

PATIENT- AND SURGEON-ADJUSTED CONTROL CHARTS FOR MONITORING INDIVIDUAL PERFORMANCE

PATIENT- AND SURGEON-ADJUSTED CONTROL CHARTS FOR MONITORING PERFORMANCE

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ABSTRACT

Objectives: To determine whether an innovative graphical tool for accurate measurement of individual surgeon performance metrics, adjusted for both surgeon-specific and patient-specific factors, significantly alters interpretation of performance data.

996 and 2009. The database was randomly divided into training
Itivariate generalised estimating equation (GEEs) regression mo
generation of patient-risk and surgeon-experience adjustment f
monitoring of individual surgeon **Design:** Retrospective analysis of all total knee replacements (TKR) conducted at the host institution between 1996 and 2009. The database was randomly divided into training and testing datasets. Using multivariate generalised estimating equation (GEEs) regression models, the training dataset enabled generation of patient-risk and surgeon-experience adjustment factors. To simulate prospective monitoring of individual surgeon outcomes, the testing dataset was mapped on control charts. Weighted κ statistics were calculated to measure the agreement between patient risk adjusted and fully-adjusted control charts.

Setting: Tertiary care academic hospital.

Participants: All patients undergoing TKR at the host institution 1996-2009.

Main outcome measure: Operative efficiency.

Results: 5,313 procedures were analysed. Adjusted control charts were generated using a training dataset comprised of 3,756 procedures performed by 13 surgeons. Operative time gradually declined by 121 minutes with 25 years of experience (P<0.0001). Charts were tested by monitoring 4 other surgeons, performing an average of 389 procedures each. Adjustment for surgeon experience significantly altered the interpretation of operative efficiency ($\kappa = 0.29$ [95% CI, 0.11-0.47], and enhanced assessment of a surgeon's improvement or diminishment in efficiency over time. Specifically, experience adjustment inverted the interpretation of surgeon efficiency from above average to below average, or from improving to declining performance.

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Conclusions: Adjustment for surgeon experience is necessary for accurate interpretation of met-

rics over the course of a surgeon's career. Patient- and surgeon-adjusted control charts provide

an accurate method of monitoring individual operative efficiency.

Main text word count: 2533

Key Words: performance curve, surgical performance improvement, performance monitoring,

control chart, total knee replacement, operative efficiency

Article focus

- In the UK, surgeons have recently been required to publish their individual performance data. In turn, monitoring of performance data is known to improve outcomes.
- Adjustment of metrics for patient case-mix significantly alters their interpretation. Surgical procedures have learning curves, owing to the technical nature of the specialty, however the effects of this on outcomes are currently not adjusted for.
- Our aim was to develop an innovative graphical tool for accurate measurement and monitoring of individual surgeon performance metrics, adjusted for both surgeon-specific and patient-specific factors.

Key messages

- Patient- and surgeon- adjusted control charts can be used to accurately assess trends in performance metrics, with the aim of informing professional development.
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al knee replacement, operative efficiency
IK, surgeons have recently been required to publish their individue
turn, monitoring of performance data is known to i • Surgeon-specific adjustment is necessary for correct assessment of operative efficiency and performance metrics; failure to do so exposes metrics to statistically significant misinterpretation.

Strengths and limitations of this study

- Use of high-granularity data on over 5000 procedures, across 14 years, performed by 17 surgeons; robust statistical demonstration of the effects of adjusting for surgeon-specific factors.
- Single centre, retrospective, and focused on operative time, which although has clear relevance to operative efficiency and financial costs, is not a clear patient-centred outcome.

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INTRODUCTION

the insinuation of such tools into the surgical sphere. In the U
cently been required to publish their individual performance dat
interest, amongst both patients and health authorities, to track st
Two expressed concerns h Increasing patient demands, costs and emphasis on safety have led to marked interest in performance tracking of individual healthcare providers $[1, 2, 3, 4, 5]$. While the adoption of techniques to monitor surgeons has lagged behind that of providers in other areas of medicine, we are now witnessing the insinuation of such tools into the surgical sphere. In the United Kingdom, surgeons have recently been required to publish their individual performance data. There has also been a growing interest, amongst both patients and health authorities, to track surgeons' individual performance. Two expressed concerns have been that surgeons will be averse to operating on high-risk patients (those demonstrating unfavorable case-mix), and less likely to take on junior trainees (those with unfavorable experience) during procedures for fear of poor performance results [1, 6, 7, 8]. Without addressing such concerns, it is possible that publication of performance data may result in unwanted changes in practice, and the generation of inaccurate, inequitable data.

Several methods of individual surgeon performance monitoring have been proposed [9, 10, 11], frequently adjusting for patient-specific characteristics, or case-mix, including demographics and medical co-morbidities. The influence of such characteristics upon surgical outcomes has been well-explored and acknowledged [12, 13, 14]. Very recently, the role of surgeon-specific factors such as operative experience and surgical team familiarity, with respect to outcomes, has also been elucidated [15, 16, 17].

The relative importance of adjusting for both patient- and surgeon-specific factors when assessing operative performance has historically been stymied by difficulties in generating research databases of sufficient granularity and robustness to carry out detailed statistical analyses. Such limitations have been ameliorated by the development of large depositories of electronic medical data. Through the parsing of such data, we are now fortunate to have the opportunity to perform inquiries once thought impossible.

While it is important that surgeons are monitored, and clear that measurements result in improvements [3], it is paramount that the 'measuring stick' with which performance is evaluated, is accurate. To address the aforementioned confounders of case-mix and surgeon-experience, we explored the use of patient- and surgeon-adjusted control charts to permit accurate performance tracking of individual surgeons.

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of Control charts, a tool initially devised in the manufacturing industry, permit iterative improvements in quality by statistical process control [18]. They comprise of mapping a process metric or outcome on a chart with a pre-determined benchmark. Upper and lower limits are placed on the chart, typically at two or three standard deviations from the benchmark value; exceeding these limits indicates an anomalous or unlikely event that is signaled, investigated and when necessary acted upon to improve the charted process. In health care they have demonstrated benefit by permitting identification of causes of variation and enabling safety monitoring [19]. Control charts have been demonstrated to result in improved health outcomes, efficiency and safety [20, 21].

