Analysis of orthopedic surgery service applying queues and simulation

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***Abstract*— At public hospital, there is a backlog of orthopedic surgeries waiting for attention. This backlog is due to factors such as population growth, insufficient medical and operational staff, and logistical challenges with supplies. This research examines patient arrival patterns for orthopedic services and their correlation with service demand. The study uses Arena® simulation software to construct a queuing model with infinite population and limited server capacity, simulating the service process. The aim is to analyze the dynamics of the processes and patient behavior. Once validated, the model will be refined in future investigations and serve as a decision-support tool to improve operational efficiency in the domain.**

Keywords - Waiting line, hospital, healthcare sector, simulation, Arena, forecasting, time series, Mexico, orthopedics, surgeries, cost reduction, service quality.

I. INTRODUCTION

The global incidence of hip fractures among older adults is rapidly increasing, estimated at 1.6 million cases. This presents a significant health challenge with far-reaching consequences for the population. Hip fractures, which result from brittle bone conditions, cause substantial morbidity, functional impairment, social repercussions, and economic burdens, along with a notably high mortality rate. Hip fractures have mortality rates and impact that are comparable to those of cardiovascular disease and cancer (World Health Organization, 2020).

The characteristics of hip fractures vary globally and are influenced by demographic aging and socio-economic factors. In developed countries, organizational efforts have focused on optimizing access to surgical interventions and fostering interdisciplinary collaboration (Dinamarca Montecino et al., 2017).The World Health Organization (WHO) predicts that there will be a significant increase in the number of hip fractures globally by 2050, with an estimated 6 million cases per year. This will put a strain on hospital resources.

Currently, surgical intervention is the preferred treatment for hip fractures, as conservative management can lead to longer hospital stays and a lower chance of returning to pre-injury functionality. Surgical approaches usually involve metallic fracture fixation devices or bone prostheses. Clinical Practice Guidelines (CPGs) recommend prompt surgical intervention, ideally within 36 to 48 hours post-event, to achieve the best possible outcomes.

Mexico's healthcare system suffers from fragmentation among its various organizations, which impedes sustainable development. This fragmentation emerged as each department developed independently. The overarching challenge confronting Mexico's healthcare system is to establish a harmonization mechanism that lays the groundwork for a universal healthcare system with equitable access (Mares, 2019).

Each healthcare sector has the capability to address patients requiring surgery. Government hospitals face challenges in accessing necessary supplies and a diverse range of implants. Orthopedic surgeries are in high demand and often have significant backlog days. Additionally, orthopedic surgeries in these hospitals are not categorized as immediate emergency care.Nationally, there has been an increase in service requests within the orthopedic field, partially due to demographic shifts. In this particular case, the problem arises from exceeding the permitted maximum utilization, resulting in patient dissatisfaction due to inadequate resource allocation.

II. LITERATURE REVIEW

A. Applications of Operations Research in healthcare organizations

Significant research has been conducted in hospitals and clinics in various countries, including Canada, Colombia, Cuba, and India, focusing on the implementation of Operations Research tools. These endeavors have made notable strides towards enhancing quality, coverage, and efficiency within healthcare institutions. Examples of research initiatives include efforts made at Sacré-Coeur Hospital in Montreal, Canada to implement initiatives targeting the replenishment system of clinical units and leveraging automation technology (Amaya et al., 2010).

In Colombia, El Tunal Hospital identified short-term improvement areas in laundry, pharmacy, and emergency departments using linear programming based on routing problems (Amaya et al., 2010).

The use of queueing theory in hospital operations has been explored in various studies. For instance, Vega de la Cruz (2017) investigated its applications in orthopedic consultations at Holguin Hospital in Cuba, while Yaduvanshi (2019) applied it to optimize waiting times at Fortis Escorts Hospital in Jaipur, India. Vega de la Cruz (2017) investigated its applications in orthopedic consultations at Holguin Hospital in Cuba, while Yaduvanshi (2019) applied it to optimize waiting times at Fortis Escorts Hospital in Jaipur, India.

