DISCRETE EVENT SIMULATION TO IMPROVE AN AMBULATORY ENDOSCOPY CENTER IN THE COVID-19 PANDEMIC

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RESUMO

Desde que a Organização Mundial da Saúde declarou pandemia para o novo Coronavírus (COVID-19), estratégias tem sido adotadas nos centros de saúde para evitar contaminação cruzada. Elas estão relacionadas ao fluxo do paciente, *layout* e limpeza. Assim, o artigo tem como objetivo utilizar a Simulação de Eventos Discretos para analisar os efeitos da pandemia em um Centro de Endoscopia Ambulatorial e propor melhorias. Depois de feitas as alterações necessárias, os resultados mostraram um impacto severo devido aos requisitos da COVID-19. Usando *o Lean Healthcare*, mudanças foram feitas no *layout* e no número de leitos. Além disso, foram propostas alternativas no fluxo de paciente e funcionários, turnos, agendamento e alocação de recursos usando o *Design of Experiments*. Como resultado, comparando com o cenário de COVID-19, o centro reduziu 87,51% nas horas-extras, 59,65% nas situações de risco e 18,66% no tempo de permanência dos pacientes, respectivamente, com o lucro aumentando em 17,52%.

PALAVRAS CHAVE. DES. COVID-19. Melhorias.
Área Principal: SIM – Simulação/ SA – PO na Área de Saúde

ABSTRACT

Since the World Health Organization declared a pandemic for the new Coronavirus (COVID-19), strategies have been adopted in healthcare center to prevent cross-contamination. They are related to patient flow, layout, and cleaning. Thus, the article aims to use the Discrete Event Simulation to analyze the pandemic effects in an Ambulatory Endoscopy Center and propose improvements. After making the necessary changes, the results showed a severe impact due to the requirements of COVID-19. Using Lean Healthcare, changes were made to the layout and number of beds. In addition, it was proposed alternatives in the patient and staff flow, shifts, scheduling, and resource allocation using the Design of Experiments. As result, compared to the COVID-19 Scenario, the center reduced 87.51% in Overtime Hours, 59.65% in Risk Situations, and 18.66% for patients' Length of Stay, respectively, with Net Revenue increasing by 17.52%.

KEYWORDS. DES. COVID-19. Improvements.
Main area: SIM – Simulation/ SA – OR on Healthcare Area

1. Introduction

The World Health Organization (WHO) declared a pandemic for the new Coronavirus (COVID-19) in March 2020. In late 2019, the virus appeared in Wuhan, in China and, since then, it has been spreading around the entire world, causing serious problems [Shu et al. 2020]. Several countries have already been considered the epicenter of the disease, such as Italy, the United States, India and more recently Brazil, causing thousands of victims in more than a year.

Since the virus is very contagious and has high transmissibility, the disease has reached expressive numbers worldwide. According to [Nicola et al. 2020], governments from the world's largest economies determined quarantine, border shutdowns, and travel restrictions to contain the spread. However, the virus spread, and the health systems must have to adapt to the new situation to provide care to patients and, at same time, avoid contamination between staff and patients. In this sense, [Wu et al. 2020] stated that it is necessary timely planning of hospital supplies, human resources, and healthcare system capacity is for patients and to guarantee health care system sustainability.

Some strategies must be adopted in a healthcare center to avoid cross-contamination. They are related to patient flow, layout, and cleaning. The facilities must ensure suitable and safe space in corridors, between chairs (in waiting rooms) and beds [Shu et al. 2020]. Moreover, a person infected with the virus may contaminate another person in a 6ft (1.8 m) radius of distance [Ali and Alhardi 2020]. In this sense, waiting rooms, queues, registration and triage must be planned to ensure a safe distance between patients and avoid crowdedness. Studying an efficient layout is essential to planning safety areas and avoid cross-contamination.

Moreover, cleaning strategies must be improved. Cleaning should be done to sanitize and disinfect rooms, beds, shared equipment, and reusable protective equipment [Ağalar and Engin 2020], since the virus may survive from two hours up to a few days on surfaces [Ali and Alhardi 2020]. However, improve cleaning affects the patient's Length of Stay (LOS), since the staff spends more time in these activities.