We believe that when appropriately adjusted, control charts may offer similar benefits in the sphere of surgical efficiency and performance. Specifically, our aim was to determine whether such a tool, when adjusted for both surgeon- and patient-specific factors, would significantly alter interpretation of performance data. We present the results of this research endeavor as a proof-of-concept of the potential value of adjusted control charts over more traditional methodologies in performance monitoring.

METHODS

Study design and population

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 For Periodic Soluti Following institutional review board approval (protocol 2006p000586), we conducted a longitudinal analysis of 5,313 knee replacement procedures performed by 17 surgeons at a single academic tertiary care center (Brigham & Women's Hospital, Boston, MA, USA) between 1996 and 2009. In order to develop the performance chart independently from the data to be monitored, the database was randomly split into training and testing datasets according to surgeon identity [22]. The training dataset included 3,756 procedures performed by 13 surgeons and was used to define the baseline parameters of the performance charts, as well as models for outcomes adjustment. The testing dataset included 1,557 procedures performed by the 4 other surgeons, with the aim of putting the performance charts to the test by checking their application to external data.

Outcome measures and data collection

Data were culled from a combination of electronic medical records, an electronic operative time tracking application, and physician employee databases. Operative time, the primary outcome

measurement, was measured in minutes and defined as the time elapsed from skin incision to skin closure. Operative time was used as a proxy for operative efficiency. For each procedure, the length of experience of each participating surgeon was calculated. The operative experience of the attending surgeon was calculated as the difference between the date of the procedure and that of the surgeon's completion of training.

Performance curve modeling and case-mix adjustment

Formal EXEC SET ALT ALT SET ALT ALT ALT SET AND SOLUTE SCHOUTER SET AND AND SOLUTE SCHOLAR SET AND ALT ALT SCHOLAR SET AND SET ALT AND SET ALT AND SET ALT AND SUPPORT SHOW THE SUPPORT OF STATE UPS THE USE OF STATE OF STAT We used the training dataset to determine the adjusted performance curve of surgeons during their career based on a multivariate generalised estimating equation (GEE) regression model, taking into consideration the clustering of patients by surgeon [23]. Operative time was the outcome of interest, while surgeon's experience was the predictor and patient case mix (patient age, sex, smoking status and the presence of comorbidities – type II diabetes mellitus, coronary artery disease and chronic obstructive pulmonary disorder) was considered as a covariate in the final model. Because the operative time curve may not necessarily be a linear function of surgeon experience, a number of possible shapes of performance curves were tested. In order to obtain the best fitting shape, surgeon experience was entered as both a linear term and a quadratic term in the final model [24]. An adjusted performance curve was drawn versus the number of years since surgeon graduation. Also, the reduction in operative time independently associated with the attending surgeon's experience was plotted. Model estimates were obtained using the GENMOD procedure in SAS™ 9.2 (SAS Institute Inc., Cary, NC, USA); all tests were 2-tailed, and *p*values <0.05 were considered significant.

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Design and comparison of patient-risk and fully-adjusted control charts

For the multiplied by the overall mean operative time. Once ad lotted on a Shewhart control chart to simulate prospective out lual surgeon over the course of his/her career [25]. Each data per time per year since graduati Surgical outcomes for the testing dataset were further adjusted using model estimates that were previously generated from the training dataset. For each surgical procedure, the expected operative time was computed by controlling for patient case-mix. For every surgeon, adjusted outcomes at a given year of experience were calculated as the ratio between the observed and the expected operative time multiplied by the overall mean operative time. Once adjusted, operative time was then plotted on a Shewhart control chart to simulate prospective outcome monitoring for every individual surgeon over the course of his/her career [25]. Each data point depicted the surgeon operative time per year since graduation. The central line value of the patient-risk adjusted chart was constant and was determined based on the overall mean operative time, while the central line value of the fully-adjusted chart varied and depicted the adjusted performance curve of surgeons as a function of their previous experience that was previously generated from the training dataset. Control and warning limits were set at 3 SD and 2 SD around the central line, respectively, to indicate whether a particular surgeon's performance differed significantly from this goal. The detection of a significantly high or poor performance was defined as a single point outside the control limits, respectively, or two out of three successive points between a warning limit and a control limit on the same side of the central line [26]. Underperforming surgeons were positioned above the upper limits (i.e. longer operative time), while surgeons with unusually good results were below the lower limits (shorter operative time) [27].

The agreement between patient-risk and fully-adjusted charts in detecting indicator variations was measured using the weighted Cohen k statistic [28]. The positions of the data points for sur-

geon individual performance were compared in terms of 5 ordinal levels based on warning and control limits.

RESULTS

A total of 5,313 total knee replacement procedures performed by 17 surgeons were analysed (Table 1). Median surgical experience was 17 years, ranging from 1 to 35 years in practice since graduation. The mean operative time was 109 minutes. A substantial decline in operative time was observed over the course of surgeon's career, resulting in a concave shaped performance curve (P<0.0001, Figure 1; to maintain anonymity, the number of years of experience has been removed from the x-axis of all figures).

For the Example 11 Start Star Figure 2 demonstrates the patient-risk adjusted operative times of 4 surgeons for TKR with respect to the expected 'benchmark' performance curve over time, with slower operative times being placed above the benchmark, indicating reduced operative efficiency, and faster operative times being placed below the benchmark, indicating improved operative efficiency. Inspection of each surgeon's performance curve revealed that surgeon A displayed better operative efficiency than surgeon B, with lower operative times. Furthermore, surgeon A's operative efficiency, unlike surgeon B's, was better than expected, demonstrating operative times below the benchmark performance curve. Surgeons C and D demonstrated similar operative times. With respect to the benchmark performance curve, however, Surgeon C performed better than expected, given his low experience, displaying superior operative efficiency. Surgeon D, relative to the benchmark performance curve, was found to display worse than expected operative efficiency.

