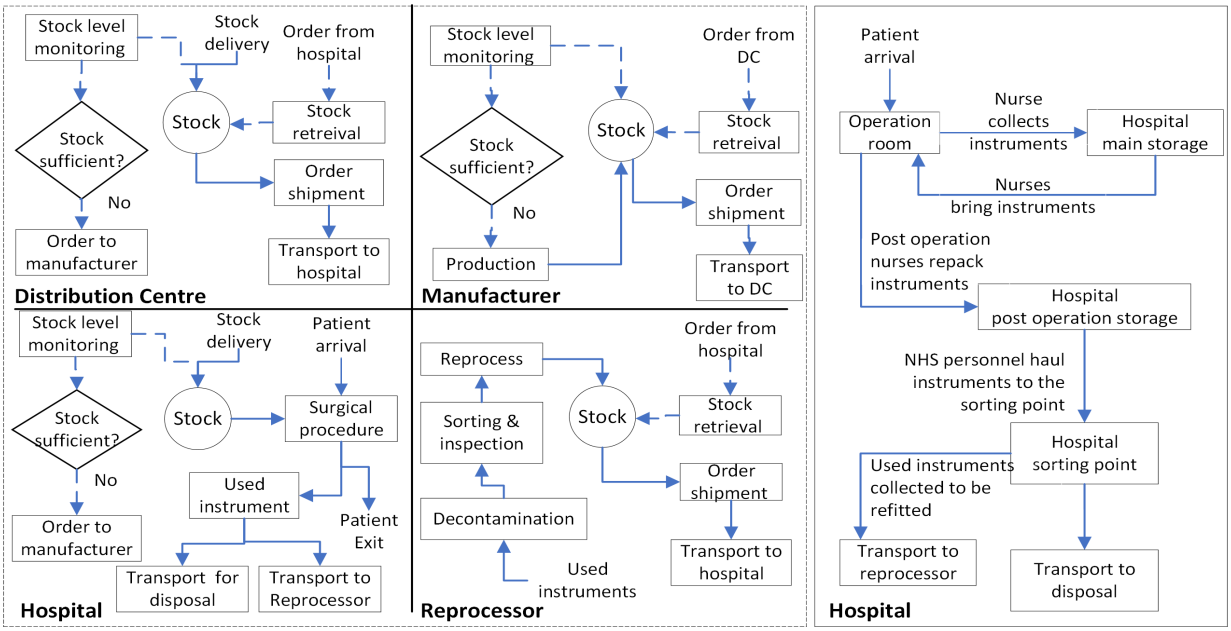

Figure 1: Overview of the simulation model logic of the flow of laparoscopic scissors at supply chain level (left side, dotted line box) and hospital settings level (right side, solid line box). Blue solid lines represent physical flows, dashed lines represent information flows.

In summary, the model is a computational representation of supply chain/hospital dynamics and is adaptable to other healthcare organizations interested to evaluate the impact of introducing CE with minimal effort and aid decision-makers in selecting the best interventions both within and outside the hospital. Next, a brief overview of each individual simulation model is provided.

2.1 Overview of the High-Level Supply Chain Model (Model 1)

The high-level SC model simulates the flow of SMDs in LE and CE, across the supply and recovery chain, from production to EOL. The CE model comprises two sub-models, the supply chain and recovery chain. The main members of the SC part of the model include manufacturers, distribution centers, hospitals, disposal facility, and transport providers, which are involved in the production, storage, usage, disposal, and movement of instruments. This model, on its own, reflects the existing LE-based system, where instruments follow a linear pathway and are discarded after the first use cycle. In the recovery chain model, the product pathways are circular in the sense that they are not discarded after the first use, but recovered after their first EOL. Consequently, in the recovery chain model, a reprocessor is positioned downstream of the hospital to facilitate the circular product flow representing the CE. To summarize, in the LE model the pathway ends with disposal, while in the case of the CE a reprocessor is augmented to SC for circular flow.

The product flow from production to disposal constitutes the linear supply chain that characterizes the LE system. This is shown by the first three quadrants in the first half of Figure 1 (left dotted rectangle) excluding the reprocessor in the fourth quadrant. For a CE system, a reprocessor is introduced after the use of SMDs in the healthcare setting, thereby forming what we call a supply and recovery chain. In the recovery chain, the used instruments are collected, reprocessed, and then returned to hospitals for further use. Next, we briefly describe the individual supply chain members included in the model.