The analysis of hospital data and the implementation of process improvement strategies in various health care institutions throughout Mexico have been the subject of much research from the fields of hospital logistics, statistical medicine, industrial planning, operations research, and health care quality. Examples of these avenues include:

- "Reducing Patient Waiting Times in the Emergency Department of a Hospital Using Simulation" by Silvia Medina, FI, Autonomous University of Baja California, Mexico, 2010.
- "Analysis of Emergency Services Applying Queueing Theory" by Gustavo Rodríguez, Technological Institute of Celaya, Mexico, 2017.
- "Applications of Hospital Logistics at the Ophthalmology Institute - ABC Medical Center" by Edgar Hernández, National Autonomous University of Mexico, 2023.

These case studies demonstrate how healthcare institutions can undertake innovative projects to improve performance. Like other organizations, healthcare institutions require investment in Operations Research development to achieve their objectives. Operations Research fundamentals encompass comprehensive planning of the service system based on patient needs and resource availability, production system planning, resource management, operational planning, procurement, and process analysis aimed at delivering quality healthcare services.

The case study describes a process in which patients first go through the emergency department and then move to a bed waiting area until their implant arrives and surgery, if necessary, based on their health condition, is performed. After the operation, patients recover in the bed area until they are discharged.

To improve service quality and economic aspects, it is recommended to use system modeling and simulation to aid in the decision-making process.

B. Queueing lines

Queueing theory aims to characterize the duration that a source spends within a system and in the queue. To achieve this, the theory requires minimal delivery data, including arrival rates and service rates, which denote the number of customers served per unit of time. The theory examines various configurations of the fundamental system and their behaviors under different input parameter qualities.

Kendall's notation summarizes the characteristics of queueing lines, including the distributions of arrival and service times, which are contingent upon probability distributions. The

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Poisson distribution is commonly used in this field, but other distributions can also be defined. Equation 1 below shows the probability distribution function of a Poisson distribution, using the average number of successes (λ) and the number of successes (k). The exponential distribution is commonly used for service rate. In a queueing line, the most important metrics are the customer's wait time in the queue and in the system, as they serve as key performance indicators (de la Mita., 2023).

Queueing theory is frequently used in the healthcare sector due to the critical importance of population health in urban areas, as shown in Table 1. Green's (2013) framework demonstrates the successful application of this discipline, highlighting its simplicity due to the minimal data requirements for defining a queueing line. However, it is also crucial to consider factors such as the development of service measurement indices and hospital occupancy. This is necessary for evaluating demand over time, across various areas and types of hospitals, as discriminatory application of queueing lines could introduce bias in system evaluation.

Furthermore, Veta et al. (2017) employed queueing theory to assess the performance of an orthopedic area in a hospital located in Havana, Cuba, utilizing a sample of 96 patients. The study included measurement indices for service quality and identified several areas within the orthopedic consultation process that require attention. Diagnosis was found to be a recurring application of queueing theory.

Queueing theory has been shown to be useful in developing prioritization models, as demonstrated by Queiroz et al.'s (2023) work. Their study established a service delivery model for patients, taking into account factors such as morbidity and urgency. Based on a series of queueing lines and employing a nearest neighbor heuristic method with dynamic variables, this model determines the optimal number of physicians, schedules to minimize waiting times, and efficient methods for utilizing available information. Hssanzadeh et al. (2022) made a noteworthy contribution by utilizing discrete simulation methods to distribute beds in a hospital to meet variable patient demand within the finite capacity of the hospital. This article highlights the utility of queueing theory for diagnosing and improving service delivery, as well as the importance of simulation as a tool for managing complex hospital systems. Simulation tools aid in the analysis of complex systems.