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stently slower operative efficiency. Experience adjustment tranctive from variable about the population mean to clearly 'highted the interpretation of Surgeon D's operative efficiency from between the patient-risk and full Control charts adjusted only for patient risk depicted Surgeon A as improving. However, after adjusting for surgical experience, Surgeon A's operative efficiency appeared to worsen relative to the population mean (Figure 3). Similarly, Surgeon B was found to be within control limits for most of his operations when considering patient-risk adjustment only; however, surgical experience adjustment showed all but one of his data-points to lie outside of the upper control limit, indicating consistently slower operative efficiency. Experience adjustment transposed Surgeon C's performance curve from variable about the population mean to clearly 'high' operative efficiency, and inverted the interpretation of Surgeon D's operative efficiency from 'high' to 'poor'. The agreement between the patient-risk and fully-adjusted control charts in detecting operative time variations over surgeons career was very low (Table II, $\kappa = 0.29$ [95% CI, 0.11-0.47], indicating the significant effect of adjusting operative time for surgical experience.

Adjustment for surgeon experience, in addition to patient risk, significantly altered the interpretation of operative efficiency, and enhanced the accuracy of assessing a surgeon's improvement or diminishment in efficiency over time*.*

DISCUSSION

Our study presents a novel methodology for the adjustment and monitoring of surgical metrics, specifically operative efficiency. Surgery is a technical specialty, improving with volume and experience. Consideration of surgeon-specific factors may seem intuitive, but remains poorly investigated. Our findings quantitatively demonstrated that such adjustment significantly altered the interpretation of operative efficiency monitoring – at times resulting in an inversion of per-

ceived trends in efficiency relative to consideration of patient-adjustment alone. Although we investigated operative time, this methodology can be applied to any surgical outcome.

Fully-adjusted control charts were shown to offer an accurate and perceptive means of interpreting trends in a surgeon's efficiency, identifying outlying or anomalous units and providing early warning of divergence from the cohort mean. We believe such factors may prove particularly advantageous in the context of surgeon monitoring and performance tracking.

Limitations

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the context of surgeon monitoring and performance tracking.
In the considered in the context of this study's limitations.
Formed at a single academic medical cente These implications must be considered in the context of this study's limitations. First, this investigation was performed at a single academic medical center, retrospectively, which may limit the representativeness of our sample. It should be noted, however, that the retrospective nature of our investigation removed any Hawthorne bias with regards to performance and therefore may provide a truer depiction of procedural dynamics than could have been ascertained through prospective methods. Second, our focus on operative time did not implicitly incorporate considerations related to patient outcomes. Studies, however, have indicated that faster completion of the TKR procedure is associated with better outcomes [29]. Indeed, in a variety of work both within surgery and outside, time of task completion has been used as a robust indicator of learning and outcome [17, 30, 31, 32, 33, 45]. Further, longer operative times and increased use of the operating theatre, as discussed below, expose patients to greater risks of surgical site infection, whilst also entailing larger financial costs and reduced efficiency, that amidst rising costs in health care, are of clear importance. Third, our investigation utilised years of training as a proxy for surgical experience, rather than number of cases performed. This limitation is a reflection of the fact that

a number of surgeons included in the dataset had been in clinical practice prior to the implementation of our surgical tracking application. Years of training, however, has been utilised as an acceptable substitute for surgical experience in prior published studies [17, 18, 19, 39]. Finally, although we adjusted control charts for patient characteristics and surgeon individual experience, there may be other factors, such as non-technical skills and teamwork which need to be accounted for to enable better interpretation of performance.

Policy Implications

better interpretation of performance.
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thudgets, equating to running-costs per Monitoring operative times with the aim of improving operative efficiency has strong financial implications. Theatres, excluding day surgery, have been shown to account for approximately 6% of NHS Trust budgets, equating to running-costs per theatre per year of £1.5 million [34, 35]. In the U.S., the cost of an operating theatre has been estimated at approximately \$130 per minute [36]. Strategies that can improve operative efficiency and reduce operative costs are therefore of importance.

The impact of surgeon-specific adjustment itself, also has implications both within and outside the sphere of individual performance-tracking. In the context of training, it is arguably inequitable to compare the performance of less and more experienced trainees; indeed it would be inappropriate to expect a surgeon who has just started their training to perform as well as a surgeon who is about to complete their training, rather, trainees must be compared to cohorts of the same level of experience. Thus, use of surgeon-specific, experience-adjusted charts will permit the performance of young trainees to be accurately and equitably monitored relative to a relevant benchmark, removing bias. This could give rise to appraisals based upon performance rather than

investigation or intervention to improve the respective surgeor
also shown that performance may decline as surgeons approace
eon-adjusted control charts have the capacity to identify this
dependent of continuing education career chronology or volume of cases alone, potentially ensuring progression only upon acquisition of sufficient expertise. The tools outlined in this study could furthermore be used to establish minimal competency requirements for operators and permit important contributors to training to be quantitatively identified. In the context of experienced surgeons, fully-adjusted control charts provide a sensitive and timely means of identifying deviations from expected benchmarks, permitting prompt investigation or intervention to improve the respective surgeon's performance. Recent work has also shown that performance may decline as surgeons approach seniority [37]; patient- and surgeon- adjusted control charts have the capacity to identify this deterioration and supplement the implementation of continuing education programs. In the broader context of outcomes research, any studies investigating the impact of an intervention on performance could gain interpretational benefit from surgeon-factor adjustment. Where groups of surgeons or departments are being compared, it is intuitive that adjustment for the respective experiences, or 'surgeon-mix' of these groups are adjusted for, in parallel with patient-mix adjustment, to improve the transparency of results.

