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Improving the Management of Healthcare Waste in Developing Countries: Applying a System Dynamics Approach

Mohammad A. Shbool
Industrial Engineering,
College of Engineering & Computing, American University of Bahrain, 942, Riffa, Bahrain.
&
Industrial Engineering,
School of Engineering, The University of Jordan, 11942, Amman, Jordan.
Corresponding author: mohammad.shbool@aubh.edu.bh, m.shbool@ju.edu.jo

Yara Altarawneh
Industrial Engineering,
The University of Texas at San Antonio, San Antonio, TX 78249, USA.
E-mail: yara.altarawneh@my.utsa.edu

Raghad Bani Hamad
Industrial Engineering,
School of Engineering, The University of Jordan, 11942, Amman, Jordan.
E-mail: raghadfaissal@gmail.com

Rand Alqa'aydeh
Industrial Engineering,
School of Engineering, The University of Jordan, 11942, Amman, Jordan.
E-mail: randabuqaoud@gmail.com

Mohammad D. Al-Tahat
Industrial Engineering,
School of Engineering, The University of Jordan, 11942, Amman, Jordan.
E-mail: altahat@ju.edu.jo

Thahabia Abedeljawad
Quality Department,
Jordan University Hospital, 11942, Amman, Jordan.
E-mail: T.Abedeljawad@ju.edu.jo

Sahar ALMashaqbeh
Industrial Engineering,
The Hashemite University, Zarqa, Jordan.
E-mail: saharm_al@hu.edu.jo

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Abstract
This study aims to develop a system dynamics model to predict healthcare waste generation and associated costs, focusing on hazardous healthcare waste. Systems dynamics approach is utilized to analyze the complex dynamics of healthcare waste management. Data collection involves precise waste categorization across 46 departments of Jordan University Hospital, facilitating the development of a comprehensive model. The developed model accurately predicts future hazardous healthcare waste output and estimates disposal costs, considering various waste types and operational limitations. Sensitivity analysis demonstrates

the model's stability, with consistent predictions across different parameter values and forecast accuracy within 5% for most waste categories. The study further evaluates two disposal scenarios for formalin chemical waste: outsourcing to external treatment providers versus internal treatment using a hospital-installed system. Scenario 2, internal treatment, could reduce chemical waste disposal costs by approximately 80%, corresponding to about a 6.45% reduction in total hazardous waste disposal costs (medical + chemical combined) in the forecast year 2031. Scenario 1, removing the hospital's internal disposal machine and relying solely on external services, results in significantly higher long-term waste management costs. Over the next decade, the model predicts patient admissions to increase from 699,925 in 2021 to 797,434 in 2031, driving medical waste from 164,982 kg to 187,967 kg and chemical waste from 2,371.5 kg to 2,701.89 kg. Long-term projections indicate waste management expenses could rise by 167% by 2041, 268% by 2051, and exceed 500% by 2071 if current practices continue. Integrating system dynamics modeling into healthcare waste management offers a comprehensive approach, considering environmental, epidemiological, and economic dimensions. This provides a versatile tool for optimizing resource allocation, reducing expenses, and enhancing patient and healthcare staff safety, particularly during crises like the COVID-19 pandemic. This study contributes to the field by developing a novel system dynamics model that independently predicts chemical waste and provides distinct forecasts for each department. It also estimates costs for hazardous waste disposal in hospitals and assesses alternative scenarios, offering insights into waste creation and management strategies. This study does not investigate the causes of excessive waste generation in specific departments. Future research could explore this aspect and further integrate recycling practices into the model and hospital waste management systems.

Keywords- System dynamics, Medical waste, Healthcare waste, Healthcare policies.

1. Introduction

Effective and sustainable waste management practices are vital for minimizing total costs and environmental impact while maximizing energy recovery and collection efficiency (Fararah et al., 2023; Xu, 2020). Integrating Circular Supply Chain Management (CSCM) within the broader circular economy framework provides a promising alternative to conventional waste management systems (Sepetis et al., 2025), emphasizing the use of data-driven tools to enhance efficiency and sustainability.

Managing healthcare waste in developing countries presents a particularly urgent challenge, demanding innovative and systemic strategies to mitigate environmental and public health risks. The significant increase in healthcare waste, especially during pandemics, elevates infection risks and underscores the need for innovative, systemic strategies to mitigate environmental and public health threats (Jayasinghe et al., 2023). For instance, a study conducted in Lebanon found an increase in clinical waste by 20% (Maalouf & Maalouf, 2021), an increase in medical waste that poses a high risk for virus transmission (Chen et al., 2021). These challenges are magnified in developing countries that generate large volumes of hazardous healthcare waste and often lack adequate waste management infrastructure (Jangre et al., 2024; Quttainah & Singh, 2024). These issues underscore the importance of integrated analytical models that can examine the complex interactions among fluctuating inputs and identify key drivers influencing waste generation, a task well-suited to system dynamics methodologies (Mahate et al., 2023; Shbool et al., 2025).

The increase in waste generation associated with population growth and pandemic-induced surges in waste volumes highlights the need for globally coordinated efforts, sustainable practices, and the integration of advanced technologies (Ceylan et al., 2020; Soyler et al., 2025). Recent research has applied system dynamics to healthcare waste prediction, enabling detailed estimation of department-specific chemical waste and supporting scenario-based planning (Shbool et al., 2025).

According to the World Health Organization (WHO), Healthcare Hazardous Waste (HHW) includes a wide range of materials such as used needles, syringes, soiled dressings, body parts, diagnostic samples, blood, chemicals, pharmaceuticals, and radioactive materials (Ding et al., 2016). Healthcare waste is typically classified into general and hazardous categories. While 75-90% is non-hazardous and similar to municipal solid waste (Al-Khatib et al., 2015), the remaining 10-25% is hazardous waste and poses serious risks to human and environmental health (Ciplak & Barton, 2012).

Due to its hazardous nature, HHW differs significantly from municipal waste and requires specialized handling across all stages: collection, storage, transportation, and disposal. The combination of these four essential stages is necessary for effective waste management. Accurate prediction of future HHW generation is therefore essential for developing efficient waste management strategies (Dente & Hashimoto, 2020). However, fluctuations in HHW volumes, driven by several factors such as department-specific activities, waste types, and patient loads, add complexity and challenge the design of effective programs. These variables impact both the financial cost of disposal and the overall quality of healthcare services.

This study aims to develop a predictive model for the quantities and disposal costs of various types of HHW, accounting for key influencing factors. System dynamics is employed to capture the complex interdependencies within healthcare waste systems. This modeling approach not only supports cost savings but also ensures the creation of a dynamic, adaptive waste management system that enhances safety for both healthcare workers and patients.

The paper's key contributions:
(i) Development of a novel predictive model that incorporates the effects of COVID-19 and independently predicts chemical waste and department-specific outputs; an approach not previously documented in the literature.
(ii) Estimation of hazardous waste disposal costs under alternative scenarios, analyzing the model's response to varying department-level waste generation rates.

This study investigates new factors, such as the impact of hospital departments on waste generation, patient population, patient volume, and the amount of chemical waste generated by various departments. This research aims to estimate waste generation and predict future amounts while considering the dynamics of multiple elements. This comprehensive method provides valuable insights into building successful and customized strategies for controlling Healthcare Hazardous Waste (HHW) in healthcare institutions. The beneficiaries of this study include hospitals worldwide, patients, and staff, as the findings can potentially prevent infections and enhance the overall quality of healthcare provided.

This study is particularly relevant for developing countries, where healthcare systems often face resource constraints, limited infrastructure for hazardous waste treatment, and data collection challenges. Jordan University Hospital, the setting of this case study, exemplifies many of these conditions and thus serves as a representative environment for evaluating system-based solutions. By employing a system dynamics model in such a context, the study demonstrates how hospitals in similar settings can improve forecasting accuracy, reduce costs, and enhance overall waste management practices. Therefore, the study offers practical value not only to Jordan but also to a wide range of healthcare institutions in developing regions facing comparable systemic limitations.

To guide the reader through the structure of this paper, Section 2 presents a review of existing literature on healthcare waste management methods, emphasizing forecasting techniques and system dynamics modeling. Section 3 details the proposed system dynamics modeling approach, including its structure and equations. Section 4 describes the steps involved in building and validating the model, along with a case study conducted at Jordan University Hospital. Section 5 presents the simulation results, sensitivity analysis, and scenario-based evaluations. Finally, Section 6 concludes the study with key findings, practical implications, limitations, and directions for future research.

2. Literature Review

Healthcare waste management has been a significant area of research, with scholars employing a range of methodologies to improve forecasting and system performance. Multiple Linear Regression (MLR) has been widely used, as seen in studies by Çetinkaya et al. (2020), Golbaz et al. (2019) and Thakur & Ramesh (2018), which focused on predictors such as patient demographics and GDP per capita.

A circular economy model was proposed by Sepetis et al. (2025) for managing hospital bio-waste and emphasized waste segregation at the source and the use of data-driven tools to enhance efficiency and sustainability. Circular economy hierarchy for managing COVID-19 healthcare waste has been investigated by Voudrias (2024) to address risks and policies for combatting future pandemics and mitigating environmental crises. The impact of the COVID-19 pandemic on medical waste management in Lebanon (Maalouf & Maalouf, 2021) and China (Zhang et al., 2013) shows the need in developing countries for proper management, training programs, and disposal of medical waste.