2.1.1 Manufacturer

The manufacturer includes two main processes: a) production and inventory management and b) order fulfillment. The first is concerned with maintaining sufficient stocks for order fulfillment and initiating the production process when the inventory reaches a minimum predefined level. This is accomplished by continuous stock monitoring and interacting with the production component when required. Whereas the second focuses on order reception, stock retrieval, and dispatch to the demand locations.

2.1.2 Distribution Centre

The primary functions of the distribution center (DC) are broadly categorized as stock and order management. This includes the following main functions: a) regular monitoring of the stock level, b) placing orders for stock replenishment, c) receiving orders from hospitals and retrieving ordered quantity from the inventory and finally, d) dispatching the quantity to the demand points by trucks.

2.1.1 Hospital

Hospitals are the end-users that govern the demand for instruments across the SRC. Accordingly, the logic controls the utilization of instruments via patient arrivals, stock control, order management, and handling of new and reprocessed instruments (in the case of CE).

2.1.2 Reprocessor

For the reprocessor, the main tasks implemented in the model include collection of used instruments from hospitals; performing quality assessment; cleaning and disinfection; and reprocessing to reinstate the used instruments to a new-like condition. After which these instruments are stored in storage for dispatching to the hospital upon orders.

2.1.3 Simulation Model Input Parameters

Key model input parameters along with the statistical distributions used are listed in Table 1. These parameters are derived either from published literature or industry-informed estimates and, where necessary, suitable assumptions were made. Note that some parameter values derived from the literature are reported as point estimates corresponding to a particular instrument type/make, as exemplified by the emissions data. Recognizing this limitation and given that instruments from different makes may be utilized in hospital, we use approximate distributions (Triangular) and include a range of ±20% as bounds around the mean as per standard simulation practice (Biller and Gunes 2010; Law 2013) to ensure a more accurate representation of different instruments in real life.

The emissions resulting from transportation are based on the UK government's publicly available database of greenhouse gas reporting (Department for Energy Security and Net Zero 2024). The values are based on the truck capacity between 7.5 to 17 tons considering average and fully laden trucks. Concerning the inventory policy, a continuous inventory review strategy is implemented that employs a Min–Max protocol and includes a re-order point, variable order quantity, and safety stock. The safety stock is calculated as, $SS = z.\sigma.\sqrt{lead\ time}$, and the reorder point as, $s = demand.(lead\ time) + SS$. Where, z = 3.5 for a 99.9% service level considered a norm for healthcare supply chains, and σ = standard deviation of demand.

Furthermore, we assume futuristic CE scenarios, and data on the reprocessing emissions is unavailable. Consequently, emissions from the reprocessing of the instruments are expert judgements based the on industry-informed figures. This figure for the current analysis is assumed to be 50% of the emissions from the manufacturing process.

Table 1: List of the key input parameters used in the simulation models.

Input parameters	Distribution/Source
Probability of instrument failure	Uniform (0.05, 0.10); (Expert judgement)
Patients per day	Poisson (50); (Data collection)
Transport emission (per ton per km)	Uniform (140.87, 250.73); (Department for Energy Security and Net Zero 2024)
Disposal (emissions per instrument)	Triangular (123.2, 154, 184.8); 154 (Rizan and Bhutta 2022) ± 30.8 (20%)
Reprocessing (emissions per instrument)	Triangular (264, 330, 396); 330 (50% manufacturing EPI) ± 66 (20%)
Manufacturing (emissions per instrument)	Triangular (528, 660, 792); 660 (Rizan and Bhutta 2022) ± 132 (20%)
Truck speed (km/h)	Uniform (48, 80); (UK Government n.d.)
Inter-facility distance	Fixed, 100 km; (Assumption)