We present this research as a proof-of-concept that i) patient- and surgeon-adjusted control charts can be utilised to inform ongoing professional development and feedback for individual surgeons, and ii) surgeon-specific adjustment is necessary for correct assessment of operative efficiency and performance outcomes; failure to do so exposes metrics to statistically significant misinterpretation. We believe this should be considered in developments regarding surgical monitoring, to permit equitable and accurate performance assessment, addressing concerns of patients, surgeons and policy-makers alike.

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FIGURE LEGENDS

Figure 1. Performance curve for individual surgeon TKR operative efficiency. The graph illustrates how operative time within the cohort changed with surgeon experience.

Figure 2. Individual performance curves for surgeons A-D**.** The graph illustrates the patient-risk adjusted operative times of the 4 surgeons selected to test the control charts, with respect to the expected 'benchmark' performance curve.

djusted operative times of the 4 surgeons selected to test the composite of the expected 'benchmark' performance curve.
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 Figure 3. Patient-risk vs. fully- adjusted control charts for individual surgeons. For each surgeon a patient-risk adjusted chart, and fully-adjusted (patient-risk and surgeonexperience adjusted) chart is displayed. The horizontal axes indicate the experience of the surgeon in years and the blue curve his/her adjusted performance over time. The central black dotted line represents the expected operative time over the course of surgeon's career. The upper red and lower green lines illustrate poor and high performance limits, set at two standard deviations (dotted warning limits) and three standard deviations (continuous control limits) around the central line. Poor and high performers are defined as those breaching the upper and lower limits, respectively. Average performers are those with operative time around the central line, without crossing the limits.

Figure 1. Improvement curve for individual surgeons

Experience (years)

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Figure 3: Patient-risk vs. fully- adjusted control charts for surgeons A-D

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Table 1. Overview of study participants

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Table 2. Agreement between patient-risk adjusted and fully-adjusted charts in detecting

* Each unit in the table represents the position of a data point on a control chart, according to 5 ordinal levels based on Warning Limits (2SD) and Control Limits (3SD), as follows: <LCL (below the lower control limit), LCL-LWL (between the lower control and warning limits), LWL-UWL (between the lower and upper warning limits), UWL-UCL (between the upper warning and control limits), >UCL (above the upper control limit).

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ABSTRACT

Objectives: To determine whether an innovative graphical tool for accurate measurement of individual surgeon performance metrics, adjusted for both surgeon-specific and patient-specific factors, significantly alters interpretation of performance data.

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monitoring of individual surgeon **Design:** Retrospective analysis of all total knee replacements (TKR) conducted at the host institution between 1996 and 2009. The database was randomly divided into training and testing datasets. Using multivariate generalised estimating equation (GEEs) regression models, the training dataset enabled generation of patient-risk and surgeon-experience adjustment factors. To simulate prospective monitoring of individual surgeon outcomes, the testing dataset was mapped on control charts. Weighted κ statistics were calculated to measure the agreement between patient risk adjusted and fully-adjusted control charts.

Setting: Tertiary care academic hospital.

Participants: All patients undergoing TKR at the host institution 1996-2009.

Main outcome measure: Operative efficiency.

Results: 5,313 procedures were analysed. Adjusted control charts were generated using a training dataset comprised of 3,756 procedures performed by 13 surgeons. Operative time gradually declined by 121 minutes with 25 years of experience (P<0.0001). Charts were tested by monitoring 4 other surgeons, performing an average of 389 procedures each. Adjustment for surgeon experience significantly altered the interpretation of operative efficiency ($\kappa = 0.29$ [95% CI, 0.11-0.47], and enhanced assessment of a surgeon's improvement or diminishment in efficiency over time. Specifically, experience adjustment inverted the interpretation of surgeon efficiency from above average to below average, or from improving to declining performance.

Conclusions: Adjustment for surgeon experience is necessary for accurate interpretation of met-

rics over the course of a surgeon's career. Patient- and surgeon-adjusted control charts provide

an accurate method of monitoring individual operative efficiency.

Main text word count: 2533

Key Words: performance curve, surgical performance improvement, performance monitoring,

control chart, total knee replacement, operative efficiency

Article focus

- In the UK, surgeons have recently been required to publish their individual performance data. In turn, monitoring of performance data is known to improve outcomes.
- Adjustment of metrics for patient case-mix significantly alters their interpretation. Surgical procedures have learning curves, owing to the technical nature of the specialty, however the effects of this on outcomes are currently not adjusted for.
- Our aim was to develop an innovative graphical tool for accurate measurement and monitoring of individual surgeon performance metrics, adjusted for both surgeon-specific and patient-specific factors.

Key messages

- Patient- and surgeon- adjusted control charts can be used to accurately assess trends in performance metrics, with the aim of informing professional development.
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Strengths and limitations of this study

- Use of high-granularity data on over 5000 procedures, across 14 years, performed by 17 surgeons; robust statistical demonstration of the effects of adjusting for surgeon-specific factors.
- Single centre, retrospective, and focused on operative time, which although has clear relevance to operative efficiency and financial costs, is not a clear patient-centred outcome.

INTRODUCTION

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Several methods of individual surgeon performance monitoring have been proposed [9, 10, 11], frequently adjusting for patient-specific characteristics, or case-mix, including demographics and medical co-morbidities. The influence of such characteristics upon surgical outcomes has been well-explored and acknowledged [12, 13, 14]. Very recently, the role of surgeon-specific factors such as operative experience and surgical team familiarity, with respect to outcomes, has also been elucidated [15, 16, 17].

The relative importance of adjusting for both patient- and surgeon-specific factors when assessing operative performance has historically been stymied by difficulties in generating research databases of sufficient granularity and robustness to carry out detailed statistical analyses. Such limitations have been ameliorated by the development of large depositories of electronic medical data. Through the parsing of such data, we are now fortunate to have the opportunity to perform inquiries once thought impossible.

While it is important that surgeons are monitored, and clear that measurements result in improvements [1, 6], it is paramount that the 'measuring stick' with which performance is evaluated, is accurate. To address the aforementioned confounders of case-mix and surgeon-experience, we explored the use of patient- and surgeon-adjusted control charts to permit accurate performance tracking of individual surgeons.

