Study on Using Linear Regression Modeling to Better Estimate Total Surgical Procedure Time

Siji Chen

Cornell University, Ithaca, NY 14853, USA

Abstract. To make the most of the resources available in the operating room, careful planning of the available block time and the patient case sequences is required (OR). These planning methods will only help if the forecasts provided by TPT can be relied upon. This study makes use of linear regression models to improve TPT forecasts. These models are given estimated surgeon-controlled time (eSCT) in addition to other parameters of relevance. Surgical procedures at six Dutch institutions between 2012 and 2016 were evaluated using data from a benchmarking database. There were 79,983 contributors, which resulted in 199,772 hours of OR being reported. We analyzed the risk variables for TPT, which revealed that eSCT, patient age, surgical type, ASA physical status category, and anesthetic procedure were all contributors. During calculating the projected TPT for each file, the eSCT was multiplied by a fixed ratio model (discussed in further detail elsewhere) by a factor of 1.33. According to the findings of the research conducted by van Veen-Berkx et al., a conservative estimate of the period during which anesthesia is stable is around 33 percent of the SCT (ACT). In conclusion, we analyzed different linear regression models to predict TPT. These models included eSCT as one of the independent factors among the other covariates. In the end, each of the regression models was retested, this time to see whether or not it was possible to predict ACT reliably without using eSCT as a covariate (which leads to TPT by adding SCT). The most accurate projections of TPT were generated by a linear regression model that used eSCT, the kind of operation, the ASA classification, and the type of anesthesia. Compared to the fixed ratio model and the ACT prediction approach, the performance of this model was very satisfactory. Significant cost savings and increases in overall productivity may be realized if more accurate estimates were included in the planning and sequencing algorithms used to enhance operating room usage.

Keywords: Linear Regression Modeling; Surgical Procedure Time; Estimate.

1. Introduction

A hospital's operating rooms (ORs) are essential because of the income they produce. It is predicted that the average income per operating room hour will range anywhere from $1,000 to $2,000 before considering the different expenses of staff and materials associated with inpatient care. (1). As a result, it should be no surprise that a sufficient number of ORs are necessary. We may be wasting a significant amount of money with each passing second. The most effective use of an operating room is contingent upon the meticulous planning of block time and the sequence in which individual patient cases will be attended to [3].

The ability to provide accurate forecasts of the overall amount of time required for a procedure is essential to the success of such planning systems (TPT; acronyms defined in Table 1). Induction of and recovery from anesthesia each take up a portion of the total procedure time (TPT) [2]. Still, the actual surgical process takes up most of this time (SCT, the duration of the essential operation, including patient positioning and draping). Because ACT induction and emergence stages are carried out in the operating rooms of Dutch university hospitals, this methodology is considered relevant to the OR.

The OR's untapped potential may be made available for use with the assistance of TPT projections. By rescheduling patient cases in line with the expected total procedural time (TPT), it is possible to reduce the likelihood of an operating room (OR) being underutilized or canceled. Instead of adding a constant length for ACT to eSCT, the TPT may be consistently derived from eSCT by utilizing a specified ratio. This is preferable to the traditional method (2). To enhance TPT predictions' accuracy, this article's purpose is to include patient and surgical data pertinent to TPT.

Table 1. Abbreviations

ACT	Anesthesia-controlled time in minutes, as observed
Age	Patient age in years
ASA	American Society of Anesthesiologists physical status classification of the patient
eSCT	Surgeon-controlled time in minutes, as estimated prior to the operation
SCT	Surgeon-controlled time in minutes, as observed
TPT	Total procedure time in minutes, as observed

When doctors know better how long each surgery will take, they can better plan for procedures, allocate resources, and anticipate expenses (TPST). When designing complex operations involving many time-consuming processes, it is essential to estimate the total amount of time a patient will require medical care [1]. This has the potential to both improve patient outcomes and reduce the costs associated with providing healthcare. Therefore, a TPST measurement technique that can be relied upon is required for clinical applications.

The use of linear regression models for the purpose of TPST forecasting is a common and well-established strategy (LRM). It has been researched and used in various medical specialties, from surgical procedures to radiographic imaging[6]. Those interested in learning more about LRM to TPST forecasting may choose from a number of different sites for this reason. On the other hand, LRM forecasts can and should be produced in the future with greater accuracy and dependability.