Input parameters	Distribution/Source
Order processing time (hours)	DC = Uniform (12,48), Manufacturer = Uniform (96, 168), Reprocessor Uniform (8, 16); Expert judgement & (NHS Supply Chain n.d.)
Instrument weight in (grams)	Gamma (25,2.4352); 60.88 (Rizan and Bhutta 2022) ± 12.176 (20%)
Instrument waste management cost (£/kg)	Gamma(25,0.02469); 0.61722 (Rizan and Bhutta 2022) ± 0.1234 (20%)
Post operation instrument repacking time	Triangular (0.6, 0.75, 0.9); 0.75 (Expert judgement) ± 0.15 (20%)
Nurses time to walk from main storage to operation room	Triangular (2.4, 3, 3.6); 3 (Expert judgement) ± 0.4 (20%)
Personnel time to walk from storage to the sorting point	Triangular (3.2, 4, 4.8); 4 (Expert judgement) ± 0.8 (20%)
Nurse wages (£/hour)	Gamma (25, 1.92); 48 (Expert judgement) ± 9.6 (20%)
NHS Personnel wages (£/hour)	Gamma (25, 1.28); 32 (Expert judgement) ± 6.4 (20%)

Notes: £ = Pounds, DC= distribution center, km/h=kilometer per hour. Emission values in gram CO_2 eq.

2.2 Overview of the Hospital Settings Model (Model 2)

The hospital setting model aims to simulate a hospital. The model consists of four main modules: NHS local warehouse, transportation, packaging/repackaging, and decontamination. Each of the four modules can be customized for hospital demand and the likely behavior of various hospitals' decisions with regard to activities relevant to medical instruments and repackaging, such as purchasing, transporting, using, repackaging, and waste.

The hospital settings model simulates one health center with the possibility of conducting two surgeries every day. However, note that the input parameters for purchasing, transporting, storing, repackaging, and decontamination of the laparoscopic instruments represent a hospital that purchases, stores, and discards many other products.

2.2.1 NHS Local Warehouse

This module represents a typical NHS warehouse containing various instruments. The available laparoscopic instruments considered in this model are single-use and refitted. The local warehouse is replenished weekly.

2.2.2 Storage Module

NHS extra personnel would be needed to oversee the hauling of instrument boxes and their storage in the designated compartments. Currently, the model defines two storage types, one for single-use instruments and another for the refitted ones.

2.2.3 Operations Module

The frequency of operations can be defined by the user. Once a patient needing a surgery arrives, nurses collect the laparoscopic instrument from the hospital's main storage and store it in the operation room for usage during the surgery. After the surgery, instruments are collected, inspected, and stored by the nurse. The instruments can be thrown away if considered unsuitable for further use or repacked and sent by the hospital to a third party to be reprocessed/refitted.

Next, we present preliminary simulation experiment results.

3 PRELIMINARY SIMULATION MODEL FINDINGS

Both models are developed and run using the Anylogic simulation software. Note that the models run for a warm-up period of 200 days to ensure that key model results reach a steady state. The results model 1 are first presented, followed by the results from the hospital settings model.

3.1 Supply Chain Model 1 Preliminary Results

The supply chain simulation model evaluates the implications of the introduction of circularity in laparoscopic scissors, considering a future scenario where these single-use scissors can be reused after their first operational life. In the context of this work, we illustrate how the adoption of CE influences system performance by focusing on key indicators such as the number of new instruments utilized, the number of instruments disposed of, and the overall resulting CO_2 emissions in the system.

We considered two scenarios to assess the impact of circularity. In the first, the impact of increasing the adoption of reprocessed instruments in the hospital is compared to the base case (LE case); and in the second, the effect of increasing the instrument use-cycles from 1 (linear case) to 5 is considered. Note that the instrument use-cycle refers to the number of times an instrument can be utilized before reaching the EOL stage - when the instrument is no longer suitable for reprocessing and, hence, for further use-cycles.

Table 2: Effect of change in the adoption rate of reprocessed instruments on the number of new instruments required and the number of instruments disposed. Mean [95% confidence interval].

Adoption of reprocessed instruments	Number of instruments disposed	Number of new instruments used	Decrease in CO_2 emissions
0	197,634 [196,292; 198,975]	197,634 [196,292; 198,975]	-
10%	3,880 [3,611; 4,149]	177,504 [176,273; 178735]	22.88% [21.97%; 23.79%]
20%	9,118 [9,100; 9,136]	158,261 [157,367; 159,157]	25.45% [24.32%; 26.56%]
30%	13,736 [13,706; 13,766]	137,650 [136,952; 138,348]	29.69% [28.53%; 30.83%]
40%	18,267 [18,241; 18,293]	118,085 [117,317; 118,852]	33.67% [32.39%; 34.93%]
50%	22,819 [22,793; 22,845]	98,429 [97,813; 99,046]	37.73% [36.68%; 39.08%]
60%	27,358 [27,318; 27,399]	79,371 [78,873; 79,869]	39.87% [38.43%; 41.29%]
70%	31,930 [31,897; 31,962]	59,114 [58,759; 59,470]	44.38% [43.03%; 45.73%]
80%	36,526 [36,493; 36,558]	39,417 [39,174; 39,661]	48.30% [46.90%; 49.70%]
90%	36,507 [36,478; 36,536]	39,222 [39,010; 39,434]	49.11% [47.58%; 50.64%]