Some tools used in the planning and improvement process are necessary to cope with the situation. [Dieckmann et al. 2020] highlight that Discrete Event Simulation (DES) is a powerful tool to analyze and evaluate metrics to improve the health systems in the pandemic, such as flows, processes, and workstations. According to [Banks et al. 2010] and [Laurindo et al. 2019] DES aims to answer "what if" questions before interfering in the operation, reducing cost and risks. Moreover, DES allows decision-makers to plann strategies on managerial (care strategies) and operational decisions (staff scheduling, resource allocation, and patient flow) [Currie et al. 2020].

In this sense, the article aims to use DES to analyze the influence of COVID-19 procedures and strategies in a one-workday in an Ambulatory Endoscopy Center (AEC). However, if it is possible, use the simulation to improve the flow to support the extra procedures due to COVID-19 disease and reallocate resources while holding on to safety measures. Moreover, the Design of Experiment is used as a planning tool to set the tests.

This article is divided as follows: section 1 presented the introduction and the problem context. Section 2 presents a theoretical background with the studies that used DES to solve problems in the COVID-19 pandemic. Then, in section 3, there is the method used in the work. Section 4 presents the case, analysis, and results. Finally, in section 5, the conclusions of the work are presented.

2. Theoretical background

Discrete event simulation is one of the most powerful and widespread tools for analysis and decision-making in industries [Bank et al. 2010] and [Gabriel et al. 2020]. However, given the complexity of management problems in the health care area, several studies report the

advantages of DES' application for management and decision-making in this sector [Zeinali et al. 2015], [Erekat et al. 2020] and [Wang et al. 2020. In the COVID-19 scenario, DES has been helping health care managers to plan their operations more safely and efficiently, thus ensuring the maintenance and improvement of this essential service to the population. In this sense, several authors report the DES applicability in the context of the COVID-19 pandemic.

[Lay et al. 2020] proposed a simulation-based tool to forecast the beds and staff requirements in short-medium term planning. They applied the tool to monitor bed occupancy in the recovery unit of a French university hospital during the COVID-19 pandemic. In the vaccination context, [Asgary et al. 2020] integrated DES and Agent-based simulation to enhance the planning, design, operation, feasibility, and effectiveness of a drive-through vaccination facility. In a complementary study, [Asgary et al. 2021] proposed an online metamodel-based tool to predict the outcomes of the previous simulation model faster.

Another study proposes a simulation model to assess the strategy for allocating hospital resources to minimize the effects of the pandemic in elective and emergency surgeries [Melman et al. 2021]. [Das 2020] used DES to evaluate the impact of the COVID-19 pandemic on the ambulatory endoscopy center workflow. [Marin-Garcia et al. 2020] propose a DES model to plan and schedule health resources in scenarios derived from the COVID-19 outbreak. Based on these studies, it is possible to observe the applicability and effectiveness of DES modeling for decision-making in the context of the COVID-19 crisis.

3. Method

A simulation study is carried out following three major phases: conception, implementation, and analysis [Spedding 2008], [Storrow et al. 2008], and [Montevechi et al. 2010]. Therefore, the study was based on the previous methods and it was divided into:

1. **Conceptual modeling**: The conceptual model was developed using IDEF-SIM. According to [Montevechi et al. 2010] and [Pereira et al. 2015], IDEF-SIM is a process mapping technique that allows the modeler to translate the conceptual modeling to computer modeling. The step is necessary to understand the entire process in the AEC.
2. **Computer modeling**: The model was built using FlexSim® software, which allows simulating hospital environments. In addition to DES (the software's main function), it was used Agent System function to evaluate patient behavior. In this approach, it is possible to estimate the contact between patients in the current scenario. In other words, how many time patients were exposed in Risk Situation (distance less than 6ft – 1.8m).
3. **Model Execution and Initial Analysis:** The model was replicated 100 times in the current scenario to evaluate the following metrics: Total Working Hours; Net Revenue; Risk Situation; Patients' LOS and Staff Utilization.
4. **COVID-19 Scenario:** The fourth step comprised of adding two triage techs for a screening stage in the beginning of the process and adding five more minutes on all cleaning routines. Moreover, proper distances were established in the waiting room. The model was ran for 100 replicas and the same metrics were evaluated.
5. **Experiment Step:** In this stage, it was proposed changes in layout, patient and staff flow, staff shifts, patient arrival scheduling, and resource allocation. The Design of Experiment (DoE) was set using Minitab® to study the effects in the simulation outputs and perform a multi-objective optimization. [Montgomery 2017] says that DoE is a collection of statistical techniques capable of generating and analyzing experimental projects in which several factors are varied at the same time.
6. **Final Scenario:** The final stage contains the results of the best scenario. It includes a brand new layout to better suit a continuous flow, changes in staff workload balancing it, a new shift, and patient's arrival time to avoid crowdedness. Again, 100 replicas were performed and the metrics were evaluated.