The goal of this research is to identify and assess several potential solutions that have the potential to aid in improving TPST forecasting by using LRM. To achieve this goal, we will first conduct a comprehensive literature review on LRM's application to TPST prediction [8]. Next, we will compare and analyze already existing models and algorithms in-depth. Finally, we will develop and test our very own solutions. In combination with patient characteristics, environmental variables, and pre-and postoperative treatment, the predictive validity of the TPST will be examined [4].

In this part of the article, we will look at the research that has been done on the subject of TPST forecasting utilizing LRM. This study will compare and contrast different studies and models so that researchers may identify which ones are the most beneficial. Based on the results of this literature analysis, it is possible to conjecture as to the degree to which various circumstances influence the accuracy with which TPST predictions may be created; nonetheless, this is likely the case [7].

After that, an analysis of the efficiency of various LRM models and methods will be carried out. When the study is done to identify which model is the most dependable, the researchers will consider each model's assumptions and limits. The study's results will be included in the development of fresh models and algorithms, which will then be utilized to address the issues identified by the investigation.

The next phase will include creating and testing an original model and algorithm suite that will be incorporated into the project. We will construct fresh new models and algorithms using what we've discovered from this literature examination. Then we will test those models and algorithms using a dataset of TPST predictions. We can assess the usefulness of the improved models and algorithms as a result.

Any improvements to the accuracy of the TPST prediction will be incorporated as soon as the project is finished. The accuracy of predictions might be improved by adding newly collected data to models and previously built algorithms [13].

The fundamental objective of this study is to enhance the precision and dependability of TPST predictions that are derived using linear regression models. This study can dramatically boost the accuracy of LRM predictions by assessing current models and algorithms, inventing new models and

algorithms, and incorporating any uncovered advances. As a consequence of this, healthcare delivery improvements in the results for patients, efficiency, and quality are all within reach.

2. Review of Literature

Although it is generally known that it is difficult to predict how long an operation will take accurately, it is nonetheless necessary to do so to maintain a smooth surgical workflow. Various methodologies and tools have been created to facilitate the process of estimating [7]. Remember that the simplicity and accuracy with which you may use any of these approaches depends on their specific peculiarities and the expenses associated with using them. It is notoriously challenging to estimate the amount of time needed for a medical procedure. Even while operating under the same conditions as before, the length of time required to complete the process might vary based on variables beyond the surgeon's control. Because of the complexity of the problem, a significant number of research have been conducted to investigate the many different strategies that can better account for uncertainty and raise the accuracy of estimations. In the past, researchers have often relied on one of the following three approaches to estimate the total duration of a surgical procedure:

To shorten the time between surgical treatments, we must first identify the underlying reasons for the problem [4].

Statistical significance and goodness-of-fit may be used to evaluate how well a distribution corresponds to a set of data. Additionally, it acquires the knowledge necessary to improve your settings to make precise estimates about the time of day.

The observed period may be explained, and a prediction technique can be created if one enters the necessary elements into a regression model. Regression is a strategy that is often used in the medical field. Even more crucially, the study reveals that the intervention has a highly favorable impact in several areas.

Regression, which is one of the most extensively used methods in statistics, has the potential to be used in a variety of different disciplines, including finance, business, and education, to name a few. In healthcare, several types of regressions are used to gain insight into the dynamic between the dependent and independent variables and provide estimations [10]. One such example of this is the work that Fritsch and colleagues did. They built a logistic regression model to determine postoperative complication risk factors by using information obtained from preoperative assessments. According to the results, a patient's age, the level of invasiveness of the therapy, a history of renal sickness or anemia, and an irregular ECG are all elements that play a part in the model [9]. The authors developed a second logistic regression model to determine the clinical characteristics leading to unexpected postoperative hospitalizations, cancellations, delays, and extended recovery room stays. The investigations highlight the factors contributing to these inefficiencies in the operating room. A higher ASA score (as established by the American Society of Anesthesiologists) was shown to be a significant predictor of case cancellations.

