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MONITORING THE EFFICIENCY OF USE OF OPERATING ROOM TIME WITH CUSUM CHARTS

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Abstract

Health care organizations often need to assess operating room (OR) performance in order to measure the efficiency. In practice, to estimate surgery durations hospitals use various estimating systems either based on surgeon's estimate and/or software. Accurate estimates are vital for high quality OR performance and efficiency. Thus, surgeons' estimates are significant inputs for effective OR suite schedule in surgeon based systems. To achieve a successful OR management, not only utilization performance measurement but also monitoring it is crucial. Control charts could be constructed for monitoring the OR efficiency. Monitoring the efficiency of use of OR time might include monitoring operative and/or non-operative times. In this study, cumulative sum (CUSUM) charts are introduced for the performance of surgery time estimations. An example involving surgical times is also provided to support our discussion. Some scenarios are defined and surgeons' estimation errors are simulated for illustrative purposes.
Key words: *control charts, CUSUM, OR efficiency, utilization, surgery time.*

Introduction

In a hospital setting, managing the OR suite is of great importance in terms of the performance of a hospital, revenues and patient satisfaction. On the other hand, it is difficult to achieve an efficient management approach due to conflicting priorities and costly resources. All these factors strongly emphasize the need for an adequate OR planning and scheduling procedure.

Cardoen et al. (2010) states that waiting time, throughput, utilization, leveling, makespan, patient deferrals, financial measures and preferences are the commonly used performance criteria to evaluate operating room planning and scheduling procedures. They mention that especially the utilization rate of the OR has been the subject to recent research. Macario (2006) states that allocation of the right amount of OR time to each service on each day of the week is the most important thing in OR management. Efficiency of use of OR time is defined by underutilized and overutilized OR time (Strum et al., 1997). Another aspect of efficient OR management is estimating surgery times with low amount of estimating error. Strum et al. (2000) emphasizes that to improve the utilization of OR, making accurate time estimates are essential. Bias, which is defined as the systematic underestimation or overestimation of case durations, affects the usage of capacity of the OR suite and available capacity of elective surgeries.

Researchers have investigated different statistical models to estimate surgery times (Strum et al., 2000; Stepaniak et al., 2009; Larsson, 2013). In practical, hospitals use various methods to estimate surgery durations including automated systems and statistical models based on the average durations of the previous surgeries. However, the most widely used methods are based on the surgeons' estimates since some factors affecting the surgery duration are taken into account by the surgeons but cannot be included in the computer based systems. Thus, surgeons' estimates are significant inputs for effective OR suite schedule.

Overestimating surgery time leads to underutilized OR time which is the positive difference between the allocated and observed OR time and results in lower utilization of resources and the performance of fewer surgeries (Dexter et al., 2005; Larsson, 2013). In contrast, underestimating surgery time leads to overutilization and results in personnel working overtime and the cancellation of surgeries. Thus, reducing estimating errors are vital for reliable, effective and efficient OR performance.

Recent studies show that not only utilization performance measurement, but also monitoring it is crucial for a successful OR management (Macario, 2006). In terms of monitoring, it is possible to just plot estimating errors (of different services, surgeons or types of surgeries) in a time series plot, or to calculate daily, weekly, etc. descriptive statistics. Moreover, statistical monitoring algorithms such as control charts can be used for evaluating utilization performance.

Control charts have been attractive tools for industrial professionals for the last decades. They practically plot important statistics on a chart and provide a visually attractive decision support environment. Traditional statistical monitoring techniques have been widely applied in industry and successfully implemented for many industrial processes. Recently, medical professionals have been attracted by these tools to monitor health related processes. Examples vary in a range from disease monitoring to financial monitoring of health care processes (for details see Thor et al., 2007 and Tenant et al., 2007). Using control charts for monitoring OR time efficiency is our focus for this study. Recent research on control charts and OR performance includes using control charts for monitoring cardiac surgical performance (Rogers et al., 2004), for monitoring the nonoperative time (Seim et al., 2006), for monitoring obstetricians' performance (Lane et al., 2007) and for analyzing the performance of surgeons in OR and setting benchmarks (Chen et al., 2010). Control charts can be used successfully for OR performance monitoring and may provide practitioners valuable knowledge on special causes of variability in their OR planning processes. They also help them eliminate the sources of variability.

