Impact of Patient and Management Variables on Operating Room Times: An Analysis through the Application of Machine Learning Techniques

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Abstract: Healthcare systems around the world need to focus their attention on improving the efficiency of their pathways in order to satisfy the ever-increasing demand. Among the main providers are hospitals, which have to treat complicated cases in a context of increasingly limited resources. The hospital component with the highest complexity and cost is the operating room (OR). In order to have a significant impact, it is important to be able to schedule OR sessions efficiently. In this study, we propose the use of Machine Learning (ML) algorithms to investigate which patient-specific demographic, clinical and organizational variables have the greatest impact on OR time. The study was conducted at the AORN "A. Cardarelli" of Naples (Italy) including in the study all patients who underwent a basic general surgery such as cholecystectomy in a time interval of one year. The large user population of the hospital made it possible to validate the results and compare them with the available literature. Knowing which critical factors impact on operating time can help clinicians to manage operating sessions in advance or to schedule them better in order to avoid time fluctuations and to achieve more efficient and standardized healthcare planning.

Keywords: Healthcare Management, Operating Room, Machine Learning, Operating Room Times, Feature Importance.

1. Introduction

Health care systems around the world, and hospitals in particular, are working in a critical economic environment, where efficiency must be improved in order to satisfy ever-increasing demand at the lowest possible cost (Fong et al., 2016). Historically, the most costly departments to manage are the surgical and anesthesiology departments due to the use of expensive drugs, highly technological resources and specialized personnel (Macario et al., 1995). A large part of these expenditure items are associated with the use of operating rooms (OR). ORs are expensive to run but are also associated with the highest income for hospitals. In the United States, for example, they generate about 70% of revenue with a utilization of allocated staff of no more than 60-70% (Li et al., 2016). Even in Italy, the country of reference for this study, interest in OR Management spread rapidly in response to the financial crisis of 2008, which led to a major reduction in funds allocated to the health sector (Rochira et al., 2020). One way to optimize its use is through the reduction of inefficiencies related to the patient's time spent in the operating block. These, in fact, can occur not only during surgery, but also between cases. The result is delays in care, dissatisfaction and frustration for both patient and OR staff (Harders et al., 2006). One way to maximize OR utilization is through the determination of an appropriate amount of time to be allocated to each surgeon and thus to each patient (Dexter et al., 1999). Computerization and digital medicine have been chosen as the main trajectory for healthcare development, involving different aspects of care (Anan'ina et al., 2021). All the techniques successfully employed in other fields, such as simulation models (Guizzi et al., 2020) even at discrete events (Romano et al., 2015a), have converged in this area (Romano et al., 2015b). On the one hand, this will make it easier to carry out clinical studies, as computerized medical records are available (Bonavolontà et al., 2019; Maniscalco et al., 2018; Montella et al., 2022) and on the other hand to optimize healthcare processes, both by using management techniques such as Lean Six Sigma Sigma (Improta et al., 2020) (Ferraro et al., 2020), and through advanced data analysis (Ponsiglione et al., 2023; Scala et al., 2023). An example is the analysis that was carried out in the COVID-19 era to study the impact of the pandemic on management data in hospital discharge forms (Improta et al., 2022; Scala et al., 2022b).This data can also be used within the OR, for the correct scheduling of interventions. OR times are linked to different long-term performance metrics, impacting patient outcomes, hospital efficiency, costs, reputation, staff well-being and overall healthcare delivery. For example, factors such as team composition, stability, teamwork, work scheduling, and disturbing elements impact three key outcomes: operative time, patient safety, and costs (Pasquer et al., 2024). So, by optimising OR times, hospitals can improve clinical outcomes, increase patient satisfaction, reduce costs and ensure better utilisation of resources, ultimately leading to improved long-term performance in various dimensions of healthcare care.

