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Dental Clinic Inventory Management with Monte Carlo Simulation

Rojas González N.[1], Ortiz Ortiz C.[2*] ,Velasco Peredo J. [3] ,Gutiérrez Ramos A. [4],Torres Mendoza R. [5]

[1,2,3,4 and 5]Facultad de Ingeniería, UNAM, Av. Universidad 3000, Coyoacán, Ciudad de México, México

[*]nathalyrojgon@gmail.com

Abstract

This paper presents a novel simulation-based methodology developed in Python for optimizing inventory management in dental clinics. Utilizing Monte Carlo simulation, the approach minimizes inventory costs and ensures high levels of patient service by accounting for demand uncertainty. A case study of a dental clinic network showcases the methodology's effectiveness in determining optimal inventory levels that balance service and cost considerations. The study introduces a new approach by modeling the distribution system of a dental clinic network as retail and employing Monte Carlo simulation to address demand uncertainty, which has not been previously reported. This unique methodology offers practical implications and can be extended to enhance inventory management and patient care in various healthcare settings. The proposed methodology optimizes inventory management in dental clinics through Monte Carlo simulation, striking a balance between inventory costs and patient service levels. Furthermore, it introduces new insights into modeling dental clinic networks and offers potential applications to improve inventory management in healthcare settings, particularly in the context of small and medium-sized enterprises (SMEs).

Keywords: Inventory management, Monte Carlo simulation, Dental clinics, Healthcare, EOQ model.

1. Introduction

Inventory management plays a crucial role in the effective functioning of healthcare supply chains. This is particularly important in dental clinics, where supplies and materials availability are essential to provide high-quality patient care. However, balancing the trade-off between ensuring an adequate supply of inventory for treatments and minimizing inventory costs is a difficult task. The challenges in inventory management in dental clinics include accurately predicting the demand for supplies, managing lead times, supplier performance variability, and maintaining adequate inventory levels. Failure to manage inventory effectively can result in stock outs, increased costs, and reduced patient satisfaction. To address these challenges, Monte Carlo simulation is a powerful tool that generates probabilistic forecasts and simulates different scenarios. By using this approach, organizations can determine the optimal levels of inventory that balance the trade-off between service level and inventory costs and ultimately optimize inventory management. In this article, we propose a simulation-based approach to determine the maximum and minimum levels of supplies inventories that balance the trade-off between service level and inventory costs in a network of dental clinics. We demonstrate the effectiveness of our methodology through a case study. The article is organized as follows. First, we provide an overview of inventory management in healthcare. Then, we discuss the challenges of inventory management in dental clinics and the benefits of using Monte Carlo simulation. Finally, we present our methodology and results, followed by a discussion of the implications and future research directions.

"Fábrica de Sonrisas" is a well-established dental clinic network that has been providing dental services in Mexico City since 2010. The network consists of four locations strategically located in different areas of the city, including del Valle Street, Insurgentes Avenue, Reforma Avenue, and División del Norte Avenue. The focus of this article is to analyze the clinic's top input investments that have proven to be crucial in generating approximately 80% of the network's revenue. By identifying these investments, the clinic can further optimize its resources and ensure that it continues to provide high-quality dental care to its patients while maintaining its financial stability.

According to data from INEGI (DENUE, 2021), dental clinics in Mexico City are divided into private and public sectors. Private sector clinics have an occupation rate of 99%.

The inventory management process of the "Fábrica de Sonrisas" dental clinic network lacks a specific policy. Inventory management is carried out manually, and inventory control is done through Excel spreadsheets. This can lead to errors and inconsistencies if not properly managed. The inventory management process relies heavily on clinic employees, who are responsible for making purchases based on stock levels. However, this approach can lead to overstocking or stock-outs, which affects the overall cost-effectiveness of inventory management. To optimize inventory management, it is important for the clinic network to implement a comprehensive inventory management policy that includes clear guidelines on forecasting demand, establishing optimal inventory levels and monitoring inventory performance.

We present the study on the design and simulation of an inventory system for the main inputs of dental clinics, aimed at selecting an inventory policy that meets the needs of the "Fábrica de Sonrisas" company.

Using a model programmed in Python, we demonstrate that the selected inventory policy for the key products ensures minimal stock-outs while reducing costs. Our research aims to contribute to the optimization of inventory management in dental clinics and to offer a practical solution that can be implemented in similar settings. The results of our study may be of interest to professionals and researchers working in the field of inventory management, as well as to practitioners seeking to improve their inventory control practices.

The paper is structured into the following sections:

Section 1 "Introduction": This section establishes the overall context of the article and provides an overview of inventory management in dental clinics. The study's objectives are highlighted, and specific challenges faced by dental clinics in this area are mentioned.

Section 2 "Inventory Management in the Healthcare Context": This section provides an overview of inventory management in the healthcare field. Key concepts are discussed, and the unique aspects of inventory management in dental clinics are highlighted.

Section 3 "Benefits of Monte Carlo Simulation in Inventory Management": This section explores the benefits of using Monte Carlo simulation in inventory management in detail. The fundamentals of this methodology are explained, emphasizing its advantages in terms of cost optimization and patient service levels.

Section 4 "Case Study": In this section, a case study of the "Smile Factory" dental clinic network is presented. The application of the proposed methodology in this network is described, and the results obtained are analyzed. Relevant aspects of the case are highlighted, and conclusions derived from the study are presented.

Section 5 "Discussion and Future Directions": This section discusses the implications of the case study findings and suggests possible future research directions in the field of inventory management in dental clinics. Practical implications are explored, and areas for improvement and development in this area are suggested.

2. State of the art

Inventory management is one of the most important decisions faced by many companies. These companies include not only retailers that stock products for sale to customers, but also companies that supply other companies. (Taylor, 2011).