4. Analysis and Results

4.1. Case Study

The case study comprises an Ambulatory Endoscopy Center that attends 25 patients daily. Patients arrive at the CAE, two every 30 minutes and they either are registered with the clerk or go to the waiting room. After registration, a PreOp RN escorts the patient to a Dress Room and then, he is weighted. The same nurse escorts him to a PreOp bay where he gets PreOp procedures. Next, the patient receives anesthesia with a CRNA. When Endo Bay is prepared, CRNA transports the patient in a bed to the room. In there, the patient may receive one of four procedures: EGD Procedure, Screening Colonoscopy, Diagnostic Colonoscopy, or Double procedure. In all procedures, the patient needs to be with an Endoscopist, an Endo Tech and a CRNA. After the procedure, the CRNA transports the patient to Recovery bay and he stays in the room with a Recovery RN until he is stable. After he is recovered, the Endoscopist meets him to do Post Procedure. Then, the patient changes clothes and CNA transports him, in a wheelchair, to the exit. When the patient leaves the PreOp bay, Endo bay and Recovery bay, PreOp RN, Endo Tech, and Recovery RN clean them, respectively. There are available one clerk, three PreOp RNs, two CRNAs, two Endoscopists, three Endo Techs, three Recovery RNs, and one CNA.

4.2. Conceptual Modeling

As mentioned in section 3, the authors opted to use the process modeling technique IDEF-SIM due to the facility for translate the conceptual model to the computer model. The process described in section 4.1 is shown in Figure 1.

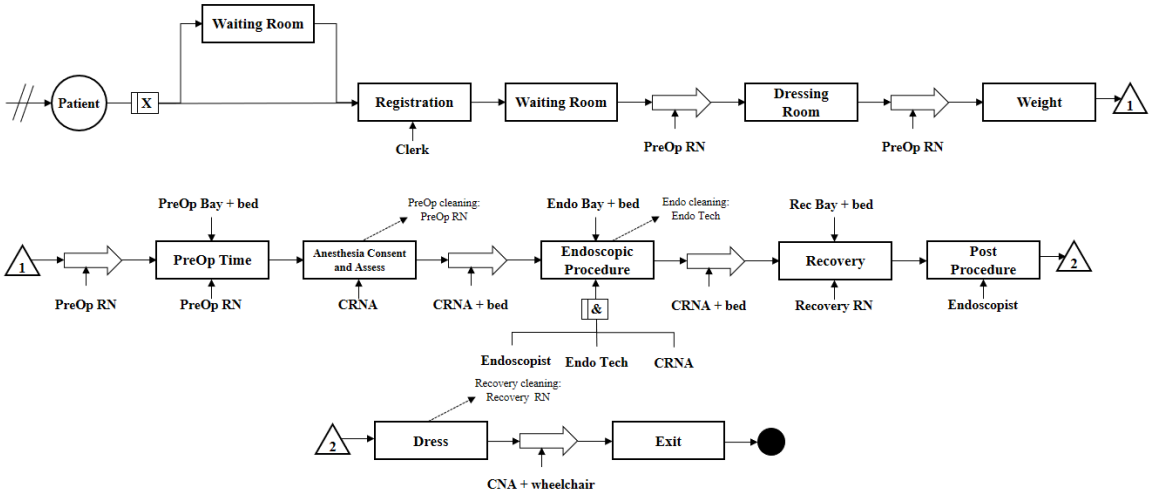


Figure 1 – Conceptual model

4.3. Computer Modeling

The model was built using FlexSim® software that allows the creation of healthcare environments in a user-friendly mode. Moreover, the model was set to count each time a patient was 6ft (1.8 m) or closer to each other, seeing it as a risk situation. In this sense, we used the Agent System approach to measure it and visually mark patients with a red shirt whenever they were too close to each other. Finally, the model was verified and validated by the professionals and specialists, using the face-to-face technique [Sargent 2013]. Figure 2 shows the model in the current state.