In this study, we consider control chart implementations for OR time efficiency. CUSUM control charts, their implementation and interpretation are considered. The paper proceeds as follows. In section 2, the general framework for the control charts for OR efficiency is given briefly. The discussion is supported by implementing the methods to the simulated case duration data and results are given. Following these applications conclusions are provided in section 4.

Materials and Methods

OR Efficiency Measures

According to Dexter et al. (2005), there are two components of inaccurate case scheduling. The first one is bias and the other one is absolute error where the error equals the actual case duration minus the estimated case duration. To Macario (2006), bias is present if the surgeon consistently makes overestimations or underestimations; while precision indicates the magnitudes of the errors of the estimates. OR efficiency is measured in terms of both the underutilized and the overutilized hours of OR time. Many researchers (e.g. Dexter et al., 2002; Dexter et al., 2007) deal with procedures based on the OR efficiency in terms of utilization.

When estimating case durations, researchers search for methods that are near perfect for preventing bias and also have small variability of errors (Joustra et al., 2013; Larsson, 2013). Joustra et al. (2013) uses (i) the mean of the estimated operation time, (ii) the average difference between prediction and actual duration, (iii) the average absolute difference between prediction and actual duration, (iv) the root mean squared error and (v) the proportion of over/underprediction by more than 10 and 30

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minutes as performance measures. Dexter et al. (2005) mentions that efficient OR suites should have bias less than 15 minutes per 8 hours. They first derive a ratio of the sum of differences between the actual and scheduled case durations to the sum of all durations performed for each service and then multiply it by eight hours to obtain the estimated bias. As a performance measure, they calculate 95% confidence intervals for bias in the service's scheduled case durations reported per eight hours of used OR time. Larsson (2013) calculates both the mean value and the standard deviation of the estimating error to determine the level of accuracy of different estimation systems.

According to the literature, there is a general consensus that the normal and log-normal distributions are the most practical and effective distributions to represent the surgical procedure times (May et al., 2000; Strum et al., 2000; Stepaniak et al., 2009). Dexter et al. (2005) shows that the statistical distributions of bias estimates are consistent with a normal distribution. In this study, we will use the mean value and the variability of the estimating error as performance measures and monitor them simultaneously. We assume that estimating error follows a normal distribution.

A Framework for Monitoring the Efficiency of Use of OR Time

Control charts have recently played a major role in statistical monitoring. Control charts for normally distributed characteristics can be divided into three major branches; Shewhart, exponentially weighted moving average (EWMA) and CUSUM charts. We consider CUSUM charts and aim to introduce them to the area of OR performance management. As a powerful monitoring algorithm, a combination of the standardized two-sided mean CUSUM (SD2mCUSUM) and the standardized two-sided scale CUSUM (SD2sCUSUM) can be applied to surgery duration data successfully. When the process professionals measure the estimating error for surgeries, they may use these control charts to monitor mean and variability shifts simultaneously. Thus, they can easily identify a special cause such as insufficient surgery duration estimation performance of a surgeon or increasing OR time bias of a service. Our approach can be summarized in three simple steps; data collection, control charting and interpretation. Data collection step is of great importance, because the quality of input data directly influences the quality of the overall monitoring process. Generally, a data gathering and parameter estimation step called Phase I study is applied. Within that phase, in-control process parameters and control limits are obtained. Control charting and real time applications are considered after achieving Phase I. In this study, we assume Phase I study is done successfully and illustrate Phase II control charts. Along with the implementation, the practitioners should follow the signals given by the control charts. In the last step, each signal and non-random pattern should be examined carefully by the OR professionals and managers to identify the special causes of variation.