One key task of supply chain management is the integrated planning and control of the inventory of all actors in the supply chain, from the source of supply to the end user, to reduce the overall inventory costs while improving customer service (Ellram 1991).An order policy should therefore not only minimize overall inventory costs, but also aim at mitigating or even eliminating the bullwhip effect, albeit these two goals are often interrelated. (Preil et al., 2021).

When customer demand is assumed to be known, the resulting models are called deterministic models. If customer demand is known and the order quantity has been determined, then specifying when the orders should be placed is relatively easy. A more realistic situation occurs when customer demand is uncertain.

In this case, the decision on when to place orders becomes more difficult. Orders should be placed early enough so that the chance of running out before they arrive is small. These more difficult problems require probabilistic inventory models.(Losee, 2021)

The dynamic environment in these inventory models refers to the fact that some changes in scarcity, unexpectedly over time, may be due to the uncertainty of factors such as demand, supply times, prices and costs, among others, associated with the management of these inventories. (Valencia-Cárdenas et al.,2015)

Inventory management in healthcare has received significant attention in the literature due to its crucial role in providing high-quality patient care while minimizing inventory costs (Huang et al.,2018). In dental clinics, where the availability of supplies and materials is essential, inventory management is particularly important (Krishnamoorthy et al.,2013). The challenge lies in accurately predicting the demand for supplies, managing lead times and supplier performance variability, and maintaining adequate inventory levels (Huang et al., 2018). Failure to manage inventory effectively can result in stockouts, increased costs, and reduced patient satisfaction (Krishnamoorthy et al., 2013).

To address these challenges, various inventory management techniques have been proposed in the literature, including demand forecasting, safety stock management, and supplier performance evaluation (Shahriari et al., 2021). The use of common techniques like the EOQ formula presents several limitations, being the lack of stochasticity the most noteworthy. (Teter et al., 2019) Thus, in recent years, the use of advanced analytical techniques, such as Monte Carlo simulation, has gained popularity in inventory management (Huang et al., 2018). Monte Carlo simulation is a powerful tool for addressing uncertainty in demand and lead times by generating probabilistic forecasts and simulating different scenarios (Saffari et al., 2019). Monte Carlo simulation repeats a lot of random experiments to find out the possible outcomes. (Kuncova et al., 2015)Several studies have applied Monte Carlo simulation in healthcare inventory management, including the optimization of blood product inventory in hospitals (Huang et al., 2018), the determination of optimal inventory levels for medical supplies in emergency departments (Saffari et al., 2019), and the management of dental supply inventory (Krishnamoorthy et al., 2013). These studies have shown that Monte Carlo simulation can effectively optimize inventory management in healthcare settings, resulting in improved patient care and reduced costs.

Monte Carlo simulation has emerged as a powerful tool in the field of inventory management. By simulating various scenarios, it allows managers to better understand the impact of different inventory policies on their supply chain performance.

A study by Chen and Simchi-Levi (2014) demonstrated the effectiveness of Monte Carlo simulation in defining optimal inventory policies for a multi-echelon supply chain. The authors used simulation to test the performance of different inventory policies under various demand and lead time scenarios and found that a policy that minimized the total cost of inventory while maintaining a desired service level was the most effective.

Another study by Berrada and Kedad-Sidhoum (2017) used Monte Carlo simulation to optimize inventory policies for a perishable product with a finite shelf life. The authors used simulation to generate demand scenarios and tested various inventory policies to find the optimal balance between product availability and waste reduction.

In a more recent study, Zolfaghari & Zanjirani (2020) used Monte Carlo simulation to optimize inventory policies for a multi-product, multi-echelon supply chain with uncertain demand and lead times. The authors used simulation to generate demand scenarios and tested various inventory policies to find the optimal balance between inventory holding costs and stockout costs.

Overall, these studies demonstrate the effectiveness of Monte Carlo simulation in defining optimal inventory policies for various supply chain scenarios. By simulating different scenarios, managers can make more informed decisions about inventory policies that balance the tradeoff between inventory holding costs and stockout costs.

Our proposal introduces a novel simulation-based approach to optimize inventory management in dental clinics, specifically addressing the challenge of demand uncertainty. This research gap represents a significant opportunity for advancing the field of inventory management in dental clinics and improving patient care outcomes.

One key aspect that sets our proposal apart is the incorporation of Monte Carlo simulation. This advanced technique allows us to model and simulate various demand scenarios, capturing the inherent variability in patient flow, treatment demand, and supply chain disruptions. By considering these uncertainties, our methodology offers a more accurate representation of real-world conditions, enabling dental clinics to make informed decisions regarding inventory levels and resource allocation.

Furthermore, the unique perspective provided by our approach lies in the modeling of the distribution system of a dental clinic network as retail. While existing literature has primarily focused on generic healthcare inventory management, our proposal recognizes the specific characteristics and challenges faced by dental clinics. By tailoring the approach to this context, we can account for factors such as specialized equipment and materials, varying treatment procedures, and the dynamic nature of patient demand within dental clinics.

By addressing these specific challenges, our proposal aims to enhance the efficiency and effectiveness of inventory management practices in dental clinics. Through the determination of optimal inventory levels that balance service level and inventory costs, we can help clinics achieve cost savings while ensuring a high level of patient service and satisfaction. Ultimately, this will contribute to improving patient care outcomes and the overall operational performance of dental clinics.

Our proposal not only fills a significant research gap in the field but also offers several key advantages. By incorporating Monte Carlo simulation and tailoring the approach to the specific context of dental clinics, we provide a comprehensive and innovative solution to address the challenges of demand uncertainty. By enhancing inventory management practices, we aim to optimize resource allocation, reduce costs, and improve patient care outcomes in dental clinics.

3. Materials and Methods

For this article, we had considered the seven steps to develop and implement a simulation model based on the article 'How to build valid and credible simulation

hypotheses.

7. The results are analyzed, and recommendations are made based on those results, which may inform decision-making processes or suggest areas for further research.

3.1. Process

To understand the system, the transformation process is diagrammed in this way, the following system operations were identified. (Figure 2).