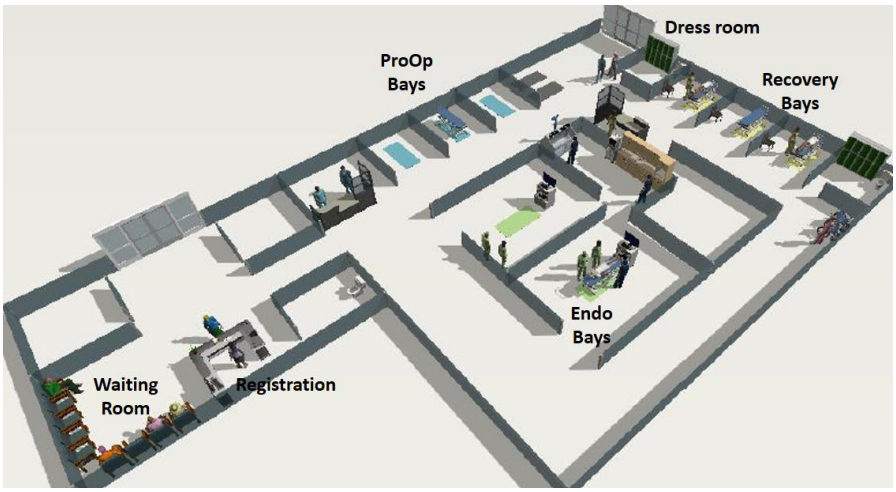


Figure 2 – Computer model – Current state

4.4. Model Execution and Initial Analysis

In the current state, the model was run 100 times. We obtained the following results concerning the Current State in a workday. All data in brackets represents 95% confidence interval.

- The EAC worked around 11.02 (10.93 – 11.10) hours;
- On average, the center obtained US$ 9,622.00 (9,447.00 – 9,797.00) as Net Revenue;
- There were around 60.70 (58.90 – 62.50) Risk Situations;
- On average, patients' LOS was 190.80 (187.80 – 193.80) minutes;
- Table 1 shows the staff utilization:

Table 1 - Satff Utilization - Current Scenario

Staff	Mean (%)	Confidence Interval
Clerk	39.43	(39.06 – 39.79)
PreOp RNs	38.82	(38.48 – 39.17)
CRNAs	53.94	(53.41 – 54.46)
Endoscopists	53.49	(52.96 – 54.03)
Endo Techs	48.69	(48.14 – 49.24)
Recovery RNs	45.82	(45.43 – 46.21)
CNA	2.66	(2.64 – 2.68)

According to the results, the number of patients inside the EAC reached a peak of 11.19 people, with a confidence interval of (11.04 – 11.34). Whereas, the maximum number of patients in the waiting room was 6.25 (6.10 – 6.40). The waiting room is a critical room since it is the place where most interactions occur. Moreover, patients waited around 69.26 (66.91 – 71.60) minutes to go to a PreOp Bay and stayed in the waiting room until be attended, causing overcrowding. The time that patients waited for this procedure represents 91.75% of the all-waiting time. This might have occurred due to a lack number of beds, therefore, being insufficient to attend to the demand on time. Indeed, the results showed that most of the time one PreOp Bay is not occupied.

4.5. COVID-19 Scenario

In COVID-19 Scenario, we only made the necessary safety changes with some minor adjusts in the reception area. First of all, we have added two screening areas, which contains one screening room, a triage tech, and one chair. When the patients arrive in the EAC, they need to stay in the triage room for safety process around 30 minutes. Then, five minutes were added in all cleaning routines. Finally, we have increased the distance between chairs in the waiting room to be greater than 6ft (1.8 m). Figure 3 shows the modifications done.

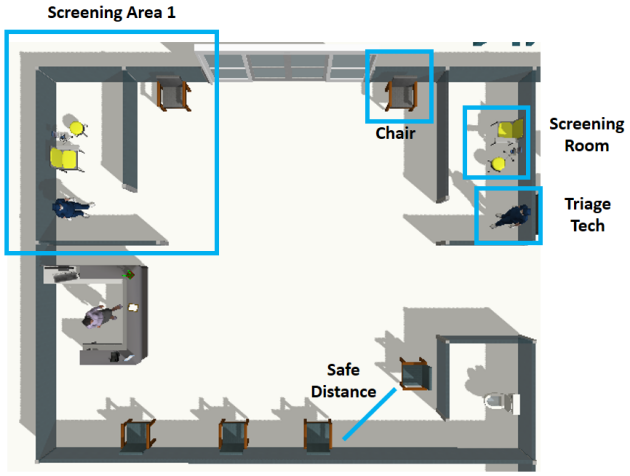


Figure 3 - Changes in Reception Area

In this stage, we ran the model 100 times and obtained the following results for one day of work. All data in brackets represents 95% confidence interval.