1.1 State of art

Given its strategic importance within the hospital, several scientific publications have dealt with this topic. Dexter et al. (Dexter et al., 1999) used a simulation model to assign OR times for each surgeon. In their study, they showed that the patient's waiting time before receiving surgery was a significant parameter influencing OR times. Phieffer et al. (Phieffer et al., 2017), instead, they use a Lean Six Sigma approach to optimize OR utilization, also showing a significant reduction in delays. Bartek et al. (Bartek et al., 2019) more in line with our research, uses Machine Learning (ML) algorithms to predict operating time using patient, surgeon and procedure data. Van Eijk et al. (van Eijk et al., 2016) show that, with respect to a specific procedure, two different surgeons as well as two anesthetists have little impact on time variability. What is lacking is the use of feature analysis techniques to study the impact of patient, organizational and scheduling variables conducted. In their research, (Devi et al., 2012) explore and evaluate various techniques, including fuzzy sets, recurrent neural networks and multiple linear regression, for ophthalmic procedures. Simulated planning is best achieved with adaptive neurofuzzy inference systems, which also prompted the healthcare professionals involved in the study to endorse its use in the real world. (Jiao et al., 2022) evaluate the prediction accuracy of sessions ending after 3 p.m., obtaining an accuracy of 89%, while (Martinez et al., 2021), on the other hand, focus on testing the performance of different models without delving into the specific contribution of independent variables. However, this approach is limiting because it does not involve clinicians in the decision-making process and does not help managers to take corrective action to optimise pathways.

Regarding cholecystectomy, several examples of ML model implementation exist in the literature. (Guédon et al., 2016) propose a real-time system for predicting the remaining time of the procedure, optimising the efficiency of the operating room by reporting an average simulation error of 14-19 minutes. On the topic of feature importance, (Thiels et al., 2017) emphasise the importance of patient-specific preoperative parameters (e.g. anaesthesia score, body mass index, gender and liver function) to refine time estimation for this particular procedure. Finally, (Ammori et al., 2001) contribute the degree of severity of the pathology to predict the duration of the procedure. These research strategies, however, are limited to simple static analyses or odds ratio measures. The authors found nothing applied to the specific context of the techniques under study.

1.2 Aim of work

In this work, we want to use the global and local interpretability techniques of ML algorithms to investigate which variables impact on the time patients spend in the operating block (OB). The target of the work is to understand which factors are controllable (such as organisational factors) and non-controllable (such as patient factors) in order to suggest to healthcare management to adopt improvement strategies aimed both at process standardisation but also at optimising OR planning. To do so, we selected a standard procedure - laparoscopic cholecystectomy - of high execution within the AORN "A. Cardarelli" of Naples (Italy).

2. Methods

The AORN "A. Cardarelli" in Naples is the main hospital in the south of Italy. It has a primary role in emergency health care. It is organized in 21 pavilions and produces 90¢000 admissions in ordinary inpatient and day surgery every year. Among the health departments present, in addition to the emergency-urgency department, there are three different operating units specializing in general surgery.

In our study, data from 466 patients who underwent laparoscopic cholecystectomy (LC) in the year 2023 in both elective and emergency-urgency were included. Specifically, the extracted data are as follows:

- Age;
- Gender;
- Diagnosis-related group (DRG);
- OB: is represented by that complex of premises and facilities necessary for the development of surgical activity, made to progressively less contaminated areas of which the ORs are the cleanest part;
- OR;
- Date of surgery;
- Operating session duration;
- Patient entrance - exit time from the OB;
- Equipe;
- Surgical schedule.

From the DRG variable it is possible to determine whether the procedure was complicated, thus defining from this a dichotomous variable (Yes / No). OR, OB and Equipe were already extracted in coded form within the hospital's digital operating register. With each day on which an LC operation was performed, it was possible to determine if the target operation was the last one of the operating day or not. The duration of the session (typically 6 hours, 12 hours or 24 hours for emergency rooms) was coded into 3 separate classes, but was also used to define the variable 'Overbook' which is worth 1 if on that day the last surgery starts after the end of the operating session. The dichotomous variable 'Festivity' was then defined, which is worth 1 if the day of surgery coincides with a Catholic-Italian religious or political holiday. Finally, from the difference of exit time and entrance time, the permanence of each patient within the OB was obtained, the dependent variable of our model.