Some studies focus on understanding the behavior of agents within hospital waiting systems rather than improving them. Gino et al. (2018) emphasized the importance of studying humans in systems. Bolandifar et al. (2023) investigated patient abandonment from hospital queues due to dissatisfaction. This application provides valuable insights into discrete event simulation. It highlights the common issue of systems overlooking patient abandonment and only considering a constant influx of arrivals.

TABLE I. LITERATURE REVIEW RESUME

Subject	***Author***	***Description***
Enhancement and contentment in service.	Rönnerstrand et al, 2020	Investigation into the perception of the Swedish healthcare system in 2005 during policy changes aimed at reducing patient waiting times.
	Canales et al.,	This study focuses on using relative metrics to measure customer satisfaction in hospitals and its correlation with service waiting times.
Inquiry about simulation in Arena Simulation®	Askarian1 et al., 2016	This project aims to evaluate the quality of service provided by the emergency department of a hospital in Turkey.
	Kelton et al., 2015	Manual dedicated to simulation using Arena Simulation, featuring comprehensive explanations and illustrative examples of the available modules within the software.
Queueing systems in the healthcare sector.	Pandey et al., 2023	This study showcases the application of a queueing system modeled as a Poisson process to estimate the expected number of patients and waiting times per patient. The analysis of improvement strategies is facilitated by this model. Statistical analysis is crucial in identifying patient profiles and subsequently estimating their arrival and service times.
	Benedetto et al., 2023	The authors use regression methods to predict waiting times and patient arrivals, with a significant emphasis on collecting and carefully treating data to maintain the model's validity.
	Sarla et al., 2022	This document investigates patient arrivals at a hospital in India within the context of COVID-19. An M/M/1 queueing model is employed to identify critical processes for patient care..

Methodologies for enhancing services in hospitals and associated pull-type environments.	Krisjanis et al., 2010	This document outlines the process for requesting and attending surgery within a hospital. The service's behavior is then simulated to determine various methodologies, starting with scheduling activities to reduce underutilization of resources.

C. *Simulation*

Simulation aims to study the behavior of systems over time. It finds application across various fields of study, allowing observation of complex objects that would otherwise be challenging to analyze. Simulation models are categorized in discrete models that examine events where arriving units at a system are discrete and simulates queues and continuous models that analyze systems that continuously evolve over time and employs differential equations for their analysis. In simulation, it's crucial to define some basic concepts, Introducción a la Teoría de Colas. De la Mota Flores Idalia. México. UNAM, DIMEI 2023. Pp 152:

- System: The object of study recreated within the simulation tool.
- Model: Theoretical models utilized to determine the behavior of variables over time in simulation.
- State: The collective qualities of the system; in queueing lines, it can be defined by expected times in the system.
- Performance: The system's output, measurable and comparable in terms of an aggregated unit.
- Variable: Can be stochastic or deterministic, with their intervention in the system classified as exogenous or endogenous.

III. CASE STUDY: ORTHOPEDIC SURGERY SERVICE IN MEXICO CITY

According to the International Osteoporosis Foudation (2022 in Mexico, musculoskeletal disorders affect around 36.4% of individuals aged 60 and older. Hip fracture is one of the most severe complications of osteoporosis. Its prevalence increases with age and significantly impacts quality of life and morbidity. After a hip fracture, about 25% of individuals require institutionalization, while the rest do not regain their pre-fracture quality of life. During hospitalization, mortality rates can reach 10%, increasing to 30% within the following 12 months,International Osteoporosis Foundation (2022) *LATAM Audit 2021: Epidemiología, costo e impacto de las fracturas por fragilidad en América Latina*, This study focuses on the orthopedic surgery department of a hospital located in Mexico City. Figure 1 provides the basis for constructing the model and collecting the necessary data inputs.