- The EAC worked around 11.69 (11.53 – 11.86) hours;
- On average, the center obtained US$ 8,606.00 (8,332.00 – 8,879.00) as Net Revenue;
- There were around 35.05 (33.97 – 36.12) Risk Situations;
- On average, patients' LOS was 227.70 (224.60 – 230.80) minutes;
- Table 2 shows the staff utilization:

Table 2 - Staff Utilization - COVID-19 Scenario

Staff	Mean (%)	Confidence Interval
Triage Techs	58.08	(57.31 – 58.86)
Clerk	37.27	(36.71 – 37.82)
PreOp RNs	36.25	(35.67 – 36.83)
CRNAs	50.76	(49.84 – 51.68)
Endoscopists	50.35	(49.42 – 51.28)
Endo Techs	45.60	(44.68 – 46.52)
Recovery RNs	42.91	(42.12 – 43.71)
CNA	2.50	(2.46 – 2.55)

In this scenario, despite Risk Situation being decreased by 42.26%, overall it lead to negative results. Overtime hours increased by 124.89%, Net Revenue decreased by 10.56% and patients' LOS had a 19.34% increase. The replicas showed that the number of patients inside the EAC reached a peak of 12.76 people (12.61 – 12.91), a 14.06% increase. However, the maximum number of patients in the waiting room was four, since there were only four available chairs. Although patients' LOS increased, the time patients waited before going to PreOp Bay was decreased to 52.83 (51.92 – 53.74) minutes, a reduction of 21.03%.

4.6. Experiment Step

In the experiment step, we gathered all improvements suggested and tested them in DoE. They include changes in layout, flow, staff shifts, patient arrival scheduling, and resource allocation. The new layout was not a tested variable because it had already shown good result when compared to the old one.

A generalized full factorial design with five levels and two replicates (2*22*33) was used, resulting in 216 experiments. Each experiment was executed 25 times in the simulation model. Table 3 shows the levels set for input factors.

Table 3 - Levels of input factors

Variable	Levels		
	-1	0	1
Flow	Current	Proposed 1	Proposed 2
Patient Scheduling and Staff Shifts	Current	-	Proposed
Number of PreOp RN	1	2	3
Number of Endo Tech	2	-	3
Number of Recovery RN	2	3	4

4.6.1. Layout

In order to reduce wastes based on Lean Healthcare principles, it was proposed a new layout, which minimized walking distances (patient and staff) and waiting time between processes. Also, patient flow has become unidirectional and risk situations have been reduced. Figure 4 shows the new layout.

