

PREPRINT

Author-formatted, not peer-reviewed document posted on 14/11/2023

DOI: <https://doi.org/10.3897/arphapreprints.e115732>

**Predictive Modeling of Total Operating
Room Time for Laparoscopic
Cholecystectomy Using Preoperatively
Known Indicators to Guide Accurate
Surgical Scheduling in a Critical Access
Hospital**

Todd Prier, Kelly Yale-Suda, Hailey Westover, Ryan Corey

Predictive Modeling of Total Operating Room Time for Laparoscopic Cholecystectomy Using Preoperatively Known Indicators to Guide Accurate Surgical Scheduling in a Critical Access Hospital

Todd Vincent Prier[‡], Kelly Yale-Suda[§], Hailey Westover^l, Ryan Corey[¶]

[‡] Rochester Regional Health, Rochester, NY, United States of America

[§] Our Lady of Lourdes Memorial Hospital, Binghamton, NY, United States of America

^l University at Buffalo, Buffalo, NY, United States of America

[¶] Bassett Healthcare Network, Cooperstown, NY, United States of America

Corresponding author: Todd Vincent Prier (typrier@live.com)

Reviewed v 1

Abstract

The financial margin of rural and critical access hospitals highly depends on their surgical volume. An efficient operating room is necessary to maximize profit and minimize financial loss. OR utilization is a crucial OR efficiency metric requiring accurate case duration estimates. The patient's age, ASA, BMI, Malampati score, previous surgery, the planned surgery, the surgeon, the assistant's level of experience, and the severity of the patient's disease are also associated with operative duration. Although complex machine learning models are accurate in operative prediction, they are not always available in resource-limited hospitals. Laparoscopic cholecystectomy (LC) is one of the most common surgical procedures performed and is one of the few procedures performed at critical access and rural hospitals. The accurate estimation of the operative duration of LC is essential for efficient OR utilization. We hypothesize that a multivariate linear regression prediction model can be constructed from a set of preoperatively known, easily collected variables to maximize OR utilization and improve operative scheduling accuracy for LC. We further hypothesize that this model can be implemented in resource-limited environments, such as critical access hospitals.

Keywords

Operating room efficiency, operating room scheduling, procedure scheduling, laparoscopic cholecystectomy, multivariate regression prediction modeling, linear regression, critical access hospitals, rural hospitals, quality improvement

Overview and background

In rural hospitals, the ability to be profitable is directly associated with staying open (Borgstrom et al. 2022). It is a well-known fact that the operating room (OR) is one of the hospital's most significant financial engines, making up approximately 40% of the hospital's net income (Veen-Berkx et al. 2014; Borgstrom et al. 2022) and almost half the hospital's margins (Hopper et al. 2022). Net profit and margins in critical access hospitals are also strongly associated with the volume of their surgical services (Hopper et al. 2022). Karim et al. (2015) have reported that a 10% increase in surgical volume can increase the total margin by 2%. Although surgery can be very profitable, it also makes up 1/3 of healthcare costs and 1/2 of hospital costs (Lee et al. 2019), making up over half the costs to surgical patients (Fong et al. 2016). When stratified by minute, OR expenses can range from \$30 per minute (Lee et al. 2019) to \$150 per minute in Manhattan, NY (Cerfolio et al. 2019). Therefore, running an efficient operating room is necessary to maximize profit and minimize financial loss (Boggs et al. 2019).

