Predictive modelling of total operating room time for Laparoscopic Cholecystectomy using pre-operatively known indicators to guide accurate surgical scheduling in a critical access hospital

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Academic editor: Editorial Secretary

Abstract

The financial margin of rural and critical access hospitals highly depends on their surgical volume. An efficient operating room is necessary to maximise profit and minimise financial loss. OR utilisation is a crucial OR efficiency metric requiring accurate case duration estimates. The patient's age, ASA, BMI, Mallampati 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 utilisation. We hypothesise that a multivariate linear regression prediction model can be constructed from a set of pre-operatively known, easily collected variables to maximise OR utilisation and improve operative scheduling accuracy for LC. We further hypothesise 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 modelling, 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 of 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 maximise profit and minimise financial loss (Boggs et al. 2019).

OR utilisation is one of the most essential metrics for OR efficiency (Boggs et al. 2019). Underutilisation 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 overutilisation – 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). More accurate prediction of the procedure durations is one method to optimise OR utilization (van Eijk et al. 2016). 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 pre-operatively 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, Costa 2017,Bartek et al. 2019,Rowland et al. 2019), type of anaesthesia (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 pre-operatively determined variables in a machine-learning programme, Stromblad et al. (2021) markedly improved the prediction of OR case duration and decreased underutilisation. Studies, such as Stromblad et al. (2021) and Bartek et al. (2019) have improved procedure duration prediction using machine-learning techniques. Unfortunately, the large datasets 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 pre-operatively 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 hypothesise that the TOT can be accurately predicted using information already collected by the system processes at our critical access hospital. We also hypothesise 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. Specifically, we hypothesise that patient characteristics, surgeon and assistant and pre-operatively 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 utilisation of OR time with less over- or underutilisation.

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 hypothesise 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 hypothesise that the TOT will be as precise as the OT in the prediction models, further simplifying the scheduling processes. Our proposed model that minimises the workload to the staff, is simple to implement, is accurate and can maximise OR utilisation has the potential to directly impact the hospital's financial margin.

Implementation

After obtaining approval via the hospital's Institutioinal Review Board, 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 anaesthesia, allowing for the controlling for the type of anaesthesia. The anaesthesiologists were not included in the model, as evidence supports that the variability imposed by the anaesthesiologist 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 instablity of the nursing teams at the study hospital, this variable was not included in the model. It is hypothesised 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 Anesthesology Physical Status Score (ASA), Mallampati 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 hyperkinesis, biliary colic, chronic cholecystitis, acute cholecystitis, biliary pancreatitis, choledocholithiasis and gangrenous cholecystitis. The pre-operative plan for LC with intra-operative cholangiography or biliary ultrasonography will also be noted. From the operative record, the presence of an assistant and their level, either advanced practice provider (APP) or surgeon, 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 dependent, it may be more variable and, therefore, be 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 utilised for internal model validation to ensure maximal usage of the dataset for model development.

Minimum sample size calculations, based on traditional prediction modelling approaches, require ten events per predictor (Riley et al. 2020) and have 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-Mallampati score and Age-BMI, would lead to a minimum sample size of 140 subjects. Using Green (1991) 'rule of thumb' with a power of 0.8, 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.

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