Machine learning approaches, such as Artificial Neural Networks (ANN), Fuzzy Logic - Artificial Neural Networks (ANFIS), and Support Vector Regression (SVM) (Golbaz et al., 2019) are used to simulate factors that represent healthcare facilities' complexities. This included bed occupancy, types of Healthcare Facilities (HCF), and the composition of Medical Waste (MW), including 'yellow waste,' 'red waste,' and 'blue waste,' as well as the average waste per bed. For example, other studies used ANN (Karpušenkaitė et al., 2016) to model hospital infrastructure parameters such as the number of wards, active and occupied beds, staff, inpatients, ownership type, and activity years. Autoregressive Integrated Moving Average (ARIMA) was used (Ceylan et al., 2020), focusing on specific types of generated waste, including total and hazardous medical waste, daylight bulb waste, hazardous vehicle waste, and overall waste, using the annual hazardous waste generation.

In some studies, researchers included both ANN and MLR predictor models, such as Jahandideh et al. (2009), where medical waste was categorized into three types: sharp, infectious, and general. The models were designed to predict the pace at which each form of waste was generated. These models' performance was evaluated based on their ability to predict total waste generation and individual waste type rates. Support Vector Regression (SVR) and Grey Modelling (1,1) were also used in many studies. System dynamics is a frequently used method that we will apply by using case study data on computer-assisted software.

System dynamics methodology has also been used to predict different types of waste. For instance, in Ding et al. (2016), system dynamics was used in a case study in Shenzhen, China, where researchers used Vensim to represent their model, focusing specifically on why and how source reduction and construction waste sorting behaviors affect environmental gains. Source reduction refers to the use of low-waste technology and effective on-site management. It has been identified as an effective waste reduction measure. In contrast, sorting behaviors such as increasing stakeholder waste awareness, refining regulations, enhancing governmental oversight, and controlling illegal dumping are prerequisites for increasing construction waste recycling and reuse rates.

In Al-Khatib et al. (2015), a system dynamics model is used to predict the generated municipal waste in Nablus City, Palestine. In this study, 100 samples of waste were sorted manually into the following waste components: (1) Organic waste (compostable, including food waste), (2) Plastics, (3) Paper and cardboard, (4) Glass, (5) Metals, (6) Textiles, (7) Other waste (leather, wood, ashes, etc.) and (8) Waste less than 10 mm size (passing through the mesh and termed as inert). This differs from our study, as our research focused on medical waste and how we divided it in the stock and flow model. In Ciplak & Barton (2012) study, the researchers used the system dynamics model to create a system that will aid in selecting and planning future treatment capacity in a case study in Istanbul, Turkey. Observations and interviews were done in Istanbul over three months to discover the factors driving healthcare waste generation. Using the software package Vensim Ple Plus, a system dynamics model was used to develop a healthcare waste management model. The model's main factors were waste segregation, population, small healthcare facilities, bed capacity, and number of inpatients and outpatients.

In Chaerul et al. (2008), using the Stella® software package, a hospital waste management model based on system dynamics was developed to determine the interaction among variables in the system. The city of Jakarta, Indonesia, was chosen as a case study. The main variables considered in their study model were the number of beds in the hospitals and the NIMBY (not in my backyard) syndrome, which suggests that individuals support a project as long as it is not in their backyard (Uji et al., 2021). The main idea in this study is that hospital management needs to segregate medical waste and infectious waste treatment before disposal.

In Al-Khatib et al. (2016), the researchers focus on the current state of waste generation without anticipating and predicting future generation rates or waste treatment and disposal costs. Although the model represents medical waste, it uses different variables from the ones we used. The variables used in their study included inpatients and outpatients in various hospitals. Still, our study included inpatients and outpatients and detailed data from each department and unit of the case study facility. Our model also predicts the waste generation rate while considering the number of cases of COVID-19, which has significantly influenced the medical waste generation rate in the past two years. In Eleyan et al. (2013), based on limited samples from Jenin district hospitals in Palestine, the researchers used system dynamics to anticipate the generation of medical solid waste in a developing metropolitan environment. When traditional statistical least-squares regression methods cannot handle such issues, the model's findings present the trend of medical solid waste generation along with its various components, indicating that a new forecasting approach may cover a variety of possible causative models and track inevitable uncertainties.

Challenges and barriers to effectively managing healthcare waste to achieve sustainable environmental development were investigated (Quttainah & Singh, 2024). The study categorizes 17 potential barriers into economic, social, technical, and regulatory dimensions, with key challenges including a lack of standardized guidelines, ineffective waste segregation, awareness gaps, and inadequate training. Addressing these barriers through policy standardization, enhanced training, and improved resource allocation is recommended to improve HCWM practices.

This study's model is similar to the previous one since it predicts medical waste generation rates and employs system dynamics. It does, however, depart dramatically by proposing a new technique as it classifies waste into two categories: general and hazardous, via textiles, plastics, glassware, paper, cardboard, and metals separated from general waste, and medical plastics, tissues, and pathological waste separated from medical infectious waste, absorbent cotton products, and waste sharps.

On the other hand, the model in this research takes a radically different approach. While we all have the same goal of accurately predicting medical waste generation rates, this study predicts the amount generated by departments separately while considering dynamically related factors such as the type of waste generated (Medical, Solid Chemical, and Formalin (Liquid chemical)), the department of which it generates from and the number of Covid-19 patients, inpatients and outpatients entering the hospital, making this study unique in its all-encompassing approach to waste prediction in COVID-19.

In summary, while prior studies have successfully applied system dynamics to model general or aggregated medical waste flows, few have captured department-level waste generation across multiple waste types with the integration of real COVID-19 case data. This study distinguishes itself by developing a disaggregated, predictive system dynamics model that estimates hazardous chemical and medical waste generation and disposal costs at the departmental level, offering new insights into operational variability and policy sensitivity within hospital settings.

3. System Dynamics Modeling Approach

System dynamics, established from control theory, can navigate the complexities of nonlinear, time-delayed, and multi-loop dynamic systems. Forrester's approach is the foundation for developing computer models that objectively evaluate complicated social systems' intricate structures, relationships, and behavioural modes. This approach allows for testing strategies and trade-offs while alternatives are still available. Software tools such as STELLA, VENSIM, and POWERSIM have influenced the usage of system dynamics modelling (Bala et al., 2017). Systems dynamics is an approach particularly well adapted to simulating complex systems like waste management systems. It can adequately deal with assumptions about system structures and track the impacts of changes in subsystems and their relationships. It is also capable of representing and expressing these changes (Chaerul et al., 2008). System dynamics facilitates the monitoring and control of the impacts of changes in subsystems and their relationships by dealing with assumptions about system design and structures in an organized way (Eleyan et al., 2013). The following section elaborates on the proposed model structure.

For consistency and clarity, this study distinguishes between two main types of chemical waste generated in the hospital: (1) solid chemical waste, which includes discarded laboratory reagents, expired pharmaceuticals, and contaminated materials, and (2) formalin chemical waste, referring specifically to formaldehyde-based liquid waste commonly used in pathology and histology units. These categories are treated separately in the model to reflect their distinct handling, environmental impact, and disposal costs.

The system dynamics modeling approach in this study is built on four core components: stocks, which represent accumulations such as patient population or accumulated waste; flows, which denote the rates of change (e.g., patient arrival and departure rates, waste generation rates); auxiliary variables, which are intermediate or policy-related inputs like COVID-19 case rates or waste disposal prices; and feedback loops, which capture the causal relationships and dynamic interactions among system elements. These components are visually represented in the stock-and-flow diagram structure using the Vensim software. The modeling process follows a systematic sequence: (1) problem definition, (2) causal loop diagram creation, (3) formulation of the stock-flow structure, (4) development of mathematical equations, (5) model validation, and (6) scenario analysis. Supplementary file, Appendix A, **Figure 1S** presents a conceptual flow diagram outlining the major components and interdependencies in the model.

3.1 Structure and Application

The proposed model in this research identifies the vital elements that can be quantified as variables; their influences and effects are then formulated mathematically. The equations used to predict the amounts of the generated HHW are explained below:

The patient population directly affects the number of patients entering the hospital. The population is controlled by arrival and departure rates; as the arrival rate increases or the departure rate decreases, the patient population increases and vice versa. In Equation (1), the arrival rate (Γ_A), which affects patient influx and the departure rate (Γ_D), which controls patient departures and shapes the composition of the patient population (P_t).

$$P_t = P_{t-1} + \text{Ƥ}(\Gamma_A - \Gamma_D) \quad (1)$$

The number of COVID-19 patients has rarely been considered as a factor due to the pandemic's novelty. The number of COVID-19 cases had a very high effect on the amount of medical waste at the beginning of the pandemic. Yet, after the new regulations introduced by the Jordanian Ministry of Health in April 2021, the amount of waste generated by COVID-19 patients decreased (according to the medical waste unit employee). The new regulations treat COVID-19 medical waste the same as medical waste from any other department. However, the number of COVID-19 patients remains a significant affecting factor that needs to be considered. Equation (2) is used to calculate the rate of COVID-19 patients entering the case study hospital:

$$\Gamma_C = \frac{\sum C_H}{\sum C_N} \quad (2)$$

where, Γ_C represents the rate of COVID-19 patients entering the case study hospital, $\sum C_H$ represents the total number of COVID-19 patients treated in the case study hospital. $\sum C_N$ denotes the total number of COVID-19 cases in the nation of the case study.