2.1 Interpretability techniques in Explainable AI

ML algorithms are also becoming increasingly present in healthcare (Scala et al., 2022a). Before being applied on a large scale, especially in a sensitive context such as healthcare, it is necessary to understand how these systems work using interpretability techniques (Carvalho et al., 2019). Explainable AI (xAI) provides a rationale that allows users to understand why a system has produced a given output. The output can then be interpreted within a given context (Antoniadi et al., 2021). Of the various techniques available, it was decided to adopt a post-hoc explainability approach, which involves implementing the models and then performing all the analyses to understand how it worked. Specifically, it was decided to identify the technically relevant parts, i.e. the features or input variables that had the biggest influence on the model's conclusion. Although these techniques represent the future of AI, according to (Retzlaff et al., 2024) there are still challenges in terms of the time-consuming process of identifying decision boundaries, the problems of scalability of explanations and the poor default presentation of xAI methods. These results therefore highlight the need to further improve these techniques by making them more efficient and user-friendly in order to improve the overall user experience. Both global and local interpretability techniques will be applied in this study. For the investigation with global techniques, Feature Importance and Partial Dependence Plots (PDP) were chosen, the former being a technique that analyses all possible interactions without retraining the model while the latter because it is intuitive and clearly understandable (Gandhi and Mishra, 2022). Feature importance is a global technique that studies how the model's prediction error changes after permuting the value of one of the chosen predictors. A feature will be important if the error increases significantly during this process (Elshawi et al., 2019). PDPs show the effect of features on model prediction. Specifically, each graph shows the prediction of the model when an instance has a specific v-value for that particular feature. Finally, the average partial relationship between the predicted response and one or more features is extracted (Goldstein et al., 2014). Among the local techniques, the Shapley model has been implemented. This technique predicts that each feature is a player and the prediction is the payoff. The Shapley value aims precisely at distributing this payoff among the various features. Specifically, for each feature f, it evaluates the model using all possible combinations of the features without f. As it is defined, it is an expensive technique especially from a computational point of view (Elshawi et al., 2019).

The last analysis presented involved the implementation of a simple linear regression model. The coefficient associated with each feature and the result of the t-test (in terms of p-value with a significance level of 95%) can provide useful information on the contribution made during prediction.

The analysis was implemented by running a special script in MATLAB Version: 9.13.0 (R2022b) Update 5 (https://www.mathworks.com).

3. Results

Before proceeding with the implementation of the techniques presented, it was decided to carry out a preliminary correlation study. Specifically, Pearson's correlation was implemented and represented here in Figure 1 in graphical form.

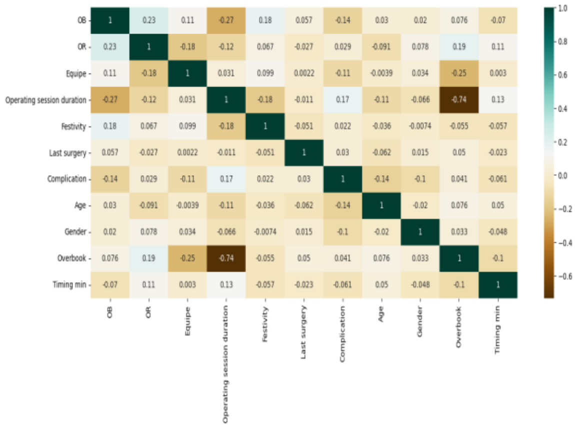

Figure 1: Correlation values between variables.

The correlation study shows that there is a strong negative correlation (-0.74) between the duration of the operating session and the risk of overbook, which is therefore more strongly associated with shorter operating sessions. Other strong negative links are registered between the duration of the session and the OB (-0.27) and between the risk of overbooking and the operating team (-0.25). Among the positive values, on the other hand, the link between OB and OR (0.23), which can be explained by the fact that the OR is part of the OB, and between overbook and the OR (0.19) is significant. As mentioned in the previous section, the first interpretability technique implemented is feature importance. The result is shown in Figure 2.