According to the transformation process, having an accurate inventory policy is critical to ensuring that the clinic operates smoothly and efficiently. A proper inventory policy will help the clinic manage its supplies, reduce costs, and maintain a high level of patient care.

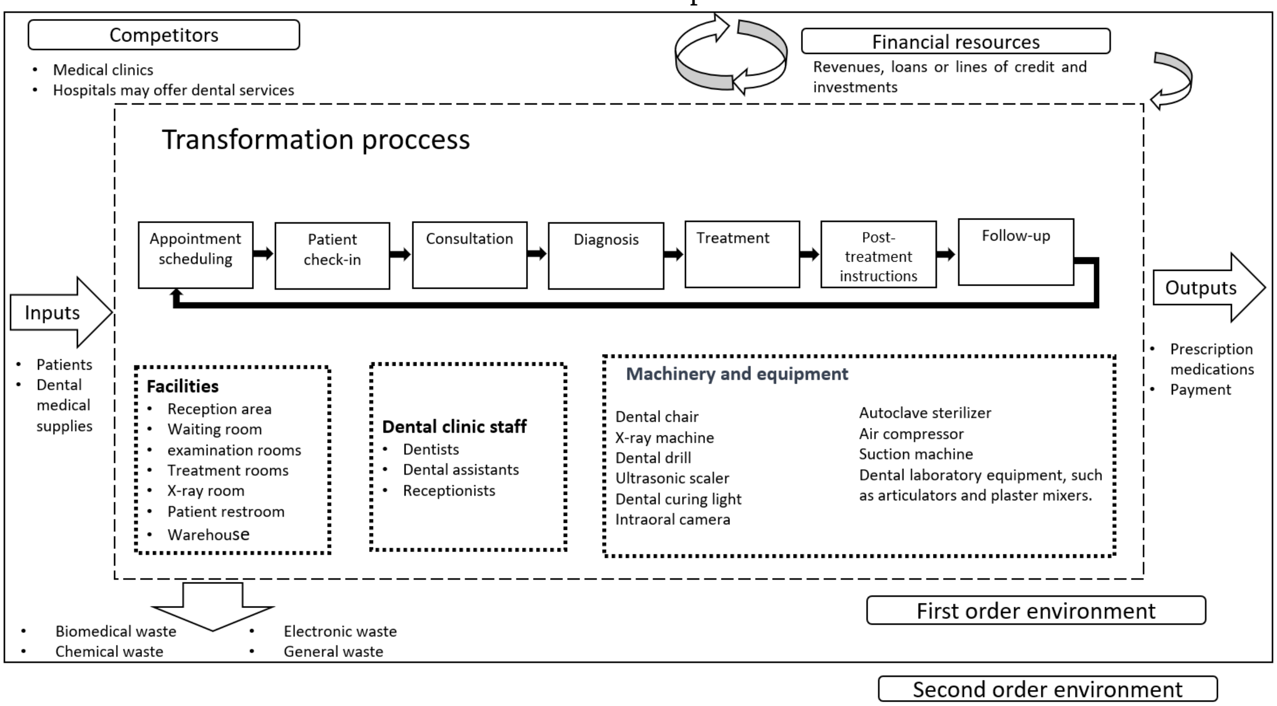

Figure 1. Transformation process of a dental clinic

models by Averill M. Law, those steps are:

1. To formulate the problem of interest.

2. To collect data to support the development of the simulation model.

3. To build a conceptual model that describes the system being simulated.

4. To develop a computer model based on the conceptual model.

5. To verify and validate the model to ensure its accuracy.

6. To conduct experiments using the simulation model to explore different scenarios and test

One of the most significant benefits of having an accurate inventory policy is that it will allow the clinic to manage its suppliers effectively. Also, can help the clinic reduce costs. Overstocking supplies can tie up valuable capital and lead to wastage, as some supplies may expire before they can be used.

Conversely, understocking can lead to lost revenue and potential damage to the clinic's reputation if it cannot meet the needs of its patients. Patients expect to receive top-quality care when they visit the dental clinic, and having the right supplies on hand is essential to providing that care.

To propose an effective inventory policy for "Fábrica de Sonrisas," it's imperative to have a deep understanding of their supply ordering process.

The input ordering process of "Fábrica de Sonrisas" involves several steps, including identifying the need for supplies, creating a purchase order, selecting a vendor, placing the order, tracking the order, receiving and reviewing the order, controlling the inventory, and ultimately delivering the services to their clients.

At "Fábrica de Sonrisas", if an order is found to be incomplete upon delivery, the clinic immediately contacts the supplier to notify them of the missing items and request that they be reordered. Once the supplier has been notified, they are expected to promptly reorder the missing items and deliver them as soon as possible to minimize any impact on the clinic's operations.

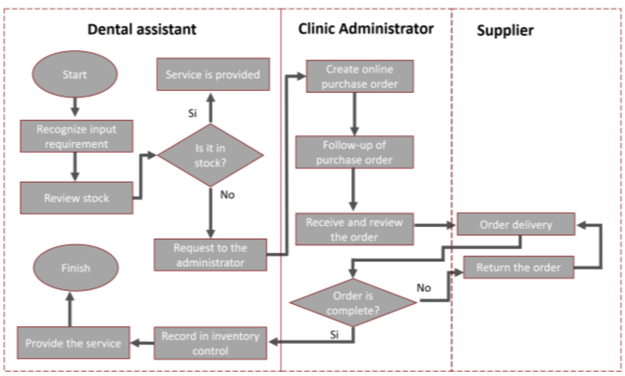

Figure 2. Input ordering process

Here is an overview of how the supply ordering process works within the network of "Fábrica de Sonrisas" in Mexico City. The largest clinic is responsible for placing the orders, and the supplies are then delivered to this clinic. The supplies are then distributed from the largest clinic to the other three branches located in Mexico City.

