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Artificial intelligence-based digital twin framework for circular economy optimization in healthcare waste management

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Abstract

Health care systems have grown to produce ever growing amounts of garbage, which further strain the environment, costs of running the system, and regulatory demands especially in the post pandemic period. The traditional methods of managing linear waste are also inefficient and do not well comply with a circular economy. The paper introduces an artificial intelligence-based, scientifically supported digital twin system that aims at maximizing the effectiveness of healthcare waste management through the application of real time sensing and analytics based on predictive algorithms and through the use of multi objective optimization that is integrated into the circle economy paradigm. The framework virtualizes the streams of waste materials in the hospital through Internet of Things based monitoring and implements the machine learning models to forecast, assess, and analyze waste and provide an optimization engine that balances the goals of both economy and environmental objectives within the regulatory constraints. Statistical results showed that there were significant and significant increases in all the key indicators. The average recycling rate rose by 20.0 to 50.7 percent which is the 30.7 percentage point, and the sample t testing group has verified that the difference is significant at $p < 0.001$, with a statistical power of 0.99. Statistically significant findings prove that the value of artificial intelligence facilitated digital twins can be used to provide the measurable, reproducible, and scalable benefits in terms of circularity, cost-effectiveness, and regulatory compliance in the management of healthcare waste and are justified in their integration into a data driven model of a sustainable approach to operating the hospital.

Keywords: Digital twin, Artificial intelligence, Healthcare, Waste management, Circular economy, Machine learning.

1. Introduction

The healthcare operations create a complicated body of wastes which directly affect the sustainability of the environment and the health of people [1]. The healthcare waste is made up of about 85 percent non-hazardous (e.g. paper, packaging, plastics), and only 15 percent of the waste is hazardous (including infectious materials, sharps, chemical or pharmaceutical waste). Segregation practices and consumption of single-use commodities allow high-income settings to produce hazardous medical waste of 11 kg per bed per day, almost twice as much as low-income settings, in high-income settings. This issue was made during the COVID-19 pandemic wherein the number of disposable personal protective equipment and medical supplies increased significantly, leading to a rise in the emissions due to healthcare waste by approximately 10% throughout the world. This has a high price to the environment: the waste and supply chain of the healthcare sector already accounts for approximately 4.4 percent of total greenhouse gas emissions on the planet. Such tendencies point to the necessity of more sustainable healthcare waste management methods.

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The circular economy (CE) provides a bright design to change the management of waste in the healthcare industry [1-3]. Unlike the linear type of use-and-dispose approach, a circular one aims at cutting waste produced and maintaining materials utilization by adopting reducing elements at source, reusing durable goods, recycling materials and energy recovery [2,4]. According to the previous research, the implementation of circular economy principles can highly enhance the level of waste management [5-8]. Indicatively, in a recent study, the adoption of circular economy in healthcare was found as the primary means of reducing the generation of waste with critical success factors that comprise the strong responsibility of the government and the involvement of the stakeholders [6,9]. Nevertheless, hospitals have been struggling in the implementation of such principles. Rigid infection control conditions, regulatory adherence problems, and the absence of real time monitoring into waste streams tend to restrict the use of reduction, reuse, and recycling into practice [10]. The poor separation that occurs even in case of recycling programs dictates the fact that even with the existence of the recycling programs, most of the objects that could have been recycled still get into hazardous streams of waste, which are both harmful to the environment and expensive to dispose of. There is still a sizable gap between the high-level CE goals and waste management in hospital setting, on a daily basis [10-12].

Digital technologies are regarded as the closer in overcoming this gap [7,13-16]. Specifically, the concept of a digital twin and artificial intelligence (AI) has become an effective means to make the system of waste management updated [2,17-19]. A digital twin is a dynamic and virtual model of a real-world system or process to which real-time updates are made with data, and makes it possible to simulate and survey the state of that system [3,20-23]. Through developing a live virtual representation of the hospital waste management procedures (generation, separation, collection, and treatment), one can prevent problems in the real world by visualizing the flows and optimizing the materials in sequence and implementing changes with the stakeholders involved in the virtual representation of the system [9,24-26]. Combined with AI, this ability is also extended: predictive models can estimate the volume and composition of waste, identify errors (including incorrect sorting of waste), and assess the results of the application of various management policies in different conditions [27-29]. Such twins based on AI can experiment with such interventions as reusing products or changing collection schedules, in the context of waste management, which do not always need to be implemented in reality. This is a quantitative foresight which is of immense value in foreshadowing and reducing the adversity (e.g. waste overflow, regulatory non-compliance) before they manifest in reality.

In the recent studies, there is some promising finding of the advantages of marrying digital twin technology with AI in the achievements of sustainable waste management. The data presented by researchers show a digital twin approach to industrial waste minimized on the general waste volumes by 27% and rose to 45% in terms of resource recovery. They created a closed-loop system by using IoT sensor networks and machine learning, and the improvements of the system were significant in terms of material efficiency and minimizing waste [30-32]. Techniques of AI have been utilized in real-time optimization in the municipal and medical waste industry: it has been demonstrated to automatically separate waste by computer vision classifiers (support vector machines), and smarter management of waste collections by smart bins with sensors and genetic algorithm (GA) optimizers has been shown to optimize waste collection routes [9,33-35]. Another pilot with explainable AI (XAI), sensor-enabled containers, and Goa-based vehicle paths has produced one of the innovative smart city medical waste solutions, increasing the efficiency of collecting waste materials and shortening the time of transportation [36-38]. These instances indicate that digitalization, automation and sustainability in waste businesses have come to a point of convergence which is also seen in bibliometric studies mapping the interrelation between AI, circular economy and predictive waste management [3,39-42].

Irrespective of these developments, it is evident that there is a void in the literature and practice: the absence of integrated approaches that are tailored to healthcare waste management to merge digital twin technology with AI-driven analytics in order to obtain a better optimization of the circular economy. The majority of hospitals continue to so-called traditional waste monitoring (e.g. audits at certain periods, storage of manual records) and pay attention to the ultimate waste disposal instead of waste reduction. The current digital solutions are likely to cover one or a few of the compliant documentation or route optimization, unless it offers a more specific solution in the shape of a closed-loop decision support system to waste reduction and resource recovery. According to the recent studies, a concrete barrier to the implementation of the theory of the circular economy is that there is no practical and integrated tool that enables hospital environmental managers to practically use the principles of a circular economy in the management of waste on the daily level, hence the identified factor is one of the significant obstacles on the way of translating the theory of the circular economy into practice. That is, the hospital managers require more intelligent platforms not only to record data as required by the regulators, but also implementational-level decisions like what materials to recycle initially, waste minimisation, or the resource that has the best sustainability impact.

The objective of the project,

(1) to create a digital twin of the waste management system in a hospital and have real-time follow-ups and simulation of the waste flows.

(2) to incorporate AI algorithms to make predictive analytics (waste forecasting, anomaly detection) and waste handling business strategies optimization.

(3) to judge the effectiveness of the framework to increase the key performance indicators like waste reduction, recycling rate, cost efficiency and compliance.

(4) to determine or define the practical implications to be applied to the healthcare facilities. Among the specific areas that we focus on, we aim at waste segregation (ensuring that the 85 percent non-hazardous portion of the waste is recycled at the highest possible rate), recycling and reuse, safe reduction of hazardous waste and at the same time, saving of costs without compromising on health and safety standards.

This research has threefold contributions. First, we introduce a single AI-based healthcare waste management digital twin - to the best knowledge, the first one to explicitly utilize these technologies in a hospital setting in the optimization of a circular economy. This paradigm expands the existing digital twin applications with detailed waste categories, regulatory limitations, and healthcare-specific (as in sterilization to reuse and recovery of materials used in medical waste) circular approaches. Second, we create a multi-level methodological strategy (data acquisition, machine learning and optimization modeling) and show the application of this strategy with the help of a detailed case study and quantitative analysis. As opposed to purely conceptual works, we actually give concrete statistical data of performance improvements that the framework has an effect on. Third, we have developed a gap between the 'conceptual well' and the practical instrument: we develop the principles of a circular economy into practical insights, which hospital waste managers can apply using a smart decision-support system. This study presents an opportunity to help healthcare facilities to enhance sustainability significantly by trying to solve practical operational issues (such as unexpected dumping of waste, stringent laws, etc.) using modern technologies. In the end, we believe that the work will provide the basis of the further applications of AI-based digital twins and contribute to the transition of more sustainable and more circular healthcare systems.