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is Control charts, a tool initially devised in the manufacturing industry, permit iterative improvements in quality by statistical process control [18]. They comprise of mapping a process metric or outcome on a chart with a pre-determined benchmark. Upper and lower limits are placed on the chart, typically at two or three standard deviations from the benchmark value; exceeding these limits indicates an anomalous or unlikely event that is signaled, investigated and when necessary acted upon to improve the charted process. In health care they have demonstrated benefit by permitting identification of causes of variation and enabling safety monitoring [19]. Control charts have been demonstrated to result in improved health outcomes, efficiency and safety [20, 21].

We believe that when appropriately adjusted, control charts may offer similar benefits in the sphere of surgical efficiency and performance. Specifically, our aim was to determine whether such a tool, when adjusted for both surgeon- and patient-specific factors, would significantly alter interpretation of performance data. We present the results of this research endeavor as a proof-of-concept of the potential value of adjusted control charts over more traditional methodologies in performance monitoring.

METHODS

Study design and population

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 For Periodic Soluti Following institutional review board approval (protocol 2006p000586), we conducted a longitudinal analysis of 5,313 knee replacement procedures performed by 17 surgeons at a single academic tertiary care center (Brigham & Women's Hospital, Boston, MA, USA) between 1996 and 2009. In order to develop the performance chart independently from the data to be monitored, the database was randomly split into training and testing datasets according to surgeon identity [22]. The training dataset included 3,756 procedures performed by 13 surgeons and was used to define the baseline parameters of the control charts, including upper and lower limits for the charts, as well as models for case-mix adjustment, and experience-adjustment. The testing dataset included 1,557 procedures performed by the 4 other surgeons; operative times of procedures by each of these surgeons was mapped on control charts developed using the training dataset, to simulate performance monitoring.
Outcome measures and data collection

Data were culled from a combination of electronic medical records, an electronic operative time tracking application, and physician employee databases. Operative time, the primary outcome measurement, was measured in minutes and defined as the time elapsed from skin incision to skin closure. Operative time was used as a proxy for operative efficiency. For each procedure, the length of experience of each participating surgeon was calculated. The operative experience of the attending surgeon was calculated as the difference between the date of the procedure and that of the surgeon's completion of training.

Performance curve modeling and case-mix adjustment

For the example 1 and participating surgeon was calculated. The oper surgeon was calculated as the difference between the date of the on's completion of training.
 For the example 1 and **For the example 1** and **For the** We used the training dataset to determine the adjusted performance curve of surgeons during their career based on a multivariate generalised estimating equation (GEE) regression model, also taking into consideration the clustering of patients by surgeon [23]. Operative time was the outcome of interest, while surgeon experience was the predictor and patient case mix (patient age, sex, smoking status and the presence of comorbidities – type II diabetes mellitus, coronary artery disease and chronic obstructive pulmonary disorder) was considered as a covariate in the final model. We included all available co-morbidities from our dataset in the case-mix adjustment model. Because the operative time curve may not necessarily be a linear function of surgeon experience, a number of possible shapes of performance curves were tested. In order to obtain the best fitting shape, surgeon experience was entered as both a linear term and a quadratic term in the final model [24]. An adjusted performance curve was drawn versus the number of years since surgeon graduation. Also, the reduction in operative time independently associated

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with the attending surgeon's experience was plotted. Model estimates were obtained using the GENMOD procedure in SAS™ 9.2 (SAS Institute Inc., Cary, NC, USA); all tests were 2-tailed, and *p*-values <0.05 were considered significant.

Design and comparison of patient-risk and fully-adjusted control charts

parison of patient-risk and fully-adjusted control charts
from procedures in the testing dataset were adjusted using mod
set. Operative times were adjusted for patient-risk alone, or for
nece together (fully-adjusted). F Operative times from procedures in the testing dataset were adjusted using models derived from the training dataset. Operative times were adjusted for patient-risk alone, or for patient-risk and surgeon experience together (fully-adjusted). For every surgeon, adjusted outcomes at a given year of experience were calculated as the ratio between the observed and the expected operative time multiplied by the overall mean operative time. Once adjusted, operative time was then plotted on a Shewhart control chart to simulate prospective outcome monitoring for every individual surgeon over the course of his/her career [25]. Each data point depicted the surgeon operative time per year since graduation. The central line of the patient-risk adjusted chart was constant and was determined based on the overall mean operative time, while the central line value of the fully-adjusted chart varied and depicted the adjusted performance curve of surgeons as a function of their previous experience that was previously generated from the training dataset. Control and warning limits were set at 3 SD and 2 SD around the central line, respectively, to indicate whether a particular surgeon's performance differed significantly from this goal. The detection of a significantly high or poor performance was defined as a single point outside the control limits, respectively, or two out of three successive points between a warning limit and a control limit on the same side of the central line [26]. Underperforming surgeons were positioned above the upper limits (i.e. longer operative time), while surgeons with unusually good results were below the lower limits (shorter operative time) [27].

The agreement between patient-risk and fully-adjusted charts in detecting indicator variations was measured using the weighted Cohen k statistic [28]. The positions of the data points for surgeon individual performance were compared in terms of 5 ordinal levels based on warning and control limits.

RESULTS

Formal Example 12 total knee replacement procedures performed by 17 surgeons experience was 17 years, ranging from 1 to 35 years in praction operative time was 109 minutes (standard deviation 30.3 minute djusted operativ A total of 5,313 total knee replacement procedures performed by 17 surgeons were analysed. Median surgical experience was 17 years, ranging from 1 to 35 years in practice since graduation. The mean operative time was 109 minutes (standard deviation 30.3 minutes). A substantial decline in risk-adjusted operative time was observed over the course of surgeon's career, resulting in a concave shaped performance curve $(P< 0.0001$, Figure 1; to maintain anonymity, the number of years of experience has been removed from the x-axis of all figures). Table 1 summarises the surgeon and patient characteristics of the training and testing datasets; Table 2 displays the number of procedures performed by each surgeon.