SD2mCUSUM and SD2sCUSUM Charts

SD2mCUSUM and SD2sCUSUM charts both have complex design parameters when compared to Shewhart counterparts. However, they have superior ability to detect small shifts. In order to simplify design complexity we consider standardized estimating errors of case durations z_i as the chart input as discussed by Hawkins and Olwell (1998) and Montgomery (2008). For our case, SD2mCUSUM essentially is a tabular CUSUM with the standardized estimating errors. In general, constructing this control chart requires knowing the process mean and process standard deviation. If the practitioner does not know the parameters, then it is possible to estimate them from the Phase I study. Basically, SD2mCUSUM plots two types of CUSUM statistics; one for positive mean shifts and the other for negative mean shifts. Let x_i be the i^{th} estimating error and z_i be the i^{th} standardized estimating error on the process. Standardization enables easily benchmark among different surgeons' estimating performances or different services' OR efficiency and reduce design complexity into a considerably simple level. The magnitudes of positive and negative CUSUMs are as follows: $Cp_i = \max\left(0, z_i - k + Cp_{i-1}\right)$, $Cn_i = \max\left(0, -z_i - k + Cn_{i-1}\right)$, where Cp_i is the i^{th} CUSUM for positive mean shift and Cn_i is the i^{th} CUSUM for negative mean shift. If Cp_i or Cn_i is larger than h, the process is considered to be out of control where h is the control limit to achieve a specified type I error for CUSUMs. We use $Cp_i, -Cn_i,\ h$ and $-h$ in our approach since one specific standardized error may have both negative and positive CUSUMs at the same time. It allows the practitioners easily distinguish between the statistics for negative and positive mean error shifts. The initial values Cp_0 and Cn_0 are chosen to be zero.

Monitoring mean is an important task of a monitoring procedure. However, process professionals should also evaluate the precision performance of the process. In other words, it is crucial to monitor variability as well. It is possible to construct a variability or scale CUSUM with the following calculations. When z_i is the i^{th} standardized estimating error, then $v_i = \left(\sqrt{|z_i|} - 0.822\right)/0.349$ is a new standardized normal quantity and sensitive to variability changes. The monitoring statistics are $Vp_i = \max\left(0, Vp_{i-1} + v_i - k\right)$ and $Vn_i = \max\left(0, Vn_{i-1} - v_i - k\right)$. The interpretation of SD2sCUSUM is similar to SD2mCUSUM. If the error variability increases Vp_i statistic will increase and eventually exceed the threshold h. On the other hand, if error variability decreases, then $-Vn_i$ statistic will decrease and eventually exceed the threshold $-h$. The initial values Vp_0 and $-Vn_0$ are chosen to be zero.

SD2mCUSUM and SD2sCUSUM charts become a pair of control charts to monitor mean and variability simultaneously. They can be plotted together using the same reference values and decision intervals on the same chart because the statistics z_i and v_i follow standard normal distribution.

Illustrative Example

A case study which explores bias and the variability of the estimating error produced by a system which solely depends on surgeons' estimations is illustrated. It is assumed that the average durations of a specific type of operation can be calculated based on historical data, and the in-control error follows a normal distribution with 0 minutes mean and 10 minutes standard deviation. Suppose there are four surgeons (A, B, C, D) performed the same type of operation with the following properties. Surgeon A makes accurate and precise estimates with 0 minutes mean estimating error and 10 minutes standard deviation; surgeon B consistently underestimates the surgery time, however s/he is precise (s/he estimates case durations with 6 minutes mean estimating error and 10 minutes standard deviation); surgeon C generally makes accurate estimates but tends to overestimate the surgery time for a period of time (s/he estimates case durations with -10 minutes mean estimating error and 10 minutes standard deviation for a period of time) and surgeon D sometimes underestimates and sometimes overestimates the surgery time with a considerably large (15 minutes) standard deviation of estimating error. We assume that all four surgeons complete 100 surgeries and simulate 100 estimating errors for each surgeon reflecting their estimating behavior. Control limits for the charts are -5 and 5 in order to achieve a specified false alarm rate. Figures 1-4 show SD2mCUSUM and SD2sCUSUM results for surgeons A-D, respectively.