2. Methodology

3.1 Framework Overview

In order to meet the research goals, we have created an AI-based framework of a digital twin where the process of healthcare waste management is virtualized, and optimized through the use of data. The framework architecture (data collection to decision support) of this study is conceptually represented and we consider methodological elements in the text in brevity. The strategy incorporates several layers, including: physical data acquisition, digital twin modeling, AI analytics, and optimization, which are supported by the circular economy criteria. The most fundamental is the digital twin of waste management system of the hospital. The twin incorporates some major physical objects and processes such as: hospital units where waste is produced (wards, operating rooms, laboratories, etc.), waste bins and containers (which are distinguished by factors like category e.g. general, infectious, sharps, etc.), internal transport routes (between wards and storage areas), on-site treatment plants (where none exist, e.g. autoclaves), and off-site disposal or recycling. The digital twin has a collection of state variables of each of the elements and is continuously updated through data streams. The sensors on the physical environment post the real-time data on the waste generation and processing: the weight sensors on smart bins detect the volume of waste of this or that type, the RFID tags or the QR codes follow the waste bags in the chain of their collection, the environmental sensors measure the conditions at the place (temperature in warehouses, the level of fill of the containers, etc.). These figures are inputted into the Physical Layer of the twin producing a live replica of the waste streams.

Most importantly above this, there is an Analytics Layer that uses artificial intelligence to understand the data that is getting in and creates insights. To achieve all these, we used a set of machine learning (ML) algorithms to process such activities as waste generation prediction, classification of waste, and anomaly detection. Time-series forecasting models (e.g. ARIMA and Long Short-Memory neural networks) make forecasts of the amount of waste of each category and each hospital unit when using historical data and exogenous variables (e.g. patient influx or surgical schedule). The classification models (based on such methods as random forests and support vectors machine) identify the instances of misclassified waste - such as whether general waste bins have products that should be in infectious waste and vice versa, resting on sensor data characteristics, or even image analysis in case of camera sensors. The ML models are trained using the past data of the historic waste in the hospital (or other hospitals) and then continuously upgraded depending on the new information thus becoming better and accurate with time. Also, the analytics layer applies prescriptive algorithms to analyze the potential interventions. Embodied in this is simulation routines that effectively carry out a change (e.g. increase in number of recycling bins on a given floor or change in frequency of pickup) in the digital twin and project the consequences (e.g. increase in material recycled or loss of overflow incidents). Through trial of numerous such situations, the system is able to distinguish effective strategies that would have a high impact on minimizing and diversion of waste.

Lastly, it has a decision-making or Optimization Layer which is to decide the best waste management strategy in accordance with the aims of a circular economy. We have developed a mathematical optimization model that represents the most important decision variables, constraints, and objectives of the problem of managing the waste in the hospital, and the solution of the problem through the application of relevant algorithms. The optimization is directed by two major objectives:

(i) exert a maximum level of circularity (i.e. maximum amount of waste without burning or going to landfills)

(ii) reduce cost (both the operation cost of dealing with waste and also the treatment/disposal cost). One kind of objective can serve with a multi-objective optimization or, with the connection of the weighted terms, with an aggregated objective. An approach that was used in our implementation is the weighted sum approach where economic and environmental goals are integrated in a single figure of merit. In particular, we will give a financial price to every route of waste processing which will reflect its economic cost and its environmental cost (disastering the disposal and rewarding the recycling). The optimization is then aimed at minimising the generalised cost.

The waste categories (e.g. general non-hazardous, infectious, sharps, pharmaceutical), and waste processing options available (e.g. reuse, recycle, incineration, landfill) are indexed with the letter N and M, respectively. We specify that the decision variable of sending the waste of type i in category N to the processing option with a specific number of variables in the choices, as j in M, is referred to as decision variable, x i j. The objective function (Equation 1) that drives the model is minimized and it is subjected to a number of constraints (to be discussed later):

$$minZ = i \in Nj \in Mcij\, xij \; + \; \lambda sumi \in Nwi \qquad (1)$$

In which cij is a unit cost of treating a waste type i by choice j, and W i is any left-over waste of a type i that ends up being discarded (in the landfill or uncontrolled dumping) instead of being recovered. The second term consequently gives a penalty (normalized by 9) on waste to leave circular loops, which effectively expresses the preference that the model has on recycle/reuse streams. Practically, we can translate wi into subsets of x j i, e.g., to consider incineration without energy recovery, landfill, as an example of a project, we may e.g. count every j in D as x j i. In that manner, the objective function will incorporate the circular economy optimization objective and the cost minimization. A large enough value of the parameter of interest, namely, a large value of the parameter, as a result, will push the solution towards the greatest amount of waste diversion, but a smaller value of the parameter will place more emphasis on cost savings - the parameter gives an opportunity to trade-off economic and environmental performance.

3.3 Constraints

Balances of materials, capacity constraints, and regulatory issues limit the optimization. In the case of every waste category (i) the total generated (which is denoted Qi) should equal all the routes that are processed:

$$j \in Mxij = Qi, \forall iinN \tag{2}$$

This will mean that all the generated waste in the model is allocated to any outcome. The data of the digital twin (or predictions of the future planning periods) gives the value of Qi per category in real-time, hence the optimization makes its decisions based on the current amounts of waste.

There is a capacity limit to some processing paths: e.g. on-site autoclave treatment can have a fixed throughput per day, recycling plants can have a limit to how much of a certain material they will take, storage areas can only hold a fixed amount of segregated garbage. and given that Uj is the options capacity of option j in the applicable time period, then we impose

$$i \in Nxij \leq Uj, \forall jinM \tag{3}$$

in the case of j with capacity limit available. An option (e.g., external landfill) can be unconstrained, so that it is taken to be unconstrained (Uj large), or be constrained such (e.g., high-temperature incinerator at the hospital).

Importantly, feasibility issues will guarantee the adherence to health regulations: the categories of hazardous waste will be removed to the allowed treatment or disposal facilities. We have binary restriction parameters a ij that means that a ij=1 only where waste type i can be processed by option j. As an example, when the Xi is the infectious waste then a i, j = recycle = 0 implies that direct recycle cannot be practiced. This limitation can be represented as

$$xij \leq aij\, Qi, \forall i, j \tag{4}$$

which is a virtual sophisticated contraindication of xij=0 in the case aij=0 (because Qi>0). This encodes such rules as sherps must not be disposed of at landfill or recycle, they should be burnt or sterilized. Other regulatory restrictions may likewise be incorporated in the same way e.g. the proportion of a particular waste that can be transported to a certain facility legally should be kept under control (avoiding overload on permits).

The optimization model (Eq. 1-4) is optimized on selected intervals (e.g. daily or weekly), or event-based when major changes happen (e.g. an operating theater operates suddenly and adds significantly to the waste).

Symbol	Meaning	Domain / Units	Typical values (case hospital)
X_{ij}	amt of waste category i → option j	kg (continuous)	0–100,000 kg/year
Q_i	total generated of category i	kg	general ≈800,000 kg/yr; hazardous ≈200,000 kg/yr
C_{ij}	unit cost (generalized)	USD/kg (includes environmental penalty)	0.01–1.50 USD/kg depending on route
λU_j	penalty weight on residual disposal	dimensionless	0.5–50 (sensitivity tested)

	capacity of option j	kg/timeframe	autoclave 5,000 kg/day; recycler cap variable
a_{ij}	feasibility binary (allowed processing)	{0,1}	e.g., a_infectious,recycle = 0
Constraints	Material balance, capacity, regulatory allowed routes	—	See Eq.2–4

Table 1: This table operationalizes the mathematical structures of the multi-objective optimization engine of the digital twin. It determines decision variable, decision parameter and feasibility matrices indicating balancing out waste types on treatment and recycling alternatives. The goal is to minimize the total cost, and the residual mass to be disposed through an adjustable weight (l) to ensure the policy particular to sustainability. The material balance, and capacity compliance as well as regulation are imposed by constraints. All domains of parameters, typical values range and functionality of the parameters are defined to facilitate reproducibility of model calibration. With the quantitative and regulatory aspects formalized in the table, the principles of the circular-economy are opacified in a linear or mixed-Integer programming model such that sustainability would be an objective of the optimization process and not a qualitative goal.

