Data Analisys approach to support Surgical Schedule Development: the case of A.O.R.N. "Antonio Cardarelli" of Naples (Italy)

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Abstract: The operating room (OR) represents one of the main bottlenecks within a hospital. In addition, it is also the component associated with the greatest economic expenditure. In a context of increasingly limited resources, healthcare management is looking for ways to reduce costs and ensure more efficient use availability. Effective OR planning is therefore indispensable. To do this, Artificial Intelligence tools can be used to achieve OR occupancy times that are a function of the patient and the surgeon and not solely of the procedure. In this study, using data from the operating registers of the AORN 'A. Cardarelli' in Naples (Italy), we aim to predict, for each patient, on the basis of his specific clinical condition and specific surgeon, the operating room occupancy time using regression models. Only through the definition of a new variable dividing the dataset into 3 complexity classes was it possible to achieve good performance by achieving an R^2-value of more than 0.5. This information will enable managers to plan using a more accurately defined occupancy rate. Basing the surgical timing on the specific characteristics of the patient and the surgeon's expertise will allow objective planning to maximize OR utilization.

Keywords: Scheduling, Occupancy Time, Operating Room, Data Analysis, Machine Learning.

1. Introduction

Health care systems around the world are increasingly focused on ensuring quality services, not only because they are related to patient health but also to contain spending (Caniato et al., 2015). Healthcare management priorities therefore focus on reducing waste and eliminating inefficiencies (Abd Manaf et al., 2016).Much of the expenditure is associated with surgical departments and in particular with the use of the operating room (OR) (Barbagallo et al., 2015). Surgery is also associated with bottlenecks, i.e. a point of congestion in the optimization of healthcare. (Mihalj et al., 2022) in their study point out that the bottlenecks associated with perioperative care are due to the infrastructure, the supply chain and especially the flow of information between staff and patient clinical information.Within ORs, social interactions involve many and highly varied actors. In addition to this, the surgeon's experience, flexibility due to emergency surgery, unexpected changes in the patient, delays or overlapping can all have a negative influence leading to inefficiency (Lee et al., 2019). One way to overcome some of these factors is through computerization and planning of the surgical programme. Having the data digitized and integrated with other information systems in the hospital can facilitate communication between operators and have all patient information quickly (Tresp et al., 2016). If this is combined with advanced data analysis techniques, it is possible to gain knowledge from the available historical information (Bonavolontà et al., 2019; Colella et al., 2022). Moreover, it is in this innovative context that our research is inserted.

1.1 State of art

The analysis of health data by means of data analysis techniques in order to extract knowledge is not new in healthcare. A large proportion of clinical studies were aimed at collecting data and analyzing them using simple statistical analysis (Maniscalco et al., 2018).Various process optimisation techniques are used in the literature, ranging from mathematical models (Gebennini et al., 2013) to simulation models (di nardo et al., 2017). Artificial intelligence and in particular Machine Learning (ML) are spreading rapidly in all sectors (Salatiello et al., 2024), including the health sector (Scala et al., 2022b). This development is mainly due to the availability of a large amount of data, directly in digital format, which was obtained because of the computerization of health care flows and documents. These techniques have not only had an impact on clinical practice (Cheng et al., 2022), but also in healthcare management. For example, (Scala et al., 2022a) use these techniques to optimize the path with lower limb fracture or (Aufegger et al., 2019) as decision support to ensure patient safety. Even management approaches such as Lean Six Sigma (Improta et al., 2020) are benefiting from ML to support context analyses and better analyze implemented corrective solutions (Improta et al., 2022). These tools can also be implemented in the