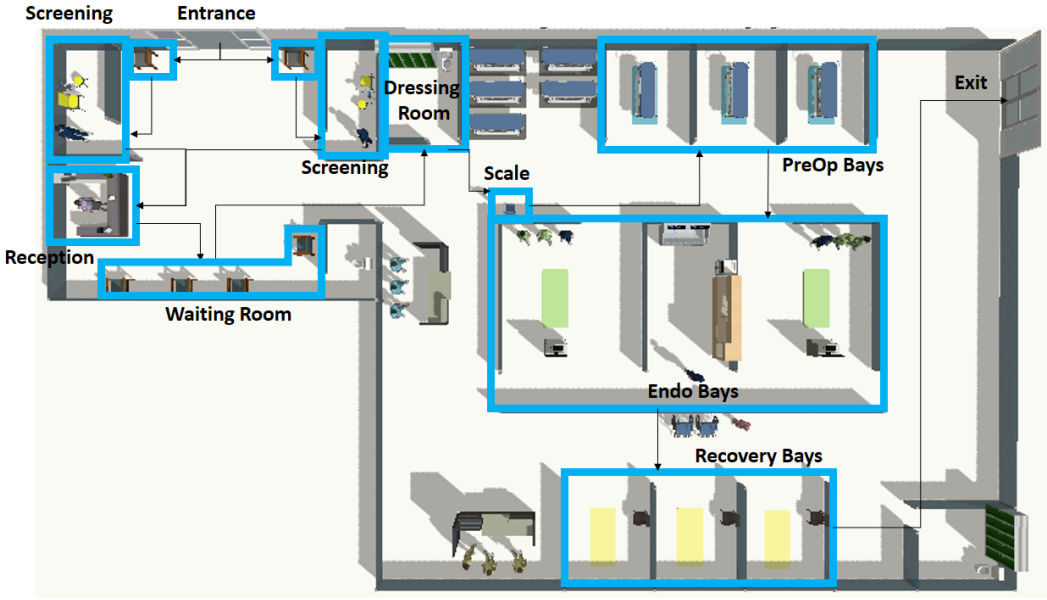


Figure 4 1- New layout

4.6.2. Flow

Two different patient flows were proposed in order to balance the workload between nurses and improve the unidirectional flow:

- **Proposed Flow 1:** In the first approach, patient's transport from Endo Bay to Recovery Bay was reassigned from CRNAs to Recovery RNs. With this change, CRNAs may care for patients earlier in PreOp procedures. Additionally, since CNA presented only 2.5% of utilization and Recovery RNs were often not utilized, we transferred CNA's functions to Recovery RNs. Thus, Recovery RNs transport patients from Recovery Bay to Exit, and move beds after cleaning routines.
- **Proposed Flow 2:** In the second approach, patient's transport from Endo Bay to Recovery Bay was also reassigned from CRNAs to Recovery RNs. Moreover, cleaning routines from PreOp and Recovery Bays could also be done by CNA in preference for her, and CNA continued having the same assignments from current scenario.

4.6.3. Patient Scheduling and Staff Shifts

In the previous scenario, some crowdedness was caused due to a high number of patients in waiting room. Therefore, we better spread out patient's arrival scheduling, starting at 06:45. Moreover, we scheduled patient not to arrive during break times. In this sense, we scheduled the patients to arrive one at each 15 minutes instead of two patients at each 30 minutes starting at 07:00.

In addition, staff shifts were also changed. Since staffs only take breaks after they are done with their current activity, we observed that it was common for two members from the same group to have a break at the same time. Thus, we set the breaks to start 30 minutes apart from each shift. Although staffs work from 07:00 to 17:30 (standard hours), triage techs start and finish 30 minutes earlier. Table 4 and 5 show the current and proposed shifts, respectively.

Table 4 - Current Shift

	Schedule 1	**Schedule 2**	**Schedule 3**
Start	07:00	07:00	07:00
Break 1	09:15 - 09:30	09:30 - 09:45	09:45 - 10:00
Lunch	11:45 - 12:15	12:00 - 12:30	12:15 - 12:45
Break 2	14:45 - 15:00	15:00 - 15:15	15:15 - 15:30
End	17:30	17:30	17:30

Table 5 - Proposed Shift

	Schedule 1	**Schedule 2**	**Schedule 3**
Start	07:00	07:00	07:00
Break 1	09:00 - 09:15	09:30 - 09:45	10:00 - 10:15
Lunch	11:30 - 12:00	12:00 - 12:30	12:30 - 13:00
Break 2	14:30 - 14:45	15:00 - 15:15	15:30 - 15:45
End	17:30	17:30	17:30

4.6.4. Resource Allocation

One of main reasons why patients waited a long time to enter in PreOp Bay was the lack of available beds. Since there are eight possible available bays (3 PreOp, 2 Endo, and 3 Recovery), we increased the number of beds from five to eight, so all of them could be used simultaneously. Also, it was proposed varying the number of PreOp RNs, Recovery RNs, and Endo Techs, as presented in Table 3. The idea is analyze the effects in the main metrics by combining different levels of this resources with previously proposed changes.

4.6.5. DoE Results

Three metrics were analyzed in the DoE: (i) Total Worked Hours, (ii) Net Revenue, and (iii) Risk Situation. After running the DoE, the adjusted R^2 for (i), (ii) and (iii) were 99.47%, 91.70%, and 91.97%, respectively. Moreover, the predicted R^2 were 98.93%, 83.17%, and 83.72%. Since these values are higher than 80.00%, it means that the models generated by DoE were suitable to analyze the data [Montgomery 2017]. Based on Lenth's method, all variables and interactions that cross Length's Pseudo Standard Errors are statistically significant (p-value < 0.05). In this way, we did not remove any variable from the analyses since all of them is significant for at least one metric.