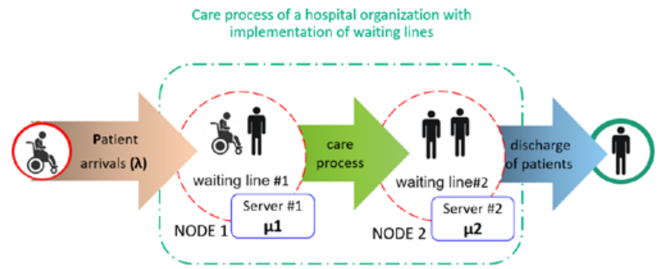

Figure 1. Representation of a queueing network with serverws in series, applied to a hospital care process. (De la Mota, 2023)

A. *Data colletion*

The purpose of the data collection was to fill the model with information on patient arrivals and waiting times. Statistical analysis was conducted to determine the distribution of this data.

Waiting times for prosthesis requests and their follow-up from initiation to completion were researched from 2021 to 2022. Table 2 displays the arrival distributions and service rates at each stage of the process.

TABLE II. PARTS OF THE ORTHOPEDIC SURGERY PATIENT CARE PROCESS

TABLE III.

Code	*Process in the orthopedic surgery area*
A	Arrival time until implant request
B	Arrival of the implant and surgery
C	Surgery wait until patient discharge
D	Patient wait in bed for surgery

B. *Distribution of patient services times*

The durations of each process were calculated from admission records outlined in Table 2, based on patient attendance and entry into the respective process. These times (measured in days) underwent a Poisson distribution test at a 90% confidence level and a chi-square hypothesis test. The parameters for each necessary distribution for simulation were then determined using R Studio.

It is important to note that the service times for one particular process did not follow a Poisson distribution. However, upon comparison to a normal distribution, it yielded a p-value of 0.5, indicating acceptability. Therefore, this distribution was assumed for that time. Subsequently, parameters for each process will be summarized. However, before doing so, it is imperative to establish the arrival distributions of patients to the orthopedic surgery area (Figures 2 to 5).