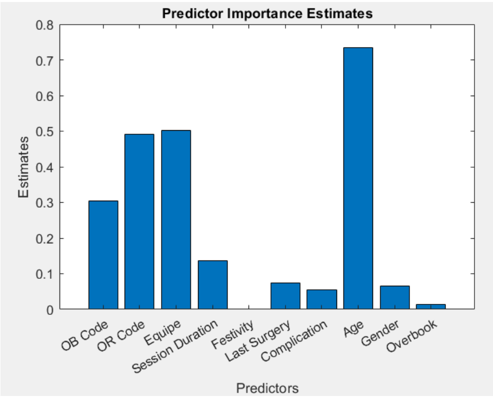

Figure 2: Feature Importance.

As can be seen from the graph, the variables that seem to most influence the prediction of the patient's time spent in the OB were the Age, Equipe and OR Code. Contrary to what was expected, complications, the Overbook and the fact that the surgery is the last one of the day do not show a relevant influence. The aspect that seems to have the least impact on prediction was the variable Festivity, but this is due to the fact that it only affects two cases in the entire dataset. Subsequently, the PDPs were obtained. The plots for each feature were presented in Figure 3.

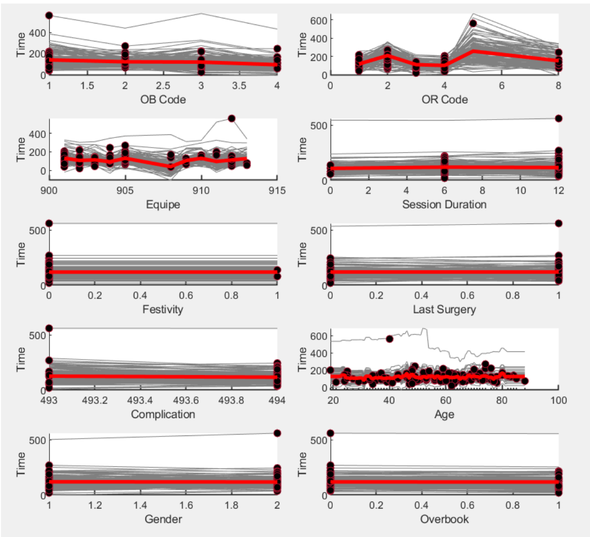

Figure 3: Partial Dependence Plots.

Within the graph, the black lines represent the individual patient and the red line the average trend. It can be seen from the graph that the time tends to decrease for complicated DRGs (494) compared to patients discharged without complications (493). For age, the most significant variable in the previous analysis, there was no significant trend but only a slight peak at the age of 80. The length of time also decreases slightly at female patients and in the case of Overbook.

Figure 4 shows the result obtained with the latest local interpretability technique.

Figure 4: Shapley Summary Plot.

Each point in the graph represents a Shapley value for a feature and a given instance. It can be seen from this graph that a high OB value (purple dots) corresponds to a negative Shapley value and thus a lower occupancy time. The highest OB value represents the emergency department, which was therefore more efficient than the others were. Shorter operating session durations (light blue dots) also correspond to negative values and thus shorter times.

Finally, we analyzed the coefficients associated with the implementation on our dataset of a very simple prediction model, such as linear multiple regression (MLR). The coefficients of the model and their statistical significance are shown in Table 1. Statistically significant contributions (p-value≤0.05) are highlighted in bold.

Table 1: MLR model coefficient and results of t-test.

	Estimate	SE	t-test	p-value
(Intercept)	150.72	29.83	5.05	**0.00**
OB Code				
2	-35.90	19.19	-1.87	**0.06**
3	-32.66	12.35	-2.64	**0.01**
4	-110.33	32.09	-3.44	**0.00**
OR Code				
2	39.97	17.74	2.25	**0.02**
3	7.68	10.15	0.76	0.45
4	-3.14	7.46	-0.42	0.67
5	183.54	25.96	7.07	**0.00**