Figure 2 demonstrates the patient-risk adjusted operative times of 4 surgeons for TKR with respect to the expected 'benchmark' performance curve over time, with slower operative times being placed above the benchmark, indicating reduced operative efficiency, and faster operative times being placed below the benchmark, indicating improved operative efficiency. Inspection of each surgeon's performance curve revealed that surgeon A displayed better operative efficiency than surgeon B, with lower operative times. Furthermore, surgeon A's operative efficiency, unlike surgeon B's, was better than expected, demonstrating operative times below the benchmark

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performance curve. Surgeons C and D demonstrated similar operative times. With respect to the benchmark performance curve, however, Surgeon C performed better than expected, given his low experience, displaying superior operative efficiency. Surgeon D, relative to the benchmark performance curve, was found to display worse than expected operative efficiency.

djusted only for patient risk depicted Surgeon A as improving
gical experience, Surgeon A's operative efficiency appeared to
mean (Figure 3). Similarly, Surgeon B was found to be within
ations when considering patient-ris Control charts adjusted only for patient risk depicted Surgeon A as improving. However, after adjusting for surgical experience, Surgeon A's operative efficiency appeared to worsen relative to the population mean (Figure 3). Similarly, Surgeon B was found to be within control limits for most of his operations when considering patient-risk adjustment only; however, surgical experience adjustment showed all but one of his data-points to lie outside of the upper control limit, indicating consistently slower operative efficiency. Experience adjustment transposed Surgeon C's performance curve from variable about the population mean to clearly 'high' operative efficiency, and inverted the interpretation of Surgeon D's operative efficiency from 'high' to 'poor'. The agreement between the patient-risk and fully-adjusted control charts in detecting operative time variations over surgeons career was very low (Table 3, $\kappa = 0.29$ [95% CI, 0.11-0.47], indicating the significant effect of adjusting operative time for surgical experience.

Adjustment for surgeon experience, in addition to patient risk, significantly altered the interpretation of operative efficiency, and enhanced the accuracy of assessing a surgeon's improvement or diminishment in efficiency over time*.*

DISCUSSION

Our study presents a novel methodology for the adjustment and monitoring of surgical metrics, specifically operative efficiency. Surgery is a technical specialty, improving with volume and experience. Consideration of surgeon-specific factors may seem intuitive, but remains poorly investigated. Our findings quantitatively demonstrated that such adjustment significantly altered the interpretation of operative efficiency monitoring – at times resulting in an inversion of perceived trends in efficiency relative to consideration of patient-adjustment alone. Although we investigated operative time, this methodology can be applied to any surgical outcome.

Fully-adjusted control charts were shown to offer an accurate and perceptive means of interpreting trends in a surgeon's efficiency, identifying outlying or anomalous units and providing early warning of divergence from the cohort mean. We believe such factors may prove particularly advantageous in the context of surgeon monitoring and performance tracking.

Limitations

efficiency relative to consideration of patient-adjustment alor
rative time, this methodology can be applied to any surgical out
control charts were shown to offer an accurate and perceptive me
argeon's efficiency, identif These implications must be considered in the context of this study's limitations. First, this investigation was performed at a single academic medical center, retrospectively, which may limit the representativeness of our sample. It should be noted, however, that the retrospective nature of our investigation removed any Hawthorne bias with regards to performance and therefore may provide a truer depiction of procedural dynamics than could have been ascertained through prospective methods. Importantly, our database covered a substantial time period and it is possible that operative technique and technology may have changed during this. Second, our focus on operative time did not implicitly incorporate considerations related to patient outcomes. Studies, however, have indicated that faster completion of the TKR procedure is associated with better

lised years of training as a proxy for surgical experience, rather
This limitation is a reflection of the fact that a number of surge-
appear in clinical practice prior to the implementation of our surg
of training, howeve outcomes [29]. Indeed, in a variety of work both within surgery and outside, time of task completion has been used as a robust indicator of learning and outcome [17, 30, 31, 32, 33, 34]. Further, longer operative times and increased use of the operating theatre, as discussed below, expose patients to greater risks of surgical site infection, whilst also entailing larger financial costs and reduced efficiency, that amidst rising costs in health care, are of clear importance. Third, our investigation utilised years of training as a proxy for surgical experience, rather than number of cases performed. This limitation is a reflection of the fact that a number of surgeons included in the dataset had been in clinical practice prior to the implementation of our surgical tracking application. Years of training, however, has been utilised as an acceptable substitute for surgical experience in prior published studies [15, 16, 17]. Finally, although we adjusted control charts for patient characteristics and surgeon individual experience, there may be other factors, such as non-technical skills, teamwork and resident involvement which need to be accounted for to enable better interpretation of performance.

Policy Implications

Monitoring operative times with the aim of improving operative efficiency has strong financial implications. Theatres, excluding day surgery, have been shown to account for approximately 6% of NHS Trust budgets, equating to running-costs per theatre per year of £1.5 million [35, 36]. In the U.S., the cost of an operating theatre has been estimated at approximately \$130 per minute [37]. Strategies that can improve operative efficiency and reduce operative costs are therefore of importance.