Table 2 shows the results for the first scenario, representing the impact of varying the adoption rate of reprocessed instruments at the hospital. It shows the impact on the number of new instruments required, the number of instruments disposed of, and the reduction in CO_2 emissions at various levels of reprocessed instrument adoption. For this scenario, it is assumed that the maximum number of times an instrument can be used before reaching the end of its life is 'five,' and the experiment termination criterion was ten years of simulation run time.

The results from the second scenario experiments are shown in Table 3. We vary the number of times an instrument is used before the instrument EOL. It is noted that for these experiments, the adoption rate is

kept constant at 50%. Furthermore, the first row in tables 1 and 2 represents the LE case and used as a baseline scenario for the comparisons.

The results for the first set of experiments show a significant improvement in the metrics against the LE setting. We observe a steady decline in the emissions, the number of new instruments utilized and disposed of as the adoption rate increases. To assess the statistical significance of differences between the various scenarios considered in this study, we conducted a series of two-sample paired t-tests for the mean number of new instruments used, disposed, and the associated CO_2 emissions.

The results of the statistical tests reveal significant differences ($p < 0.05$) between the means of all scenarios, with one notable exception. The comparison between the 80% and 90% adoption scenarios does not yield statistically significant differences in any of the performance indicators ($p > 0.05$), suggesting that the impact of increasing adoption rates on the selected performance indicators plateaus at approximately 80% adoption. This suggests that further increases in adoption beyond the 80% threshold does not result in substantial improvements in the number of new instruments used, disposal rates, or CO_2 emissions. This happens because the higher utilization rate of instruments, more instruments reach the EOL stage, meaning reprocessing is frequently starved, hence not enough reprocessed instruments are available for use.

Considering the results of the second scenario experiments, a significant drop of approximately 30% in emissions can be seen from Table 3 as we transition from LE to CE, i.e., from instrument life of 1 to 2. However, it becomes evident that upon extending the life of the instruments further, the rate of decrease diminishes and stabilizes when the instrument life reaches four times (row four, Table 3). This can be attributed to the moderate adoption rate employed for this scenario, implying that more instruments stay within the system and do not reach the EOL stage. This could also mean that if the life of instruments is increased further, without changing the adoption rate, a relative increase in the emissions may be observed because of unnecessarily reprocessing the instruments collected from the hospital when they are not even getting utilized again.

Table 3: Effect of change in the number of times instruments that can be used after reprocessing on the number of new instruments required and the number of instruments disposed. Mean [95% confidence interval]

Instrument use-cycle	Number of instruments disposed	Number of new instruments used	Decrease in CO_2 emissions
1	197,634 [196,292; 198,975]	197,634 [196,292; 198,975]	-
2	91,198 [91,105; 91,292]	98,653 [98,067; 99,238]	31.17% [30.29%; 32.05%]
3	45,591 [45,536; 45,645]	98,518 [97,945; 99,090]	35.71% [34.85%; 36.57%]
4	30,402 [30,368; 30,436]	98,444 [97,928; 98,959]	37.05% [36.18%; 37.92%]
5	22,823 [22,794; 22,852]	98,969 [98,408; 99,530]	37.27% [36.39%; 38.15%]

3.2 Hospital Settings Model 2 Preliminary Results

This section provides preliminary findings from the detailed hospital settings model that focuses on four cost components: transportation expenses from the local warehouse to the hospital, repackaging costs for surgical instruments destined for reprocessing, personnel expenses related to instrument preparation for waste management, decontamination and reprocessing.