Using Minitab® and the metamodels from DoE, we carried out a multi-objective optimization to maximize (ii) and minimize (i) and (iii). Table 6 presents the three best solutions.

Table 6 - DoE best solutions

Solution	Flow	Shift	PreOp RN	Endo Tech	Recovery RN	Total Hours	Net Revenue	Risk Situation
1	Flow 2	Prop.	2	3	2	10.56	10113.10	14.39
2	Flow 2	Prop.	2	3	3	10.31	9823.00	12.06
3	Flow 1	Prop.	2	3	3	10.40	9978.30	17.36

According to the optimization, the best solution is: the second proposed flow, the proposed shift, 2 PreOp RNs, 3 Endo Techs and 2 Recovery RNs.

4.7. Final Scenario

The Final Scenario presents the new layout, proposed flow 2 (section 3.5.2.2), proposed shift and arrival schedule (section 3.5.3), eight available beds, and 15 employees (2 Triage Techs, 1 Clerk, 2 PreOp RNs, 2 CRNAs, 2 Endoscopists, 3 Endo Techs, 2 Recovery RNs, and 1 CNA). In order to confirm the changes and the best solution given by the optimization, the model was replicated 100 times. We obtained the following results for one workday. All data in brackets represents 95% confidence interval.

- The EAC worked around 10.58 (10.52 – 10.63) hours;
- On average, the center obtained US$ 10,114.00 (9,936.00 – 10,291.00) as Net Revenue;
- There were around 14.14 (13.30 – 14.98) Risk Situations;
- On average, patients' LOS was 185.20 (182.80 – 187.60) minutes;
- Table 7 shows the staff utilization:

Table 7 - Staff Utilization - Final Scenario

Staff	Mean (%)	Confidence Interval
Triage Techs	63.41	(63.01 – 63.80)
Clerk	40.97	(40.64 – 41.30)
PreOp RNs	58.05	(58.50 – 58.95)
CRNAs	55.17	(54.63 – 55.70)
Endoscopists	55.32	(54.78 – 55.86)
Endo Techs	53.91	(53.16 – 54.65)
Recovery RNs	68.54	(68.19 – 68.90)
CNA	51.19	(50.40 – 51.99)

In Final Scenario, all metrics have been greatly improved when comparing to both Current and COVID-19 Scenario. The results compared to COVID Scenario are a reduction of

87.51%, 59.65%, and 18.66% for Overtime hours, Risk Situation, and LOS, respectively, with Net Revenue being increased by 17.52%.

Risk Situation decreased mainly because patients arrive separately every 15 minutes and staff workload is balanced. Consequently, the number of patients inside the center reached a peak of 11.00 people (10.87 – 11.13), a 13.79% decrease. In addition, the maximum number of patients in the waiting room was 2.28 (2.15 – 2.41). Moreover, the time patients waited before going to PreOp Bay was decreased to 7.95 (6.76 – 9.14) minutes, a reduction of 84.95%.

5. Scenario Comparison

In general, Final Scenario performed best in all metrics, even when compared to Current Scenario, which does not have COVID-19 requirements. Figure 5 shows the confidence interval for main metrics.