OR utilization is one of the most essential metrics for OR efficiency (Boggs et al. 2019). Underutilization has been identified as the most important as it leads to fewer cases and less net income (Walsh 2017, Boggs et al. 2019). Although the financial loss from time running over the schedule – or overutilization – can lead to increased overtime costs, more significantly, is the decrease in satisfaction and job motivation leading to loss of nursing staffing (Stepaniak et al. 2009). Therefore, an accurate case duration estimation is critical (Walsh 2017, Lee et al. 2019, Boggs et al. 2019). Classically employed methods to predict case duration are inaccurate (Kayis et al. 2015, Thiels et al. 2017). A standard process uses the average time of the previous ten cases and is reported to have half of the procedure times running over schedule (Rozario and Rozario 2020). Glance et al. (2018) study confirmed variable case duration with standard general surgical procedures. A more accurate prediction of operative time can be predicted preoperatively using the surgeon and team variables (Kayis et al. 2015). Patient and team variables that are associated directly with the total operating room time (TOT), or the time elapsing from the patient entering the OR until the patient leaves the OR, are the surgeons (Strum et al. 2000, Kayis et al. 2015, van Eijk et al. 2016, Glance et al. 2018, Bartek et al. 2019, Rozario and Rozario 2020), the hospital (Glance et al. 2018), assistants, and OR team (Cassera et al. 2009, Cahan et al. 2021), the age (Strum et al. 2000), gender (Strum et al. 2000), and the health of the patient (Strum et al. 2000, Bartek et al. 2019, Costa 2017, Rowland et al. 2019), type of anesthesia (Costa 2017, Rowland et al. 2019), and oncologic surgery (Costa 2017, Stromblad et al. 2021), and type of surgery (Lee et al. 2019). Using these preoperatively determined variables in a machine learning program, Stromblad et al. (2021) markedly improved the prediction of OR case duration and decreased underutilization. Studies, such as Stromblad et al. 2021 and Bartek et al. 2019 have improved procedure duration prediction using machine learning techniques. Unfortunately, the large data sets and technical expertise to create machine learning models are inconsistently available at most rural and critical access hospitals.

The non-endoscopic surgical volume in rural hospitals tends to be ambulatory, and laparoscopic cholecystectomy (LC), hernia repair, and appendectomy predominate (Stinson et al. 2021). General surgery cases for benign diseases are shorter and have fewer overall variations in duration (Costa 2017). The difficulty and duration of laparoscopic cholecystectomy have been preoperatively predicted using patient-related variables and the severity of the pathology (Thiels et al. 2017, Vannucci et al. 2022). Essentially, the increased severity of the biliary pathology was associated with a prolonged operative time.

Objectives

We hypothesize that the TOT can be accurately predicted using information already collected by the system processes at our critical access hospital. We also hypothesize that there is no difference between TOT and operative time (the time from the incision to completion of placing the dressings; OT) predicted in this fashion. Preoperatively known surgeon, institution, and patient factors can be used to create an accurate regression model to predict laparoscopic cholecystectomy case duration. Specifically, we hypothesize that patient characteristics, surgeon and assistant, and preoperatively determined diagnoses associated with the severity of the pathology directly influence the OT and TOT and allow for accurate prediction of operative duration that lead to improved utilization of OR time with less over or under utilization.

Impact

Although there are many predictive models for LC scheduling, the difference in our proposed model is that it uses data already collected in every OR, is easily accessible, and does not increase the workload of the involved staff. Previous predictive models for LC have used laboratory and radiographic data indicating that the complexity of the pathology predicts a longer operative time. We hypothesize that if we simplify the data collection process and instead use the known clinical diagnosis that indicates the increasing complexity of the surgical pathology, the model will be as accurate and easier to construct. We also hypothesize that the TOT will be as precise as the OT in the prediction models, further simplifying the scheduling processes. Our proposed model that minimizes the workload to the staff, is simple to implement, is accurate, and can maximize OR utilization has the potential to directly impact the hospital's financial margin.

Implementation

After obtaining approval via the hospital's IRB, we plan to initiate an observational cohort study by performing a retrospective chart review of all LC from a single surgeon at a single institution from July 2008 to July 2022, thus controlling for the surgeon. LC is only performed under general anesthesia, allowing for the controlling for the type of anesthesia. The anesthesiologists were not included in the model, as evidence supports that the variability imposed by the anesthesiologist is a non-significant contributor to TOT (van Eijk

et al. 2016, Rowland et al. 2019). Although the OR nursing team has been associated with the OR duration (Cassera et al. 2009, Cahan et al. 2021), the complexity of the variable due to the degree of nursing turnover over the study time period, especially during COVID, and the associated instability of the nursing teams at the study hospital, this variable was not included in the model. It is hypothesized that the contribution of the nursing variable will be minimal and including it will not significantly decrease the accuracy of the model.

The patient's age, gender, BMI, American Society of Anesthesiology Physical Status Score (ASA), Malampati score, previous history of upper abdominal surgery, elective, inpatient, or emergent surgery, and diagnosis leading to surgery as defined by the surgeon in the chart will be recorded. The diagnosis categories are defined as biliary dyskinesia, biliary hyperkinesia, biliary colic, chronic cholecystitis, acute cholecystitis, biliary pancreatitis, choledocholithiasis, and gangrenous cholecystitis. The preoperative plan for LC with intraoperative cholangiography or biliary ultrasonography will also be noted. From the operative record, the presence of an assistant and their level, either APP or MD, the time from room entrance to exiting the operating room (TOT), and the operative time (OT) -- the time elapsed from skin incision to dressing placement -- will also be recorded. The times will be those within the operative record.