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Vol. 2, No. 2, 2013

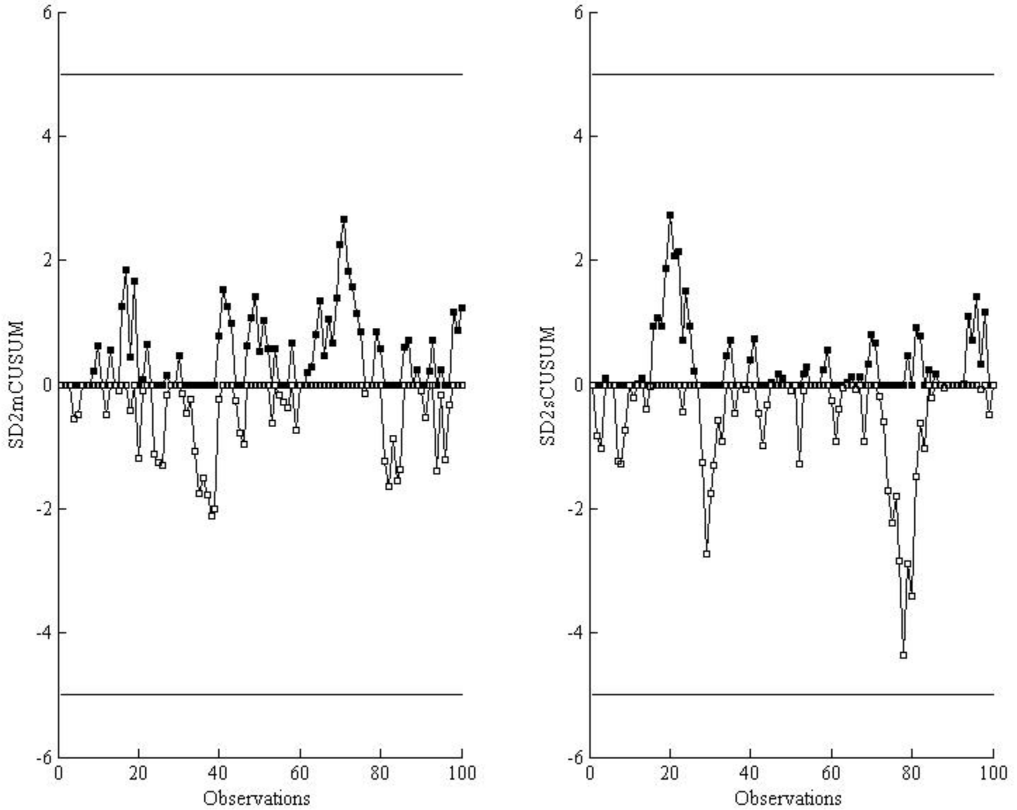

Figure 1: **SD2mCUSUM and SD2sCUSUM charts for surgeon A.**

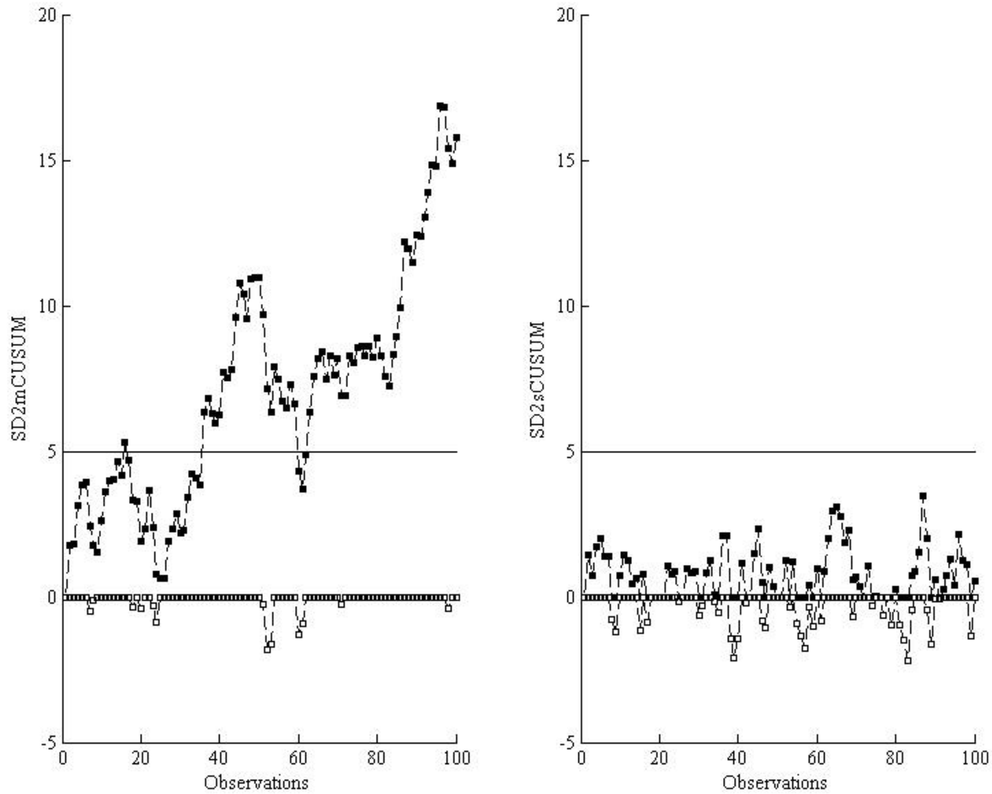

Figure 2: **SD2mCUSUM and SD2sCUSUM charts for surgeon B.**

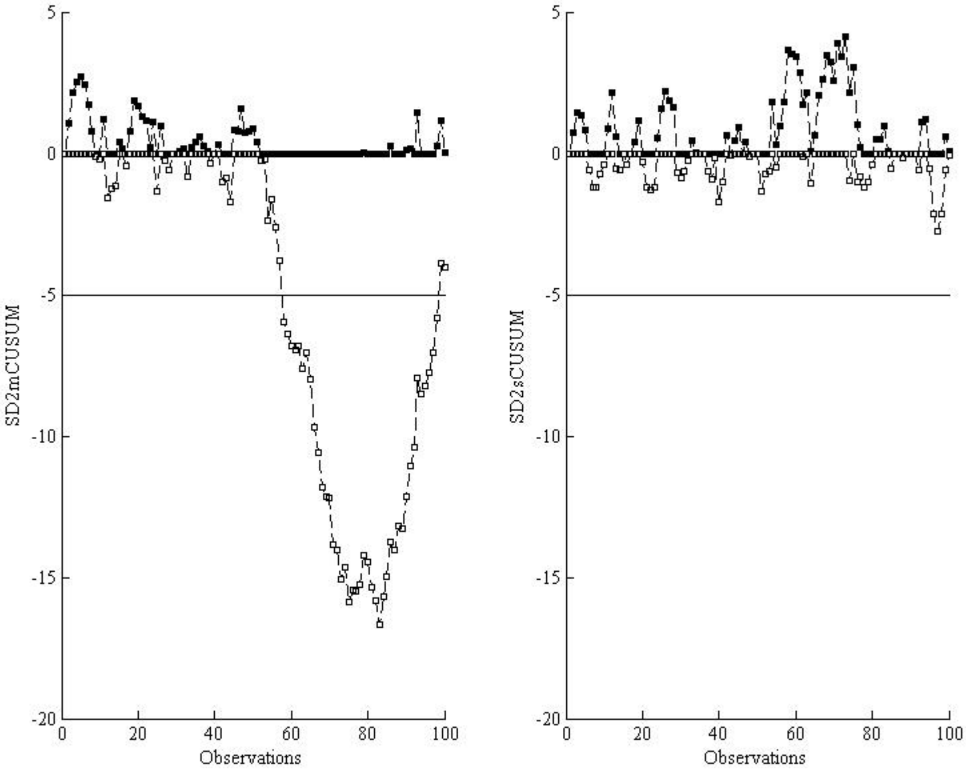

Figure 3: **SD2mCUSUM and SD2sCUSUM charts for surgeon C.**

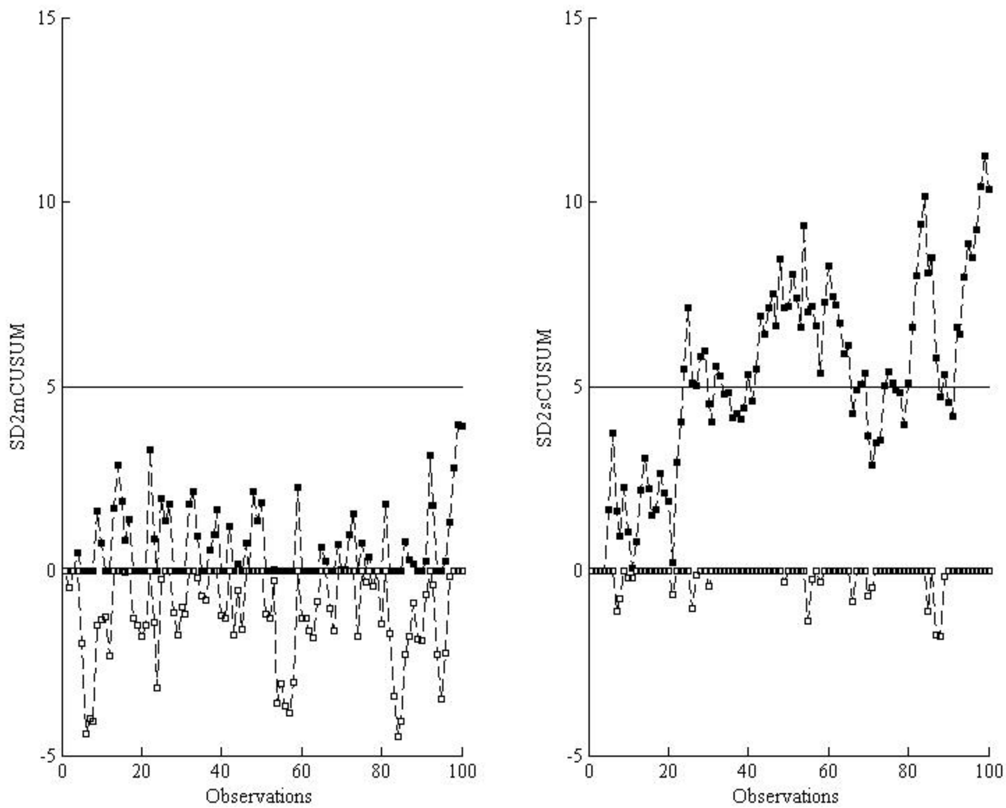

Figure 4: **SD2mCUSUM and SD2sCUSUM charts for surgeon D.**

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In Figure 1, it can be seen that the estimates of the surgeon A are consistent with the in-control process or in other words, surgeon A has accurate and precise estimates. The control charts generate no signals and show that surgeon A works quite consistent with the in-control distribution. Figure 2 is a good example of a surgeon who consistently underestimates the surgery durations. This case is important because the operations tend to finish later than expected and the bias creates a bottle-neck for planning the future operations. As it can be seen in Figure 2, the mean bias increases so SD2mCUSUM statistic exceeds its upper control limit persistently after about 30th operation. SD2sCUSUM chart for surgeon B shows that the variability of the errors is in-control. Surgeon C is considered to overestimate the surgery durations for a short time period of her/his operations. The bias can be observed looking at Figure 3. SD2mCUSUM for surgeon C shows that s/he underestimates surgery durations in