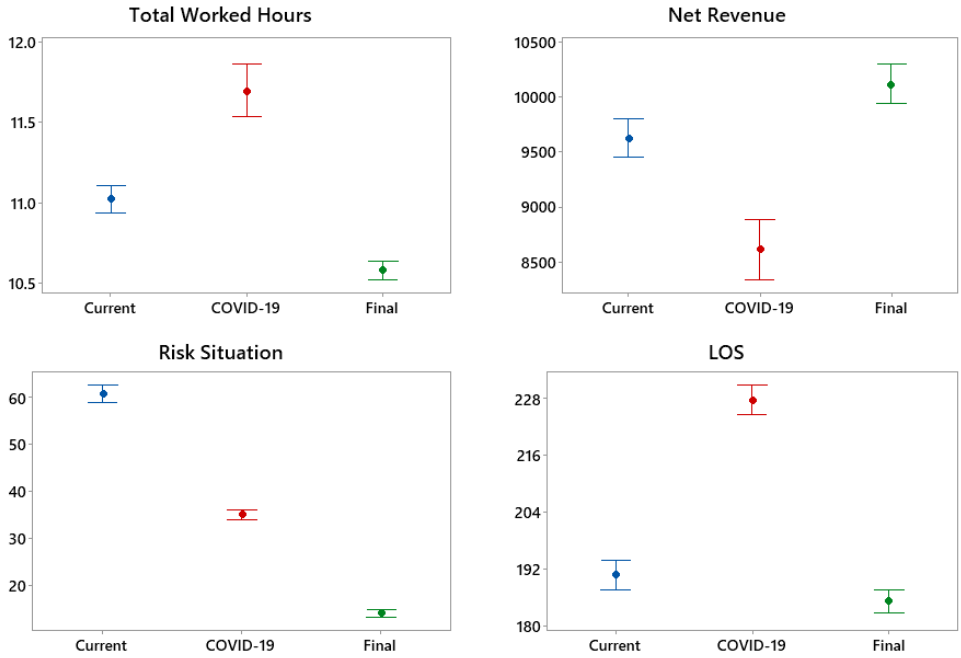


Figure 5 - 95% Confidence Interval for main metrics

When comparing Final Scenario to Current Scenario, there was a great reduction in Total Worked Hours (3.99%) and Risk Situation (76.71%) and an significantly increase in Net Revenue (5.11%). Based on patient's point of view, even after adding 30 minutes at the beginning of the process, LOS still was reduced by 2.94%. Due to improvements in the process, waiting time for locations has been reduced from 75.52 to 28.83 minutes (61.82%), as presented in Figure 6.

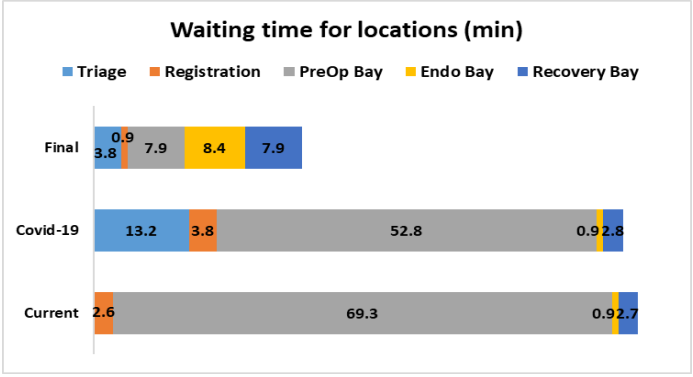


Figure 6 - Waiting Time for Locations

5. Conclusions

This study aimed to analyze how COVID-19 pandemic affects the AEC and if it was possible to enhance workflow or resource allocation while holding on to safety measures. The first step of the study was to implement safety measures into the model. We increased the distance between chairs in the waiting room, added a screening process at the beginning of patient flow that spend around 30 minutes, and raised all cleaning routines by five minutes. As the results showed a quite harsh impact due to COVID-19 requirements, the second step was to look for improvements in the process in order to mitigate this impacts in the EAC.

Using Lean Healthcare principles, we made layout changes to have unidirectional flow and avoid patient cross and process' wastes. In addition, we increased the number of bed from five to eight, so that eight patients could be attended at same time. Next, we proposed alternatives in patient and staff flow, staff shifts, patient arrival scheduling, and resource allocation to be studied with DoE.

We performed a generalized full factorial design with five levels and two replicates ($2*2^2*3^3$), resulting in 216 experiments. Three metrics were analyzed: Total Worked Hours, Net Revenue, and Risk Situation. As a result, the best scenario comprises the new flow (where the CNA could perform all cleaning routines and patient movement from Endo Bay to Recovery Bay is done by a Recovery RN), the new staff and patient arrival scheduling (section 3.5.3), 2 PreOp RNs, 3 Endo Techs, and 2 Recovery RNs.

Although the Final Scenario has all additional COVID-19 requirements, it still managed to outperform the Current Scenario. After running 100 replicas, the results show, on average, that the AEC worked 10.58 hours, obtained US$ 10,114.00 as Net Revenue, and had 14.14 Risk Situation with patients' LOS of 185.20 minutes. Comparing to COVID-19 Scenario, we can see a reduction of 87.51%, 59.65%, and 18.66% for Overtime hours, Risk Situation, and patients' LOS, respectively, with Net Revenue being increased by 17.52%.

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