The Impact of Pandemic Context on ED: The Case of A.S.L. Napoli 3 Sud

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Abstract Early in 2020, Italy was among the first nations in Europe to be severely impacted by the COVID-19 epidemic. In this study, we want to evaluate, through the application of the Define, Measure, Analyze, Improve, and Control (DMAIC) cycle methodology of Lean Six Sigma (LSS), the impact of Covid-19 on the LOS of patients in the Emergency Department (ED-LOS) of the "Maresca" Hospital based in Torre del Greco Naples (Italy). Statistical analysis was conducted in the study therefore involved a statistical comparison of data between 2019 (pre-covid) and 2020 (during the pandemic). The work was conducted by analyzing the five main phases of the DMAIC cycle. The findings indicated that in 2020, there was an overall increase in emergency department length of stay (ED LOS). However, an exception was observed for patients with yellow and red triage codes, whose ED LOS significantly decreased during the pandemic. The implications of the study were the use of an LSS approach to examine the effects of COVID-19 to achieve significant results that will provide support to doctors for department management, optimizing hospital flows. The limits of the study are the time range and the sample of the reduced data.

Keywords Length of stay · Emergency department · DMAIC cycle · Lean six sigma

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1 Introduction

The impact of COVID-19 and the pandemic on hospitals and emergency departments has been profound and multifaceted, affecting many aspects of the healthcare system. Here are some of the main effects: overload of healthcare facilities, reorganization of hospitals, exhaustion of healthcare staff, impact on non-covid-19 care, economic strain, and long-term consequences. Lean Six Sigma (LSS) is a management methodology that combines the principles of Lean and Six Sigma to improve organizational processes by eliminating waste and reducing inefficiencies. While Lean focuses on identifying and removing various forms of waste, such as excess inventory, unnecessary movement, waiting times, overproduction, and defects, Six Sigma emphasizes the use of statistical methods and data analysis to detect and minimize errors or variations in processes. Despite their distinct origins, both Lean and Six Sigma share the common goal of optimizing processes for greater efficiency and effectiveness [1, 2]. The lean concept aids in process simplification and waste reduction for greater productivity. Six Sigma tools find and fix flaws, improving the quality of the product or service, and organizations can frequently cut expenses by getting rid of waste and errors [3, 4].

One important methodology in the Six Sigma framework is the DMAIC (Define, Measure, Analyze, Improve, and Control). This methodical technique offers an organized means of streamlining procedures and resolving issues. The use of statistical techniques and data-driven decision-making to direct the improvement process is emphasized throughout the DMAIC cycle. Achieving quantifiable and long-lasting improvements in the targeted process is the aim. DMAIC project success also depends on team members' constant cooperation, communication, and feedback [5–9]. Through process analysis, LSS is a methodology that is becoming more and more popular in the healthcare sector to investigate how COVID-19 has impacted emergency department (ED) operations. Clearly articulate the necessity of the Lean Six Sigma study by demonstrating how it addresses critical performance issues, enhances process efficiency, or solves specific problems within the organization or industry. It is a very successful approach for cutting healthcare costs while increasing the effectiveness and caliber of the services provided [10, 11].

This article assessed the effect of COVID-19 on ED-LOS using an LSS approach, namely the DMAIC cycle. The Hospital based in Torre del Greco Naples (NA) provided the dataset used.

1.1 Literature Review

A bibliography on techniques for enhancing healthcare services through quantitative analysis might include a range of topics such as Lean Six Sigma, data mining, predictive analytics, and other statistical methods. For instance, an LSS technique is used in Italy by Cesarelli et al. [12], Ferraro et al. [13], and Montella et al. [14] to decrease treatment-associated infections and decrease postoperative hospital stays in patients following laparoscopic cholecystectomy.

The literature confirms that reducing hospital stays is often associated with better patient outcomes and cost savings [15]. Shorter stays can lead to a lower risk of hospital infections, faster recovery times and higher patient satisfaction. They also contribute to financial savings by reducing the costs of long-term care and freeing up hospital resources for other patients [16, 17]. By streamlining processes and implementing effective discharge planning, hospitals can improve both the quality of care and operational efficiency for the benefit of patients and health systems [18–21]. While it is critical for revenue management and customer happiness in the hospitality industry, monitoring and controlling the length of stay may also be necessary to optimize patient care and resource allocation [22–29].