On the other hand, the patient's age was found to be a significant predictor of unplanned admissions. The most common reasons for PCU hospitalizations that are much longer than anticipated are patients' ages and the length of their conditions. Delays often have the most substantial consequences in situations involving youngsters and people who need monitoring throughout anesthetic treatment [1].

A multi-regression model was utilized in this research to determine which factors contribute to the disproportionately high rates of hospitalization for people living in low-income areas due to chronic health issues. This was done to determine what variables contribute to these rates. When making their forecasts, they took into account a variety of criteria, including access, illness prevalence, patients' willingness to seek medical assistance, and physicians' ways of practice. They determined the predicted rates of long-term hospitalization for individuals suffering from chronic conditions [12]. The authors made a discovery that there is a connection between the ease of access to care and the admission rates. Both the patients' assessments of their access to care and the prevalence of the

disorders were considered independent factors in this study. These results may reduce the number of optional hospitalizations in the region.

Other studies have been published that indicate varying degrees of accuracy in estimating the amount of time an operation will take. Some of these procedures are as simple as taking the mean of the previous data to arrive at an estimate. In contrast, others engage in complex statistical analysis to enhance their forecast. Research carried out in 1999 uses the historical data's median and mean to highlight its findings [6]. The estimate derived through linear programming, the estimate derived from the median, and the estimate derived from the mean were all examined and contrasted. The authors discovered that because of the small sample size of unique events, sample averages were a superior measure when attempting to anticipate the total time required for a series of procedures and patient turns. In addition, Broka and colleagues discovered that the median of the several surgeons' historical time duration periods over a year helped make accurate predictions for future durations.

Nonetheless, another research concluded that the most critical factors in determining procedure duration were the surgeon and the kind of surgery being performed; however, the average amount of time required to finish the operations was insufficient. After conducting an exhaustive analysis, Spangler et al. (2004) concluded that a second-order regression model performed much better than the sample mean when it came to forecasting the location parameter of a lognormal distribution for surgery time. When estimating how long it will take to treat a particular surgical case, the correct Current Procedural Terminology (CPT) code that reflects the procedure being performed is more crucial than anything else. In another research, the influence of a particular surgeon was investigated by using regression analysis to construct a model of the length of time required for surgery [8]. The most important criteria were team composition, experience, and time of day; age, background, gender, and team composition all had less impact than team composition, experience, and time of day. Techniques from the field of data mining have also been used to the issue of determining how long a procedure will take to complete. These types of research using DM analysis have shown that statistical methods are more dependable than estimations made by surgeons [11].

The precision of surgeon estimations has been the subject of several investigations. Oral and maxillofacial surgeons are more likely to overestimate the amount of time it will take for patients to recover after surgery than they are to underestimate it. In 2016, the same happened. Surgeons tend to overestimate the amount of time it will take them by an average of 12.9 minutes. In the two trials before this one, the researchers found that surgeons had a predisposition to making inaccurate estimations when doing procedures. According to the findings of Joustra et al., it is common practice for surgeons to overestimate or underestimate the time required for an operation [8]. The surgeon estimate was shown to be a significant explanatory variable in the statistical models. In many studies, researchers have contrasted the estimated and actual amounts of time surgeons spend in their profession. Larsson compared the estimates provided by surgeons to the average value attained for the four surgical procedures performed the most often. The research authors found that the Surgeon-based method performed very well when detecting complicated scenarios, in contrast to the average value technique, which produced more accurate estimations [10].

In a subsequent investigation, Wright et al. (1996) compared surgeon-based and regression model estimates. They discovered that surgeon-based estimates were more accurate than regression model estimates. The model that was used took into consideration a wide variety of characteristics, some of which are listed below: gender, bilaterality, resident assistant rank, important diagnoses, case complexity, and the utilization of past data by surgeons. In contrast, Eijkemans et al. (2019) construct a lognormal regression model and evaluate its prediction in light of surgeon estimate [5]. They do this using a lognormal regression model. The surgeon's prognosis, the anticipated number of surgeries, the number of surgeons and anesthesiologists, and their combined years of experience were all included as predictors, along with a variety of patient factors such as age, gender, prior hospital admissions, and body mass index [13]. Compared to surgeon expectations, underestimates were lowered by 2.8 minutes for each case, while overestimates were reduced by 6.6 minutes per case. It was also shown that parameters related to the surgical team were more predictive of the duration of