The waste generation rate plays a pivotal role in model development. As per the available data, using Equation (3), we calculate the waste generation rate (Γ_p) in kilograms per bed per day (Kg/bed/day) by dividing the mean waste quantity for a department ($\bar{\mu}$) in kilograms per day (Kg/day) by the total number of treated patients in the case study hospital, excluding those who were admitted due to Covid-19 ($\sum p$) (beds).

$$\Gamma_p = \frac{\bar{\mu}}{\sum p} \quad (3)$$

COVID-19 is implemented as a factor that influences the waste generation in the model; the rate equation for the departments in which COVID-19 patients are isolated has been modified as follows:

The total rate of waste generation for hospital patients is added to the number of COVID-19 patients in the hospital (Γ_T) (Kg/bed/day), shown in Equation (4), is equal to the mean amount of waste for the department ($\bar{\mu}$) in (Kg/day), divided by the total number of patients who are treated in the hospital ($\sum p$) (bed) summed to the total number of Covid-19 patients that are also treated in the hospital ($\sum p_c$) (bed).

$$\Gamma_T = \frac{\bar{\mu}}{\sum p + \sum p_c} \quad (4)$$

The cost equation of both the medical and chemical waste generation models is described in the following Equation (5), where (C_T) (USD) is the total cost and (C_M) (USD) is the medical waste disposal cost and (C_C) (USD) is the chemical waste disposal cost. Equation (5) below estimates the costs of hazardous waste disposal.

$$C_T = W_M * P_M + W_C * P_C \quad (5)$$

The chemical waste disposal cost is equal to the weight of the chemical waste predicted by the model (W_C) (Kg) multiplied by the price of the disposal of one Kilogram (P_C) (USD/kg). The medical waste disposal cost is equal to the weight of the medical waste (W_M) (Kg) multiplied by the price of the disposal of one Kilogram (P_M) (USD/kg).

The percentage of change ($\%\Delta$), used in sensitivity analysis, is a key equation for later usage in the results. It is determined in Equation (6) by dividing the original value (V_O) by (V_N).

$$\%\Delta = \frac{V_N - V_O}{V_O} * 100\% \tag{6}$$

where, (V_N) the result of multiplying a factor (λ) by the variable (V_O) in Equation (7):

$$V_N = V_O * \lambda \tag{7}$$

Now, with all equations in place and the data well presented, the model is ready to be built, as detailed in the subsequent sections.

3.2 System Dynamics Model Steps of the Research

To construct the system dynamics model, a structured approach was adopted, starting with system thinking to clearly outline the relationships among factors and progressing toward more detailed structural diagrams. The following subsections provide comprehensive explanations of each step.

The main key factors used to build the system dynamics model are shown in **Figure 1** below.

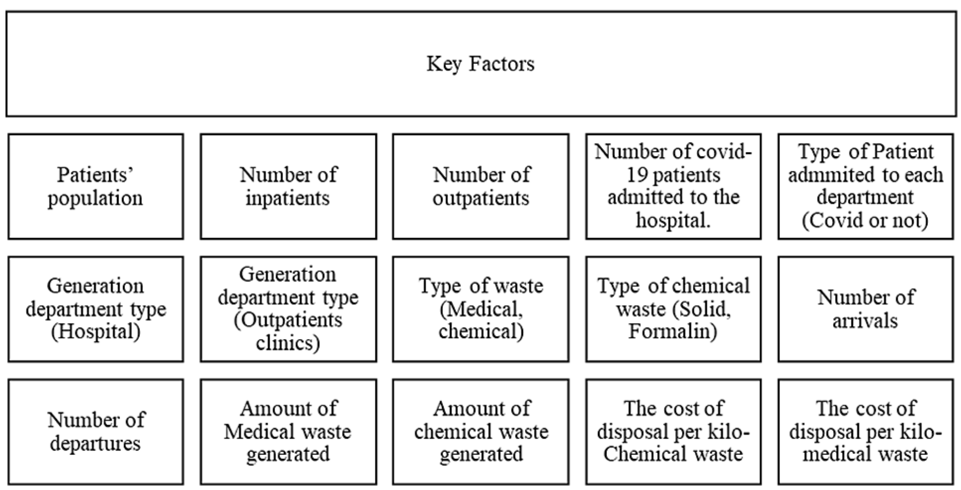


Figure 1. Key factors used to build the system dynamics model.

The causal relationships between the relevant variables (factors) are represented in the causal loop diagram, shown in **Figure 2**. The first step in building a system dynamics model is to create a causal loop (influence) diagram, which is a representation of the main feedback using arrows and elements (causal links) that connect the signs (either positive (+) or negative (-) that represent the state of the relationship between different elements. If the symbol is positive (+), the elements all head in the same direction. As one aspect increases, the other increases as well. This is called a reinforcing loop. If the sign is negative (-), the two elements are heading in opposite directions, with one rising and the other declining. This loop is called a balancing loop.

Following that, depending on the number of positive (+) or negative (-) signs in the loop, the entire loop is given a sign, either positive (+) or negative (-). The loop is given a positive (+) sign if the number of negative (-) signs is even, indicating that the system is unstable. If the number is odd, the loop is given a negative (-) sign, suggesting that it is in equilibrium. For this paper's case study, a notation of the causal loop diagram is shown in **Figure 2** below.

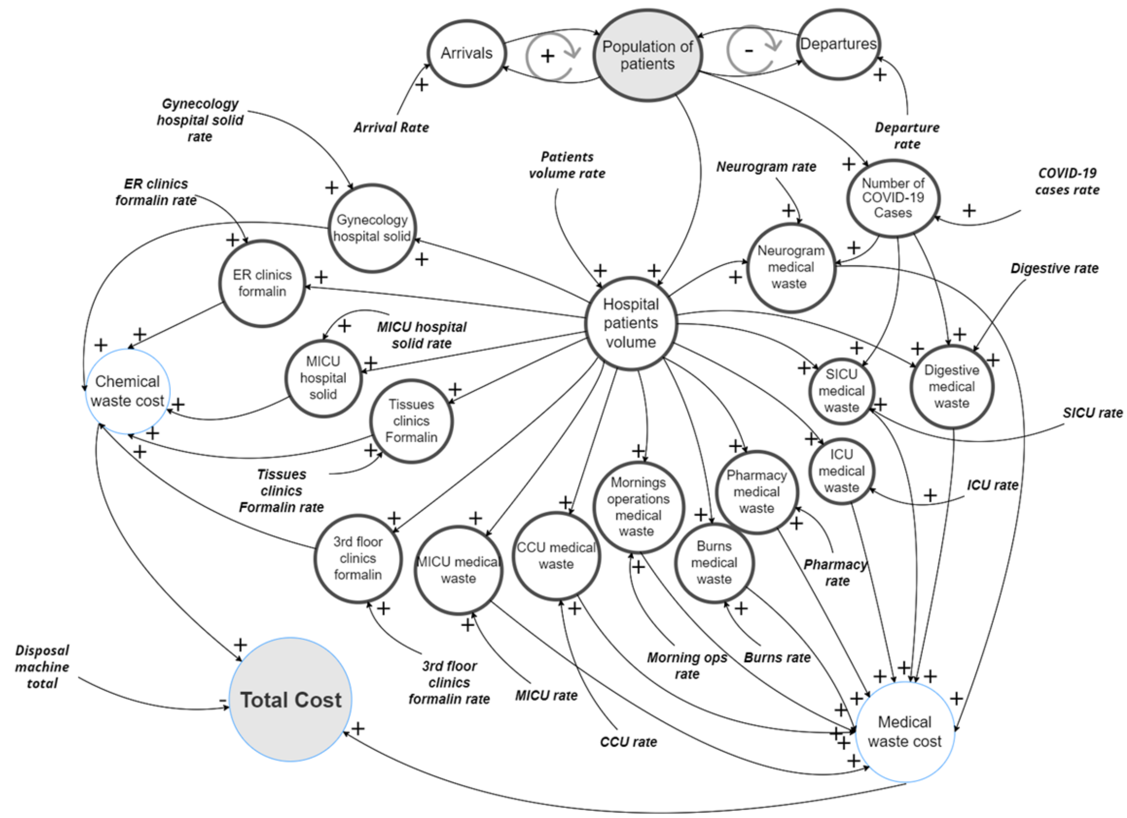


Figure 2. Healthcare waste management system thinking model (Causal loop diagram).

Having established a comprehensive understanding of the causal relationships, the next phase involves translating this into a more detailed structural representation.

3.3 Structural Diagram

The structural diagram, or the stock flow diagram (SFD), is a more complex visual representation than the causal loop diagram (CLD). Stock variables, flow variables, auxiliary/constant variables, and connectors comprise the system dynamics modeling framework. Stock variables, represented as rectangles, reflect a substantial cornerstone in the system. Flow variables, represented by valves, describe the rate of change in stock variables and the factors influencing them. Auxiliary/constant variables are intermediate values employed in calculations, while connectors (arrows) are information links that demonstrate cause-and-effect interactions inside the model. These elements create the foundation for a stock and flow model, simplifying complex systems into three building blocks: stock, flow, and converter (circle).

Connectors highlight dependence and effects. Stocks are a collection of quantities that represent a system's status. Stocks have initial values that are affected only by incoming and outgoing flows over time, offering system inertia and providing the data used to make decisions and take action. Stocks can also cause delays in a system. Flows, on the other hand, use rates to regulate stock changes. Because flows are typically measured by considering accumulated quantity over time, they are always expressed per some unit of time.

The model depends on the patient population, which is directly affected by the patient's arrival and departure, and is summed up as the patient population. Hospital chemical and medical waste generation could be directly proportional to the population.