This process is similar to a retail chain's operation, where a central warehouse receives supplies and then distributes them to different stores. By gaining a thorough understanding of this process and analyzing the inventory levels at each branch, we can propose a more efficient inventory policy that can help "Fábrica de Sonrisas" optimize their supply chain and improve overall operations.

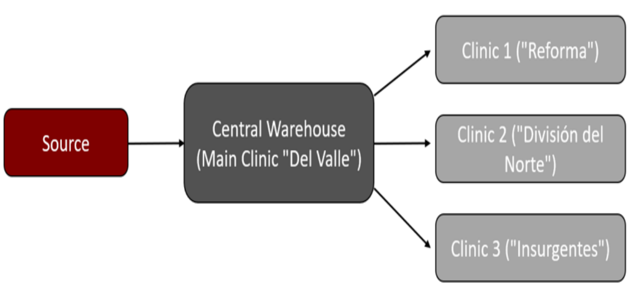

Figure 3. Distribution system of "Fábrica de Sonrisas".

3.2. ABC analysis to inventory management

A way to classify items into different groups is ABC analysis. The three categories named 'A', 'B', and 'C' respectively, lead to the term ABC analysis. Thus, the items are grouped in order of their estimated importance. (Kessentini, Ben Saoud, Charra, & Sboui,2016).

Assumptions:

- The ABC analysis will solely focus on the supplies required for the clinic's most sought-after service, which is the application of brackets.
- Bracketing requires 11 distinct types of items.
- Precising inventory stock and cost data for each item are readily available.

Input variables:

- Unit cost per item
- Stock per item

Decision variables:

The decision variables used in ABC inventory analysis are based on the value of the items and are determined as follows:

- A-items: These are the most important and valuable items in the inventory. Typically, they account for a small percentage of the total inventory items but contribute to a large percentage of the total inventory value. The decision variable for A-items is to closely monitor their stock levels and order them frequently to ensure that they are always in stock.
- B-items: These items have moderate importance and value, accounting for a moderate percentage of the total inventory items and value. The decision variable for B-items is to monitor their stock levels but not as closely as A-items. They should be ordered less frequently than A-items but more frequently than C-items.
- C-items: These are the least important and valuable items, typically accounting for a large percentage of the total inventory items but contributing to a small percentage of the total inventory value. The decision variable for C-items is to maintain a low stock level and order them infrequently, as they do not have a significant impact on the overall inventory value.

The unit cost per item and stock per item are used to calculate the total value of each item in the inventory, which is then used to classify the items into A, B, or C categories.

3.3. Economic Order Quantity (EOQ) Model

The simulation is based on some assumptions taken from the EOQ model, which are as follows:

- The inventory management for the dental clinic follows the Economic Order Quantity (EOQ) model without shortages.
- Historical records were used to obtain data of 20022. A weekly demand for 48 weeks, from

Monday to Saturday, was considered for the analysis.
- The items in the ABC analysis category for inventory management are bracket and dental bibs.

Input variables:

- Item's demand
- Item´s cost

Decision variables:
The decision variable for this model is the number of units to order or quantity to order (Q), which is a positive integer.
The cost parameters are known with certainty:
• c = unit cost ($/unit)
•i = annual cost of maintaining inventory (% per year)
• h= ic = annual cost of holding inventory ($/unit per year)
• A= ordering cost ($/order)
• D= weekly demand
• K(Q)= average annual cost according to batch size

$$K(Q) = cD + \frac{AD}{Q} + \frac{hQ}{2} \quad (1)$$

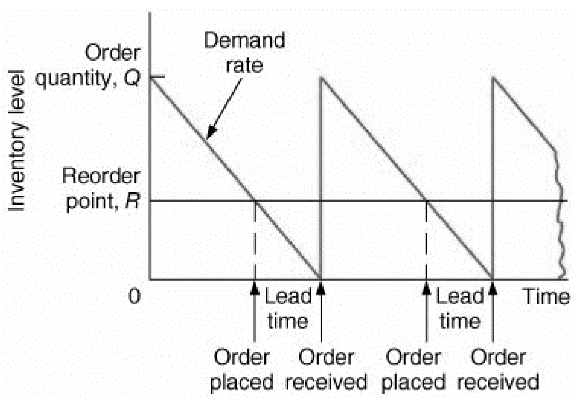

Figure 4. The basic EOQ Model. (Anderson, Sweeney, & Williams, 2019)

Indicators of performance:
- Reorder point
- Average price
- Holding cost
- Ordering cost
- Shortage cost

3.4. Python program simulation model

The Inventario function in Python simulates inventory control for a product, using the NumPy, Matplotlib, and Pandas libraries. It takes three arguments: ts (the length of the simulation in weeks), s (the reorder point), and S (the order-up-to level).

To start the simulation, the function sets various parameters such as the cost of ordering, cost per unit of the product, and cost of holding inventory. It also defines two helper functions: leadTime, which always returns zero since lead time is constant at two days, and demandRandom, which generates a random distribution of demand.

During the simulation loop, the function initializes a dictionary called amtD and a list called sim to store simulation data. At the beginning of each week, the function calculates the inventory position based on the beginning inventory level and the outstanding orders from previous weeks. If the inventory position is less than the reorder point, the function places an order. At the end of the week, the function computes the inventory level, along with the costs associated with ordering, holding inventory, and disruptions.

After the simulation is complete, the function prints the total cost of inventory control and returns a Pandas Data Frame with the simulation results.

3.5. Data collection

To develop our simulation-based approach for optimizing inventory management in the dental clinic, we first needed to collect accurate and reliable data on demand, lead times, and supplier performance for each item in our inventory. We collected this data through a combination of electronic records and manual tracking, and for items that were not recorded electronically, we manually tracked their demand. We also collected information on the time it took for each item to be delivered from the supplier to each clinic, using manual tracking and communication with suppliers.

Data on the demand for supplies and inventory were collected through information provided by the owner of the dental clinics and a written record of all appointments. This record contains details on the services provided throughout the year 2022.