OR and in the planning and scheduling of operating sessions. (Bartek et al., 2019) uses ML algorithms to predict operating time using patient, surgeon and procedure data. (Fairley et al., 2019) instead use ML to predict the post-anaesthesia care unit time for each type of surgical procedure. (Eshghali et al., 2024), finally, implement it not only to plan surgical sessions but also to modify them when a case arrives in an emergency that requires priority and must be treated before those scheduled. In their paper, (Devi et al., 2012) proposes and tests the implementation of different techniques such as fuzzy sets, recurrent neural networks and multiple linear regression on ophthalmic procedures. The results show improved simulated planning with adaptive neurofuzzy inference systems, which pushes the authors towards real-world applications.(Jiao et al., 2022), in addition to comparing the use of neural networks with a Bayesian approach, they test their results by evaluating the accuracy in predicting sessions that ended after 3:00 p.m., reaching a value with the first model of 89%. Simpler, on the other hand, is the study proposed by (Martinez et al., 2021), which merely tests the performance of different models without going into detail on the contribution of the independent variables used. Also on the specific procedure studied, there are several examples available in the literature. (Guédon et al., 2016) proposed a system capable of predicting, in real time, the time remaining to complete the procedure in order to start preparing the next patient and thus optimise operating time. The results showed an average simulation error between 14-19 minutes and even the medical staff involved recognised its applicability. On the other hand, (Thiels et al., 2017) show how the inclusion of patient-specific preoperative parameters such as anaesthesia scores, body mass index, gender and liver function can optimise the time estimation for this particular procedure. Finally, this is the context of the study proposed by (Ammori et al., 2001) that adds more accurate clinical components on the area undergoing the surgical procedure among the predictors.

1.2 Aim of work

In this work, ML algorithms - and in particular regression models - were implemented to predict the time spent by a patient undergoing laparoscopic cholecystectomy (LC) surgery within the operating block (OB). The context is that of the AORN "A. Cardarelli" in Naples, one of the main hospitals in southern Italy.

2. Methods

As anticipated in the previous section, the work was developed by extracting from the hospital's information system the data of 466 patients who underwent LC surgery in 2023, both urgent and planned. The hospital chosen to conduct our analysis is the AORN 'A. Cardarelli' in Naples, one of the most relevant hospitals in Italy and the largest in the south of the country. In particular, it is the main emergency access point and handles over 90,000 admissions each year. Within it, there are three different general surgery-operating units that deal with the surgical procedure under study plus a specific OR for the emergency department that works on a 24-hour cycle.

Both demographic variables of the patients (Age, Gender) and specific variables of the process (OB Code, OR Code, Patient entrance - exit time, Equipe, Date of surgery, etc.) were extracted from the hospital discharge forms and the surgical registry. From these, appropriately processed, the following independent variables of the models were obtained:

- Age;
- Gender (Male/Female);
- Complication (Yes - if the DRG is in the version with complications /No - otherwise);
- OB Code (already encoded in numerical form in the operating register);
- OR Code (already encoded in numerical form in the operating register);
- Festivity (Yes - if the date of intervention is a typical Italian national or religious holiday /No - otherwise);
- Operating session duration (6 hours; 12 hours, 24 hours)
- Equipe (already encoded in numerical form in the operating register);
- Last Surgery (Yes - whether the intervention in question is the last one of the session/ No-otherwise).
- Overbook (Yes - if the last surgery whatever is scheduled on that specific day starts after the end of the session / No – otherwise)

The dependent variable of the model was obtained as the difference between the exit time and the entry time of the patient within the OB.

The frequencies of the dichotomous variables are shown in Table 1.

Table 1: Distribution of dichotomous variables

		N° of observation	%
OB Code			
	1	315	67.6
	2	69	14.8
	3	58	12.4
	4	24	5.2
OR Code			
	1	112	24.0
	2	79	17.0
	3	75	16.1
	4	181	38.8

	5	3	0.6
	8	16	3.4
Equipe			
	901	96	20.6
	902	107	23.0
	903	110	23.6
	904	16	3.4
	905	69	14.8
	908	10	2.1
	909	12	2.6
	910	14	3.0
	911	5	1.1
	912	19	4.1
	913	8	1.7
Operating session duration			
	6	222	47.6
	12	233	50.0
	24	11	2.4
Festivity			
	No	464	99.6
	Yes	2	0.4
Last Surgery			
	No	291	62.4
	Yes	175	37.6
Overbook			
	No	48	10.3
	Yes	418	89.7
Gender			
	Male	207	44.4
	Female	259	55.6
Complication			
	No	273	58.6
	Yes	193	41.4

The distribution shows that 67.8% of LCs are performed in OB1 and only 5.2% in OB4 associated with the emergency department. In the teams, the distributions are less clear-cut, but the first three alone perform more than 60% of the interventions. Another interesting fact is that the percentage of men and women included in the dataset is almost similar, with a slightly higher number for women. For the Age, the only continuous variable in the dataset, the distribution is shown in Figure 1.