As the case study data was collected after the COVID-19 pandemic began, the effect of COVID-19 cases is included in this study. It directly connects with the patient population, affecting all the factors included in this study. Equations are now ready to be implemented in a system dynamics software, and the one chosen for this study is Vensim. The base of the model, which includes COVID-19 and patient population metrics, is shown in (Supplementary file, Appendix A, **Figure 1S**).

The construction of the chemical waste part in the model shown in (Supplementary file, Appendix A, **Figure 2S**) is as follows: The orange rectangles represent the amount of solid chemical waste produced by specific departments in the hospital, whereas the blue rectangles represent the amounts of formalin chemical waste produced by particular departments in the hospital. The quantities of these waste types are then aggregated, factoring in the respective generation rates of each department, and directed into a single designated stock, 'Chemical waste.'

The medical waste model is constructed similarly to the chemical waste model. The central unit that both models consist of is the same. The main difference between the units of the two models is that the medical waste model has COVID-19 cases as a variable, as COVID-19 patients only produce medical waste. An important note is that not every department delivers the same types of waste. Supplementary file, Appendix A, **Figure 3S** shows the medical waste model with every department as a parameter for the total medical waste.

Similar to the chemical waste model, the building unit represents the department's stocks, which are connected to the total stock through a flow. This flow is defined by the equation, which is connected to the variables via a connector (the pink arrow). The start of the connector (blue arrow) is considered a variable in the stock equation at the end of the connector. So, the COVID-19 cases, the number of patients in the hospital, and the population are considered factors in the equations of each department where the medical waste is generated. However, not every department has Covid-19 cases as a variable, which was explained previously.

The equations employed in predicting costs for medical and chemical waste generation rate models involve specific variables. The cost is computed in the medical waste model by incorporating the predicted medical waste weights as a critical variable. This process is illustrated through connectors linking the expected values of medical and chemical waste to a dedicated stock representing each waste type's disposal cost. As shown in the equations, the weights are multiplied by the disposal cost associated with each hazardous waste category.

A specific economic barrier occurs in healthcare waste management due to the capacity limits posed by a specialized medical waste disposal machine in the hospital. This machine has a particular capacity limit and is designed to handle medical waste generated on-site effectively. Cost estimations are within an average increasing pace when not exceeding the machine's capacity.

However, if the disposal machine's capacity is exceeded, the hospital will face unexpected logistical challenges and increased costs. These complications arise from the need to find alternative waste disposal methods. Outsourcing waste disposal services or investing in additional machinery and expanded storage facilities become necessary solutions to excessive waste. As a result, when the disposal machine's working capacity is reached, the model's cost predictions encounter a significant and unexpected increase.

This Scenario highlights the importance of including operational constraints, such as machine capacity, in the cost modeling framework for medical waste management. Accurate quantification of waste generation alone is insufficient to generate reliable long-term cost predictions in the healthcare sector; the model must also integrate these operational realities to ensure comprehensive and practical outcomes.

4. Case Study Application

With a clear understanding of the importance of operational constraints established, the subsequent sections outline the detailed methodology and practical application of the developed model, beginning with a specific case study.

4.1 Case Study Hospital

The model was developed and implemented in a case study conducted at Jordan University Hospital in Jordan. The case study area's selection criteria were carefully constructed based on multiple vital conditions. The chosen location had to be a healthcare facility with a specialized medical waste unit. Also, the chosen site must have admitted COVID-19 patients throughout the epidemic and adopted segregation procedures to keep them away from other patients. A waste treatment machine was also required for the facility's infrastructure. These requirements meant that the case study area was well-suited for medical waste management research and analysis, particularly in the context of the COVID-19 pandemic.

Jordan University Hospital has 46 departments, including inpatient and outpatient clinics. Each of these departments disposes of either medical waste, chemical waste (including both types of solid chemical waste or formalin), or both. The waste is collected using various containers from all departments of the case study hospital, such as the operating room, laboratory, emergency room, clinics, etc. The waste is segregated into several colored containers, each of which signifies a particular type of waste to be disposed of. Hazardous chemical (solid and liquid) waste is labeled blue, infectious medical waste is red, general medical waste is yellow, and domestic (general) waste is black. Following that, staff from the medical waste unit categorize the hazardous waste into two categories: medical waste and chemical waste. According to this categorization, the waste is collected and weighed from each hospital department, including the outpatient clinics that produce hazardous waste.

Staff members assist in weighing and documenting hazardous waste data, classifying it clearly into chemical and medical categories. This information is meticulously recorded daily, analyzed using statistical tools in Excel, and categorized by department name, collection date, waste type, and precise weight in kilograms. This detailed record-keeping facilitates accurate computation of waste production rates per bed per day, crucial for integrating into the system dynamics model. Following that, the data is documented and saved for analysis. This data is analyzed using statistical Excel. The amount of hazardous waste generated during the year is calculated and recorded daily. The data is then categorized according to department name, collection date, waste type (chemical solid/chemical formalin/medical), and precise weight in kilograms. The waste production rate per bed per day in kilos is computed for each hospital department and outpatient clinic to integrate the equations on which the model is built.

These factors integrate the equations implied in the system dynamics model. Although each factor affects the following one in a domino-like effect, the annual change in the predicted amounts is not constant or linear due to the various variables affecting the quantities generated.

4.2 Model Validation

Model validation is crucial to guarantee that the model abstracts the system under study. The validation process quantifies the model's accuracy by comparing the model/experimental results with collected data. The first check was carried out by checking the dimensional consistency and the model structure by running the model (SD software offers options to check the units and the model structure). Validation tests of SD models can be categorized as the test of model structure, the test of model behavior, and the test of policy implications (Barlas, 1989; Elsawah et al., 2017). Supplementary file, Appendix A, **Figure 4S** explains the process of verifying and validating an SD model.

The model is verified by comparing the results of running the model with the specific data provided by the case study facility. As each variable is added to the model, the model executes, and the data from the case study facility is compared to the initial value the model returns, indicating the precision with which the data was entered into the model.

The validation process for the model involved three approaches:

(i) ***Validation using Vensim*****:** Before simulating the model, it should be examined for errors in equations and units. This stage is critical for guaranteeing the model's accuracy and reliability in modeling real-world systems. Vensim provides two methods for this check:

- ***'Check Model'*****:** This option is used for checking Model Syntax, which involves checking the model's equations and structure for inconsistencies or errors in the mathematical expressions.
- ***'Units Check'*****:** This option is created exclusively to check unit errors, ensuring that the units given to variables and parameters within the model are consistent and accepted.

These tests were conducted on this model, and they yielded no mistakes. The model's mathematical expressions, structure, and units were confirmed by using both the 'Check Model' and 'Units Check' options, decreasing the possibility of errors and building confidence in the model's validity.

(ii) ***Historical data analysis:*** This validation method matches the model's inputs to historical data values and determines whether the model's outputs accurately represent real-world behavior. The data used in this method must be excluded from the equations and rates implemented in the model for the comparison to be accurate in the first place.

When the total amount of medical waste weight anticipated by the model for 2022 was examined, it nearly approximated 167,148 Kg/year. Surprisingly, the actual amount for 2022, as reported by the hazardous waste unit employees, was 167676 Kg, demonstrating a precise prediction with an error of only 0.3149%. Similarly, the model anticipated that the total chemical waste weight in 2022 would be 2,402.64 Kg/year, with a monthly average of 200.22 Kg. With a margin of error of 2.9567%, this forecast was near the actual value of 194.3 Kg the hazardous waste unit staff provided. Importantly, this % error is within an acceptable range, confirming the model's validity.

The error is calculated according to Equation (8):

$$\varepsilon\% = \frac{\overline{\sum\mu}_{\boldsymbol{P}} - \overline{\sum\mu}}{\overline{\sum\mu}} * 100\% \tag{8}$$

In which $\varepsilon\%$ represents the Integration error and $\overline{\sum\mu}_{\boldsymbol{P}}$ represents the predicted mean of waste and $\overline{\sum\mu}$ represent the mean waste quantity for a department.

(iii) ***Euler integration method:*** The model's time step never exceeded a fourth of the system's shortest time constant, which in this case was one year. This rigorous selection was based on established system dynamics techniques, and the chosen time step of one-quarter of a year consistently adhered to the suggested time step limitations throughout the model's execution and validation. This process not only maintains the model's numerical stability but also its accuracy in reflecting the dynamic behaviors of the system, supporting its validity for practical application (Ciplak & Barton, 2012).

5. Results and Discussion

Shown below in **Table 1** are the system dynamics model predictions for the next ten years. These results include the number of patients, the amounts generated for both types of waste, and the expected cost as well.

Table 1. Predictions for the next ten years.