To analyze the data, it was classified by service type to obtain the number of services provided in 2022. The results are presented in Table 1. This process allowed us to gain a deeper understanding of the clinic's demand patterns and identify which supplies are needed most frequently.

By using a combination of owner-provided information and appointment records, we were able to gather a comprehensive dataset that accurately reflects the clinic's inventory and demand needs. The data analysis provided valuable insights into the clinic's operations and will inform our recommendations for improving inventory management.

We identified 58 types of services provided by the network of dental clinics in 2022. Among all services, 4,186 events were identified. However, for the purposes of this article, we only focused on 12 services that accounted for 80% of the service events in 2022. Out of these 12 services, we chose the service with the highest number of events as a first approximation. In this case, it was the application of metal brackets.

Table 1. Number of events by services during 2022 of the "Fábrica de sonrisas" dental clinic network.

Service	Number of events per year 2022
Metal bracket application	502
Complete dental consultation	470
Check-up consultation	442
Dental cleaning	292
Implant/bichectomy evaluation	282
Zirconium implant	249
Bichectomy and Lipectomy	248
Endodontics	185
Deep Resin	174
Orthodontic Consultation	171
Minimally invasive resin	112
Zirconia Crown	110

To identify the specific supplies and quantities needed for each service offered by the dental clinics, additional information was gathered from clinic staff through a series of targeted questions. This information was obtained in addition to reviewing appointment records and information provided by the owners. The aim of the questioning was to obtain an exhaustive list of supplies needed for each service and the quantities required. It is worth noting that the quantities were estimated by the dentists and dental assistants of the clinics, due to a lack of standardization of processes. Therefore, it is important to acknowledge that the accuracy of the quantities cannot be guaranteed. The comprehensive results of this research are presented in Table 2

Table 2. Detail of supplies required for the service of application of metal brackets.

Item	Article
Brk-1	Dental bibs
Brk-2	Brackets
Brk-3	Resin for brackets
Brk-4	Gloves
Brk-5	Prophylaxis paste
Brk-6	Sodium hypochlorite
Brk-7	Mouth guard
Brk-8	Prophylaxis brush
Brk-9	Ejectors
Brk-10	Adhesive
Brk-11	Etching acid

After identifying the necessary supplies for each service provided by the clinic, we calculated the initial inventory quantity for each type of supply. We also collected data on the prices of these supplies by consulting with clinic staff and external suppliers. To determine the critical supplies for the clinic's operations, we conducted an ABC analysis that classifies supplies based on their frequency of use and value. Category A items are the most important and require the most attention in inventory management. The ABC analysis results are presented in Table 3, which shows 10 inputs classified as category A.

However, for the purposes of this article, we will focus on the three most expensive inputs dental bibs and brackets kit. Future research can analyze the other inputs classified as category A.

Table 3. ABC analysis results

Item	Article	% Acumulated value	% Acumulated inventory
Brk-1	Field	57.9%	35.9%
Brk-2	Brackets kit	75.3%	36.2%
Brk-3	Resin for brackets	90.7%	36.4%
Brk-4	Gloves	96.0%	55.7%
Brk-5	Prophylaxis paste	97.0%	58.5%
Brk-6	Sodium hypochlorite	97.8%	86.1%
Brk-7	Mouth guard	98.6%	94.4%
Brk-8	Prophylaxis brush	99.1%	97.2%
Brk-9	Ejectors	99.6%	97.2%
Brk-10	Adhesive	99.9%	100.0%
Brk-11	Etching acid	100.0%	100.0%
Total percentage		100.0%	100.0%

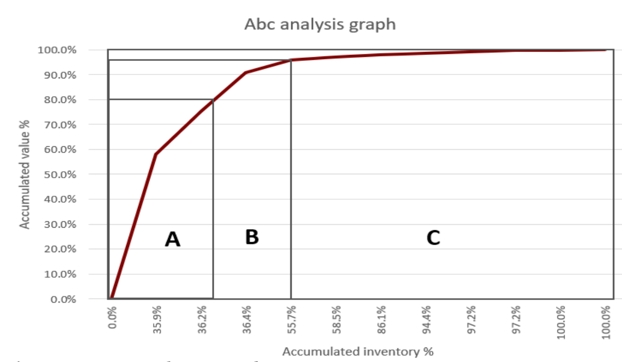

Figure 5. ABC analysis graph

We analyzed the data from the demand for each service in 2022 and the inputs required for each service, as well as the inventory control records and purchase orders to estimate the demand distribution for two specific inputs dental bibs and brackets kit. Figure 4 presents the results of this analysis.

To estimate the demand for each input, we multiplied the historical demand data for each type of service by the estimated quantity of each input required for that service. . Adding up the estimated distribution demand for each input across all services provided us with an overall estimate of the demand for that input.

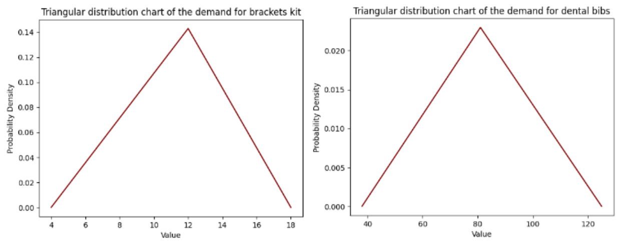

Figure 6. Distribution of demand for dental bibs and bracket kits.

To calculate the costs associated with inventory management, we first identified the costs of ordering and holding inventory. For the cost of ordering, we interviewed personnel involved in the ordering and receiving process to determine their salaries and the time it takes to perform these activities. Based on this information, we estimated the cost of ordering and also considered the cost of issuing the purchase order.

The inventory maintenance cost was estimated by calculating the cost of capital, which was determined by multiplying the unit cost of the input by the equilibrium interbank interest rate (TIIE). We also estimated the cost of physical space by finding out the cost of renting the space and dividing it by the square meters. Finally, we multiplied this value by the amount of space occupied by each entry.

The results of these calculations are presented in Table 4 and Table 5.