The model considers that the hospital can purchase single-use and refitted instruments, and both are assumed to be available in sufficient quantity to fulfill any level of demand. Further, it was assumed that refitted instruments are available at 70% of the price of a new instrument. We consider a range of best and worst-case scenarios. In the best case, the hospital always obtains all instruments as refitted from the local warehouse. In the worst-case scenario, the hospital always obtains the single-use instruments. Six scenarios are analyzed considering different adoption levels of the refitted instruments: 1. 100% single-use & 0% refitted; 2) 80% single-use & 20% refitted; 3) Scenario 3: 60% single-use & 40% refitted; 4) 40% single-use & 60% refitted; 5) 20% single-use & 80% refitted; and 6) 0% single-use & 100% refitted. In Scenario

6, it was assumed that the refitted instruments are available at a reduced process from a third-party reprocessor that has sufficient inventory to fulfill the demand.

3.3 The adoption of refitted instruments in hospital

The hospital simulation model was configured to run for a simulated period of 3 years, with a sufficient warm-up period to attain a steady-state behavior. The presented results correspond to 500 replications and are reported as mean with 95% confidence intervals as shown in Figure 3. The results displayed in Figure 3a show that hospitals purchasing single-use instruments have a significantly higher total per-patient cost. As expected, purchasing single-use instruments leads to higher per-patient costs compared to purchasing 100% refitted devices.

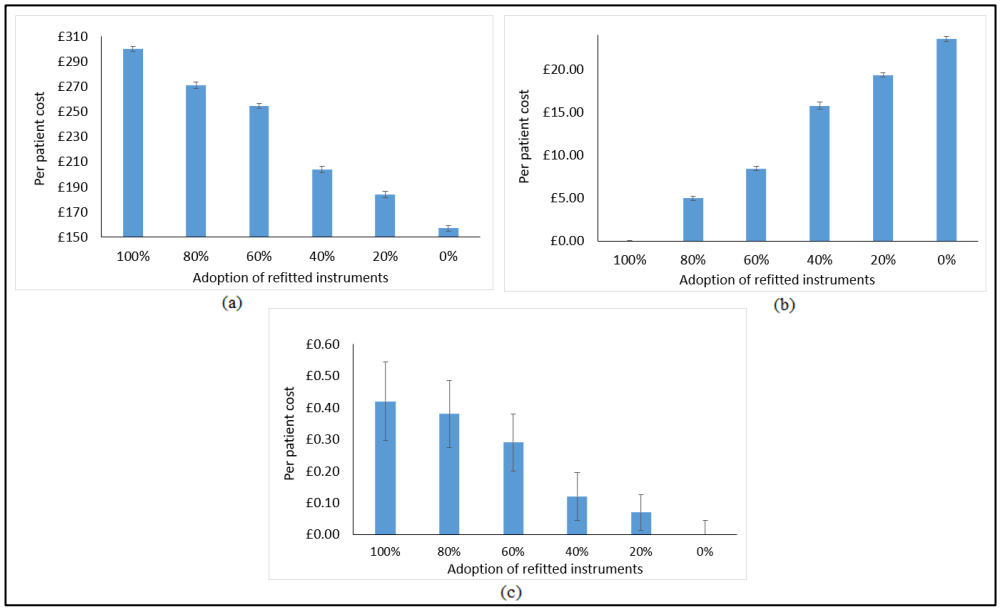

Figure 3: Box plots of the effect of change in the adoption of refitted/reprocessed instruments in the hospital setting on a) the total purchase cost, (b) the repackaging cost, and (c) waste management cost.

This cost takes into account the costs incurred in the processes of handling, transporting, and managing surgical instruments within the healthcare facility. As anticipated, this outcome aligns with our expectations, as single-use instruments typically have higher initial purchase costs compared to refitted instruments, which are available at a discounted price. Thus, it can be argued based on the simulation results that the single-use instruments may not offer the same level of cost-effectiveness over the long term. However, when we consider the repackaging costs (Figure 3b), purchasing single-use instruments leads to lower costs compared to the refitted instruments. The main reason behind this difference in repackaging cost is that the used instruments require repackaging before collection by a third party, whereas the single-use devices are disposed of and not used for any other medical procedures. Moreover, upon analyzing the waste management cost illustrated in Figure 3c, it becomes evident that choosing single-use instruments leads to higher waste management costs compared to refitted instruments. When examining the various cost components, single-use instruments are cost-effective in terms of waste management costs, whereas refitted instruments are more cost-effective in terms of repackaging expenses. However, the overall cost per patient is notably higher for single-use instruments than for refitted instruments.