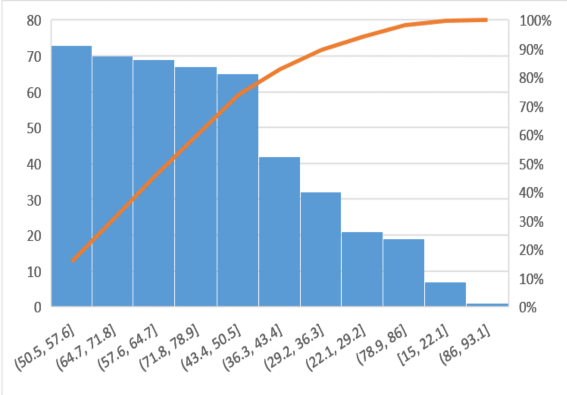

Figure 1: Pareto diagram for Age.

The Pareto diagram shows that 80 per cent of patients are over 50 years old, in line with the particularity of the selected surgery (Scala et al., 2023).

2.1 Regression Algorithms

The analysis was implemented in MATLAB Version: 9.13.0 (R2022b) Update 5 (https://www.mathworks.com). Specifically, the App available in the software called Regression Learner was used, which allows multiple algorithms to be simulated simultaneously.

On the first screen, the user is asked to select the dataset and choose how to perform testing and validation. For this study, it was decided to extract a 10% from the dataset to be used for testing and to perform a validation using Cross Validation with a fixed number of folds equal to 5.

It was therefore decided to implement the following available algorithms, and for each one it was decided to test different variants depending on the value assumed by one or a combination of hyperparameters. These variants are summarized in Table 2.

Table 2: Regression algorithms implemented with different alternatives

Model Type	Alternatives
Linear Regression (LR)	1-Linear, Robust Option: Off
	2-Interaction, Robust Option: Off
	3-Linear, Robust Option: On
Stepwise Linear Regression (SLR)	1-Initial Term: Linear, Upper bound on terms: Interaction
Tree	1-Minimum leaf size: 4

	2-Minimum leaf size: 12
	3-Minimum leaf size: 36
Support Vector Machine (SVM)	1-Kernel Function: Linear, Kernel Scale: Automatic
	2-Kernel Function: Quadratic, Kernel Scale: Automatic
	3-Kernel Function: Cubic, Kernel Scale: Automatic
	4-Kernel Function: Gaussian, Kernel Scale: 0.83
	5-Kernel Function: Gaussian, Kernel Scale: 3.3
	6- Kernel Function: Gaussian, Kernel Scale: 13
Ensemble	1-Learning rate: 0.1
	2-Default value
Neural Network (NN)	1- Number of fully connected layers: 1, First layer size: 10
	2- Number of fully connected layers: 1, First layer size: 25
	3- Number of fully connected layers: 1, First layer size: 100
	4-Number of fully connected layers: 2, First layer size: 10, Second layer size:10
	5-Number of fully connected layers: 3, First layer size: 10, Second layer size:10, Third layer size: 10

In this way, it will be possible to determine not only the best algorithm, but under which conditions it is likely to achieve that performance. Of the selected algorithms, the simplest is the linear algorithm that performs prediction by linearly combining the independent variables using appropriate coefficients. Stepwise Linear Regression is an alternative to the linear model that adds or removes terms based on the performance obtained. Tree models, on the other hand, perform prediction by analyzing the value assumed by a feature at each node in a binary manner. Depending on the value assumed, a specific path is determined leading from the root (beginning) to the leaf, where the output value is assigned. Depending on the levels, the tree will be coarser (Minimum leaf size: 36) or finer (Minimum leaf size: 4). The Ensemble algorithm enhances its performance by inserting more Tree predictors. SVM can also be used for regression problems, by defining a space within which the various instances should fall. One degree of freedom is represented by the choice of kernel. Finally, NN is typically a feedforward and fully connected network. The first layer is connected to the input and intermediate layers multiply the independent variables by a suitably created matrix of weights and adds a bias vector. After each layer, there is an activation function, except for the last. The performance of the various models will be evaluated in terms of Root Mean Squared Error (RMSE) and R^2.