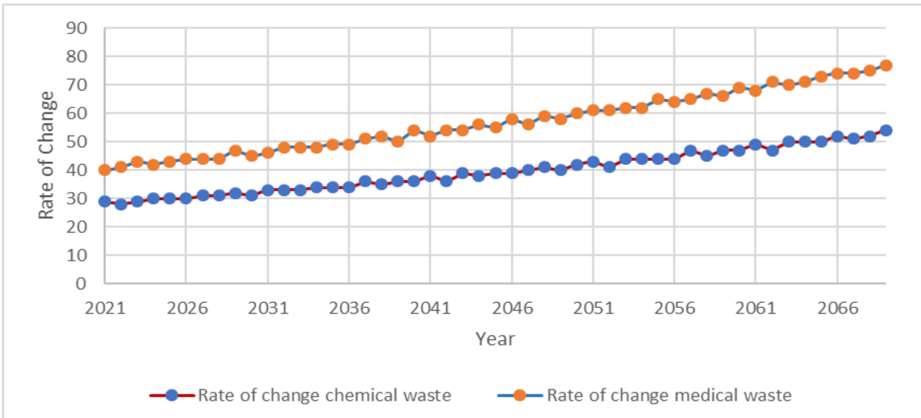
Time (Year)	The patient's number entering the hospital	Medical waste weights (Kg)	Chemical waste weights (Kg)	Disposal cost of medical waste (USD)	Disposal cost of chemical waste (USD)	Total waste cost (USD)
2021	699925	164982	2371.5	13141.2	1897.2	15038.4
2022	709114	167148	2402.64	14224.2	1922.11	16146.3
2023	718423	169343	2434.18	15321.3	1947.34	17268.7
2024	727854	171566	2466.13	16432.9	1972.91	18405.8
2025	737410	173818	2498.51	17559.1	1998.81	19557.9
2026	747090	176100	2531.31	18700	2025.05	20725.1
2027	756898	178412	2564.54	19855.9	2051.63	21907.6
2028	766835	180754	2598.21	21027	2078.57	23105.6
2029	776902	183127	2632.32	22213.5	2105.85	24319.3
2030	787101	185531	2666.87	23415.5	2133.5	25549
2031	797434	187967	2701.89	24633.4	2161.51	26794.9

Over the next decade, a continuous increase in patient admissions is predicted, with the number of patients growing from approximately 699,925 in 2021 to approximately 797,434 in 2031. This increased pattern reflects the hospital's growing demand for healthcare services.

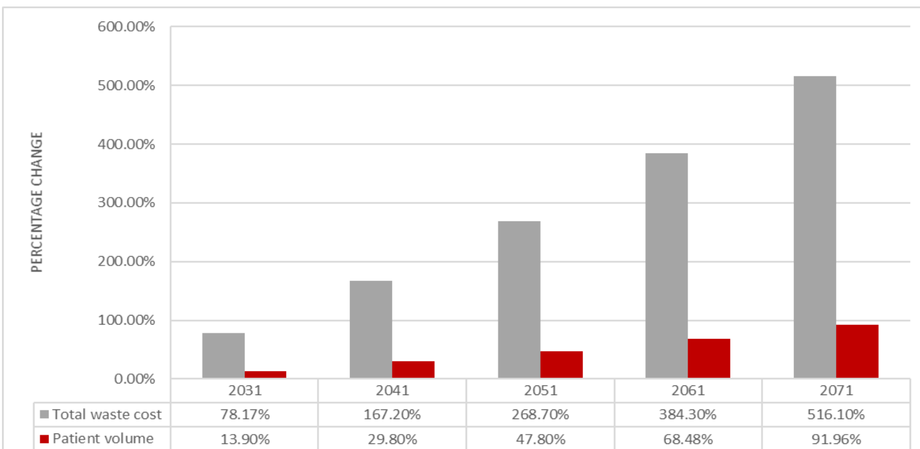
An increase in patient admissions results in an increase in both medical and chemical waste generation. Medical waste increases in weight from 164,982 kg in 2021 to 187,967 kg in 2031, while chemical waste increases in weight from 2,371.5 kg in 2021 to 2,701.89 kg in 2031. This increase in waste output emphasizes the apparent connection between patient volumes and waste generation, indicating the need for proactive waste management strategies as patient numbers increase. As a result, the financial ramifications become apparent. In Jordanian Dinars (USD), the cost of disposing of medical waste rose from 13,141.2 USD in 2021 to 24,633.4 USD in 2031. At the same time, the cost of disposing of chemical waste in USD rises from 1,897.2 in 2021 to 2,161.51 in 2031. The "Total waste cost" column, which represents the total cost of disposing of medical and chemical waste, shows a constant upward trend throughout the ten years, rising from 15,038.4 USD in 2021 to 26,794.9 USD in 2031.

These numerical insights highlight the critical importance of waste management planning in healthcare institutions, as increased patient numbers necessarily lead to increased waste generation and, as a result, higher waste disposal costs. Proactive resource allocation and waste reduction methods are critical for mitigating the financial burden of waste management, allowing hospitals to run cost-effectively while still providing necessary healthcare services. In addition, these predictions are valuable tools for healthcare budgeting and strategic decision-making, providing information about the changing demands and financial constraints connected with waste management.

The model also predicts the amounts of HHW for the next 10, 20, 30, 40, and 50 years, reflecting the rate of change in generated amounts. **Figure 3** shows the predicted rates of change for the following decades.



(A)



(B)

Figure 3. (A) Temporal dynamics of generation rates, (B) Predicted percentage growth over the next five decades.

The results presented in **Figure 3** reveal a detailed prediction of waste management expenses and patient admissions in the case study hospital over a multi-decade timeframe. The "Total waste cost" column, calculated as a percentage of the baseline year, 2031, accurately depicts financial consequences. The predictions indicate a concerning trend in waste management expenses. Waste management expenses are expected to double by 2041, reaching approximately 167.20% of the baseline cost. This ten-year growth indicates a rapid and significant increase in the financial load placed on healthcare facilities. The rising trend continues to increase in the years that follow. The model predicts that 2051 waste management costs will be 268.70% higher than the baseline, representing a more than twice rise over 2031. This exponential growth pattern is expected to continue, with expenses increasing by 384.30% by 2061 and 516.10% by 2071. These estimates emphasize the cumulative effect of increased waste management costs over time, underlining the critical importance of proper resource allocation and financial planning.

The data reveals a significant increase in waste management expenses in healthcare facilities, highlighting a distinct economic barrier due to the limited capacity of specialized medical waste disposal machines. This machine is designed to manage on-site medical waste efficiently, but its capacity limit significantly impacts the estimated costs. Under normal circumstances, when waste stays within this limit, costs follow an expected gradual increase. However, exceeding this capacity creates unexpected logistical issues and expense increases, forcing hospitals to consider other disposal options, such as outsourcing or investing in extra machinery and storage. As a result, when the machine's capacity is surpassed, the cost forecasts of the model undergo a considerable and unexpected increase.

Meanwhile, the "Patient volume" column, shown as a percentage relative to the baseline year, reveals a significant increase during the next few years. Patient admissions are expected to be about 30% higher than the baseline by 2041, reflecting increased healthcare service demand. This trend is expected to continue, with patient volume exceeding the baseline by 47.80% by 2051, 68.48% by 2061, and 91.96% by 2071. The predictions indicate a consistent increase in patients seeking healthcare services.

5.1 Sensitivity Analysis

As a part of the validation process, sensitivity analysis is a crucial phase. Sensitivity analysis is an approach for structure and behavior validation tests. The effects of changes in specific variable values will be assessed. Sensitivity analysis helps in testing the reliability and validity of the developed model. A sensitivity analysis test is conducted on the main variables that affect the system. Furthermore, it helps identify the most influential variable and the parameters significantly impacting the model behavior (Elsawah et al., 2017).

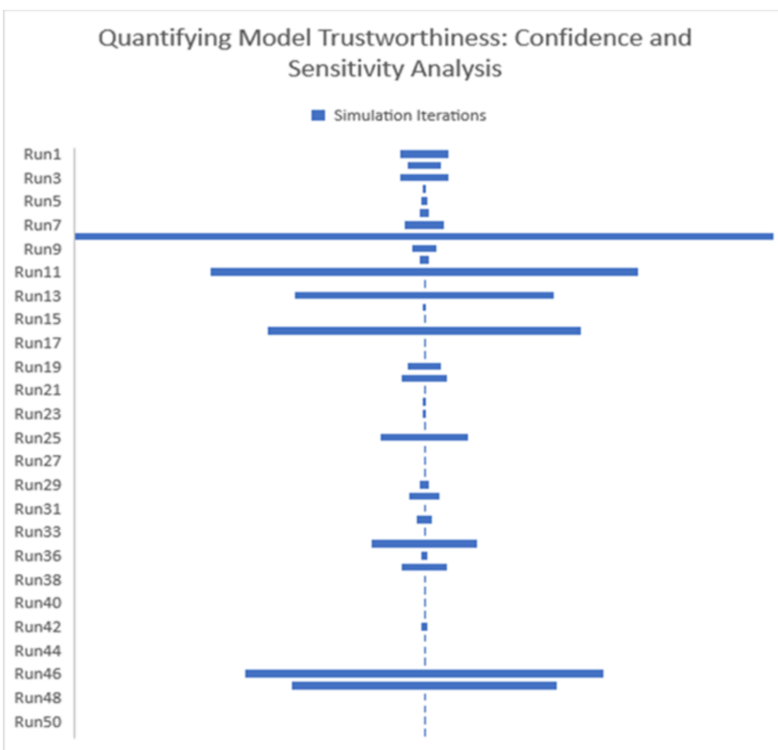


Figure 4. Quantifying model trustworthiness: confidence and sensitivity analysis.

The analysis results shown in **Figure 4** revealed that changes in parameters such as population growth rate significantly impacted HHW generation and associated costs, which is compatible with results shown in previous studies (Rafew & Rafizul, 2021).

The confidence level, especially in the context of a model's sensitivity analysis, is critical in determining the certainty and durability of the model's predictions. The confidence level in sensitivity analysis demonstrates the range within which the model's outcomes are predicted to fall with a high degree of certainty. For example, establishing a 95% confidence interval suggests a 95% chance that the model's findings will fall within that range when subjected to changes in input parameters.