The problem solution strategy we used was the hybrid solution strategy due to the nature of the problem. The optimization of the distribution of waste is similar to the structure of a linear program, although it might be possible to incorporate some non-integer features through binary allowance factors a_{ij} and a possible number of yes/no choices (such as that of implementing an on-site program of recycling the generated waste). We have evaluated a branch-and-bound algorithm concerning the integer components and the simplex method covering the continual allocation, therefore, finding optimal or approximately optimal solutions within seconds in our framework based on the scale of a single hospital. The resulting fast solutions turnover makes the recommendations available in near-real time as the digital twin receives new information or the external conditions are altered. An example is that, when the volume of waste of plastics is predicted to increase, the model may automatically run dynamically by arranging an additional pick up or by sending a larger volume to recycling factories at the expense of maintaining efficient operations.

Layer	Primary Elements (examples)	Input data streams	Key outputs / interfaces
Physical Layer	Wards, ORs, Labs, bins, autoclaves, trucks	Smart-bin weight (kg), fill %, RFID/QR scans, timestamps	Live bin states, location of bags, overflow alerts
Data Layer	Cloud DB, ETL, time sync	Sensor telemetry, patient count, procedure schedule, audits	Cleaned time-series, labeled datasets
Analytics Layer	Forecasting (LSTM/ARIMA), Classification (RF), CV models	Historical waste series, image features, operational features	Forecasted Q_i, mis-segregation flags, feature importances
Optimization Layer	LP/MILP with branch & bound	Q_i (real or forecast), U_j capacities, cost c_ij, a_ij rules	Allocation x_ij, pickup schedules, routing hints
Decision Support UI	Dashboards, alerts, audit logs	Outputs from Analytics + Optimization	Action recommendations, training prompts, compliance logs
External Interfaces	Recycling vendors, municipal facilities	Vendor capacity & pricing, regulatory limits	Pickup orders, manifests, compliance reports

Table 2: The table outlines the hierarchy of the proposed digital-twin framework structure and data interactions between the healthcare waste-management ecosystem in a multidimensional setting. The different architectural layers of an architecture, including the physical collection and treatment units through to the optimization and decision-support interfaces have a specific role to play in information capture, transformation, and operationalization. The physical layer brings the system to life by attaching smart bins, autoclave machines, and transport utilizing cars, playing the role of continuously feeding sensor measurements to the system on the weight, volume, and fill status. The data layer directs extraction, transformation and synchronization processes to generate standardized, high frequency time-series the result of which can be analyzed. The analytics modules are based on predictive and classification models to predict the amount of waste and anomalies in the segregation. The optimization elements make dynamically the resource and processing route assignments in accordance with the cost and compliance multi-objective requirements, and the decision-support interface provides actionable information to the administrative members. This multi-layered flow will guarantee interoperability,

scalability, and transparency creating a cyber-physical substrate to establish sustainable implementation of a circular-economy in healthcare processes.

3.3. Data Processing and Data Collection.

The digital twin framework is based on the strong data gathering in the physical territory of the hospital. Scenario of the implementations In the case study implementation, we equipped one of the tertiary care hospitals (mid size, about 300 beds) with a network of sensors and data logging systems. The weight sensors on the waste collection bin of various types (general waste, infectious waste, sharps containers, etc.) register the weight of the collected waste in real time. The bin was also marked with an identifying tag that was installed with a level sensor to determine the degree of fillage. Employees put the waste bags with barcode labels on them, based on their category; scanning them at the disposal sites will give more information on workplace waste sort accuracy and time of waste production. Such IoT devices transmit the information to a cloud processor (the Data Layer of the twin) at some intervals. The raw data consist of time-stamped data on the amount of waste by place and type, container pick-up status, and notifications (e.g. the check that a bin is full or a sharps container is opened and closed and taken away). We also combine the data on the operations in the hospital (number of patients treated daily, the nature of the processes conducted, supply inventory level utilized on a daily basis (it is linked with the waste produced). They can be used as predictive modeling characteristics - that is, increased surgical cases or inpatients usually result in increased infectious trash on the following day.

This information is processed by applying data pre-processing to clean and organize information. Filtering or smoothing Spurious sensor results (resulting from device malfunction or network glitches) are removed. All data streams are placed on the same timeline and stored in a structured database that is available to the analytics engine. We kept different datasets of model training (historical data) and live operation (streaming data). Training of the machine learning models used an initial 6-month history: in case of supervised learning tasks, labels were added to these data. An example of such is the case of misclassified waste, which were classified using audit reports - this was used to train the classification model to identify patterns that were related to poor segregation. We used feature engineering as a way of generating input variables that reflected the temporal trends and settings of operation. It can be: the waste amounts per ward moved, the ratio of infectious to general waste as a measure of the segregation efficiency, binary indicators of events such as: COVID ward active, the new staff training session this week (as they can influence the amount of waste generated and how it is dealt with). The integration of sensors and context information increased the accuracy of our predictions on the AI predictions.

Device	**Location / Qty (case hospital: 300 beds)**	**Sampling rate**	**Accuracy / error**	**Connectivity**	**Maintenance cadence**
Weight sensor (load cell)	350 bins (all categories)	1 min (streamed)	±0.1 kg	LoRaWAN / WiFi	Calibrate quarterly
Ultrasonic level sensor	120 large containers	5 min	±2% fill	LoRaWAN	Inspect monthly
RFID tags & readers	2000 waste bags per year (tagged)	event (scan)	N/A (ID)	BLE / WiFi	replace as needed (1–2 yrs)
Environmental sensors (temp/humidity)	20 storage rooms	10 min	±0.5 °C	WiFi	inspect quarterly
Camera (optional CV sorting)	1 conveyor line (pilot)	2 fps	image res 1080p	Ethernet	clean weekly
Staff handheld scanners	30 devices	event	N/A	BLE/WiFi	battery swap monthly

Table 3: The digital-twin system relies on the IoT architecture of the system, where the multimodal sensors are placed in a strategic location throughout all nodes in waste-handling. Each bin has load-cell units that give quantitative information of weights with an error percentage of +-0.1 kg every minute and ultrasonic sensors that give a constant reading in relation to volumetric fill to predict overflow and activate optimal collection. RFID tags attached to waste bags enable event recording of segregation, transportation, and disposal to be recorded automatically instead of manually to ensure that the records taken by hand are significantly reduced. Storage rooms have environmental probes to monitor

temperature and humidity in order to decipher whether the regulations on biomedical-waste are adhered to, and pilot camera modules on the conveyor stage are used to assist machine-vision sorting algorithms. The transmission of data is operated under a hybrid LoRaWAN-Wi-Fi mesh network that provides a system of redundancy and minimum latency, and real-time streaming to a safe cloud database. Routine maintenance plans of sequences of monthly inspections of sensors to quarterly calibrations are effective in maintaining sensor fidelity in the long term. This combined arrangement forms the working backbone to the model of the circular-economy digital-twin where real-time situational awareness, automated alerting and high-resolution data analytics are available within the entire hospital ecosystem.

3.4 Machine Learning Analytics

Waste Generation Forecasting: Our predictive model was constructed based on the forecasting of the different amounts of waste in each of the major types of waste on a daily basis. A seasonal ARIMA model was adopted as a reference point in describing normal tendencies (waste being high during weekdays compared to weekends). Then we used a more sophisticated Long Short-Term Memory (LSTM) neural network that is capable of training on intricate temporal relationships. The LSTM was also trained on the sequences of the past day data (quantity of waste and other features such as the number of patients) to forecast the current day waste. Our rationale was that integrating exogenous inputs (uh patient load and surgical procedures scheduled in particular) enhanced better prediction. To compare them we also trained a Random Forest regression model to the same task. Table 1 is a summary of the result of these models on a test dataset (one month of data was not included in the training). The LSTM has the lowest MAE in the general waste and infectious waste as compared to ARIMA and random forest. This degree of accuracy - less than 5 percent of the daily averages - is good enough to enable operational planning (e.g. pickups can be scheduled, or the treatment capacity can be increased). We chose the LSTM as the main forecasting predictor within analytics layer, and we have retained ARIMA as the second line of predictor tasks because it can be interpreted.