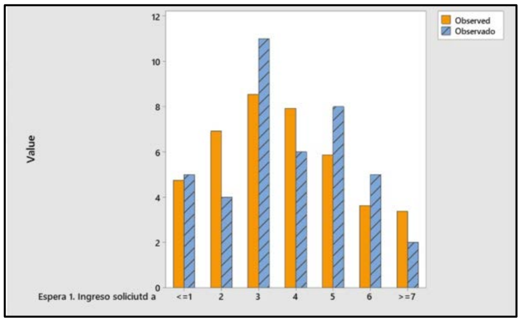

Figure 2. Poisson Distribution Test for Process A

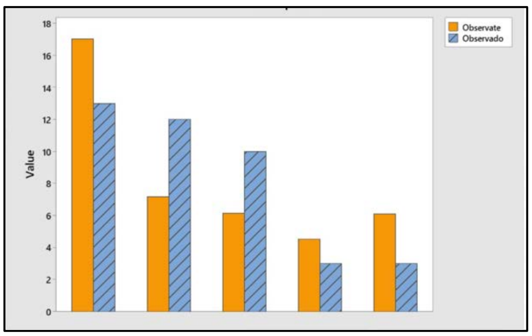

Figure 3. Poisson Distribution Test for Process B

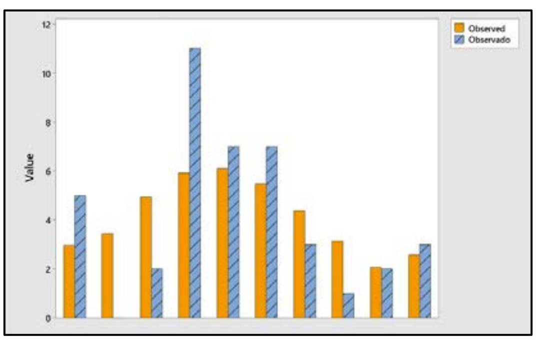

Figure 4. Poisson Distribution Test for Process C

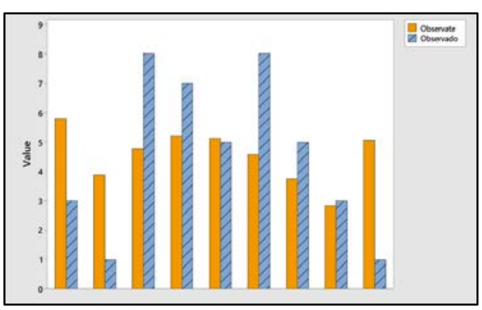

Figure 5. Poisson Distribution Test for Process D

C. Distribution of patient arrivals of system.

To determine the patterns of patient arrivals, we utilized records of all admissions to the orthopedic surgery area in the hospital from 2021 to 2022. As there were days with no admissions due to non-homogeneous periodicity, we analyzed the data monthly. However, the arrival rate per day was used for simulation purposes. The figures provided in this section include graphs that illustrate normality tests and a box plot that demonstrates the distribution of arrivals per month throughout the specified years (Figures 6 and 7).

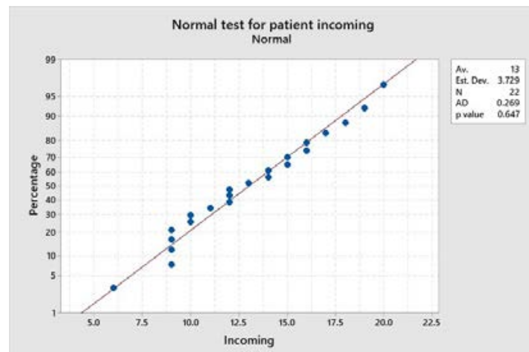

Figure 6. Normality test for arrivals to the surgery area

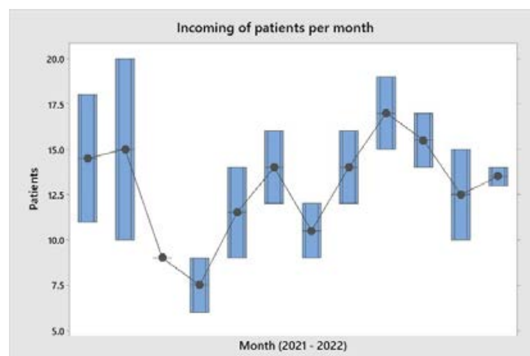

Figure 7. Normality test for arrivals to the surgery area

D. Generation of distribution parameters

The fitdistr function from the MASS library in R Studio® was used to generate the distribution parameters.

The distribution over time was determined through individual and Poisson distribution tests. For individual tests, the p-value was compared against the significance level (5%) to determine if the data fit the distribution well. For individual tests, the p-value was compared against the significance level (5%) to determine if the data fit the distribution well. A higher p-value indicated a better fit. The null hypothesis assumes a distribution with the specified characteristics. The Poisson test was conducted using a significance level of 5%.Table 3 presents the results and parameters of the selected distribution. If multiple distributions exist for a given time, their ability to simulate the process will be compared.

TABLE IV. PARAMETERS DISTRIBUTION

Incoming	Queue parameter	Distribution	Parameter value
A	Average incomings	Normal	μ=1.21, σ=0.482
B		Normal	μ=1.21, σ=0.482
C		Normal	μ=1.21, σ=0.482
D		Normal	μ=1.21, σ=0.482
A	Attention time	Poisson	$\lambda = 3.87$
B		Normal	μ=5.2, σ=1.458
C		Poisson	$\lambda = 7.49$
D		Poisson	$\lambda = 10.16$

Source: Own elaboration

E. Simulation

The simulation was performed using Arena Simulation® and the discrete event simulation module. The layout consists of three create modules (Figure 8), representing the arrival of patients with specific prosthesis requirements. These attributes are assigned values based on the proportion of patients recorded in the time series used. They are then connected to an allocation module that stores an attribute divided into the types of prostheses.