nce. Thus, use of surgeon-specific, experience-adjusted charts
young trainees to be accurately and equitably monitored relation
ying bias. This could give rise to appraisals based upon perform
y or volume of cases alone, p The impact of surgeon-specific adjustment itself, also has implications both within and outside the sphere of individual performance-tracking. In the context of training, it is arguably inequitable to compare the performance of less and more experienced trainees; indeed it would be inappropriate to expect a surgeon who has just started their training to perform as well as a surgeon who is about to complete their training, rather, trainees must be compared to cohorts of the same level of experience. Thus, use of surgeon-specific, experience-adjusted charts will permit the performance of young trainees to be accurately and equitably monitored relative to a relevant benchmark, removing bias. This could give rise to appraisals based upon performance rather than career chronology or volume of cases alone, potentially ensuring progression only upon acquisition of sufficient expertise. The tools outlined in this study could furthermore be used to establish minimal competency requirements for operators and permit important contributors to training to be quantitatively identified. In the context of experienced surgeons, fully-adjusted control charts provide a sensitive and timely means of identifying deviations from expected benchmarks, permitting prompt investigation or intervention to improve the respective surgeon's performance. Recent work has also shown that performance may decline as surgeons approach seniority [38]; patient- and surgeon- adjusted control charts have the capacity to identify this deterioration and supplement the implementation of continuing education programs. In the broader context of outcomes research, any studies investigating the impact of an intervention on performance could gain interpretational benefit from surgeon-factor adjustment. Where groups of surgeons or departments are being compared, it is intuitive that adjustment for the respective experiences, or 'surgeon-mix' of these groups are adjusted for, in parallel with patient-mix adjustment, to improve the transparency of results.

Representative Concernant Control Concernant C We present this research as a proof-of-concept that i) patient- and surgeon-adjusted control charts can be utilised to inform ongoing professional development and feedback for individual surgeons, and ii) surgeon-specific adjustment is necessary for correct assessment of operative efficiency and performance outcomes; failure to do so exposes metrics to statistically significant misinterpretation. We believe this should be considered in developments regarding surgical monitoring, to permit equitable and accurate performance assessment, addressing concerns of patients, surgeons and policy-makers alike.

Contributorship Statement All authors fulfill the ICMJE criteria for authorship.

Competing interests None

Data Sharing Statement Further information on data used in the study is available on request.

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PATIENT- AND SURGEON-ADJUSTED CONTROL CHARTS FOR MONITORING PERFORMANCE

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ABSTRACT

Objectives: To determine whether an innovative graphical tool for accurate measurement of individual surgeon performance metrics, adjusted for both surgeon-specific and patient-specific factors, significantly alters interpretation of performance data.

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Article focus

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INTRODUCTION

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interest, amongst both patients and health authorities, to track st
Two expressed concerns h Increasing patient demands, costs and emphasis on safety have led to marked interest in performance tracking of individual healthcare providers $[1, 2, 3, 4, 5]$. While the adoption of techniques to monitor surgeons has lagged behind that of providers in other areas of medicine, we are now witnessing the insinuation of such tools into the surgical sphere. In the United Kingdom, surgeons have recently been required to publish their individual performance data. There has also been a growing interest, amongst both patients and health authorities, to track surgeons' individual performance. Two expressed concerns have been that surgeons will be averse to operating on high-risk patients (those demonstrating unfavorable case-mix), and less likely to take on junior trainees (those with unfavorable experience) during procedures for fear of poor performance results [1, 6, 7, 8]. Without addressing such concerns, it is possible that publication of performance data may result in unwanted changes in practice, and the generation of inaccurate, inequitable data.

Several methods of individual surgeon performance monitoring have been proposed [9, 10, 11], frequently adjusting for patient-specific characteristics, or case-mix, including demographics and medical co-morbidities. The influence of such characteristics upon surgical outcomes has been well-explored and acknowledged [12, 13, 14]. Very recently, the role of surgeon-specific factors such as operative experience and surgical team familiarity, with respect to outcomes, has also been elucidated [15, 16, 17].

The relative importance of adjusting for both patient- and surgeon-specific factors when assessing operative performance has historically been stymied by difficulties in generating research databases of sufficient granularity and robustness to carry out detailed statistical analyses. Such limitations have been ameliorated by the development of large depositories of electronic medical data. Through the parsing of such data, we are now fortunate to have the opportunity to perform inquiries once thought impossible.

While it is important that surgeons are monitored, and clear that measurements result in improvements [1, 6], it is paramount that the 'measuring stick' with which performance is evaluated, is accurate. To address the aforementioned confounders of case-mix and surgeon-experience, we explored the use of patient- and surgeon-adjusted control charts to permit accurate performance tracking of individual surgeons.

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is Control charts, a tool initially devised in the manufacturing industry, permit iterative improvements in quality by statistical process control [18]. They comprise of mapping a process metric or outcome on a chart with a pre-determined benchmark. Upper and lower limits are placed on the chart, typically at two or three standard deviations from the benchmark value; exceeding these limits indicates an anomalous or unlikely event that is signaled, investigated and when necessary acted upon to improve the charted process. In health care they have demonstrated benefit by permitting identification of causes of variation and enabling safety monitoring [19]. Control charts have been demonstrated to result in improved health outcomes, efficiency and safety [20, 21].

We believe that when appropriately adjusted, control charts may offer similar benefits in the sphere of surgical efficiency and performance. Specifically, our aim was to determine whether such a tool, when adjusted for both surgeon- and patient-specific factors, would significantly alter interpretation of performance data. We present the results of this research endeavor as a proof-of-concept of the potential value of adjusted control charts over more traditional methodologies in performance monitoring.

METHODS

Study design and population

mance monitoring.
 Example 10
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develop the performance chart independently from the da** Following institutional review board approval (protocol 2006p000586), we conducted a longitudinal analysis of 5,313 knee replacement procedures performed by 17 surgeons at a single academic tertiary care center (Brigham & Women's Hospital, Boston, MA, USA) between 1996 and 2009. In order to develop the performance chart independently from the data to be monitored, the database was randomly split into training and testing datasets according to surgeon identity [22]. The training dataset included 3,756 procedures performed by 13 surgeons and was used to define the baseline parameters of the control charts, including upper and lower limits for the charts, as well as models for case-mix adjustment, and experience-adjustment. The testing dataset included 1,557 procedures performed by the 4 other surgeons; operative times of procedures by each of these surgeons was mapped on control charts developed using the training dataset, to simulate performance monitoring.

Outcome measures and data collection

Data were culled from a combination of electronic medical records, an electronic operative time tracking application, and physician employee databases. Operative time, the primary outcome measurement, was measured in minutes and defined as the time elapsed from skin incision to skin closure. Operative time was used as a proxy for operative efficiency. For each procedure, the length of experience of each participating surgeon was calculated. The operative experience of the attending surgeon was calculated as the difference between the date of the procedure and that of the surgeon's completion of training.