Table 4. Inventory order costs by input (figures expressed in Mexican pesos)

Article	Unit cost	Wage cost	Costs to issue the order	Total
Dental bibs	17.9	8.4	3.1	11.5
Brackets kit	700	8.4	3.1	11.5

Table 5. Inventory holding costs by input (figures expressed in Mexican pesos)

Article	Cost of capital	Cost of physical space	Total
Dental bibs	2	0.3	2.3
Brackets kit	78.7	0.3	79

3.6. Simulation and scenarios

To develop the simulation model, we used an influence diagram as shown in Figure 5 to consider the various factors that impact the total cost of inventory. The simulation was conducted over a period of 48 weeks, which approximates one year of business days, excluding vacation periods and holidays. For the purposes of this simulation, we focused on items dental bibs and brackets kit, as outlined in the previous section.

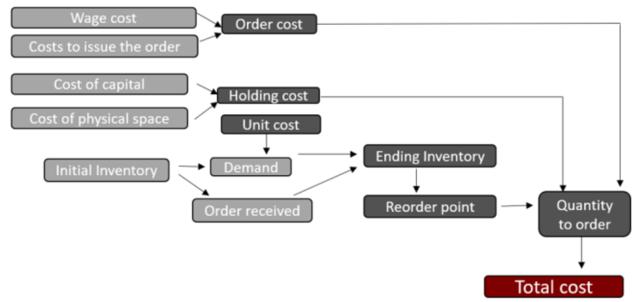

Figure 7. Influence diagram of total inventory cost

A tailored-made simulation program in Python was developed in order to have total control of the inputs and consider specific processes related to the actual “Clinica de sonrisas” inventory management.

The simulation starts by setting the fixed parameters such as fixed costs, variable costs, inventory holding costs, and the initial inventory level. Additionally, several inventory management policies were defined, which include reorder point and a fixed order quantity. The stochastic component of the simulation refers to the demand for each item, which is represented by a random distribution.

Based on the initial parameters and the demand at every time step the EOQ model and the associated costs are computed.

The Monte Carlo simulation reports the descriptive statistics for the ordering cost, variable cost and total cost based on 1,000 iterations.

Since the ordering cost is irrelevant compared to the holding cost and variable cost, the optimization of the inventory policy would provide the reorder point needed to avoid disruptions of the operations at the dental clinic, i.e., to not run out of supplies, at a minimum cost.

By performing a grid search along the inventory policies, the most efficient inventory policy is determined for each item. This was done based on several scenarios, with each scenario consisting of varying the reorder point and fixed order quantity for each input from 1 to n-1, where n is the maximum inventory level determined for each input (as shown in Table 6). By testing multiple scenarios, we were able to determine the optimal inventory policy for each input, minimizing the overall cost of inventory management.

Table 6 presents the recommended maximum inventory levels for "Dental bibs" and "Braces kit". These values indicate the maximum quantity of each item that should be maintained in inventory to ensure an adequate supply in the dental clinic. It is crucial to consider these maximum inventory levels when managing and controlling inventory to strike a balance between product availability and associated costs. By adhering to these recommended levels, the clinic can optimize inventory management practices and ensure a consistent supply of dental bibs and braces kits.

Table 6. Maximum inventory level per item.

Item	Maximum inventory level
Dental bibs	900
Braces kit	400

4. Result and Discussion

To optimize our inventory policy, we experimented with different reorder points for both inputs filed and brackets kit. We then calculated the average cost for each policy and determined the mean, to identify the most efficient strategy.

Table 7 provides a comprehensive summary of the simulation results for dental bibs inventory, highlighting key metrics related to order cost, variable cost, holding cost, and total cost. These metrics offer insights into the financial implications of managing.

The data in the table reveals the following findings:

1. Count: The count indicates the number of data points or observations considered for the analysis, which in this case is 1000. This large sample size enhances the reliability and representativeness of the results.

2. Mean: The mean represents the average value for each cost metric. For example, the mean order cost is 141.49, the mean variable cost is 49514.14, the mean holding cost is 35631.82, and the mean total cost is 85287.46. These values serve as reference points for understanding the typical costs associated with managing dental bibs inventory.

3. Std: The standard deviation reflects the degree of variability or dispersion within the data. It quantifies how much the values deviate from the mean. For instance, the standard deviation for order cost is 8.18, for variable cost is 2540.86, for holding cost is 1241.57, and for total cost is 2168.85. A higher standard deviation indicates a wider range of costs, highlighting the potential variability in managing dental bibs inventory.

4. Min: The minimum values represent the lowest observed costs for each metric. In this case, the minimum order cost is 114.8, the minimum variable cost is 42247.68, the minimum holding cost is 32061.56, and the minimum total cost is 78896.74. These values provide insights into the lowest achievable costs in managing dental bibs inventory.

5. 25%, 50%, 75% (Quartiles): These quartiles divide the data into four equal parts, indicating the values below which a specific percentage of the data falls. For example, the 25th percentile (Q1) for order cost is 137.76, for variable cost is 47,822.18, for holding cost is 34,752, and for total cost is 83,844.67. The 50th percentile (Q2) represents the median, which is the midpoint of the data, and the 75th percentile (Q3) signifies the values below which 75% of the data fall. These quartiles provide insights into the distribution and range of costs associated with dental bibs inventory management.

6. Max: The maximum values indicate the highest observed costs for each metric. Notably, the maximum order cost is 172.2, the maximum variable cost is 57,704.36, the maximum holding cost is 39816.4, and the maximum total cost is 91,534.3. These values highlight the upper limits of costs that may be incurred in managing dental bibs inventory.

The significance of these results lies in their ability to inform decision-making processes regarding inventory management in dental clinics.

Table 7. Dental bibs inventory simulation results summary.