The analysis was performed on a sample of 52 simulation iterations (Runs), yielding 51 degrees of freedom. The sample size's square root is calculated to be around 7.2111. The dataset's mean is 0.1534, with a sample standard deviation of 1.7123. The 95% confidence interval was calculated using a critical t value of 2.0076, providing an interval of (-0.3233, 0.6301). However, 90.20% of the sensitivity analysis data points fall within this 95% confidence interval, implying that the model's predictions are consistent and stable across various parameter values. In other words, the model's output is not overly sensitive to minor changes in the input parameters. While this level of stability may indicate a stable model, it is crucial to remember that the remaining 9.80% of data points may still show some variability beyond the confidence range.

Finally, the level of confidence and stability necessary in a model is determined by the application and the tolerance for variance. A higher confidence level, such as 95%, provides a narrower range of expected outcomes but may necessitate a higher model validation and calibration level. A lower confidence level, on the other hand, may allow for a broader range of potential results but with less severe model constraints.

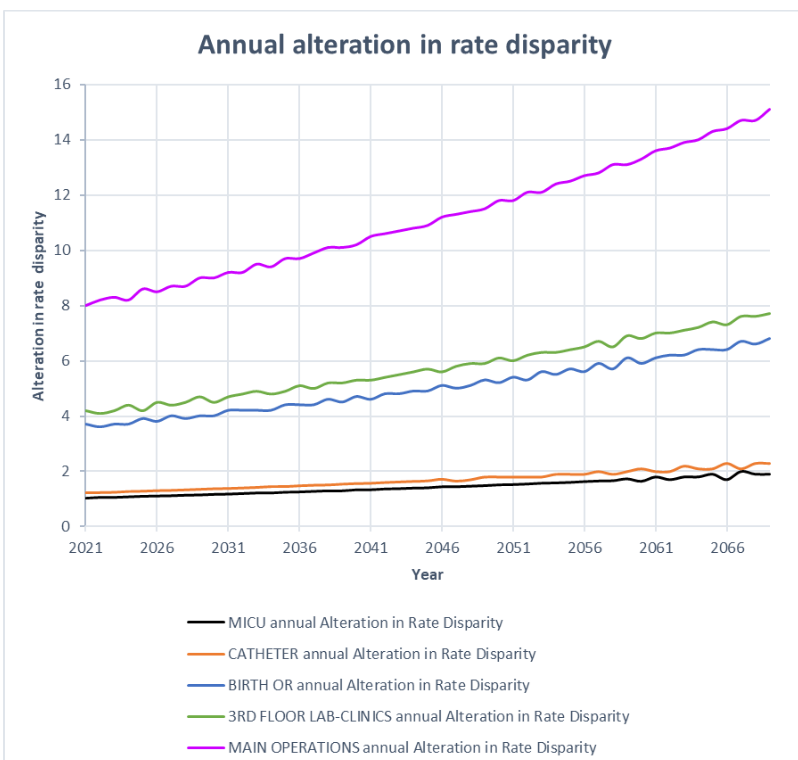


Figure 5. Annual alteration in rate disparity showing the changes in rates over the next five decades.

The percentage contribution of specific departments to the total alteration in rate disparity for the most affected departments is shown in **Figure 5**. The "MAIN OPERATIONS" department is the most significant contributor, accounting for approximately 29.66% of the total alteration in rate disparity. The "BIRTHS OR" department represents 13.36% of the total, while "KIDNEY DEPARTEMENT-CLINICS" contributes 11.26%. The "3RD FLOOR LAB-CLINICS" and "MAIN OPERATIONS" departments each make significant contributions, comprising approximately 15.23% and 6.54% of the total generation, respectively. Departments like "MICU" and "CATHETER" also play substantial roles, contributing approximately 3.80% and 4.49%, respectively. These percentages reveal the relative importance of each department's change in rate disparity in the context of healthcare delivery and disparity control.

The data on annual changes in rate discrepancy presented in the graph above relates to specific healthcare departments chosen due to a history of creating significant amounts of medical waste, as the departments dealing with large amounts of medical waste frequently have specific obstacles and complexities in their operations, which can have an impact on the overall rate variance within these departments.

The continuously increasing trajectory in rate variance alterations among most of these departments over time is noticed in this dataset. This trend reflects the changing dynamics of healthcare, which include changes in patient demographics, scientific improvements leading to more complex operations, and changes in healthcare policies affecting the rates. However, it is crucial to note that not all departments follow this general pattern. Departments such as "MAIN ER" and "CATHETER" have generally constant change rates, with slight swings within a specific range. This stability is most likely due to these departments' well-established procedures and patient demographics, resulting in consistent care delivery. Fluctuations in their change rates can be ascribed to seasonal variations or slight fluctuations in patient volume, both of which are managed within their operational frameworks.

On the other hand, the "MAIN OPERATIONS" department stands out as an anomaly in the statistics, with a substantial increase in rate disparity alteration throughout the years. This sudden increase is related to the predicted increase in surgical procedures, possibly due to the rise in new surgeries or an inflow of patients. It also indicates inefficiencies in resource allocation, which demand a thorough evaluation and intervention.

There are distinct variations in rate disparity alterations between departments, with "KIDNEY DEPARTMENT-CLINICS" and "BIRTH OR" typically displaying higher rate disparity adjustments. These inequalities are due to the particular nature of their services, such as managing complex situations or patients with various comorbidities. Thus, focused quality improvement programs, increased staff training, and resource reallocation are required to ensure equitable care delivery.

Furthermore, long-term data analysis reveals department variations such as "3RD FLOOR LAB-CLINICS." These oscillations could be attributed to various variables, including changes in diagnostic test volumes, testing methods, and variances in the patient population requiring diagnostic services. Understanding and managing these changes over time is crucial to ensuring consistent diagnostic service quality.

In conclusion, the data on annual changes in rate disparity within high-medical-waste-producing healthcare departments reveals a multifaceted interplay of factors influencing healthcare delivery. The chosen departments are known for their significant medical waste output and present distinct operational challenges impacting the observed rate disparities. Addressing these challenges requires a comprehensive analysis encompassing changes in patient populations, medical practices, healthcare policies, resource allocation, and department-specific conditions. Strategic interventions are imperative to ensure that healthcare facilities can provide equitable and high-quality care within these departments while effectively managing medical waste.

These findings highlight the severe problems that healthcare organizations face. The continuous and significant increase in waste management expenses and patient admissions requires careful planning and resource allocation. Hospitals must plan to increase waste volume by investing in waste disposal infrastructure and expanding waste storage facilities. Simultaneously, financial planning must be adjusted to account for predicted cost increases, ensuring that increased financial strain does not affect the delivery of high-quality healthcare services. Moreover, as waste generation increases, a shift toward more sustainable waste management and recycling procedures may be required to mitigate environmental impacts.

5.2 Scenario Thinking

Scenario planning provides a systematic process that helps managers consider the consequences of future events (Kaplan, 2009). Scenario thinking is incorporated into scenario planning. Furthermore, it is the strategic aspect that is necessary in a business environment. Therefore, scenario planning is an effective tool for managing the changes at the industrial or environmental level. It is the linkage between strategic action and future thinking (Lindgren & Bandhold, 2009). In the same context, scenario development plays a crucial role in strategic planning and links the development of the visions and the required actions (Pereverza et al., 2017). Furthermore, scenario planning is used as a decision-making process for long-term and strategic planning.

5.3 Scenarios in Predictive Modeling for Healthcare Waste Management

Scenarios provide insights into several aspects of waste management, ranging from using external disposal organizations to handling specific waste streams such as medical and chemical waste. These scenarios attempt to provide a deeper understanding of the predictive modeling approach and the effect of modifying factors by simulating numerous situations and considering challenges such as waste volume, resource allocation, and compliance with safety requirements.

A. **First Scenario:** *"Eliminating the waste disposal machine and depending solely on external disposal services"*.

The medical waste unit at the case study hospital has a medical waste disposal machine that can effectively dispose of up to 138,700 kg annually. However, to test the efficiency of the disposal machine, it is imperative to consider scenarios where no such machine is available or operational within the healthcare facility.

In the first Scenario, the healthcare facility's waste management strategy relies heavily on an outside disposal business, with no use of the internal disposal machinery. This scenario allows for analyzing waste management dynamics when the dedicated medical waste disposal machine is idle. The challenges and incentives involved in this arrangement are better understood when simulating this Scenario. **Figure 6** shows a comparison between the real-life medical waste disposal cost data and the first scenario data. To apply this Scenario, the amounts disposed of using the machine were added to the original amounts disposed of by the third-party company in the original Scenario. The overall cost is represented in the chart below.

These findings highlight the financial repercussions of not using a dedicated medical waste disposal system. "Scenario 1" continually incurs greater costs for medical waste management over the next decades than the "Current" Scenario. Understanding these cost variances is critical for healthcare facilities as it underlines the potential benefits of using effective waste management solutions, such as using a specialized disposal machine, to cut costs and optimize resource allocation.