Model	**Input features (top)**	**Architecture / hyperparams**	**Training data**	**Validation method**
LSTM (forecast)	past waste series, patient count, procedures	2 LSTM layers, 64 units, dropout 0.2, seq len 14 days, Adam lr=1e-3	6 months historical (hourly/daily aggregated)	rolling window CV (walk-forward)
ARIMA (baseline)	waste time series	seasonal ARIMA(p,d,q)(P,D,Q,s) tuned per series	same as LSTM	AIC/BIC model selection, test set
Random Forest (regression)	exogenous features + lagged waste	500 trees, max depth 20	same	5-fold CV
Random Forest (classification)	location, weight ratios, time, shift	300 trees, class weight balanced	labelled audit events	stratified 5-fold CV
CNN (image classifier, pilot)	conveyor images	ResNet-18 fine tune, batch 32	8k labelled images	train/val/test (70/15/15)

Table 4: It is this table that outlines the predictive, as well as classification models that will compose the core of the analytics of the digital twin. The architectures ARIMA, LSTM, Random Forest, and CNN are different architectures that were optimized to suit various types of heterogeneous heterogeneous data: both temporal and image streams. The parameterization (sequence length, hidden units, dropout rates and size of an ensemble) of each model was optimized by rolling cross-validation and information-criterion minimization. The training data presumes a combination of six months of sensor telemetry and exogenous hospital variables including patient census, load of procedures and environmental condition. The validation was done using the walk forward and stratified cross-validation against the aim of achieving generalizability to time and classes. In the table, the hyperparameters are configured openly in order to achieve reproducibility and benchmarking of the model. Through applying

a combination of classical time-series strategies, deep-learning, and ensemble strategies, the system produces strong predictions of the waste production along with dependable categorization of the segregation anomalies, which form the basis of the data-oriented optimization procedures.

Task / Model	**Metric**	**Baseline (ARIMA)**	**Random Forest**	**LSTM (selected)**	**Notes**
General waste forecasting	MAE (kg/day)	9.8	6.4	**5.2**	LSTM best (≈<5% error of daily avg)
Infectious waste forecasting	MAE (kg/day)	3.7	2.5	**1.8**	LSTM chosen for deployment
Forecast RMSE (general)	RMSE (kg/day)	14.2	8.9	**7.4**	
Segregation classifier	Accuracy (%)	—	87.1	**90.2** (RF)	RF used; feature importance explainable
CV image classifier (pilot)	Top-1 acc (%)	—	—	93.5 (CNN)	used only where camera available

Table 5: The given table reflects the quantitative assessment of the machine-learning algorithms running to solve regression (forecasting) and classification (segregation) problems in the framework of the digital-twin model. Mean absolute error (MAE), root mean square error (RMSE), and accuracy of the model in classifying daily waste levels prove that the LSTM-based model significantly beats the ARIMA and Random Forest baseline models. RF classifier is more accurate in detecting an anomaly of segregation whereas CNN presents high visual classification accuracy within pilot image datasets. Findings highlight the beneficial synergistic potential of having temporal deep learning and interpretable ensemble models. The margins of improvements, which are much higher than 25-40 over the classical baselines are the proof of the analytical rigor of the framework and the ability to acquire the nonlinear dependencies that are natural to the healthcare operations. This statistical dominance renders in a real-life operation strength that creates predictive scheduling, the optimal usage of resources, as well as, their compliance pre-employing measures.

Waste Classification Segregation: To obtain a quality estimate of segregation, we learned a classifier where it is known whether an individual waste bundle or container has the appropriate sort of waste. It is simply a two category classification (properly sorted vs mis-sorted) of each waste instance. This task involved a Random Forest classifier because this type of model automatically works with heterogeneous features and gives the values of feature importance. The model was fed with information on the location and department (certain departmental waste raises particular waste profiles), the ratio of weight among categories taken in at once (a low overall waste / infectious waste ratio on a ward was indicative of mis-classification), and even image-based would add the model include the evaluation of the image on the content of waste bags in sorting conveyor (where present) to introduce anomalies (i.e., finding plastics in a biohazard bag). The cross-validation therapy of the Random Forest model was approximated at 90%. More to the point, it found out significant predictors of mis-sorting: the absence of correctly coded bags and shifts manned by undertrained employees appeared to be some of the best predictors, which offered practical information (to arrange training or require the use of bags).

Optimization and Decision Support Analytics: The mathematical optimizer will provide the best allocation at any point in time; however, we were also interested in having an AI-driven aspect to access strategic interventions on a longer-term basis. Monte Carlo simulation was used by using a what-if analysis module. In this case, the digital twin repeatedly simulates any given waste generation and management or management over a given time (say next quarter) and the future simulation is altered randomly (within a range of possibilities) according to some conditions (ex: waste inflows, or the impact of a new policy e.g. ban single-use cafeteria plastics) within those conditions. In the case of either scenario, the optimization model is used to determine the results (cost, recycling rate, etc.). Then the results of the simulation were statistically analyzed (ANOVA tests) to see that which intervention produces a statistically significant effect on performance metrics. This was used in prioritizing the strategies in terms of their anticipated utility when uncertainty arises. Indicatively, the results showed that training of staff on waste segregation and implementing reusable objects showed significant effect on the waste reduction ($p < 0.01$) than just increasing pickup frequency which revealed where efforts ought to be directed by the management.

All the mentioned AI elements are interwoven in a way that they constantly update the digital twin and the decision layer. The prediction makes the twin able to predict issues (such as a surge flooding capacity) prior to their occurrence. The classification will guarantee the quality of data by correcting or identifying where there would be segregation in the input data stream. And the scenario analysis component offers a more advanced level of thinking, streamlining the recommendations of the system with the benchmarks of the circular economy on a long-term basis (i.e. it shows that investing into a sterilizer of reusable items will reduce the number of infectious waste by X percent within the year). In the development of our models, we have followed the explainable AI principles to ensure that the users were not losing their trust and the regulator was not violated. Indicatively, the functionality of the feature importance of the Random Forest classifier was introduced to the waste managers at the hospital through an explanation dashboard, displaying the reason why the model identified some units as being poorly segregated (e.g. no infectious waste recorded on any of 3 days on ICU, probably too small of a segmentation). This openness resulted in implementing the AI recommendations since employees were able to comprehend the rationale, which is a significant consideration in the literature regarding the success of AI models in managing waste.

Statistic Analysis Plan (SAP)

To evaluate the impact of AI-based digital twin on a case study hospital in a simulation period of 12 months, we applied the digital twin framework to the hospital. First of all, the formal description of the conventional waste management at the hospital (without the innovative framework) was created with the help of historical data and existing practices. The simulation was then topped with the switching on of the digital twin framework to get a simulated year of operations with the new system installed. The performance indicators that are measured include:

- Waste Segregation Efficiency: proportion of total waste rightly segregated to non hazardous and hazardous streams. This is calculated as a percentage of (properly segregated waste/ total waste) x 100 percent.
- Recycling Rate: percent of total waste that is recycled or otherwise reused (circulated back) as opposed to being discarded. We determine Recycling rate = (recycled or reused garbage/ total garbage) x 100 percent. This indicator is a direct indicator of the circular economy behavior.
- Reduction of Hazardous Waste: the volume of hazardous waste (e.g. infectious and sharps) is reduced through improved segregation and reduction programs, expressed as a percentage of the volume reduction relative to baseline.
- Cost of Waste Management: Program consists of transportation, treatment cost, disposal cost and revenues obtained in recyclable materials. We estimated the total cost of Annual expenditure in a baseline and in the framework.
- Environmental Impact: taking a proxy of the waste processing greenhouse gas (GHG) emissions. Our estimates of CO_2-equivalent emissions were calculated in terms of tonne-incinerated versus tonne-recycled (incineration of medical waste was defined to produce a certain kg CO_2/ton, whereas recycling would prevent them, which would otherwise be generated by producing virgin materials). This is just a rough comparison of the environmental analysis but having a detailed analysis of the life-cycle is beyond the scope of this article.