4 CONCLUSIONS

This paper is the first study that evaluates the implementation of CE scenarios in healthcare supply chain of SMDs. It takes a different perspective by including the operational element to the analysis of CE and, thus, builds upon the existing work (John et al. 2024; Leiden et al. 2020; Rizan and Bhutta 2022) which considers only the environmental and financial elements. We present two complementary DES models that adopt an integrated high- and micro-level approach. The first model offers an overall systems perspective of the supply chain performance by comparing the linear and circular economic flow of laparoscopic scissors in the system. The two scenarios tested in the high level supply chain model include: i) an increase in the adoption of the reprocessed instruments in hospitals and ii) the number of times instruments can be reused. The effect of these scenarios is evaluated using high-level performance indicators, including environmental and operational metrics. Complementing this high-level model, the second model translates system-level changes into patient outcomes estimating the per-patient costs in healthcare settings. These include transportation, repackaging, decontamination and personnel costs associated with preparing and handling instruments for use, decontamination and waste management processes.

Our preliminary results from the SC model show that a net reduction in CO_2 emissions by approximately 48% can be achieved with the adoption of reprocessed laparoscopic scissors. These outcomes substantiate the overall positive environmental impact associated with the introduction of CE. Moreover, the experiments demonstrate that as the adoption rate of reprocessed instruments increases in hospital, the reprocessor needs to maintain a larger inventory to ensure an uninterrupted supply of the instruments. Further, the outcomes of the second model demonstrate a reduction in total per-patient cost, in specific terms, the cost decrease from £301 to £159 with the introduction of reprocessed instruments. While the overall per-patient cost decreases, new expenses, such as repackaging emerge, highlighting the importance of a comprehensive and detailed evaluation of cost-benefits associated with the transition to CE for hospital settings.

The initial findings presented in this paper will be further extended with additional scenarios in the future. The results presented in this paper show the outcome of changes in the adoption rate of circular products in healthcare supply chains, providing valuable insights for CE implementation. Nonetheless, the limitations present in our models should be considered. For example, the scope of our models is limited to single-use laparoscopic scissors, whereas the use of other types of laparoscopic scissors, such as hybrid or fully reusable instruments, is not considered. Further, the supply chain model utilizes synthesized data to represent emissions during the reprocessing stage, due to the lack of real-world data. Additionally, the hospital setting model assumes that the probability of instrument failure during procedures is between 5 to 10%, and that the hospitals have sufficient capacity to collect and dispatch all the instruments for reprocessing. Furthermore, it is noted that the results of the hospital setting model are applicable to hospitals that have similar processes to those described in the model. As a result, the quantitative results presented in this paper should be treated as indicative.

This study is the first step towards creating an evidence base that shows that changes to hospital practices through upstream (manufacturer) intervention can reduce total cost per patient much more than downstream (hospital) interventions aimed at increasing recycling rates. Our future research will aim to develop the evidence base further by exploring different behavioral interventions, as well as the inclusion of hybrid laparoscopic scissors. We also plan to identify the optimum ordering policy, and the case of bigger storage on-premises. Other possible additions include integrating the impact of transportation from suppliers to the hospital by comparing different distances between distribution centers, to consider national and international locations.

ACKNOWLEDGMENTS

The work is part of the research project "Circular Economy for Small Medical Devices" (ReMed), funded by the Engineering and Physical Sciences Research Council (EPSRC) (EP/W002566/1). The authors thank the ReMed research team and industrial partners for their input. Thanks also go to Paul Broadbury (Vanguard), Heidi Barnard (NHS Supply Chain), and Agnese Hanson (NHS England) for their feedback.

REFERENCES

Abe, Tolu K., Benita M. Beamon, Richard L. Storch, and Justin Agus. 2016. "Operations Research Applications in Hospital Operations: Part III." *IIE Transactions on Healthcare Systems Engineering,* 6(3): 175-191.

Biller, Bahar, and Canan Gunes. 2010. "Introduction to Simulation Input Modeling." In *2010 Winter Simulation Conference (WSC)*, 49–58.

Van Boerdonk, P. J. M., H. R. Krikke, W. Lambrechts, and Philips Benelux. 2020. "New Business Models in Circular Economy: A Multiple Case Study into Touch Points Creating Customer Values in Health Care." doi: 10.1016/j.jclepro.2020.125375.

Brailsford, S. C., P. R. Harper, B. Patel, and M. Pitt. 2016. "An Analysis of the Academic Literature on Simulation and Modeling in Health Care." Pp. 231–51 in *Operational Research for Emergency Planning in Healthcare: Volume 2*. London: Palgrave Macmillan UK.