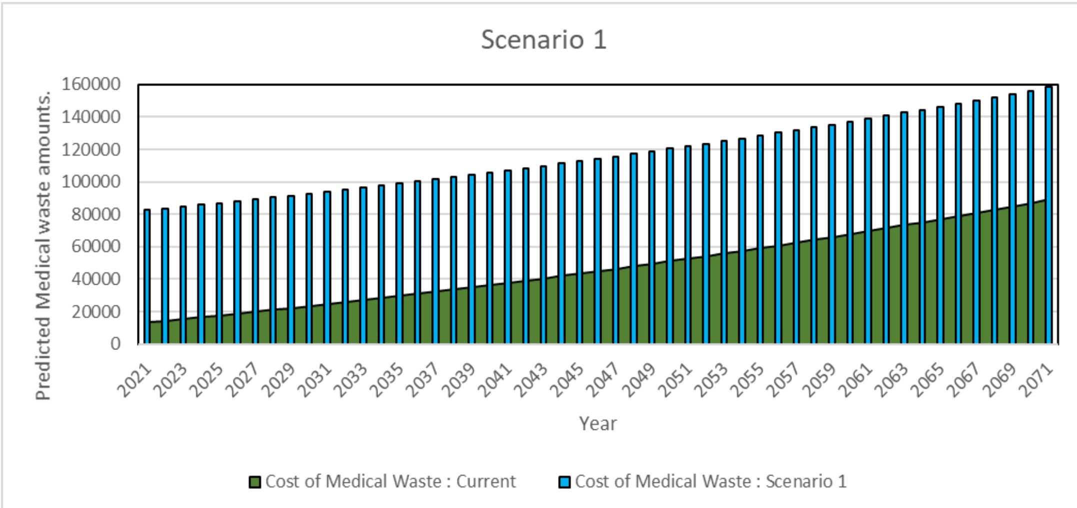


Figure 6. First scenario results.

B. Second Scenario: *"Adopting Formalin Disposable System for Safety Practice"*.

Figure 7 shows a scenario developed in response to a critical problem confronting the hospital: the disposal of formalin waste through an external third-party company. The hospital took a different approach by recognizing the financial and operational difficulties of outsourcing waste management. As a result, "Scenario 2" was created, which involved placing a formalin disposal machine on the hospital premises. This Scenario was designed to address the urgent requirement for effective and sustainable formalin disposal and examine the long-term effects on chemical waste generation and associated expenses.

Over 50 years, the following graphs demonstrate data on chemical waste and its associated expenses for two separate scenarios: one with a formalin disposal system ("Scenario 2") and one without ("Current").

- **Scenario 2 vs. Current Chemical Waste:**

As shown in **Figure 7**, the "Current" Scenario has a significantly greater amount of chemical waste than "Scenario 2," indicating that the formalin disposal system in "Scenario 2" has an immediate positive influence on waste reduction. However, in both circumstances, chemical waste accumulates over time. In the long run, the "Current" Scenario produces more chemical waste.

- **Chemical Waste Cost (Scenario 2 vs. Current):**

Similarly, the cost of chemical waste in the "Current" Scenario is significantly higher than in "Scenario 2," as shown in **Figure 7**, exhibiting cost reductions due to the formalin disposal equipment. Both scenarios predict an increase in the expense of chemical waste over time. The "Current" Scenario has a significantly larger cost in the given period. An 80% reduction in chemical waste disposal costs is attributable to the assumption of the presence of the formalin waste disposal unit in the second Scenario. The formalin waste disposal equipment is intended to manage and process formalin waste within the hospital. This saves money by eliminating reliance on third-party waste disposal services and simplifies the disposal procedure for hazardous chemical waste, particularly formalin.

To contextualize the observed cost savings in Scenario 2, it is essential to note that the analysis assumes the installation of a commercial-grade formalin waste treatment unit within the hospital premises. Based on publicly available procurement data and industry consultations, we estimate the capital cost of such a system to range between \$21,000 – \$35,000, with annual operational and maintenance costs approximating \$1,500 – \$2,500. These values are not included in the scenario's financial output but should be considered when evaluating the payback period and overall cost-effectiveness of the intervention. Despite the initial investment, the system is expected to yield substantial long-term savings by eliminating recurring third-party disposal expenses and improving safety compliance related to hazardous waste handling.

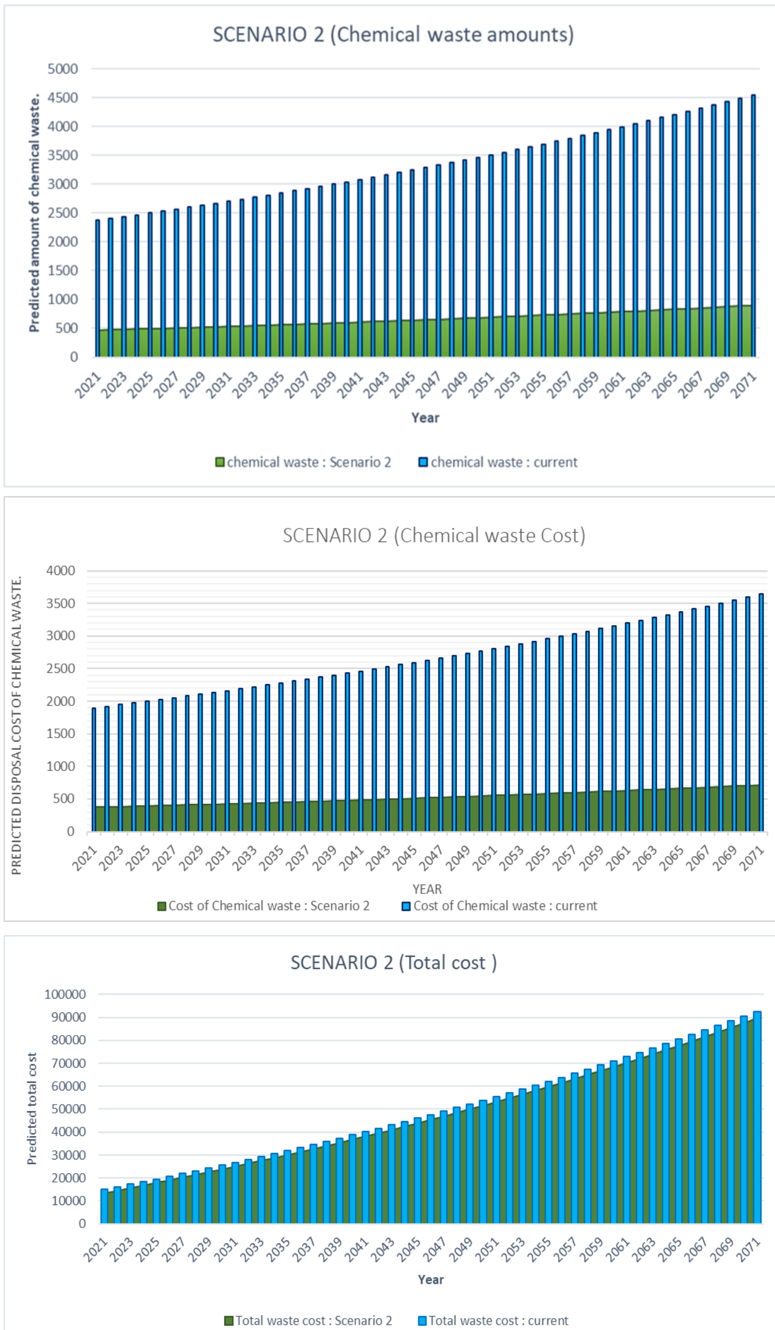


Figure 7. Scenario 2 Predicted chemical waste amounts, chemical waste disposal cost and total disposal cost.

- **Total Waste Cost (Scenario 2 vs. Current):**

In both scenarios, the total waste cost is the cumulative cost of chemical waste over time. In "Scenario 2," introducing a formalin disposal system resulted in a lower total waste cost as shown in **Figure 7**, due to reduced chemical waste generation and cost savings. This reduction only applies to chemical waste, particularly formalin waste, resulting in a minimal difference due to the enormous amounts of medical waste produced. However, chemical waste, especially formalin, is often more hazardous to the environment and human health, requiring more cautious treatment and disposal.

6. Conclusion

This study highlighted the critical relevance of system dynamics modeling for analyzing and simulating the complex dynamics of healthcare waste management, particularly in the context of the COVID-19 pandemic. system dynamics has evolved into a powerful tool for assessing long-term decision-making difficulties in various disciplines, including industrial management. The ability to manage system structure assumptions while successfully tracking subsystem changes and their interconnections is acknowledged, particularly in an area as complex as healthcare waste management. Jordan University Hospital's location in this case study provides optimal conditions for researching medical waste management. It is an ideal site, with facilities specializing in waste management and waste treatment gear, and it has had previous involvement with COVID-19 patients during the pandemic. The data collection process included exact waste categorization across the hospital's 46 departments, all contributing to medical and chemical waste generation. This systematic method was the foundation for developing a thorough and wholly integrated System Dynamics model. The developed model is a vital tool in the decision-making process. The proposed model helps determine the future economic effect of recycling. The model also allows policymakers to propose suitable, preventive, or proactive procedures or any other approach to recycling several waste types.

The system dynamics account considers crucial elements, such as patient population, COVID-19 cases, and waste generation rates. These components are connected and continuously influence one another, replicating the complexities of hospital waste management in the real world. A series of equations has been created to outline these complex interactions, serving as the foundation for predicting HHW output.

The model also goes beyond waste prediction and into cost estimation, addressing the economic aspects of hospital waste management. Medical and chemical waste disposal costs are calculated, with the weights of various waste types serving as vital factors. Moreover, operational limitations are considered, particularly the capacity limits of the waste disposal machine in hospitals, which can interfere with cost predictions.

The study also focuses on the model's sensitivity to parameter changes, particularly in the context of sensitivity analysis. The study provides confidence in the model's stability, with most data points falling inside a 95% confidence interval. This shows that the model's predictions are consistent and stable across various parameter values.