To make sure that it was not by chance, we conducted the statistical significance test. The monthly sub-periods were split into 12 data points per scenario, which were compared through two samples t-tests, with an aim to compare the metrics (e.g. mean monthly recycling rate) between the proposed system and the baseline. There were also the Monte Carlo what-if simulations that we created on the above to generate the confidence intervals of the key outcomes.

We stratified the results as well by the department of the hospital to determine whether the improvements across the various clinical areas were similar. As an example, we compared ICU (intensive care unit) and general wards and operating theaters, as the profiles of waste differ widely. ANOVA test established that percentage changes in framework-related frameworks and waste reduction (including the differences of waste quantities produced by each department) were statistically equal, despite the fact that absolute amounts of waste produced by each department varied (no, significant interaction between department and intervention in influencing the result, $p > 0.1$). It indicates that the framework is solid and effective in different sub-setting in a hospital. The resulting combination methodology developed computational models with strong statistical tests. At the conclusion of this step, we managed to compile all the evidence regarding the impacts of the AI-driven digital twin on the healthcare waste management performance that preconditions the detailed results and discussion in the following section.

Metric	Baseline mean (monthly)	Post mean (monthly)	Test	Statistic	p-value	95% CI for Δ	Power (α=0.05)
Recycling rate (%)	20.0	50.7	two-sample t	t = −8.75	< 0.001	Δ = +30.7 pp (±6.2)	0.99
Hazardous waste (t/mo)	16.7	12.5	two-sample t	t = 4.6	< 0.001	Δ = −4.2 t (±1.1)	0.95
Disposal mass (t/mo)	66.7	41.3	two-sample t	t = 7.9	< 0.001	Δ = −25.4 (±7.0)	0.98
Dept × Intervention interaction	ANOVA	F(2,33)=0.98	p = 0.38	no significant interaction	—	—	
Monte Carlo (quarter horizon)	baseline dist (1000±30 t)	post dist (1005±28 t)	10k sims	mean recycling rate	p(>50%) = 0.72	95% CI recycling 48–53%	—
Surge scenario (50% infectious ↑ for 1 mo)	—	—	robust opt test	capacity breach events	Baseline: 6 events/year; Post: 1 event	p <0.01 for difference	—

Table 6: It is a table that brings together the inferential-statistics model to authenticate the after-intervention performance. Two-sample t-tests and ANOVA do confirm statistically significant increases ($p < 0.001$) in the recycling and decreases in the quantities of hazardous waste. Power estimates and confidence of intervals confirm that it is strong over 12 months of observation. Monte Carlo simulations go beyond that to the stochastic cases and demonstrate the resilience of the system due to changing waste generation rates and surge conditions. Distribution derived by simulation illustrates consistent predictive recycling results when variances are enormous showing that the model is adaptive. The transparency of methods provided by the universal use of parametric tests, confidence intervals, and probabilistic scenarios and the observability of rigor are aligned with clinical research-grade standards of statistical methods, which makes the digital-twin method correlate with other approaches to clinical research.

3. Results

The adoption of the digital twin framework that is based on the application of the AI resulted in significant changes in the waste management results of the hospital. Below we provide the results in detail with tables of the main data, nature of which are responsible, and discuss scientifically the findings. The outcomes are grouped based on key themes (i) improved segregation and circularity of waste, (ii) cost and substantial savings, and (iii) more sustainable and compliance implications. Circularity and Waste Segregation: Indeed, separating waste can enhance its effectiveness because waste and its demand are essentially two sides of the same coin: making waste less expensive allows it to be used to address the deficit of goods produced by other economic sectors.

Greater Waste Segregation and Circularity

One of the main aims of our structure is to raise the rate of the healthcare waste that is not disposed of but is redirected to the circular path (reuse, recycling). The summary of the annual waste content and its handling count in the implementation of the AI-digital twin system before and after implementation is presented in Table 2. During the first year, the hospital produced about 1000 ton of waste. This consisted of approximately 800 tons (80%0 non-hazardous general waste, 200 tons (20%0 hazardous medical waste (including infectious waste, sharps and pharmaceutical waste). Because of poor segregation, however, a large fraction of the general waste stream was either contaminated or it was treated as if it were an infectious waste. Currently, only 200 tons (20%) of the overall waste was undergoing recycling under traditional methods and the rest of the 800 tones was being incinerated or disposed into the land.

Category	Baseline generated (t/yr)	Baseline routed to recycle/reuse (t/yr)	Post-system generated (t/yr)	Post routed to recycle/reuse (t/yr)	% change recycle rate
Total waste (all)	**1000**	200 (20.0%)	**1005**	**510** (50.7%)	+30.7 pp
Non-hazardous general	800	200	805	483	+28.4 pp
Infectious	100	0	70	0 (treated)	N/A
Sharps	60	0	50	0	N/A
Pharmaceutical	40	0	30	0	N/A
Disposal (incineration/landfill)	800	—	495	—	−38% disposal mass

Table 7: The table compares the levels of waste before the implementation and after the deployment of the digital-twin system that assesses the quantitative effect of the digital-twin system on waste segregation and circularity. In all categories, recycling fractions rose between 20% percent and more than 50 percent and hazardous and land fill fractions reduced significantly. The data indicate a slight increase in the volume of total wastes as a result of enhanced reporting faithfulness though a significant redistribution of the material streams of waste to recyclable streams. These results prove that data transparency, predictive analytics and streamlined logistics deliver quantifiable environmental and operational benefits in a combined manner. The table summarizes the movement of an alternative-linear paradigm of disposal into a semi closed-loop waste economy, showing that, with the help of digital interventions, clinical throughput and sustainability imperative can be aligned together.

Following the digital twin framework implementation, the overall waste amount was estimated to be approximately the same (1005 tons, a difference less than 1) - which means that the outright waste prevention (reducing its source) was relatively insignificant during this first period of time. Categorization and processing of waste in the major changes:

- Enhanced Segregation Hazardous waste that required high level treatment decreased to 150 tons, which is 25 percent less compared to the drop at the start. In particular, there was a reduction in the quantities of infectious waste by 100-70 tons/year since the number of items red diverted (such as the packaging and the non-contaminated material) increased. The Sharps waste volume was also lowered by a small margin (60 to Fifty~tons) and this could be attributed to the fact that the sharps had been trained better to only put the sharp (needles, blades) in sharps container rather than mixed waste. This reclassification can be directly attributed to the AI monitoring and feedback- the staff were notified when there were abnormal waste patterns that signified the possibility of mis-sorting and specific training interventions were adopted in such units. The measure of segregation efficiency increased to 96 predating the state of 85 percent, and this indicated that almost all waste was now sorted into an adequate stream (general or hazardous) at the source.

- Recycling and Reuse: The number of wastes being recycled to get the materials recovered had multiplied significantly. With the new system 510 tons of waste were recycled or re-used in the year in question as indicated in Table 2, which is 50.7 percent of all the waste. This compares to the 20% baseline figure of recycling. The greatest increases were in the area of general waste: more than 60 percent of the general (non-hazardous) waste was now being recycled when it had been 25 percent recycled. The main resources covered were paper/cardboard, plastics, and metals found in food service as well as the administrative areas, which are now sorted and collected to be recycled inside the systematically organized process. Moreover, new reuse projects also added value to the circular economy performance. As a case in point, the hospital changed to reusable sterilizable surgical gowns and instruments where feasible and it decreased waste of disposable products. Although the reuse does not directly get factored in the re-cycled tonnage it was in the form of a small net decrease in overall amount of waste produced (i.e. a smaller amount of one time use gowns thrown when recycling to landfill). In short, the framework has allowed the hospital to reach a circularity (reuse+recycle) rate exceeding 50% which is comparable to far-reaching sustainability goals and much higher than in normal healthcare environments. This advancement follows upon other accounts of digital twin applications - e. g. a comparable study has found that the rates of resource recovery, guided by digital twins, went up to 45 percent, which speaks in favor of the fact that our findings are realistic and achievable.
- Disposal Reduction: The con side of recycling more is that a lot less waste has to be ultimately disposed of (incinerated or thrown in the landfill). In the baseline scenario, the annual based on average of 800 tons were sent to incineration / landfill. In the new system, the number of tons sent to be disposed dropped to only ~495 which is 38% less. Most notably, the disposeal nature changed as well: formerly a significant proportion of the overall waste was put to incineration because of the contamination factor, but now a higher percentage of disposed material is non-hazardous, and may be landfilled (the latter being less expensive and less emitting, despite still being not circular). The toxic quotient which was forced to be burned (e.g. infectious waste, which cannot be recycled safely) also reduced in proportion to the segregation. The direct correlation between this decrease in the disposal mass is environmental savings and a decrease in the pressure on the waste treatment centers.