between her/his 50th and 80th operations. The results for surgeon D are indicated in Figure 4. Figure 4 shows that surgeon D is not very concentrated on making case duration estimations. S/he provides adequate average error; however, her/his variability of case duration estimation is higher than the in-control variability. SD2sCUSUM statistics positively tend to exceed upper limit which shows that s/he provide a large standard deviation of the estimating error.

Conclusions

Making accurate and precise estimations for surgery durations helps to (i) decrease the risk that cases will be cancelled due to lack of time, (ii) improve the utilization of resources and (iii) increase the efficiency of use of ORs. Therefore, it is essential to decrease the estimating errors.

As the bias is an important issue for OR time efficiency, the need for monitoring tools which able to detect bias emerges. Accumulation control charts, SD2mCUSUM and SD2sCUSUM for our case, have the potential to detect consistent overestimation or underestimation of case durations which is defined as bias. Cumulative statistics of these control charts successfully reflect a persistent estimation behavior of a surgeon. They are also proven techniques to be effective when the bias is considerably small. Monitoring the mean value of the bias in estimated case durations, we can observe whether there is a tendency of underestimation or overestimation of surgery durations. On the other hand, the variability of the bias shows whether surgeons are focused or not focused on the estimating durations.

Ongoing debate on monitoring OR efficiency indicates that monitoring OR time is as important as measuring it. In this study, the simulated cases present the importance of measuring and monitoring the mean and variability of estimating error. For surgeon B and C, we show that shifts in mean bias can be detected using CUSUMs. In such cases, instead of relying solely on surgeons' estimates, a combined estimation method of historical mean and surgeons' estimate could be applied, if the hospital has a long historical duration data set. The results of variability increase are obvious for surgeon D even if s/he is accurate. It is concluded that surgeon D should focus on estimation more seriously and improve her/his duration estimation performance.

This study is a practical monitoring approach that would contribute to improve the efficiency of surgeon based surgery time estimation systems. Our illustrative case involves surgeons. However, the method can easily be adapted to other fields such as benchmarks of various type of operations', surgical services' or hospitals' OR efficiency. The methods introduced in our study have their own setbacks. A problem can emerge for rare operations. If the total number of operations is low in count, then it is inevitable to have problems about parameter estimation and distributional assumptions. For such cases, some other approaches should be considered and ongoing research of the authors deals with these challenges.

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