the treatment than those related to the patient. When correlating each surgeon with each CPT, separate studies indicated that the operation length is affected by various parameters, including the kind of anesthetic used, the patient's age, gender, and ASA score [3]. This retrospective research looked at patients with a single CPT for cardiothoracic, orthopedic, neurological, or general surgical services. Patients were categorized according to the kind of surgery they had had. The second part of this study focuses on determining how well different CPT codes can estimate the total time required for surgery. Li and colleagues, in a study that was later published, investigated the consequences of using several CPT codes to describe the same service. They have explored the idea of incorporating all operations when predicting the time required for surgery because the CPT specifies what procedures a specific surgical case would contain [9]. The research also evaluated two different types of regression and found that linear regression was superior to log-linear regression in terms of the quality of the results it produced.

3. Methodology

To get at our findings about the procedures of eight distinct institutions, we analyzed the data included in a Dutch benchmarking database covering the years 2012-2016. Because there was no exchange of personally identifiable information between the participants, formal permission was not required. Because only two of the institutions provided baseline estimations of SCT in addition to their observed and recorded SCT, we could not utilize the data they provided. Estimates could be derived for TPT and SCT based on the remaining data but not for eSCT. When we were figuring out how to calculate the eSCT, we considered that the typical wait time for an ACT in the Netherlands is 20 minutes. However, since practices and facilities may differ significantly, estimating how long patients will remain under anesthesia can be challenging. It is necessary to consider the projected eSCTs generated by reducing the session by 20 minutes to accomplish the purpose of assessing the alternatives discussed in this study.

Table 2. Characteristics of the dataset and their distribution.

Variable[a]		Percentage of dataset
Patient age	1–9[b]	9.1
	10–19	7.3
	20–29	7.6
	30–39	8.3
	40–49	12.3
	50–59	16.7
	60–69	20.5
	70–79	13.8
	80–89	4.2
	90–99	0.3
	100–103	<0.0
American Society of Anesthesiologists classification	1	32.9
	2	45.2
	3	20.4
	4	1.4
	5	<0.0
Main specialism	Ophthalmology	15.8
	Ear, nose, and throat	11.6
	Cardiothoracic surgery	10.6
	Orthopedic surgery	8.8
	Neurosurgery	8.4
	Plastic surgery	6.8
	Oral and maxillofacial surgery	4.5
	Obstetrics and gynecology	4.3
	Abdominal surgery	4.3
	Urology	4.0
	Surgical oncology	4.0
	Traumatology	3.5
	Obstetric and gynecological oncology	3.1
	Miscellaneous	2.7
	Pediatric surgery	2.1
	Vascular surgery	2.0
	Hepatobiliary surgery	1.4
	Transplant surgery	0.9
	Anesthesiology	0.8
	Pediatric gastroenterology	0.1

Percentages are rounded to one decimal place.
[a]*See **Table 1** for the meaning of the abbreviations.*
[b]*Records describing patients with age 0 were omitted, because their number was so high that we suspected that users had entered 0 to indicate missing data.*

Elements of the TPT comprised the eSCT, age, the kind of operation (which was given by the hospital), the ASA physical status category, and the route of anesthesia (again identified by hospital-supplied codes). The amount of time spent under anesthesia, time spent in induction, and time spent awake were all recorded in the database as independent variables. Our observed ACT is calculated by adding the lengths of our induction and emergence durations. Only data pertaining to scheduled procedures were evaluated since it is not possible to provide an accurate estimate of TPT/SCT for operations that were not planned in advance.

R 3.3.1 was used for all statistical analyses and data manipulation throughout the process. Due to the extreme unlikelihood of the observation, missing data alarms were raised when the TPT was found to be 0. We didn't bother to account for any possible gaps in the data since there is a significant possibility that some records are missing. There may be several potential gaps in the data. A total of 79,983 individuals submitted a combined total of 199,772 hours of OR. The general distribution of these features over the whole dataset is shown in tables 2 and 3, respectively. The years 2012–2015 were represented in the data used for the training, whereas 2016 was described in the data used for the testing.