8	0.00	0.00	-	-
Equipe				
902	-13.94	9.75	-1.43	0.15
903	-17.87	6.62	-2.70	**0.01**
904	132.19	32.30	4.09	**0.00**
905	0.00	0.00	-	-
908	-22.70	15.18	-1.49	0.14
909	-20.27	14.50	-1.40	0.16
910	-13.91	12.18	-1.14	0.25
911	-11.37	20.76	-0.55	0.58
912	-6.82	11.09	-0.61	0.54
913	0.00	0.00	-	-
Operating session duration				
6	-22.29	28.57	-0.78	0.44
12	-25.37	27.59	-0.92	0.36
Festivity				
Yes	-29.73	35.55	-0.84	0.40
Last Surgery				
Yes	-3.50	4.18	-0.84	0.40
Complication				
Yes	-10.17	7.07	-1.44	0.15
Age	0.27	0.13	2.08	**0.04**
Gender				
Female	-8.79	4.04	-2.18	**0.03**
Overbook				
Yes	0.68	8.79	0.08	0.94

There are significant influences in the OB Code, for some ORs and Equipe, for Age and Gender. Based on the value of the coefficient, for example, a lower permanence is observed for women, as already estimated with the PDPs.

4. Discussion and Conclusion

In this work, we studied the occupancy time spent in the OB for patients who underwent LC surgery in 2023 at the AORN "A. Cardarelli" in Naples (Italy). Patient-specific and organizational features were collected from the surgical register and hospital discharge forms for a total of 466 observations. The aim of the study was to understand which of the identified features was a predictor of occupancy time by investigating what happens within the predictive models using local and global interpretability techniques. To do this, we decided to investigate a single basic procedure for which there was a shared protocol within the hospital between the various operating units involved so that the result would be clinically valid. The presence of a shared protocol between the various teams helps to better characterise the phenomenon and a basic assumption that eliminated the variability caused by different surgical approaches. Having chosen different structures or different procedures would certainly have allowed for more discussion and the possibility of making new comparisons, but would have made the study lose its purely and directly applicative objective. Introducing the manager to how a model works helps him to understand the strengths and weaknesses of his specific pathways, which will naturally differ from those implemented by other hospitals because they are linked to organisational and structural aspects and, above all, to the social and health status of their catchment area. The results of the analysis showed that Age was the variable that had the greatest influence on the prediction followed by Surgery Team and OR. The PDPs with Shapley value support showed a reduction in time associated with increasing values of OB Code and Gender. In particular, lower values were observed for the OB in the emergency room and for female patients. This work provides important insights into the applicability of ML algorithms within a hospital's surgical planning. The analysis shows, in fact, that it is not enough to assign a fixed time based on the surgical procedure, but that the patient's age and the team performing the surgery will influence the outcome. (Thiels et al., 2017) also show that the female sex is associated with a reduced operating time when compared to the male sex, while (Ammori et al., 2001) validate age as an important predictor. This result is easily explained by the fact that older patients are also the more fragile ones who are most likely to be associated with additional secondary diagnoses that may make the procedure more complex than the standard one. The skill of the surgeon also remains an important element in the variability of the OR time as expected in our study and as also confirmed in the literature by (Eijkemans et al., 2010). We obtained outcomes partly in line with the expected values from the healthcare personnel involved in the study, apart from complications. The fact that complications did not influence the analysis is mainly due to the method by which this was derived. In fact, in this case it was only characterised by the DRG, which indicates the presence in the patient of specific secondary diagnoses which, in order to be treated, attribute additional complexity to care in general and not specifically to the surgical procedure. To do so, it is necessary to include additional variables that have a known clinical evidence such as the anaesthesia score and type of anaesthesia, body mass index or specific tests on the function of the organs concerned (Haji et al., 2009). The results obtained, although using methods other than simple statistics, have led to clinical considerations also expected in the literature that allow us to validate the use of these tools as a support for healthcare management. However, this work is not without its limitations. The analysis is in fact monocentric, based on a specific surgical procedure in only one year of observation. Future developments will involve the extension of this analysis both in terms of the number of patients included and the variables under investigation and the interpretability techniques implemented. The aim will be to provide clinicians with a validated tool able to perform, on the basis of waiting lists and new urgent cases arriving at the hospital, an accurate planning and thus a more efficient use of ORs.

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