In every situation, monitoring and assessing the LOS can yield insightful information for better decision-making and workflow enhancement [30–32]. It is noteworthy that distinct sectors and fields may employ distinct techniques for determining and interpreting the duration of stay, contingent upon their particular needs and goals [33–35].

2 Methods

LSS DMAIC framework approach has been adopted for assessing the impact of CoViD-19 on Length of Stay of patients accessing to the ED of the "Maresca" hospital in Torre del Greco (Italy). According to the DMAIC framework, two different scenarios, namely the so-called "as-is" scenario, which in this study that reflects the examined healthcare system operations before the burden of CoViD-19, and the "to-be" scenario, which in this study reflects the examined healthcare system operations during the CoViD-19 epidemics. The Define, Measure, and Analyze phases of the Lean Six Sigma DMAIC cycle focus on studying and understanding the "as-is" scenario. In the Define phase, problems and project objectives are identified and defined. During the Measure phase, data is collected to establish a baseline of current performance. The Analyze phase involves a thorough examination of the data to identify the root causes of the problems. In contrast, the Improve and Control phases focus on the "to-be" scenario. The Improve phase involves developing and implementing solutions to address the root causes and enhance performance. Finally, in the Control phase, measures are put in place to ensure the sustainability of the improvements over time, and a statistical comparison between the "as-is" and "to-be" scenarios is conducted to assess the effectiveness of the implemented solutions.

2.1 Study of the "As-Is" Scenario

In the Define phase, the objective of the study, the system under consideration, the timeframe for the analysis, the team of experts and stakeholders involved in the analysis, and the Critical to Quality (CTQ), i.e. the quantitative metric adopted to carry out a quantitative assessment of the "as-is" process, are defined.

With the aim of assessing the impact of CoViD-19 on ED stay, the length of stay for patients accessing the ED of the "Maresca" hospital in Torre del Greco (Italy) has been chosen as CTQ. A timeframe of one year before the burden of CoViD-19 (year 2019) and one year access the CoViD-19 epidemics (year 2020) have been chosen as windows to collect data for the "as-is" and the "to-be" process, respectively.

Then, the Measure phase proceeded with the retrospective data collection in the period from January 2019 to December 2019 through the hospital information system. During the Measure phase, the following variables were collected on 40.825 patients who accessed the examined ED in the year 2019: age, gender, triage color code (white, green, yellow, red), the arrival mode (autonomous, via ambulance), discharge mode (home discharge, hospitalization, transfer to other hospital, deceased in the ED, refuses hospitalization, leave without being seen-LWBS, abandonment before ED record closure, discharge to territorial facilities, dead on arrival), time of admission (0:00–06:00, 06:00–12:00, 12:00–18:00, 18:00–24:00), and length of stay in the ED (ED_LOS) expressed in minutes. Main descriptive statistics regarding the collected data for the "as-is" scenario are reported in Table 1.

Then, the gathered data were critically analyzed by the research team within the Analyze phase of the DMAIC framework, characterized by periodic meetings in order to examine the scenario under study. All the emerged relevant aspect has been taken into consideration for the statistical comparison with the "to-be" scenario, i.e., across the CoViD-19 pandemic.

2.2 Study of the "To-Be" Scenario

The typical Improve phase of the DMAIC cycle dealt with the implementation of protocols and procedures taken to contain the spread of the COVID-19, such as the activation of new clinical pathways, the measures to contain the LOS, the social distancing, and the control of the contagion.

Analogously to previous steps, data of 42.498 ED accesses from January 2020 to December 2020 are retrospectively collected to verify the impact of improvement measures put in place on the chosen CTQ indicator, i.e., the ED LOS.

Main descriptive statistics regarding the collected data for the "to-be" scenario are reported in Table 2.

From Table 2, it can be noted that the number of ED accesses across the CoViD-19 pandemic unexpectedly increased despite the restrictive measures taken to control the contagion.