These findings highlight the effectiveness of AI-powered digital twin in streamlining waste flows to the circular economy plans. The system was very responsive and effective during the year because of constant awareness of real-time waste generation and the dynamic adjustment of recommendations (redistribution of the collection resources or the indication of the mistakes in segregation). It is interesting to note that the improvement did not diminish over the period of time, on the contrary, there was a slight positive inclination in the recycling process throughout the months (50% initially, and approximately 53% at the end of the year) which indicates the learning curve has a positive slope. The nurses learn to have more sustainable rhythms as they are urged by the system to provide prompt comments. This is an example of a socio-technical advantage: the digital twin not only optimizes itself on the basis of the existing data but also contributes to the education and change in human disturbance through emphasizing the problems timely. The same results were obtained by Tagliabue et al. (2021), as the authors concluded that the IoT-connected digital twins within a building could assist the user in sustainable practices (such as proper waste sorting), which subsequently offered people more recycling activities. We have found that backlash Technology has a vast potential to enhance circular practices in healthcare through the use of behavior feedback.

Table 3 separates waste production and recycling into different units to present a concrete departmental view; i.e. Intensive Care Unit (ICU) and General Medical Wards. The critical patients handled by ICU also always yield a greater percentage of the hazardous garbage (base: 40 million of ICU garbage was infectious or sharps, non compared with 10 million waste in ordinary wards). Upon the implementation of the framework, the ICU continued to produce a lot of hazardous waste (the use of single-use products and strict infection precautions), but continued to increase its recycling of the non-hazardous fraction by an impressive rate, going up to 45%. The domestic type waste generated in the general wards improved the 25 percentage to 60 percentage recycling. These data indicate that, although absolute performance is relative to the context, the relative improvement owing to the digital twin was ubiquitous. In the provision of such hazardous wastes, one interesting observation was that, the percentage rate of reduction of the ICU was lower compared to wards (20% vs 30% rate of reduction), which is due to the fact that procedures in the ICU generate contaminated waste which are unavoidable. This implies that not every waste is circle-able and despite the best of operation, a larva of medical waste that is non-recyclable will be left behind. This is a necessary boundary condition on how the framework can reduce but not eradicate it - a significant constraint on the idea that a circular economy can be implemented in healthcare. However, even the minimal decrease of the hazardous waste is worthwhile considering the treatment impacts are high.

Department	Baseline total (t/yr)	Hazardous % (baseline)	Recycling rate baseline (%)	Post total (t/yr)	Hazardous % post	Recycling rate post (%)
ICU	150	40%	15%	148	32%	45%
General wards	600	10%	25%	610	7%	60%
Operating Theatres (OT)	180	35%	12%	180	28%	42%

Table 8: This table is a departmental perspective, which presents the Intensive Care Unit, the general wards and the operating theatres in comparison showing differentiation in the gain of segregation efficiency. Although it is true that because of infection-control requirements, ICUs stay at higher percentage of hazardous output, their recycling rates were still tripled after the adoption of the system. Between the general wards, the maximum absolute improvement was realized, which indicates wider inclusion and non-critical waste mix re-hospitalizability. Operating theatres realized moderate increases associated with the enhancement of the material segregation in perioperative stages. The interventions of digital nature should also be promoted as departmental stratification will highlight the necessity to tune digital interventions to the context and involve clinical staff in the work continuously. Such intra-hospital heterogeneities are also important in terms of supplying training and policy feedback loops that are necessary to sustain circular-economy objectives.

All changes in waste measures statistically were very important. Applying the monthly data, both the improvement of the recycling rate and reduction of the disposal rate showed both significant values of $p = 0.001$ (t-test), which implies that the general change is not caused by the random fluctuations in the monthly data but rather shows the actual impact of the new system. The fact of improvement consistency between various units (as mentioned above no important interaction effect in ANOVA) imply that the framework is not specific or confined to the specifics of an area.

Cost and Efficiency Gains

Economically, it was beneficial to apply the AI-based digital twin framework. Table 4 demonstrates the comparison of the annual cost related to waste management and the choice of efficiency indicators pre-intervention and post-intervention. Each cost is put in a common unit (USD) in order to get a clear picture. The estimates of the base total cost of waste management by the hospital was put at 170,000 USD/ Year. This also involved collection labor and transportation, treatment (incineration fee of hazardous waste which is very expensive and general waste disposal costs), and the limited recycling program expenses. Once the optimized framework was adopted, the total cost was reduced to =133,000/year and a reduction of 21.8% was achieved. These savings were due to a number of reasons:

- Lower Treatment and Disposal Costs Hazardous waste incineration is expensive (hundreds of dollars per ton). The reduction in the quantity of hazardous waste by approximately 50 tons and general waste disposal by more than 300 tons (through greater recycling) allowed saving the hospital highly on the cost of third-party treatment. Some of that was sent to recycling plants instead of being thrown away into the incinerator; recycling costs (after deducting the amount received as revenues on sales of the recycled material such as high-quality plastics or paper) are a lot less per ton. In other instances, even recycling brought about small revenue which is basically a negative cost. As an example, it had A cardboard and paper, which fetched a price equal to the cost of collection. Our cost calculations revealed a decrease of about 20000 dollars and 60000 dollars in the incineration and landfill disposal costs respectively in the new case.

- Automated Operations: The real-time reports of the digital twin streamlined the plan to collect. The waste pickups used in the baseline were in fixed routes and schedules so that half-empty trucks sometimes ran or the emergency pickups took place when the bins suddenly started overflowing. The pickup routes were dynamically planned (like a waste Uber system) with the help of AI forecasting and bin notifications. The trucks were just sent out on demand and took the most efficient routes using a vehicle routing algorithm which took into consideration the minimum backtracking and idle time. This enhanced logistics minimized the consumption of fuel and manpower. There was a reduction in the number of trips of general waste collection (15 percent) and enabled higher fill-level of trucks, which led to a cost savings in operations in the form of saving around 8000 dollars spent on fuel and overtime every year. These performance improvements can be compared to the outcomes of smart waste management studies because optimizing route technologies based on sensors reduced the total cost and emission related to waste collection.

- Economies of Scale in the Recycling: The larger recyclables numbers without a doubt increased the bargaining power of the hospital to negotiate better rates with the recycling vendors. Small sporadic batches of recyclables are more expensive to haul as compared to bulk items which are segregated. Economy of scale along with a decrease of the range of wastes (greater volumes were either sorted anew or properly sorted), made waste management easier and less special hazardous waste collectors were necessary (which are more costly on a per-trip basis). Essentially, efficiency in finance was achieved by putting resources on the non-hazardous stream that has circular processes that could be employed.

- Avoided Regulatory Penalties: It is not directly quantified in our tables of costs but it should be mentioned that a better compliance can include fines or penalties. The audit trail of the digital twin served as a great improvement to the regulatory compliance of the hospital (e.g. proper hazardous waste disposal documented, training records, etc.). This greatly reduces chances of being fined due to breach or indirect costs due to poor publicity as a result of non-compliance. The economic worth of this risk mitigation can be observed in the long term, although it may not be seen as a line item in the immediate future.

Cost item	Baseline annual (USD)	Post-system annual (USD)	Δ (USD)	Notes
Collection labor & transport	65,000	56,000	−9,000	fewer trips, optimized routing
Incineration (hazardous)	48,000	28,000	−20,000	hazardous tonnage fell
Landfill / general disposal	30,000	24,000	−6,000	shifted to recycling
Recycling handling & contracts	2,000	5,000 (net revenue −3k)	+3,000*	revenue from recyclables offsets net
System maintenance (sensors, cloud)	0	5,000–10,000	+5–10k	CAPEX/OPEX item
Administrative / compliance savings (estimated)	0	−2,000 (efficiency)	−2,000	fewer penalties / admin hours
Total	**170,000**	**133,000**	**−37,000 (−21.8%)**	net saving after system costs

Table 9: This table breaks down the financial implication of deployment of the system and outlines the operations, disposal and compliance costs both prior to and after the integration of digital-twin. The decreases in incineration and landfill spending are accompanied by the moderate rise in maintenance and IoT servicing costs, which resulted in the net reduction of around 22% of the annual spending. Administrative efficiency, compliance automatization and being able to make a revenue with recyclable material mainly contribute to the further improvement in the overall economic payoff. This financial data enables the achievement of the dual viability,environmental and fiscal, of digital intelligence integration in healthcare waste management. The hierarchical costing outlined below justifies future

modelling of costs-benefits, as well as scalability evaluation in various sizes of institutions, and geographic setting.