	Order cost	Variable cost	Holding cost	Total cost
count	1,000	1,000	1,000	1,000
mean	141	49,514	35,632	85,287
std	8	2,541	1,242	2,169
min	115	42,248	32,062	78,897
0.25	138	47,822	34,752	83,845
0.5	138	49,497	35,626	85,303
0.75	149	51,279	36,445	86,786
max	172	57,704	39,816	91,534

Table 8 presents a summary of the simulation results for the inventory of brackets kits. This table contains important metrics related to order cost, variable cost, holding cost, and total cost, which provide valuable insights into the financial aspects of managing brackets kit inventory.

The information in the table can be interpreted as follows:

- Count: The count value indicates the number of data points or observations considered in the analysis, which in this case is 1000. This sample size ensures the reliability and representativeness of the results.

- Mean: The mean represents the average value for each cost metric. For example, the mean order cost is 69.68, the mean variable cost is 395,488.49, the mean holding cost is 226,809.26, and the mean total cost is 622,367.43. These values serve as reference points for understanding the typical costs associated with managing brackets kit inventory.

- Std: The standard deviation measures the variability or dispersion within the data. It indicates how much the values deviate from the mean. In this case, the standard deviation for order cost is 2.93, for variable cost is 16,482.23, for holding cost is 5,028.79, and for total cost is 15,750.27. A higher standard deviation suggests a wider range of costs, highlighting the potential variability in managing brackets kit inventory.

- Min: The minimum values represent the lowest observed costs for each cost metric. For instance, the minimum order cost is 68.88, the minimum variable cost is 376,747.36, the minimum holding cost is 210,763.81, and the minimum total cost is 600,797.68.

These values provide insights into the lowest achievable costs in managing brackets kit inventory.

- 25%, 50%, 75% (Quartiles): These quartiles divide the data into four equal parts, indicating the values below which a specific percentage of the data falls. For example, the 25th percentile (Q1) for order cost is 68.88, for variable cost is 387,678.38, for holding cost is 223,415.22, and for total cost is 614,529.96. The 50th percentile (Q2) represents the median, which is the midpoint of the data, and the 75th percentile (Q3) signifies the values below which 75% of the data fall. These quartiles provide insights into the distribution and range of costs associated with managing brackets kit inventory.

- Max: The maximum values indicate the highest observed costs for each cost metric. Notably, the maximum order cost is 80.36, the maximum variable cost is 467,264.63, the maximum holding cost is 241,799.10, and the maximum total cost is 689,556.68. These values highlight the upper limits of costs that may be incurred in managing brackets kit inventory.

The purpose of this table is to provide a concise summary of the simulation results related to the inventory costs of brackets kits.

Table 8. Brackets kit inventory simulation results summary.

	Order cost	Variable cost	Holding cost	Total cost
count	1,000	1,000	1,000	1,000
mean	70	395,488	226,809	622,367
std	**3**	**16,482**	**5,029**	**15,750**
min	69	376,747	210,764	600,798
0.25	69	387,678	223,415	614,530
0.5	**69**	**391,581**	**227,047**	**619,130**
0.75	69	395,979	230,196	623,565
max	80	467,265	241,799	689,557

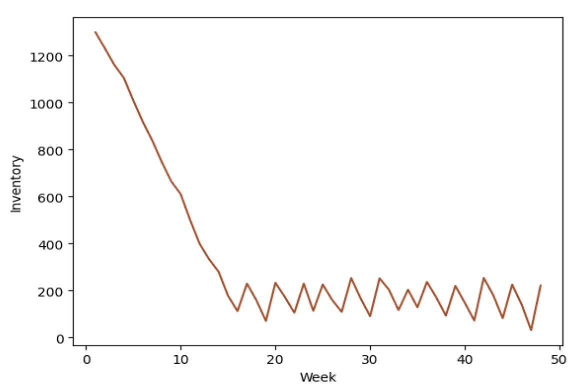

Figure 8. EOQ flow for dental bibs.

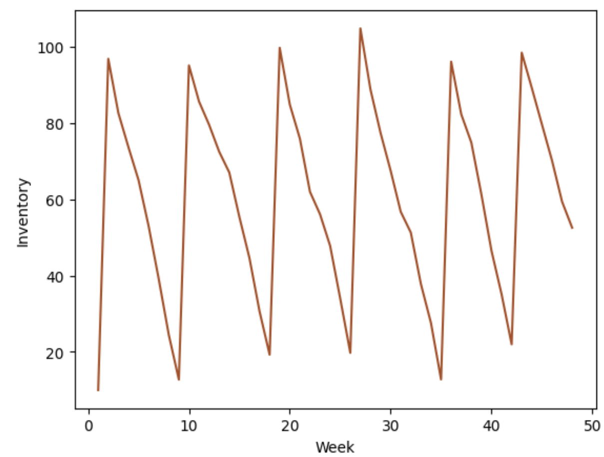

Figure 9. EOQ flow for braces kit.

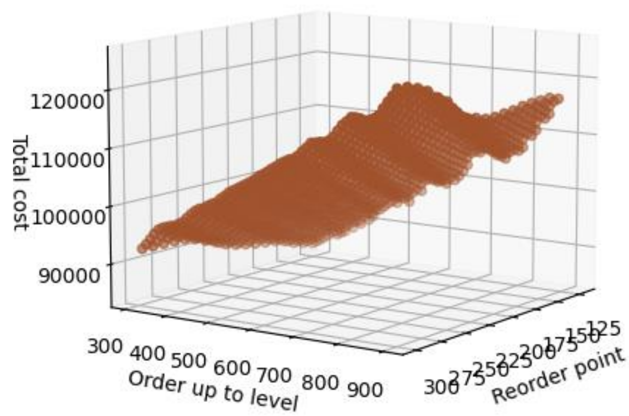

Figure 10. Inventory policies and total cost for dental bibs.