Table 1 Distribution of the collected data for the "as-is" scenario (before COViD-19 burden)

Gender	N
M	21,784
F	19,041
Triage code	
White	1265
Green	34,366
Yellow	4657
Red	531
Arrival mode	
Autonomous	35,390
Via ambulance	5343
Time of admission	
0:00–6:00	4027
6:01–12:00	12,035
12:01–18:00	12,715
18:01–0:00	12,048
Age	
Under 18	4421
18 < Age < 40	11,187
40 < Age < 65	15,147
Over 65	10,070
Discharge mode	
Discharge to home	15,385
Hospitalization	10,954
Transfer to another hospital	613
Deceased in ED	80
Refuses hospitalization	0
LWBS	2600
Abandon before ED record closure	1593
Discharge to territorial facilities	9583
Dead on arrival	17
Length of stay (LOS)	
ED_LOS	40,825

2.3 Comparative Statistical Analysis

The Control phase of the DMAIC cycle aimed at carrying out a statistical comparison of the ED_LOS values between the two considered scenarios. For this purpose, after assessing the normality of the data through a Shapiro–Wilk test, the distributions

Table 2 Distribution of the collected data for the "to-be" scenario (during COViD-19)

	Year 2020 N
	42,498
Gender	
M	23,111
F	19,387
Triage code	
White	1288
Green	34,255
Yellow	4644
Red	533
Arrival mode	
Autonomous	36,218
Via ambulance	6214
Time of admission	
0:00–6:00	3991
6:00–12:00	13,597
12:00–18:00	12,776
18:00–0:00	12,134
Age	
Under 18	5493
18 < Age < 40	11,700
40 < Age < 65	15,090
Over 65	10,215
Discharge mode	
Discharge to home	20,730
Hospitalization	8781
Transfer to another hospital	501
Deceased in ED	114
Refuses hospitalization	0
LWBS	2686
Abandon before ED record closure	1929
Discharge to territorial facilities	7748
Dead on arrival	9
Length of stay (LOS)	
ED LOS	42,498

of ED_LOS values have been compared between the two scenarios, and for each patients' subgroup (e.g., age-based groups, triage code-based groups, gender-based groups, etc.), by means of a Student's t-test for normally distributed data or U-Mann Whitney test for non-normally distributed data. The statistical tests have been carried out in IBM SPSS Statistics v.29 with a 95% Confidence Interval and a significance level alpha equal to 0.05.

3 Results

Table 3 shows the comparison on ED-LOS. To assess the statistical significance between the two destructions, the t-test was implemented at the 95% significance level.

From Table 3, it can be observed that ED_LOS both before and during the pandemic has an increasing trend with patients' age and shows higher values in the case of patients moved to other hospitals, for those patients accessing the ED between 12:00 and 18:00, and for patients arriving by ambulance. Interestingly, it can be noted that while in 2019 the ED-LOS is far higher for yellow and red triage color codes, during the pandemic the ED_LOS do not show apparent significant differences between the four triage color codes; since the number of patients for each color code did not vary significantly between year 2019 and year 2020 (see Tables 1 and 2), we can hypothesize that a more effective strategies for the management of patients with higher triage code have been implemented during the pandemic.

Overall, the comparison between the two scenarios showed a statistically significant increase in the ED-LOS across the pandemic (as it can also be seen in the boxplot in Fig. 1), thus suggesting that CoViD-19 burden extended the average length of stay within the ED. An exception is made for those patients with yellow and red triage codes, whose ED-LOS instead decreased significantly during the pandemic.

4 Discussion and Conclusions

The LSS methodology, specifically the DMAIC cycle analysis, has been applied to evaluate the impact of COVID-19 on the ED activities of the "Maresca" hospital based in Torre del Greco (Naples), Italy.

The work objective is to investigate how the ED-LOS in 2020 had changed from the previous year. To do this, in the measurement phase, the 2019 situation (pre-COVID) was characterized by first calculating the CTQ and classifying the patients into subgroups based on their age, gender, triage score, arrival mode, recovery time, and discharge mode. The same was found in the Control Phase for the year 2020, and comparisons were made using the t-test statistical test.