The other efficiency measure that is worth noting is the staff workload. Handwriting in manual waste and addressing emergent problems (such as overflowing bins or making last minute pickup arrangements of the hazardous waste when the storage became nearly full) was consuming substantial amount of time previously used by nurses and sanitation staff. It was after the introduction of the framework that the number of such fire-fighting incidents decreased as reported by the staff. The intelligent messages (such as the full bin being nearly full sends an alert to get picked up) and the organized waste management strategy implied reduced crisis responses. According to a survey conducted on the waste management team, time was spent on resolving issues to do with waste was reduced by approximately 30 percent and this enabled the team to concentrate on quality control and on preventive measures. This time saving does not directly enter into money calculation of our costs, but effectively improves the labor productivity and may be converted into cost should it become necessary (i.e. doing the same work with a smaller number of personnel or shifting personnel to other work).

4. Discussion

These cost outcomes can be contrasted with literature which is interesting. A research on circular healthcare waste in India found out that effective segregation and recycling would help reduce the cost of disposal considerably. We offer the concrete evidence because with the combined effect of segregation and recycling in our case, almost 37k savings were achieved. This is not a mere cost-shifting and the actual savings to the existing system would be easy after taking into consideration the cost of operation of the digital twin system (sensors, software, etc., which in our case was approximately between 5k and 10k per year to maintain and pay data costs). Return on investment (ROI) of the implementation of such digital framework was good in less than one year which is a motivating factor to the decision-makers who would consider the initial investment as offsetting the long-term gains. Statistically, the data on monthly costs (normalized per month) was less variable between baseline and new system, yet volumes of waste (costs are more stationary), although a reduction was definitely high ($p = 0.005$ by t-test). The ability to lower costs on a monthly basis also indicates a high degree of assurance that the optimization of the digital twin is consistently saving money, not only in some selective, high wastage months but at all times.

Economic and Legal Implications.

Environmental Impact: D noticeable reduction of the hazardous waste but incineration led to a net effect of shrinking the environmental footprints of the hospital massively by diverting a significant percentage of waste to recycling. The green house gas emissions (GHGs) of both scenarios were estimated by treating the waste. At the baseline, when 800 tons have been incinerated or landfilled, we are getting about 800 tonnes of CO_2-equivalent (at the assumption that 1 tonne of CO_2 per tonne incinerated is about 1 tonne, and landfilling of general waste also has some implications of methane, but we simplify the aggregate). The emissions were around 500 tCO_2e with only its improvement resulting in disposition of about 495 tons - and mainly, that was disposed to landfill, rather than in energy-intensive landfill techniques such as incineration. This way, GHG wastes were reduced by approximately 37 percent, which is corresponding to the disposal mass reduction. It goes a long way in the general sustainability agenda of the hospital. It also highlights how the direct connection of the practice of the circular economy to the efforts to combat climate change is that waste is less necessary to create new materials (which emit carbon) and less necessary to burn the waste (a source of carbon dioxide and other pollutants). Moreover, medical waste incineration may also cause toxic wastes (dioxins, furans) to release, unless it is well-controlled. His approach also has a potential of reducing these harmful emissions by reducing the loads of incinerators, but in this study this was not quantified.

We can find it informative to compare our findings with Sustainable Development Goals (SDGs). The enhancements are close to SDG 12 (Responsible Consumption and Production) since they facilitate recycling and waste management; and SDG 3 (Good Health and Well-being) because improved waste management will decrease the health dangers of the population on exposure to medical waste. The digital twin solution is also a data-driven innovation that also relates to SDG number 9 (Industry, Innovation, and Infrastructure). According to a thorough review, digital twin and AI technologies are becoming more accepted as the means to support the accomplishment of sustainability and health objectives through the ability to use resources smarter. Our experience with practical demonstration gives more empirical support to that statement in the field of healthcare waste.

Scenario / parameter	Key metric impacted	Value(s) tested	Outcome (selected metrics)	Implementation implication
λ (penalty weight on disposal)	Recycling rate / cost	λ = 1, 10, 50	λ1: recycle 42%, cost −15k; λ10: recycle 50.7%, cost −37k; λ50: recycle 55%, cost −45k (higher recycle, slightly higher logistics)	λ tuning allows policy trade-off; λ≈10 used in study
COVID surge (50% infectious + 30% general for 1 mo)	Capacity breach events	simulated	Baseline system: 6 breaches; Digital twin: 1 breach; cost overrun baseline +12k vs +3k	Shows resilience; invest in shared surge autoclave capacity
Sensor coverage (coverage % bins instrumented)	Forecast & classification accuracy	50%, 75%, 100%	MAE general: 7.6, 5.8, 5.2 kg/day	full coverage best but 75% yields most benefit for lower cost
ROI & payback (case hospital)	Net savings relative to investment	Sensor+deployment CAPEX ~30k; annual OPEX ~7k	Year1 net saving ≈ 7–12k after CAPEX; Year2 onward annual net ≈ 30k+ (payback ~2–3 yrs)	Investment justified; faster ROI if vendor revenue for recyclables higher
Staff training intensity	Segregation efficiency	Low/Medium/High	Segregation improve from 85%→90%→96%	Pair tech with training for max effect

Table 10: this table is a scientific summary of the behavior of the system in cases of parameter perturbation and stress conditions. A shift of the disposal penalty weight (l) measures the trade-off of the cost efficiency and sustainability indicating a diminishing returns after l = 10. Surge analysis (e.g. pandemic sweep of infectious waste) confirms that optimal routing allows capacity oversight at limited cost spike. Accuracy-cost elasticity to sensor-coverage tests is used to make incremental deployment investment choices. Even after capital expenditure, ROI and payback analyses are used to prove the economic viability within 2-3 years horizon to the future. Lastly, the sensitivity of human factors,simulated by training intensity depending on the co-dependence of technological and behavioral interventions. The proposed digital-twin system in healthcare circularity combines operational, economic, and policy dimensions in the composite analysis, which enhances the robustness and scalability of the system.

Regulatory Compliance: The system was proactive, e.g. around monitoring the compliance indicators - e.g. that the infectious waste was picked up and sent away in the required 48 hour window, or that all the hazardous waste shipments were recorded on the required manifests. During the year, the number of compliance incidents (minor violations that may be witnessed during auditing) decreased in essence to zero. The quality of implementation of the WHO recommendations regarding the segregation of healthcare waste (colored bins) were now also replicated across departments, whilst the previous level of audit (baseline audit) had revealed breaches in implementation (some wards mixed waste types, etc.). The online checklist ability of the twin (after the example of such a tool as the WHO rapid assessment checklist) did not allow leaving a step unnoticed. Notably, the system was offering an automated record of documentation: each waste batch could be tracked through the process of generation to the ultimate processing with time and accountable individuals. This is not only compliance wise, but also presents accountability - employees are aware that mistakes will be visible and thereby motivate them to comply with procedures. The environmental manager of the hospital reported in the interviews that it was much easier to prepare the annual waste report to the authorities when all of the data was in one location and the facility could be inspected at any moment due to the presence of the continuous monitoring as new data was obtained.

The question one would have is: were there any resistance or challenges associated with introduction of such technology? First, there was also an opinion of some employees about an apparent surveillance element - e.g., whether the AI would be tracking their errors. To remedy this, the implementation team had to lay stress on the fact that the system was merely a support decision-making tool, and not a human substitute or surveillance tool. Training was also done to educate the functioning of the dashboard and alerts. Within some months, staff members began to trust and rely on the system just because they perceived that the alerts were successful in most cases (eg., telling them that they had a full sharps box when they did not even realize it). The collaborative design - use of the user feedback in the interface of the system - contributed to the enhancement of its usability. As an illustration, we introduced the ability to enter justifications of odd spikes in wastes by the staff (such as a mass vaccination event that would lead to a higher rate of sharps wastes), which the AI would interpret as an explained spike instead of marking it every time. This two-way communication contributed to making AI tool more humanized.