3. Results

Once the independent variables of the model were defined, the algorithms in Table 2 were implemented in order to predict the patients' time spent in the OB. Table 3 shows the results for each model type according to the best alternative.

Table 3: Results of Regression algorithms

Model Type and Alternative		Validation		Test	
		RMSE	R^2	RMSE	R^2
LR	3	48.30	0.001	24.38	0.178
SLR	1	49.74	-0.059	32.70	-0.478
Tree	3	48.25	0.003	29.38	-0.194
SVM	1	48.17	0.007	24.98	0.137
Ensemble	2	47.23	0.045	29.34	-0.189
NN	5	104.43	-3.669	77.10	-7.216

As can be seen from the values in Table, in general, the performance of the models is low. In some cases, the R^2 value is less than 1, showing that the model fits the data really poorly. Of these, the LR performed best on the test set, while the Ensemble performed best downstream of validation. In any case, the value remained below 0.05, the minimum threshold recognized in some scientific papers as ideal for the goodness of the model (Loperto et al., 2022). At this point, we wondered whether the variables included in the model were not representative of the patient's clinical condition. In fact, as we did not have access to the patients' medical records, we could only characterize the complications through the DRG attributed at discharge. For this reason, we decided to add a variable to our model, called "Complexity", which would take into account, based on the observed time spent, a correlation between the minutes spent and the complexity of the clinical case treated. The first task was to analyze the distribution of the patients' time spent in the OB.

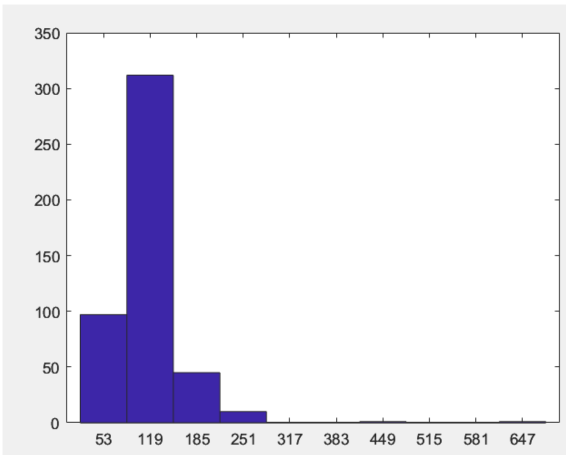

Figure 2: Patient histogram by time spent in OB.

Figure 2 shows that the minimum staying time is 20 minutes and that the peak is obtained at 119 minutes. The distribution terminates within 300 minutes with only a few outliers going beyond 440 minutes. The observed values show that the distribution does not have a normal trend, which is also confirmed by the "chi2gof" test implemented in Matlab to check the normality of the distribution. At this point, quartiles were calculated at 25% (q1) and 75% (q3) of the occupant time. From these, using a for loop and the if-else construct, the new variable was constructed. For each patient, the variable takes the following values:

- 1 - if the patient remains in the OB a time less than or equal to q1;
- 2 - if the patient remains in the OB a time between q1 and q3;
- 3 - if the patient remains in the OB longer than q3.

With the addition of the new variable, the algorithms were implemented again. Table 4 shows the results obtained.