Table 3. General data sets use statistics.

Number of types of anesthesia described[a]	32
Number of types of surgery described[b]	4,458
Mean estimated total procedure time (TPT)	126 min
Median estimated TPT	90 min
Mean observed TPT	150 min
Median observed TPT	109 min
Mean observed anesthesia induction time	27 min
Median observed anesthesia induction time	23 min
Mean observed anesthesia emergence time	13 min
Median observed anesthesia emergence time	11 min

Times are rounded to whole minutes.
[a]Type of anesthesia was based on the hospitals' internal anesthesia codes. Examples of code meanings are "general," "arterial line," "epidural," "spinal," "local," etc.
[b]Type of surgery was based on the hospitals' procedure codes and descriptions. These precisely record the surgical procedures performed. As an example of the level of detail: there are different verification codes and descriptions for cataract surgery using different types of implanted lenses.

If you want to construct a precise TPT model, you will need to incorporate a minimum of ten data points for each potential predictor. Recent studies reveal that the actual number is likely far lower than reported (3). Our dataset had over 80,000 records, which allowed us to investigate all conceivable predictors and interactions.

In the initial step of the process, we predicted each record's TPT using the fixed ratio model developed by van Veen-Berkx and colleagues. In this study, multiples of 1.33 were applied to the eSCT of each patient (2). It has been found by van Veen-Berkx et al. that a value of 33% of SCT is adequate for evaluating ACT. This conclusion was reached based on their research. We used both predicted and observed TPT in our calculations, which allowed us to determine absolute error, mean squared error, and adjusted R-squared. The adjusted R-squared measures the proportion of the TPT's unpredictability attributed to the model's input parameters.

All linear regression models were constructed using the data collected between 2012 and 2015, and then they were evaluated with the data contained in 2016. In this section, we were able to conduct an objective analysis of the models' performance on test data in comparison to their performance on their training data.

We evaluated p-values for each independent variable and updated R-squared values to choose the optimal linear regression model for predicting TPT using eSCT and the other components. This allowed us to pick the model with the highest predictive accuracy.

In addition, we retested all of the regression models in which eSCT was not included as a predictor so that we could come up with different predictions for ACT (which leads to TPT by adding SCT). This allowed us to compare our findings to those of previous research that hypothesized about the ACT's consequences (4, 5).

Last but not least, we re-executed the analysis but this time with the missing data filled in with our best guesses to determine whether or not the lack of incomplete records impacted the results. We employed a linear regression model for the continuous variables, and for the categorical variable that stood in for ASA categorization, we used a proportional probability model to estimate the missing data. Both models were used to estimate the missing information. It took a lot of work to deduce the anesthetic approach or the surgical process since there was such a bewildering number of possibilities.

4. Results

When applied to the data for 2012–2015, the fixed ratio model has an MAE of 39.5 minutes and an MSE of 3,859.6 minutes. The mean squared error for 2016 projections was 3,275 seconds, while the median absolute error was 38 minutes. MSE and MAE are abbreviations for mean squared error and median fundamental error, respectively.

Table 4. The order of the linear regression models with the highest adjusted R-squared value for predicting the whole duration of the process.

Independent variable(s)[a]					Adjusted *R*-squared
Estimated surgeon-controlled time	Type of anesthesia	American Society of Anesthesiologists	Age	Type of operation	
+	+	+	+	+	0.8499
+	+	+		+	0.8498
+		+	+	+	0.8491
+	+			+	0.8491
+	+		+	+	0.8491
+		+		+	0.8490
+			+	+	0.8483
+				+	0.8483
+	+	+	+		0.7853
+	+	+			0.7852
+	+		+		0.7846
+	+				0.7843
+		+			0.7763
+		+	+		0.7763
+			+		0.7757
+					0.7756

Models were based on the 2012–2015 data. Adjusted R-squared values are rounded to four decimal places.
[a]*See **Table 1** for the meaning of the abbreviations.*

Because of the enormous sample sizes, all of the predictor variables included in the linear regression models could reach high statistical significance (p 0.01). Aside from the anesthesia and the precise surgical technique, none of the other circumstances were remarkable. Nevertheless, when each variable in the model was considered, the influence on the outcome was very significant. It was best to stop adding variables to the model when the adjusted R-squared did not improve further after adding additional predictors since this indicated that the model was complete.