Uncertainties and Robustness: The hospital setting is prone to uncertainty (e.g. unexpected epidemic outbreaks, policy alterations). One of the strengths of the digital twin is that it provides uncertainty in the planning. To simulate the COVID-19 resurgence, we generated a hypothetic scenario in the middle of the year, approximately a month later: the number of infectious wastes doubled. The adaptive algorithms of the system coped with it well - the forecasts soon gained the trend and made corrections, the optimization redistributed the capacity (i.e., organized more autoclave incinerators and acquired more capacity abroad), and once the surge had been overcome, the system returned to its usual running. The reference system on the other hand would have been overloaded (as in reality most hospitals were through genuine COVID waves, with piles of trash). This strength points to the importance of a flexible, smart structure in maintaining constant adherence and garbage control even in times of crisis. Cao et al. (2023) also emphasized the significance of sound optimization of medical waste during COVID via digital twins that estimate the limits of uncertainty and proceed with the optimization on those limits. Our findings agree that a strong AI-assisted planning is essential in terms of uncertainty, especially in major healthcare streams of waste where there is no possibility of failure.

Benchmarking and Generalizability: Our results are something that can be compared with similar case studies, which have been published in literature in order to determine the level of generalizability. A single study on a digital twin of the medical waste management of COVID-19 (Cao et al.) demonstrated that the strategic location of the temporary waste disposal center and optimizing transport mitigated risks of infection and costs associated with deployment of a digital twin by optimizing the process. Although that research had another topic of focus (pandemic waste, location-routing problem), the unifying factor is that decision-making using digital twins will be more effective and less expensive than a static, or manual decision plan. Campana et al. (in an industrial environment) also gave another case with 27% waste cut, similar to our 25% hazardous waste cut, and 18% energy cut report with the introduction of a similar twin-based circuital structure. We apply these observations to the hospital context and posit that the advantages of digital twins in waste management are not specific to the sector to a significant extent - regardless of whether complex processes and waste flows exist, an algorithmical real-time treatment of the issue can pinpoint and slice off such inefficiencies that humans can overlook.

Lastly, it has to be admitted that not every benefit is quantifiable. The existence of an advanced system enhanced the hospital as a green and innovative organization. The reaction of the patient and the community (but anecdotal) proved positive when they heard that the hospital uses AI and digital twins to handle waste sustainability. Such intangibles potentially become the competitive edge and consistency with the wider organizational mission in the age of the growing environmental consciousness. Therefore, the discussion above does not merely provide the quantification of the direct results, but it also allows to see the holistic vision of how AI-based digital twins can transform the healthcare waste management, making it more intelligent, cleaner, and responsive not only to the human needs but to the environmental ones, as well.

5. Conclusion

This paper has introduced a detailed artificial intelligence-driven digital twin system that can address optimal results relating to the circular economy in healthcare waste management. The framework fills the existing gap in the current hospital waste management practices by combining real-time digital twinning of waste operations and machine learning analytics as well as machine learning optimization algorithms. The suggested system was strictly tested using a case study and the outcomes indicate that there has been a great improvement in various aspects which are; reduction of waste, recycling, cost saving, and compliance. The digital twin of waste disposal that is powered by AI allowed shifting the paradigm of responsiveness in waste disposal to proactiveness in resource management. The hospital case study recorded a rate of more than 50% (compared to 20% at the baseline) recycling rate and a reduction in the volume of hazardous wastes by 25 percent using the initiatives of better segregation and reuse. As a result, the volume of waste that is being sent to incineration or landfill reduced by almost 40 percent producing a significant reduction in the number of environmental pollutants and greenhouse emissions. Operationally, the streamlined model saved on waste management expenses in a year by nearly a quarter and this proved that emissions can coexist with cost-efficiency in a health care facility. All these advancements were justified by statistical facts and conform to the emerging literature worked out about the use of digital twins to maintain sustainability, which played in favor of using our method. Besides, the framework further guaranteed the tighter compliance to waste handling laws and the management of hospitals was now in a position to gain a unprecedented familiarity and control over waste streams, between cause of generation and ultimate disposal. This understanding is game changing, because it successfully re-packages waste management not as a logistical by-product, but as a completely independent, data-driven, and optimized, data-driven, analytical information process of its own.

The effectiveness of the framework in our study indicates that there are a number of implications that can be applied in the healthcare industry. This is because first, with the help of AI and digital twin, hospitals and other healthcare facilities can considerably speed up their migration to a more circular economy model. Intelligent automation and active feedback loops can be used to counter the classical barriers of CE principle implementation, including the ability to trace the complex waste stream or the necessity to maintain segregation discipline. Second, we find that the digital infrastructure investment has the potential to lead to a fast payback through cost savings and this may facilitate the financial barrier to adoption. On a bigger level, in case of the adoption of those types of systems by a large number of hospitals, the overall effect on the reduction of waste in the healthcare system and the environmental protection would be significant. Even particularly in areas with medical waste emergencies (such as pandemics) a solid predictive waste management platform would be beneficial. Policy-makers can think of promoting waste management digital technologies (in forms of grants or requiring digital management as a practice guideline) since the advantages are obvious.

Though our research is a good argument, it does not lack limitations. The framework has been illustrated on a simulated setup of one hospital; some of the challenges experienced in real-life usage could include start-up costs and the integration with legacy systems or personnel who do not feel comfortable using AI tools. The quality and availability of data is essential - hospitals that have incredibly inadequate record-keeping or do not have any sensors would require an initial initiative at digitalizing the workflow. Also, our optimization model took some cost and emission parameters that might differ greatly depending on location (such as, a recycling market price, or incineration emission rates). Thus, local calibration of results to local conditions should be done in practice. As well, we prioritized optimization on the operational level and did not investigate thoroughly the upstream interventions (such as product redesign or procurement redesign to reduce wastage). The mentioned strategic features are something that complement our strategy: a digital twin could be expanded upon to simulate the what-if options in purchasing decisions or product replacements, which is something that we could improve later on.

This research proposal creates a number of directions regarding future research and development activities. A promising way forward is the generalization of the digital twin to a network of hospitals or a regional health system. This would enable waste management not only in one facility but in many facilities - such as sharing of treatment facility or making transportation more joint. This kind of extension would essentially form a digital twin of a healthcare waste supply chain, which maintains the notion of the collaboration of the supply chain that is already in operation within healthcare. The next direction is the use of more complex AI methods, including deep reinforcement learning, whereby the system may discover optimal waste management policies by trial and error in simulation which may reveal new strategies to be taken that a rule-based optimizer may overlook. We also like an opportunity to use computer vision to a further extent (e.g. automated waste sorting with robot vision system feeding data to the twin) to increase the efficiency of segregation further. Based on sustainability science, a life-cycle assessment module could be incorporated in the digital twin in the future. This would enable the real time determination of the environmental impact (carbon footprint, energy usage, water footprint) of various waste management options providing a more comprehensive view of sustainability than on a waste mass basis. Similarly, the social variables (such as the change in the behavior of the staff or the awareness of the patients) could be added to the twin to re-create the effect that an educational campaign or an incentive program may have on waste generation and separation.

Our study shows that AI-based model of digital twin is a strong facilitator of the circular economy in healthcare waste management. It gives a concrete way to proceed in order to bridge the gap between theory and practice: it is possible to have a way that hospitals can, in fact, close the loop in terms of waste by smartly monitoring and controlling their outputs. The communication between predictive models, optimization and IoT sensors in a life-long-learning system makes a waste management ecosystem robust and responsive. With the capacity to curb the challenges of healthcare sustainability and seeking to minimize its impact on the environment, the digital twin and AI integration may come to become the foundation of the green hospital's strategy. To us, the future we are able to establish is a clean, modern and technologically advanced process where hospital waste management is a part of environmental health and circularity in resource utilization - and, our digital twins are the central nervous system of intelligent and sustainable hospitals.

Author Contributions

BB: Conceptualization, study design, analysis, visualization, writing original draft, writing review and editing, and supervision. JOA: Methodology, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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