Charnley, Fiona, Divya Tiwari, Windo Hutabarat, Mariale Moreno, Okechukwu Okorie, and Ashutosh Tiwari. 2019. "Simulation to Enable a Data-Driven Circular Economy." *Sustainability* 11(12):3379. doi: 10.3390/su11123379.

Department for Energy Security and Net Zero. 2024. "Government Conversion Factors for Company Reporting of Greenhouse Gas Emissions - GOV.UK." https://www.gov.uk/government/collections/government-conversion-factors-for-company-reporting. Accessed 29th January 2024.

Ellen MacArthur Foundation. 2013. "TOWARDS THE CIRCULAR ECONOMY." 1–99. https://shorturl.at/lrCwa. Accessed 6th May 2023.

UK Government. n.d. "Speed Limits." *The Highway Code, Road Safety and Vehicle Rules*. https://www.gov.uk/speed-limits. Accessed 18th June 2024.

Guzzo, D., E. Jamsin, R. Balkenende, and Costa. 2019. "The Use of System Dynamics to Verify Long-Term Behaviour and Impacts of Circular Business Models: A Sharing Platform in Healthcare." In *PLATE – Product Lifetimes And The Environment : Proceedings, 3rd PLATE CONFERENCE*, 309-315.

Hibbs, Stephen P., Stephen Thomas, Nikhil Agarwal, Charlotte Andrews, Sylvia Eskander, Aaliyah Sharif Abdalla, Julie Staves, Matthew J. Eckelman, and Michael F. Murphy. 2024. "What Is the Environmental Impact of a Blood Transfusion? A Life Cycle Assessment of Transfusion Services across England." *Transfusion* 64(4):638–45.

Huster, Sandra, Simon Glöser-Chahoud, Sonja Rosenberg, and Frank Schultmann. 2022. "A Simulation Model for Assessing the Potential of Remanufacturing Electric Vehicle Batteries as Spare Parts." *Journal of Cleaner Production* 363.

John, Joseph, Michael Collins, Kieran O'flynn, Tim Briggs, William Gray, and John Mcgrath. 2024. "Carbon Footprint of Hospital Laundry: A Life-Cycle Assessment." *BMJ Open* 14:80838. doi:10.1136/bmjopen-2023-080838.

Katsaliaki, K., and N. Mustafee. 2011. "Applications of Simulation within the Healthcare Context." *Journal of the Operational Research Society* 62(8):1431–51.

Keil, Mattis, Tobias Viere, Kevin Helms, and Wolf Rogowski. 2023. "The Impact of Switching from Single-Use to Reusable Healthcare Products: A Transparency Checklist and Systematic Review of Life-Cycle Assessments." *European Journal of Public Health* 33(1):56–63.

Law, M. Averill. 2013. "A Tutorial on How to Select Simulation Input Probability Distributions." In *2013 Winter Simulation Conference (WSC),* 1-15.

Leiden, Alexander, Felipe Cerdas, David Noriega, Jörg Beyerlein, and Christoph Herrmann. 2020. "Life Cycle Assessment of a Disposable and a Reusable Surgery Instrument Set for Spinal Fusion Surgeries." *Resources, Conservation and Recycling* 156.

Lieder, Michael, Farazee M. A. Asif, Amir Rashid, Aleš Mihelič, and Simon Kotnik. 2017. "Towards Circular Economy Implementation in Manufacturing Systems Using a Multi-Method Simulation Approach to Link Design and Business Strategy." *International Journal of Advanced Manufacturing Technology* 93(5–8):1953–70.

Meister, Julia A., Jack Sharp, Yan Wang, and Khuong An Nguyen. 2023. "Assessing Long-Term Medical Remanufacturing Emissions with Life Cycle Analysis." *Processes* 11(1).

Michelini, Gustavo, Renato N. Moraes, Renata N. Cunha, Janaina M. H. Costa, and Aldo R. Ometto. 2017. "From Linear to Circular Economy: PSS Conducting the Transition." *Procedia CIRP* 64:2–6. doi: 10.1016/J.PROCIR.2017.03.012.

NHS England. 2022. *Delivering a "Net Zero" National Health Service Classification: Official*. https:// https://www.england.nhs.uk/greenernhs/a-net-zero-nhs/. Accessed 19th January 2024.