Table 4: Results of Regression algorithms with new variable

Model Type and Alternative		Validation		Test	
		RMSE	R^2	RMSE	R^2
LR	1	37.24	0.390	23.98	0.559
SLR	1	39.51	0.313	24.24	0.549
Tree	3	37.16	0.392	21.48	0.646
SVM	2	38.41	0.351	25.00	0.520
Ensemble	1	38.44	0.350	24.40	0.543
NN	1	57.44	-0.452	24.68	0.533

Adding a variable, probably related to patient complexity that correlates with time spent, resulted in an overall improvement in the performance of the algorithms. All exceeded the threshold of 0.5 and the best was the regression algorithm based on decision trees. Figure 3 shows the regression line obtained with the Tree model on the test set.

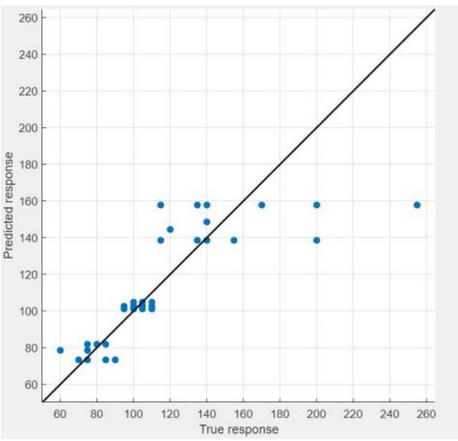

Figure 3: Predicted VS True response with Tree Model.

The model works well on lower values, while it loses predictive power on higher values of permanence, even associated with a lower number of observations.

4. Discussion and Conclusion

The objective of this work was to predict the time patients spend in the OB for a LC surgical procedure performed in the year 2023 in the hospital AORN 'A. Cardarelli' - Naples (Italy). To implement the regression algorithms, used in the prediction of continuous output variables, the independent variables were first defined. Using operating registers and hospital discharge forms, both demographic variables (such as sex and age) and organisational variables (such as OB code, OR code, DRG, date of surgery, operating session duration and operating planning) were extracted for the 466 patients included in the study. At this point, the algorithms were implemented in the Matlab environment. The implementation was disappointing and the chosen models failed to characterize the phenomenon, with R2 values often negative. We assumed that we did not have clinical data on the patient that would allow us to define the complexity of the patient (apart from the DRG assigned after discharge). For this reason, an additional independent variable called "Complexity" was created based on the observation of time spent in the OB, which could take 3 different values assigned according to quartiles. With the addition of this variable, the performance of the algorithms improved significantly, reaching a R^2 value of 0.646 with the Tree model.

This line of research includes (Edelman et al., 2017)'s article, which aims to improve the accuracy of the models precisely by adding new additional variables. Specifically, the variables added that were not present in our model concerned the anaesthesia classification and the type of anaesthesia used. Using a simple regression model as a classifier, the authors show how better performance can be achieved with these new variables. Even (Eijkemans et al., 2010)'s study, although not using advanced data analysis techniques, identifies through odds ratios the contribution made by different variables. The surgeon's estimate had the greatest effect while higher body mass indexes corresponded to longer times. These variables are in line with what other studies have reported (Ammori et al., 2001; Thiels et al., 2017) already presented in the state of the art, to which they also add anatomical site-specific clinical considerations and the degree of complication of the procedure to be performed especially in elective surgery. According to (Stepaniak et al., 2010), the type of procedure, the time of day and the surgeon's experience also influence the operating time. Thus, including more procedures might benefit the model in terms of accuracy, but might cause the study to lose the specific focus it needs to provide healthcare management with a directly applicable tool for individual cases. From the analysis carried out, it is possible to define the limits of our work. The variables included were not representative of the phenomenon and therefore needed further investigation. The result, although positive in the second application, was the creation of an ad hoc variable based on the observation of the output. Also based on the articles presented above, it will be necessary to access all the entries in the surgical register in order to better characterise the patient. Furthermore, the study was monocentric and based on a single surgical procedure. On the one hand, this limited the generalisation of the results by not offering the possibility of also comparing different protocols in different hospitals or different operating techniques for treating the same clinical need. On the other hand, as mentioned above, such a structured model could have limited practical application. Future developments will involve the collection of additional variables and more years of observation to better characterise the timing and obtain better predictive models.

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