The model predictions can be used to decide the size and location of the medical waste storage unit. It can also assist in choosing the appropriate type and size of disposal machine based on the predicted waste volumes. Furthermore, the model will make it easier to implement safe and sustainable procedures that protect the well-being of patients and staff. Estimating disposal expenses will reduce the disposal costs either by the hospital's disposal machine or by the external disposal service. Furthermore, the model will help hospitals prepare for the predicted increase in patient numbers. The model supporting rescheduling waste disposal is based on which departments generate the most waste. This optimization will guarantee that efficient waste management procedures are implemented.

One limitation of the paper, which may be addressed in future work, is the absence of research into the causes of excessive waste generation in specific departments. Additionally, there is potential for further development and integration of recycling practices within the model and the hospital's waste management system.

In conclusion, integrating system dynamics modeling into this study results in a comprehensive and coordinated approach to healthcare waste management. This approach considers environmental, epidemiological, and economic dimensions, providing a versatile tool to help hospital administrators, policymakers, and waste management professionals optimize resource allocation, reduce expenses, and improve patient and healthcare staff safety, particularly during crises like the COVID-19 pandemic.

Conflict of Interest

The authors declared no potential conflicts of interest concerning this article's research, authorship, and/or publication.

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AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

Appendix A

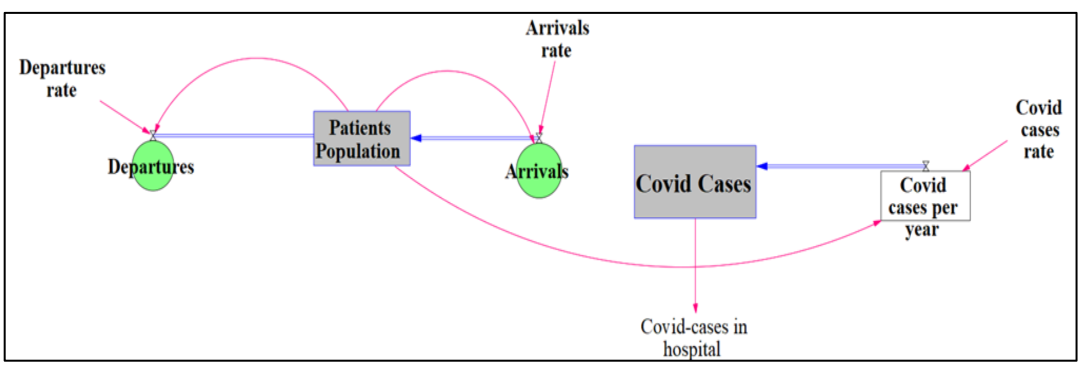

Figure 1S. Initial data integration: the foundation of the system dynamics model with COVID-19 and patient volume metrics.

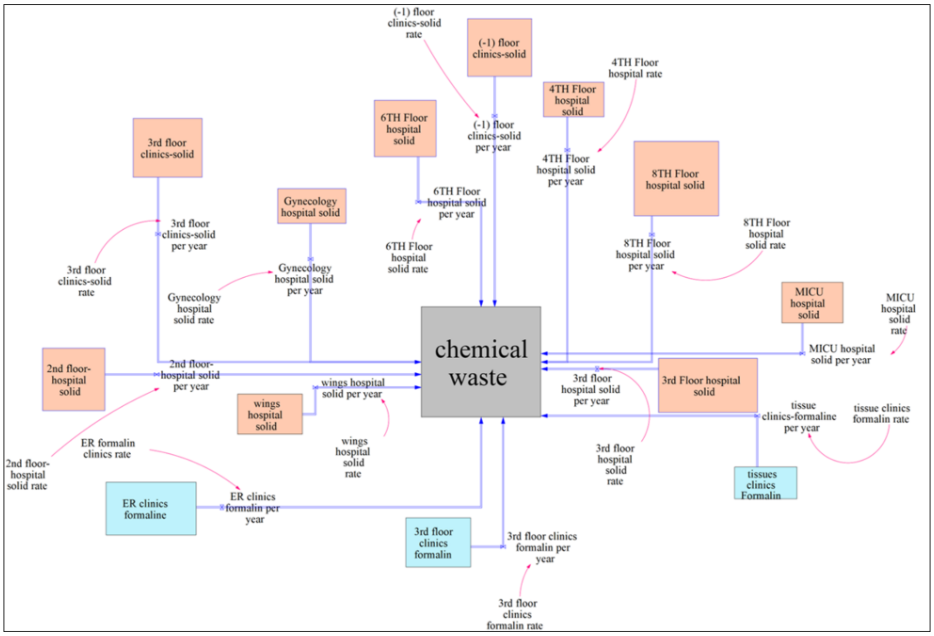

Figure 2S. The solid and formalin chemical waste flow model.

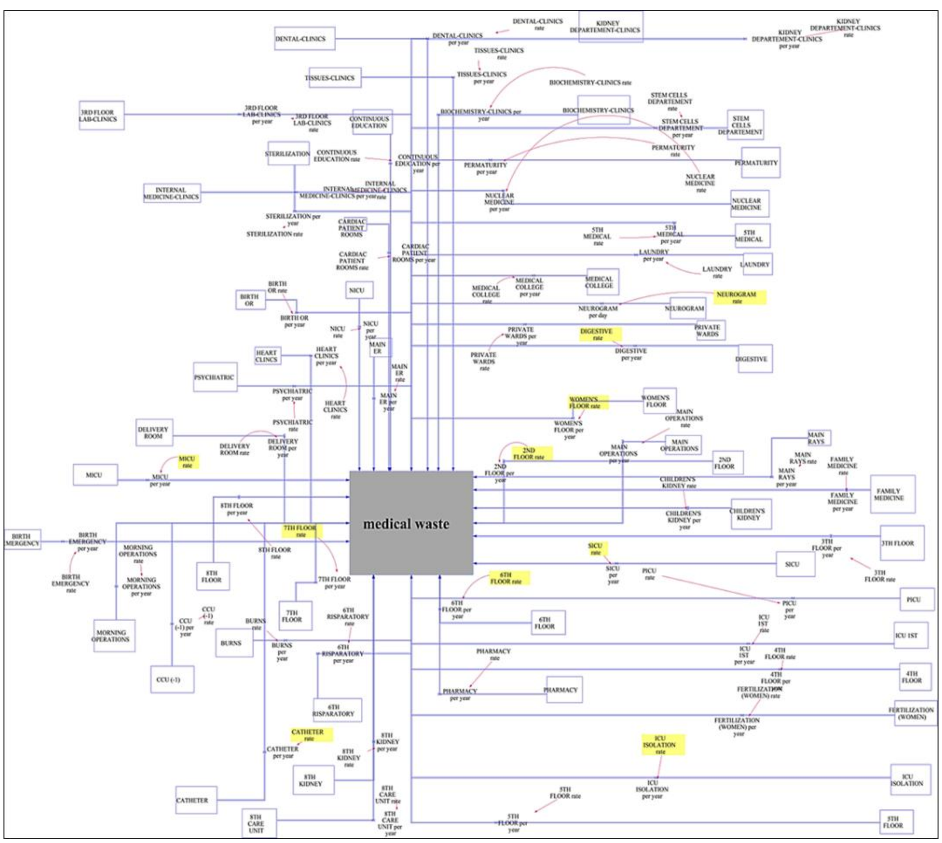

Figure 3S. Generic medical waste management model including variables and COVID-19 impact.

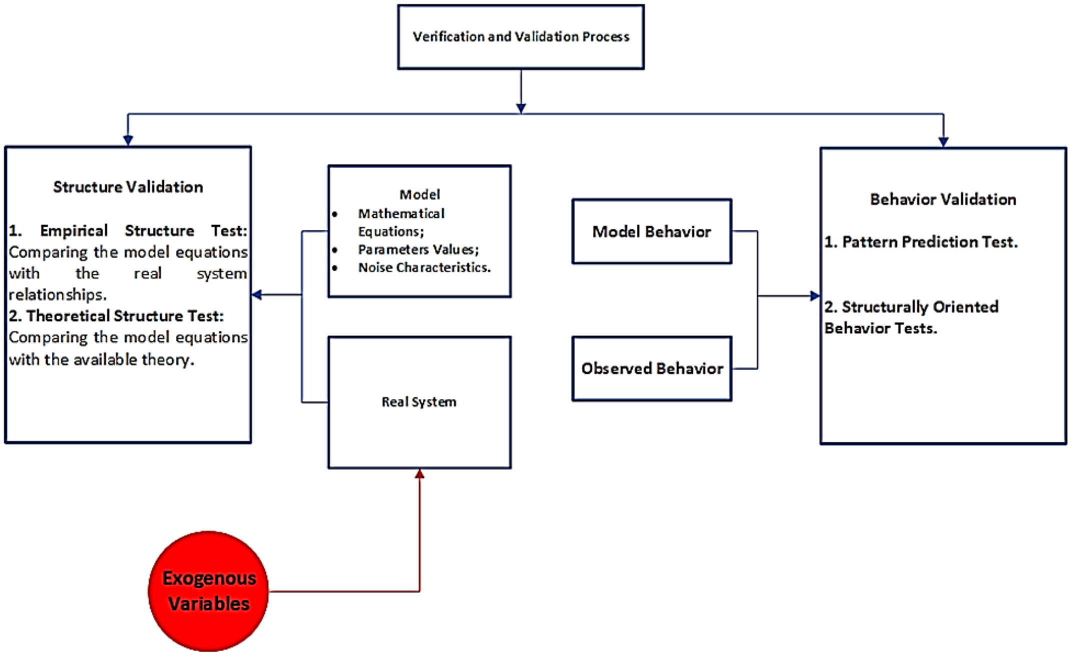

Figure 4S. System dynamics model validation process.

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