NHS Supply Chain. n.d. "Delivery Information." https://rb.gy/wi4azx. Accessed 20th February 2024.

Pieroni, Marina P. P., Tim C. Mcaloone, and Daniela C. A. Pigosso. 2019. "Business Model Innovation for Circular Economy and Sustainability: A Review of Approaches." *Journal of Cleaner Production* 215:198-216. doi: 10.1016/j.jclepro.2019.01.036.

Rizan, Chantelle, and Mahmood F. Bhutta. 2022a. "Environmental Impact and Life Cycle Financial Cost of Hybrid (Reusable/Single-Use) Instruments versus Single-Use Equivalents in Laparoscopic Cholecystectomy." *Surgical Endoscopy* 36(6):4067–78.

Robinson, Stewart. 2014. *Simulation: The Practice of Model Development and Use*. Palgrave MacMillan.

Tako, Antuela A., and Stewart Robinson. 2012. "The Application of Discrete Event Simulation and System Dynamics in the Logistics and Supply Chain Context." *Decision Support Systems* 52(4):802–15.

Tennison, Imogen, Sonia Roschnik, Ben Ashby, Richard Boyd, Ian Hamilton, Tadj Oreszczyn, Anne Owen, Marina Romanello, Paul Ruyssevelt, Jodi D. Sherman, Andrew Z. P. Smith, Kristian Steele, Nicholas Watts, and Matthew J. Eckelman. 2021. "Health Care's Response to Climate Change: A Carbon Footprint Assessment of the NHS in England." *The Lancet Planetary Health* 5(2):e84–92.

AUTHOR BIOGRAPHIES

MOHD SHOAIB is a Research Associate at Nottingham Business School, Nottingham Trent University. He is currently working as a research associate on an EPSRC research project on the circular economy of small medical devices (ReMed). He holds a Ph.D. in Industrial Engineering and Operations Research from the Indian Institute of Technology Delhi. His research interests include simulation modeling and optimization and their application in healthcare delivery systems, supply chains, and circular economy. His email address is mohd.shoaib@ntu.ac.uk.

ANTUELA TAKO is a Professor of Operations Research at Nottingham Business School, Nottingham Trent University. She holds a PhD in Simulation and an MSc in Management Science and Operational Research from the University of Warwick. Her research interests include alternative simulation approaches (discrete-event simulation, system dynamics, agent-based simulation and hybrid simulation), facilitated and participative simulation, conceptual modeling, modelling human behaviour and systems thinking, applied primarily in healthcare, sustainability and circular economy, supply chains and emergency services. Antuela is Associate Editor of the Journal of the Operational Research Society and Journal of Simulation and Area Editor of Health Systems. She co-leads the Business, Operations, and Economics Work Package in the ReMed Project. Her email address is antouela.takou@ntu.ac.uk and her webpage is https://www.ntu.ac.uk/staff-profiles/business/antuela-tako.

RAMZI FAYAD, Research Fellow, Faculty of Medicine & Health, University of Leeds. Ramzi has obtained his PhD in Manufacturing Engineering and Operations Management from Nottingham University and is currently a research fellow in the ReMed Project at the University of Leeds. With more than ten years of experience in commercial and academic fields, his research interests are Circular Economy, System Optimisation, Condition Monitoring, Vibration Analysis, and Operational Research. He is passionate about implementing data driven solutions to solve lean production/management problems across various business sectors, and an expert in coordinating and improvement all aspects of human and non-human business systems/processes through analytical modeling and simulation techniques. His email address is r.fayad@leeds.ac.uk.

ARMANDO VARGAS-PALACIOS, Senior Research Fellow, Academic Unit of Health Economics, University of Leeds
Dr Vargas-Palacios, holds a PhD in Health Economics from the University of Sheffield. His research focuses on the economic evaluation of medical interventions, new technologies, treatment pathways, and medical devices. He is an expert on the use of simulation techniques (such as discrete event simulation) to evaluate system wide implications of the implementing a new technology or an alternative treatment pathway. He is part of the NIHR Surgical MedTech Cooperative, Leeds, as an expert in Health Economics, which supports the development of new technologies in the field of surgery aimed at improving health care provision and quality of life for the patients. Armando is co-leading the Work Package 2c (Business, Operations, and Economics) in ReMed Project. His email address is a.vargas-palacios@leeds.ac.uk.