Data analysis using ANOVA and linear regression will test the null hypothesis that there is no difference within the OT and TOT groups for (LC) for the different diagnoses. Multivariate linear regression will be used to build a prediction model from the OT and a separate model of TOT using all of the variables as predictors from the data collected. As the TOT includes time in the OR that is non-surgeon dependant it may be more variable and therefore be a less accurately predicted with our model. The two models will be compared using likelihood ratio testing.

Missing data will be excluded from the analysis as long as it is missing completely at random. Original bootstrapping with replacement will be utilized for internal model validation to ensure maximal usage of the data set for model development.

Minimum sample size calculations based on traditional prediction modeling approaches require ten events per predictor (Riley et al. 2020) and has been previously recommended for LC case duration prediction (Vannucci et al. 2022). Our model, when also including interaction terms for age-ASA, BMI-ASA, BMI-Malampati score, and Age-BMI would lead to a minimum sample size of 140 subjects. Using Green (1991) 'rule of thumb' with a power of .8, an alpha of 0.05, and the R2 of 0.18 from Thiels et al. (2017), the minimum sample size for the entire model is 162.

Conflicts of interest

The authors have declared that no competing interests exist.

References

- Bartek MA, Saxena RC, Solomon S, Fong CT, Behara LD, Venigandla R, Nair BG, (2019) Improving operating room efficiency: Machine learning approach to predict case-time duration. *Journal of the American College of Surgeons* 229 (4): 346-354 3. <https://doi.org/10.1016/j.jamcollsurg.2019.05.029>
- Boggs SD, Tan DW, Watkins CL, Tsai MH (2019) OR management and metrics: How it all fits together for the healthcare system. *Journal of Medical Systems* 43 (6): 147-8. <https://doi.org/10.1007/s10916-019-1272-y>
- Borgstrom DC, Deveney K, Hughes D, Rossi IR, Rossi MB, Lehman R, Puls M, (2022) Rural surgery. *Current Problems in Surgery* 59 (8): 101173. <https://doi.org/10.1016/j.cpsurg.2022.101173>
- Cahan EM, Cousins HC, Steere JT, Segovia NA, Miller MD, Amanatullah DF (2021) Influence of team composition on turnover and efficiency of total hip and knee arthroplasty. *The Bone & Joint Journal* 103-B(2): 347-352. <https://doi.org/10.1302/0301-620X.103B2.BJJ-2020-0170.R2>
- Cassera MA, B.S Z, Bin MD, Ph.D M, V. D, B.S D, M. C, M.D, Swanströ m, L. L, M.D. FA (2009) Surgical time independently affected by surgical team size. *The American Journal of Surgery* 198 (2): 216-222. <https://doi.org/10.1016/j.amjsurg.2008.10.016>
- Cerfolio RJ, Ferrari-Light D, Ren-Fielding C, Fielding G, Perry N, Rabinovich A, Pachter HL, (2019) Improving operating room turnover time in a new york city academic hospital via lean. *The Annals of Thoracic Surgery* 107 (4): 1011-1016. <https://doi.org/10.1016/j.athoracsur.2018.11.071>
- Costa JAdS (2017) Assessment of operative times of multiple surgical specialties in a public university hospital. *Einstein (São Paulo, Brazil)* 15 (2): 200-205. <https://doi.org/10.1590/s1679-45082017gs3902>
- Fong AJ, Smith M, Langerman A (2016) Efficiency improvement in the operating room. *The Journal of Surgical Research* 204 (2): 371-383. <https://doi.org/10.1016/j.jss.2016.04.054>
- Glance L, Dutton R, Feng C, Li Y, Lustik S, Dick A (2018) Variability in case durations for common surgical procedures. *Anesthesia and Analgesia* 126 (6): 2017-2024. <https://doi.org/10.1213/ANE.0000000000002882>
- Green SB (1991) How many subjects does it take to do A regression analysis. *Multivariate Behavioral Research* 26 (3): 499-510. https://doi.org/10.1207/s15327906mbr2603_7
- Hopper W, Zeller R, Burke R, Lindsey T (2022) The association between operating margin and surgical diversity at critical access hospitals. *Journal of Osteopathic Medicine (Online)* 122 (7): 339-345. <https://doi.org/10.1515/jom-2022-0028>
- Karim S, Holmes G, Pink G (2015) The effect of surgery on the profitability of rural hospitals. *J Health Care Finance* 41 (4): 11-16.
- Kayis E, Khaniyev TT, Suermondt J, et al. (2015) A robust estimation model for surgery durations with temporal, operational, and surgery team effects. *Health Care Manag Sci* 18: 222-233. <https://doi.org/10.1007/s10729-014-9309-8>