The allocation modules converge into a decision point where patients can choose to either continue waiting in the queue or withdraw. This decision may arise if some patients opt to seek care elsewhere due to the large number of individuals ahead of them. If the patient chooses to remain, they proceed to wait for the prosthesis request process while occupying a bed, depicted by the process module of the same name. Although there is a chance that the patient may not need to wait in bed, as indicated by the second decision point, the probability of this happening is low.

After being in the waiting area, patients undergo surgery and then move to a recovery area, which corresponds to the waiting beds. It is expected that the longest waits will occur in the bed area, as two processes converge at this point. During the simulation, a 30-day period is analyzed to evaluate the process. The output specifies the process queues and the average patient wait time.

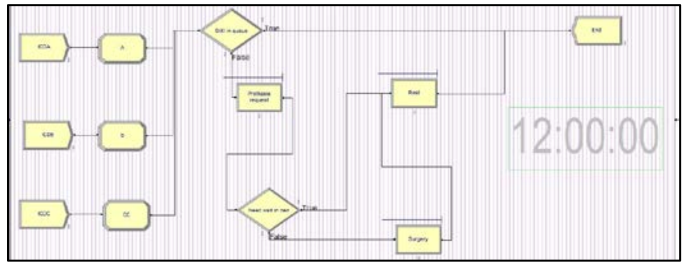

Figure 8. Diagram of the surgery area process.

IV. RESULTS

Figure 9 shows that most waiting time is concentrated in the implant request and bed waiting stages, with an average time of 11.17 and 18 days, respectively. This validates the model, as it aligns with the known experience that delays and patient complaints are most prominent in these areas. The prolonged durations in these processes suggest that they could be mitigated through an appropriate implant inventory policy utilizing demand planning. Currently, implants are ordered once a week based on admissions before the cutoff day.

To reduce bed waiting time, it is necessary to ensure implant availability and optimize bed allocation to patients from various areas over time. This is due to the variable influx of patients throughout the year and the shared resource of beds. Dynamic programming, utilizing conventional algorithms, can effectively address this allocation challenge.

The report in Figure 10 displays the longest queue for patients awaiting their implants, which is crucial to reduce for operational efficiency. However, it is also important to consider the impact on patient quality of life, as they endure their condition while waiting. The report also highlights excessive utilization that needs to be curtailed, as the hospital operates with a maximum occupancy rate of 0.8. The system's output suggests a capacity to attend to four patients per month, indicating potential for improvement through service and workspace redesign.

ARENA Simulation Results
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Summary for Replication 1 of 2

Project: Unnamed Project Run execution date : 3/19/2024
Analyst: omar_orla@hotmail.com Model revision date: 3/19/2024

Replication ended at time : 30.0 Days
Base Time Units: Days

TALLY VARIABLES

Identifier	Average	Half Width	Minimum	Maximum	Observations
Pedido de protesis.WaitTimePerEntity	8.3201	(Insuf)	.00000	15.279	7
Cirugia.VATimePerEntity	--	--	--	--	0
Cirugia.TotalTimePerEntity	--	--	--	--	0
Pedido de protesis.TotalTimePerEntity	11.177	(Insuf)	2.0000	18.279	7
Recuperacion.WaitTimePerEntity	18.000	(Insuf)	18.000	18.000	1
Recuperacion.VATimePerEntity	9.0000	(Insuf)	9.0000	9.0000	1
Cirugia.WaitTimePerEntity	--	--	--	--	0
Recuperacion.TotalTimePerEntity	27.000	(Insuf)	27.000	27.000	1
Pedido de protesis.VATimePerEntity	2.8571	(Insuf)	.00000	5.0000	7
Paciente.VATime	2.7500	(Insuf)	.00000	11.000	4
Paciente.NVATime	.00000	(Insuf)	.00000	.00000	4
Paciente.WaitTime	4.5000	(Insuf)	.00000	18.000	4
Paciente.TranTime	.00000	(Insuf)	.00000	.00000	4
Paciente.OtherTime	.00000	(Insuf)	.00000	.00000	4
Paciente.TotalTime	7.2500	(Insuf)	.00000	29.000	4
Cirugia.Queue.WaitingTime	--	--	--	--	0
Recuperacion.Queue.WaitingTime	18.000	(Insuf)	18.000	18.000	1
Pedido de protesis.Queue.WaitingTime	10.613	(Insuf)	.00000	26.670	8