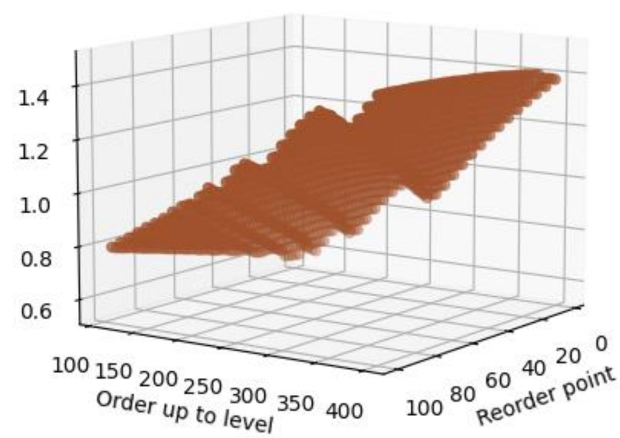

Figure 11. Inventory policies and total cost for braces kit.

After running the Python program, we were able to identify the minimum and maximum inventory levels for both the brackets kit and dental bibs, along with their respective costs. This allowed us to optimize our inventory management by minimizing costs while ensuring that we always have enough inventory to avoid stockouts. The detailed results are presented in

Table 9.

Table 9 presents the optimal inventory policies for two items: dental bibs and brackets kits. The table provides information on the minimum and maximum inventory levels for each item, as well as the corresponding total cost in Mexican pesos.

For dental bibs, the minimum inventory level is 130 units, while the maximum inventory level is 310 units. These values represent the recommended range of inventory quantities to ensure efficient management of dental bibs. The total cost associated with maintaining this optimal inventory policy for dental bibs is $85,287.00 Mexican pesos.

Similarly, for brackets kits, the recommended minimum inventory level is 24 units, and the maximum inventory level is 110 units. These values indicate the ideal inventory range for braces kits to support smooth operations. The total cost linked to maintaining this optimal inventory policy for braces kits amounts to $621,367.00 Mexican pesos.

These optimal inventory policies are crucial for dental clinics as they help strike a balance between having enough stock to meet patient demands while minimizing excess inventory and associated costs. By adhering to these recommended inventory levels, dental clinics can ensure efficient inventory management, avoid stockouts or overstocking, and optimize their financial resources.

Table 9. Optimal inventory policies (figures expressed in Mexican pesos)

Item	Min	Max	Total cost
Dental bibs	130	310	85,287
Braces kit	24	110	6,213,367

Conclusions

The findings of this study emphasize the significance of adopting a fixed inventory policy to reduce costs and ensure a constant supply of crucial inventory items for "Fábricas de Sonrisas." By utilizing the Monte Carlo simulation model and Python programming, valuable insights into inventory operations were gained, and the ideal reorder point for each inventory item was identified. Demand data analysis highlighted that some inventory items have lower demand, underscoring the importance of a well-defined inventory policy. Implementing the suggested measures would enable "Fábrica de Sonrisas" to optimize its inventory management process, increasing efficiency and profitability. These findings have far-reaching implications for businesses relying on inventory management and can serve as a blueprint for improving operational efficiency.

It is crucial for "Fábrica de Sonrisas" to implement an inventory control system that allows for better identification of supply and demand. This system should collect and analyze data on the consumption and availability of inventory items, improving forecasting and decision-making regarding inventory management. It is also important to regularly evaluate supplier performance, as it significantly impacts inventory management quality. Furthermore, it may be useful to assess the possibility of implementing technology-based solutions to improve inventory visibility and tracking accuracy. By implementing these measures, "Fábrica de Sonrisas" can enhance its inventory control and ultimately improve overall operations, resulting in increased patient satisfaction and financial stability.

In conclusion, the study has demonstrated the importance of effective inventory management for "Smile Factory" to ensure a constant supply of crucial inventory items while minimizing costs. The results provide valuable insights into optimal inventory control measures that can be adopted by the organization and applied by other companies. Implementing the suggested measures can increase overall operational efficiency and improve patient satisfaction while ensuring financial stability. However, it is essential to continuously monitor and evaluate the inventory management system's performance to identify areas for improvement and optimize its benefits fully. Future research can explore more advanced forecasting techniques, such as machine learning algorithms or time series analysis, to predict demand and optimize inventory levels. Another area of interest could be the implementation of real-time inventory tracking systems, such as RFID or other technologies, to improve inventory accuracy and reduce the risk of stockouts or overstocking. Additionally, the model can be replicated for all dental clinic network supplies.

Possible limitations of this study should be taken into consideration. Firstly, the findings and recommendations are based on the specific context of "Smile Factory" dental clinics. The applicability of the proposed inventory management measures may vary in different healthcare settings or organizations with distinct operational characteristics. Therefore, further validation and customization of the approach are necessary before implementation in other contexts.

Secondly, the study focuses primarily on demand uncertainty and the optimization of inventory levels. Other factors that may impact inventory management, such as supply chain disruptions, lead time variability, and external market factors, were not extensively explored. Future research could consider incorporating these additional variables to provide a more comprehensive understanding of inventory management in dental clinics.

Thirdly, the data used in this study relied on historical records and assumptions. While efforts were made to ensure data accuracy and representativeness, there may be inherent limitations and potential biases in the data collection process. The results and recommendations should be interpreted with caution, and ongoing data monitoring and analysis are necessary to validate and refine the proposed inventory management approach.

Furthermore, the Monte Carlo simulation model employed in this study relies on assumptions and simplifications to represent the complex dynamics of inventory management. Alternative modeling approaches or more sophisticated simulation techniques could be explored to enhance the accuracy and robustness of the results.

Lastly, the study did not extensively explore the financial implications and cost-benefit analysis of implementing the proposed inventory management measures. Further research could delve into the economic aspects, considering factors such as investment costs, cost savings, and return on investment to provide a more comprehensive evaluation of the proposed inventory management approach.

Despite these limitations, the study provides valuable insights and a foundation for further research and improvement in the field of inventory management in dental clinics. By acknowledging these limitations and addressing them in future studies, the understanding and effectiveness of inventory management practices in the healthcare industry can be further enhanced.

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