- Lee D, Ding J, Guzzo T (2019) Improving operating room efficiency. *Current Urology Reports* 20 (6): 1-8. <https://doi.org/10.1007/s11934-019-0895-3>
- Riley RD, Ensor J, Snell KI, Harrell FE, Martin GP, Reitsma JB, Smeden M, (2020) Calculating the sample size required for developing a clinical prediction model. *BMJ* (Online 368: 441. <https://doi.org/10.1136/bmj.m441>
- Rowland MJ, Urman RD, Xu X, Ehrenfeld JM, Preiss DA, Vacanti JC (2019) The impact of airway technique on anesthesia control time. *Journal of Medical Systems* 43 (3): 72-10. <https://doi.org/10.1007/s10916-019-1191-y>
- Rozario N, Rozario D (2020) Can machine learning optimize the efficiency of the operating room in the era of COVID-19? *Canadian Journal of Surgery* 63 (6): 527-529. <https://doi.org/10.1503/cjs.016520>
- Stepaniak PS, Heij C, Mannaerts G, Quelerij M, Vries G (2009) Modeling procedure and surgical times for current procedural terminology - anesthesia-surgeon combinations and evaluation in terms of case-duration prediction and operating room efficiency: A multicenter study. *Anesthesia and Analgesia* 109 (4): 1232-1245.
- Stinson WW, Sticca RP, Timmerman GL, Bjordahl PM (2021) Current trends in surgical procedures performed in rural general surgery practice. *The American Surgeon* 87 (7): 1133-1139. <https://doi.org/10.1177/0003134820947390>
- Stromblad, T. C, Baxter-King RG, Meisami A, Yee S, Levine MR, Ostrovsky A, Wilson RS, (2021) Effect of a predictive model on planned surgical duration accuracy, patient wait time, and use of presurgical resources: A randomized clinical trial. *JAMA Surgery* <https://doi.org/10.1001/jamasurg.2020.6361>
- Strum DP, Sampson AR, May JH, Vargas LG (2000) Surgeon and type of anesthesia predict variability in surgical procedure times. *Anesthesiology* May;92(5):1454-66 <https://doi.org/10.1097/00000542-200005000-00036>.
- Thiels CA, Yu D, Abdelrahman AM, Habermann EB, Hallbeck S, Pasupathy KS, Bingener J (2017) The use of patient factors to improve the prediction of operative duration using laparoscopic cholecystectomy. *Surgical Endoscopy* 31 (1): 333-340. <https://doi.org/10.1007/s00464-016-4976-9>
- van Eijk RP, Veen-Berkx E, Kazemier G, Eijkemans MJ (2016) Effect of individual surgeons and anesthesiologists on operating room time. *Anesthesia and Analgesia* 123 (2): 445-451. <https://doi.org/10.1213/ANE.0000000000001430>
- Vannucci M, Laracca GG, Mercantini P, Perretta S, Padoy N, Dallemagne B, Mascagni P (2022) Statistical models to preoperatively predict operative difficulty in laparoscopic cholecystectomy: A systematic review. *Surgery* 171 (5): 1158-1167. <https://doi.org/10.1016/j.surg.2021.10.001>
- Veen-Berkx E, Bitter J, Elkhuizen S, Buhre WF, Kalkman CJ, Gooszen HG, Kazemier G (2014) The influence of anesthesia-controlled time on operating room scheduling in dutch university medical centres. *Canadian Journal of Anesthesia* 61 (6): 524-532. <https://doi.org/10.1007/s12630-014-0134-9>
- Walsh A (2017) The data proves it: First case starts and turnover time are not your best metrics. *HealthITOutcomes*. June 13.