Figure 9. Arena Simulation ® variable report

DISCRETE-CHANGE VARIABLES

Identifier	Average	Half Width	Minimum	Maximum	Final Value
Paciente.WIP	34.628	(Insuf)	.00000	68.000	68.000
Anestesiologo.NumberBusy	.00000	(Insuf)	.00000	.00000	.00000
Anestesiologo.NumberScheduled	1.0000	(Insuf)	1.0000	1.0000	1.0000
Anestesiologo.Utilization	.00000	(Insuf)	.00000	.00000	.00000
PAT.NumberBusy	1.0000	(Insuf)	.00000	1.0000	1.0000
PAT.NumberScheduled	1.0000	(Insuf)	1.0000	1.0000	1.0000
PAT.Utilization	1.0000	(Insuf)	.00000	1.0000	1.0000
Cirugia.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
Recuperacion.Queue.NumberInQueue	3.9333	(Insuf)	.00000	6.0000	6.0000
Pedido de protesis.Queue.NumberInQueue	29.694	(Insuf)	.00000	61.000	61.000

Figure 10. Arena Simulation ® variable report

V. Conclusions

The validation of the model is supported by its alignment with observed data, as the simulation produces results similar to historical records. In the hospital case study, it is important to further investigate the behavior of the orthopedic surgery area and explore ways to improve it, ranging from the prosthetic request process to bed availability.

Moving forward, it is crucial to examine patient flow within the healthcare sector using dynamic models. Similarly, managing limited resources such as beds requires dynamic planning, similar to a combinatorial optimization problem. Improvement strategies must be based on demand and informed by reliable, up-to-date data. Therefore, the hospital should develop areas and tools that facilitate autonomous decision-making.

Additionally, involving patients in the decision-making process is crucial. Currently, decision-making roles primarily reside with hospital and governmental authorities. However, patients possess valuable information that can be leveraged to inform decision-making processes. It is important to maintain a balanced perspective and avoid biased language. Therefore, future research should utilize real-time feedback, such as satisfaction survey results, to evaluate service quality and identify underlying root causes (Figure 11). This will pave the way for more comprehensive research.

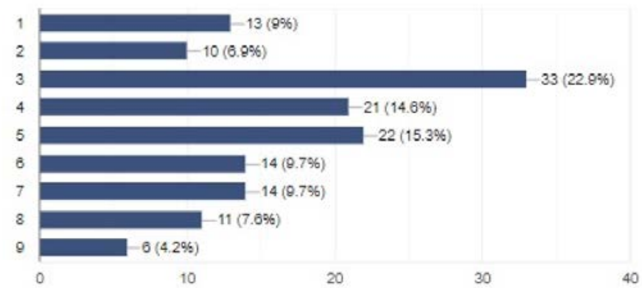

Figure 11. On a scale of 1 to 9, with 9 representing the highest level of satisfaction, do you agree and feel satisfied with the care and progress of the attention process you've experienced leading up to your surgery? 144 responses

The aim of this study is to establish a foundation for future research on reducing waiting times for orthopedic patients in a Public-Private Hospital. The study will utilize data from 2021 to 2023 for analysis. The ongoing process of attending to orthopedic patients will serve as a continuous data source, updated with new surgery schedules, patient waiting times, and consistent demand for supplies and implants. Therefore, it is crucial to continue monitoring health-related research and improving patient care for those requiring orthopedic surgeries. This involves setting goals, evaluating financial resources, and reviewing management strategies. Additionally, incorporating tools like Inventory Theory can provide a comprehensive plan for time optimization.

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