Table 3 Results of statistical comparison of the ED LOS between the two examined scenarios

	ED_LOS year 2019 (mean ± standard deviation)	ED_LOS year 2020 (mean ± standard deviation)	*p*-value
Gender			
M	233 ± 562	300.3 ± 715.1	0.000
F	239.9 ± 583.1	306.7 ± 740.1	0.000
Triage code			
White	143.5 ± 409.8	299.3 ± 722	0.000
Green	176 ± 391	300.9 ± 718.6	0.000
Yellow	655.2 ± 1147.5	305.6 ± 755	0.000
Red	682.4 ± 1149.6	304.8 ± 740	0.000
Arrival mode			
Autonomous	185.9 ± 446.1	238.1 ± 570.5	0.000
Via ambulance	569.7 ± 1024.4	682.1 ± 1239.7	0.000
Time of admission			
0:00–6:00	227.1 ± 565.1	284.5 ± 724.9	0.000
6:00–12:00	239.3 ± 539.9	285.2 ± 659.3	0.000
12:00–18:00	252.9 ± 606.6	331.2 ± 798	0.000
18:00–0:00	218.4 ± 567.3	300.1 ± 719.4	0.000
Age			
Under 18	112.8 ± 274.6	122.7 ± 352.9	0.126
18 < Age < 40	149.9 ± 304.3	195.9 ± 423.2	0.000
40 < Age < 65	209 ± 474.5	279.8 ± 633.8	0.000
Over 65	427.2 ± 894	557.9 ± 1111.2	0.000
Discharge mode			
Discharge to home	198 ± 488.4	258.3 ± 666.2	0.000
Hospitalization	346.9 ± 752.1	453.4 ± 886.5	0.000
Transfer to another hospital	777.7 ± 1278.3	1048.9 ± 1752.5	0.003
Deceased in ED	827.1 ± 1126.3	882.1 ± 1325.4	0.763
Refuses hospitalization	–	–	–
LWBS	193.3 ± 500.1	358.2 ± 837.6	0.000
Abandon before ED record closure	253.9 ± 572.4	294.8 ± 444.5	0.017
Discharge to territorial facilities	138.9 ± 268.7	179.9 ± 461.9	0.000
Dead on arrival	954.2 ± 1911.8	37.8 ± 49.9	0.167
Length of stay (LOS)			
Overall ED_LOS	236.2 ± 572	303.2 ± 726.6	0.000

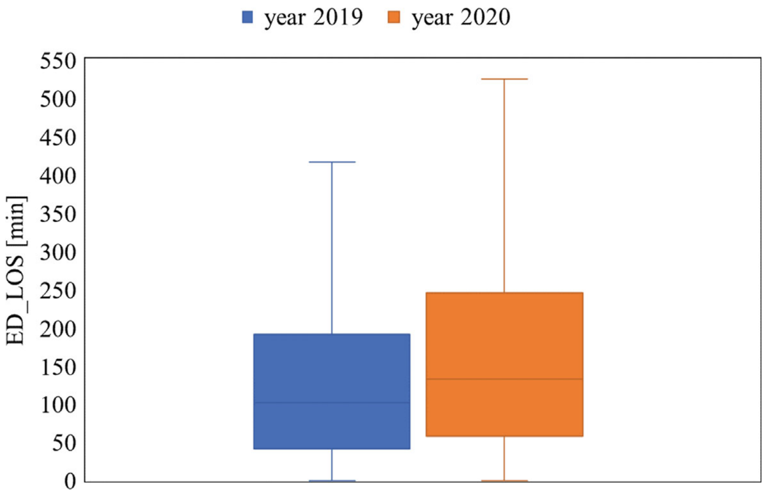

Fig. 1 Box plot

The results highlighted that in 2020 there was a general lengthening of times the ED LOS. An exception is made for those patients with yellow and red triage codes, whose ED LOS instead decreased significantly during the pandemic.

The limitations of the study are several, although the LSS provided a systematic approach to analyze the problem, factors such as admission diagnosis or personnel on duty work were not included. Further developments will involve overcoming these limitations, including through advanced data analysis techniques [36–39], such as simulation models [40].

To further optimize the clinical emergency path, decrease patient waiting times in the ED, and enhance treatment efficiency, additional indicators of patients in the emergency process will be added, such as disease types (internal medicine, surgery), treatment measures, and treatment order.

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