One of the most effective strategies for TPT forecasting is the use of a linear regression model that takes into consideration all of the known independent components. Only the variables eSCT, sort of operation, ASA classification, and type of anesthesia were maintained in the model when it was shown that including patient age did not significantly improve the model's ability to predict outcomes (see Tables 4 and 5) accurately. When utilizing the best model available, the MAE was 29.2 minutes from 2012-2015, while the MSE was 2,320.7 minutes. 2016's predictions had a median a posteriori estimate of 31.3 minutes for their accuracy (MSE: 2,366.9 minutes). The R-squared value after modifications for this model was 0.8498.

Table 5. Ordered by the highest adjusted R-squared value, the linear regression models' ability to predict ACT during anesthesia.

Independent variable(s)[a]				Adjusted *R*-squared
Type of anesthesia	American Society of Anesthesiologists	Age	Type of operation	
+	+	+	+	0.6316
+	+		+	0.6314
+		+	+	0.6256
+			+	0.6246
	+	+	+	0.5991
	+		+	0.5988
			+	0.5925
		+	+	0.5925
+	+	+		0.3801
+	+			0.3677
+		+		0.3067
+				0.2561
	+	+		0.1346
	+			0.1346
		+		0.0162

Models were based on the 2012–2015 data. Adjusted R-squared values are rounded to four decimal places.
*[a]See **Table 1** for the meaning of the abbreviations.*
Models for predicting total procedure time included estimated surgeon-controlled time as independent variable, models for predicting ACT did not.

In a similar vein, the best predictors of ACT were all independent characteristics, even though including patient age resulted in a bit of improvement in accuracy. The direct forecast of TPT was similar to the final model, which was based on operation type, ASA classification, and type of anesthesia. The MAE for predictions made between 2012 and 2015 was 34.7 minutes, while the MSE for forecasts made in 2016 was 3,269.7 minutes. The value of R2 was calculated to be 0.6314 after considering all factors that may serve as confounding factors.

The most important takeaways are outlined in Table 6. FIGURE 1 illustrates the expected and observed TPTs for the three models discussed earlier. Similarly, it was shown that various criteria worked best together to predict ACT, but the inclusion of patient age did help boost accuracy to some degree. The final model, which included ASA classification, anesthetic type, and operation type, did not outperform the direct prediction of TPT. The mean absolute error (MAE) for predictions made between 2012 and 2015 was 34.7 minutes, and the mean, standard error (MSE) for predictions made in 2016 was 3,269.7 minutes. In this scenario, the final corrected value of R2 was calculated to be 0.6314.

The most significant results are summarized in Table 6, which may be seen below. Figure 1 presents the TPTs that were anticipated and ultimately obtained for each of these three models.

The outcomes were substantially the same regardless of whether the missing data were left out before analysis or if imputation was performed afterward.

Table 6. The best linear regression models and the fixed ratio model's performance

	2012–2015		2016	
	Mean absolute error (MAE)	**Mean squared error (MSE)**	**MAE**	**MSE**
Fixed ratio model	39.5	3,859.6	38.5	3,275.9
Most accurate model for predicting total procedure time (TPT)[a]	29.2	2,320.7	31.3	2,366.9
Most accurate model for predicting anesthesia-controlled time (ACT)[b]	34.7	3,269.7	34.2	2,878.7

Errors are the difference between predicted TPT and observed TPT in minutes and are rounded to one decimal place.
[a]Linear regression model based on the independent variables estimated surgeon-controlled time (eSCT), type of operation, American Society of Anesthesiologists (ASA) classification, and type of anesthesia.
[b]Linear regression model based on the independent variables type of operation, ASA classification, and type of anesthesia. TPT was predicted by adding predicted ACT to eSCT.

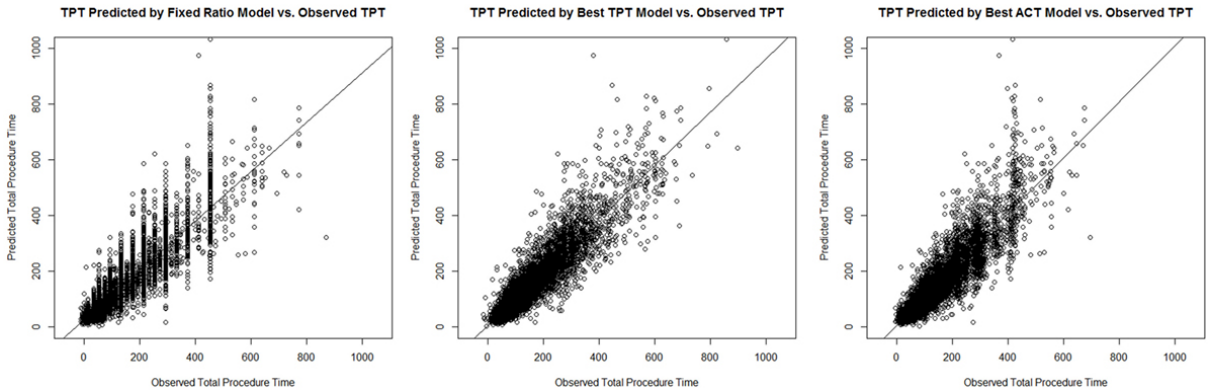


Figure 1. Total procedure times (TPTs) are compared to what was actually completed, and the fixed ratio model and the best two linear regression models for predicting TPT and anesthesia-controlled time are compared to one another (ACT).

5. Discussion

In trying to forecast TPT, the model with the best linear regression fared much better than the model with the fixed ratio. The overall average MSE for the training set saw a staggering 25% rise during the process. It is anticipated that there will be a significant decrease in errors. The impact on the outcomes of the 2016 exams was negligible, which was no surprise to everyone, but the information acquired was nevertheless quite helpful [2].

If implemented, these more precise estimates mitigate the detrimental impacts of both under- and overestimation. If the projections were too high or too low, the operating room and its employees could be badly impacted. When you overestimate, you run the risk of having to pay for more time or having to push back your plans. In 2016, underestimation and overestimation were both present at the hospital in our dataset with the most thorough records, which resulted in a total overestimation of

3,118 hours for all of the included procedures. Underestimation occurred at the hospital with the most detailed records in 2016. If they had followed the technique outlined in this study, they would have overestimated the amount of time by no more than 179 hours at the most (which is based on their data). More processes might have been finished if the time had been allocated differently.

Planners' confidence in their ability to improve OR consumption is directly proportional to the precision with which expected periods of operation are accounted for. The data on case length may be utilized to better plan for consumption, which could result in gains both financially and in terms of productivity.

Despite this, the most important thing we found was that direct TPT prediction is more accurate than independent ACT prediction (using the same available components but without eSCT).

The most accurate model suggests that TPT may be computed by calculating ACT and then SCT. This model considers everything from the eSCT and the particulars of the surgical procedure to the ASA classification of the patient and the technique for producing and maintaining anesthesia. This enables predictions to be made despite the lack of sufficient evidence. Because the model was going to be used in a computational setting, we tried to make it as simple as possible by removing any extraneous information that it included. The outcome was an increase in both the readability and the speed of the model's execution.

In contrast to the SCTs that were reported in the past, our findings are based on regression models that were constructed and validated using surgeons' accurate preoperative predictions of SCT. These models were then used to conclude the SCT. Estimations of the SCT are also essential for making forecasts within the framework of actual planning practice. As a consequence of this, the findings of our study show that the stated performance of the models is compatible with the basic version, in contrast to the positive bias that is projected when using historical data. In 2016, the model performed very well on data not included in the training process.

Due to far more data available for training, our forecasts for the 2016 TPTs were significantly improved. According to these results, the suggested method may be able to increase performance even further when applied to even bigger datasets, such as those that are becoming more readily accessible to data analysts working in the healthcare industry. The research results could be improved by adjusting to account for geographical variances. There may be a need for more specific examples regarding the infrastructure, delivery, and practitioner healthcare methods.

When building models comparable to those discussed in this article, it is recommended that hospital data analysts and surgical managers incorporate as much of their institution's historical data as possible. The strategy that has been described has the potential to be easy to implement and might result in more accurate estimations of future processing times.

One of the limitations of the research is that all the data was collected from academic institutions. No evaluations are available to determine how well this fits with the conventional scheduling of operating rooms at community hospitals. We have also taken all pertinent data from these institutions and averaged it on the premise that there are no significant discrepancies between them that would significantly affect the TPT.

The fact that the other data was gathered semi-manually and the timestamps were recorded manually is one of the most significant shortcomings of the system. As a first problem, it likely led to some inconsistencies in the data, which resulted in a delay in identifying critical operating times. Second, the final report included many holes in its content. About twenty-one percent of the first submissions had comprehensive and accurate information about all of the essential parameters. Imputation of the missing data produced results that were remarkably comparable to our first study, suggesting that the absence of partial records had no influence on the results.

Both of them draw attention to the fact that there is a pressing need to create automated registration systems that could be integrated into conventional surgical practices. If the findings of this data analysis will be taken seriously and put into action, then an approach of this kind is critical.

Even if the new model has excellent performance over the long run, it is essential to keep in mind that there is still a significant amount of variation between people. Consequently, their forecasts may

become less accurate and less helpful when attempting to address problems that occur in the actual world.

6. Conclusion

It is more effective to use a linear regression model to predict TPT based on eSCT, the type of operation being performed, the ASA classification of the patient, and the type of anesthetic being administered than it is to use the techniques that are currently in use, which involve using a set duration for ACT or a constant ratio between eSCT and TPT. It has also been shown that forecasting TPT after the event by first predicting ACT separately yields less accurate results.

References

[1] Fowler, A. J., et al. "Age of patients undergoing surgery." Journal of British Surgery 106.8 (2019): 1012-1018.

[2] Ballard, David H., et al. "Medical 3D printing cost-savings in orthopedic and maxillofacial surgery: cost analysis of operating room time saved with 3D printed anatomic models and surgical guides." Academic radiology 27.8 (2020): 1103-1113.

[3] Lai, Alvina G., et al. "Estimated impact of the COVID-19 pandemic on cancer services and excess 1-year mortality in people with cancer and multimorbidity: near real-time data on cancer care, cancer deaths and a population-based cohort study." BMJ open 10.11 (2020): e043828.

[4] Shipe, Maren E., et al. "Developing prediction models for clinical use using logistic regression: an overview." Journal of thoracic disease 11. Suppl 4 (2019): S574.

[5] Hanna, Timothy P., et al. "Mortality due to cancer treatment delay: systematic review and meta-analysis." bmj 371 (2020).

[6] Feng, Xue, et al. "Brain tumor segmentation using an ensemble of 3d u-nets and overall survival prediction using radiomic features." Frontiers in computational neuroscience 14 (2020): 25.

[7] Sud, Amit, et al. "Effect of delays in the 2-week-wait cancer referral pathway during the COVID-19 pandemic on cancer survival in the UK: a modelling study." The LanceOncology 21.8 (2020): 1035-1044.

[8] Padula, William V., and Benjo A. Delarmente. "The national cost of hospital-acquired pressure injuries in the United States." International wound journal 16.3 (2019): 634-640.

[9] Evans, Jonathan T., et al. "How long does a knee replacement last? A systematic review and meta-analysis of case series and national registry reports with more than 15 years of follow-up." The Lancet 393.10172 (2019): 655-663.

[10] Treasure, Tom, et al. "Pulmonary metastasectomy versus continued active monitoring in colorectal cancer (PulMiCC): a multicentre randomised clinical trial." Trials 20.1 (2019): 1-13.

[11] Liu, Shuai, et al. "Prediction of gene expression patterns with generalized linear regression model." Frontiers in Genetics 10 (2019): 120.

[12] Lüdecke, Daniel, et al. "performance: An R package for assessment, comparison and testing of statistical models." Journal of Open Source Software 6.60 (2021).

[13] COVID, IHME, and Christopher JL Murray. "Forecasting COVID-19 impact on hospital bed-days, ICU-days, ventilator-days and deaths by US state in the next 4 months." MedRxiv (2020).