Performance curve modeling and case-mix adjustment

surgeon was calculated as the difference between the date of the poor and the poor and the poor and the difference corrections of the poor and the poor and the adjustment ining dataset to determine the adjustment the poor We used the training dataset to determine the adjusted performance curve of surgeons during their career based on a multivariate generalised estimating equation (GEE) regression model, also taking into consideration the clustering of patients by surgeon [23]. Operative time was the outcome of interest, while surgeon experience was the predictor and patient case mix (patient age, sex, smoking status and the presence of comorbidities – type II diabetes mellitus, coronary artery disease and chronic obstructive pulmonary disorder) was considered as a covariate in the final model. We included all available co-morbidities from our dataset in the case-mix adjustment model. Because the operative time curve may not necessarily be a linear function of surgeon experience, a number of possible shapes of performance curves were tested. In order to obtain the best fitting shape, surgeon experience was entered as both a linear term and a quadratic term in the final model [24]. An adjusted performance curve was drawn versus the number of years since surgeon graduation. Also, the reduction in operative time independently associated with the attending surgeon's experience was plotted. Model estimates were obtained using the

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GENMOD procedure in SAS™ 9.2 (SAS Institute Inc., Cary, NC, USA); all tests were 2-tailed, and *p*-values <0.05 were considered significant.

Design and comparison of patient-risk and fully-adjusted control charts

from procedures in the testing dataset were adjusted using mod
set. Operative times were adjusted for patient-risk alone, or for
nee together (fully-adjusted). For every surgeon, adjusted outc
ce were calculated as the rat Operative times from procedures in the testing dataset were adjusted using models derived from the training dataset. Operative times were adjusted for patient-risk alone, or for patient-risk and surgeon experience together (fully-adjusted). For every surgeon, adjusted outcomes at a given year of experience were calculated as the ratio between the observed and the expected operative time multiplied by the overall mean operative time. Once adjusted, operative time was then plotted on a Shewhart control chart to simulate prospective outcome monitoring for every individual surgeon over the course of his/her career [25]. Each data point depicted the surgeon operative time per year since graduation. The central line of the patient-risk adjusted chart was constant and was determined based on the overall mean operative time, while the central line value of the fully-adjusted chart varied and depicted the adjusted performance curve of surgeons as a function of their previous experience that was previously generated from the training dataset. Control and warning limits were set at 3 SD and 2 SD around the central line, respectively, to indicate whether a particular surgeon's performance differed significantly from this goal. The detection of a significantly high or poor performance was defined as a single point outside the control limits, respectively, or two out of three successive points between a warning limit and a control limit on the same side of the central line [26]. Underperforming surgeons were positioned above the upper limits (i.e. longer operative time), while surgeons with unusually good results were below the lower limits (shorter operative time) [27].

The agreement between patient-risk and fully-adjusted charts in detecting indicator variations was measured using the weighted Cohen k statistic [28]. The positions of the data points for surgeon individual performance were compared in terms of 5 ordinal levels based on warning and control limits.

RESULTS

For the Example 12 Set of the system of the performed by 17 surgeons experience was 17 years, ranging from 1 to 35 years in praction operative time was 109 minutes (standard deviation 30.3 minute divised operative time wa A total of 5,313 total knee replacement procedures performed by 17 surgeons were analysed. Median surgical experience was 17 years, ranging from 1 to 35 years in practice since graduation. The mean operative time was 109 minutes (standard deviation 30.3 minutes). A substantial decline in risk-adjusted operative time was observed over the course of surgeon's career, resulting in a concave shaped performance curve $(P< 0.0001$, Figure 1; to maintain anonymity, the number of years of experience has been removed from the x-axis of all figures). Table 1 summarises the surgeon and patient characteristics of the training and testing datasets; Table 2 displays the number of procedures performed by each surgeon.

Figure 2 demonstrates the patient-risk adjusted operative times of 4 surgeons for TKR with respect to the expected 'benchmark' performance curve over time, with slower operative times being placed above the benchmark, indicating reduced operative efficiency, and faster operative times being placed below the benchmark, indicating improved operative efficiency. Inspection of each surgeon's performance curve revealed that surgeon A displayed better operative efficiency than surgeon B, with lower operative times. Furthermore, surgeon A's operative efficiency, unlike surgeon B's, was better than expected, demonstrating operative times below the benchmark

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performance curve. Surgeons C and D demonstrated similar operative times. With respect to the benchmark performance curve, however, Surgeon C performed better than expected, given his low experience, displaying superior operative efficiency. Surgeon D, relative to the benchmark performance curve, was found to display worse than expected operative efficiency.

djusted only for patient risk depicted Surgeon A as improving
gical experience, Surgeon A's operative efficiency appeared to
mean (Figure 3). Similarly, Surgeon B was found to be within
ations when considering patient-ris Control charts adjusted only for patient risk depicted Surgeon A as improving. However, after adjusting for surgical experience, Surgeon A's operative efficiency appeared to worsen relative to the population mean (Figure 3). Similarly, Surgeon B was found to be within control limits for most of his operations when considering patient-risk adjustment only; however, surgical experience adjustment showed all but one of his data-points to lie outside of the upper control limit, indicating consistently slower operative efficiency. Experience adjustment transposed Surgeon C's performance curve from variable about the population mean to clearly 'high' operative efficiency, and inverted the interpretation of Surgeon D's operative efficiency from 'high' to 'poor'. The agreement between the patient-risk and fully-adjusted control charts in detecting operative time variations over surgeons career was very low (Table $3, \kappa = 0.29$ [95% CI, 0.11-0.47], indicating the significant effect of adjusting operative time for surgical experience.

Adjustment for surgeon experience, in addition to patient risk, significantly altered the interpretation of operative efficiency, and enhanced the accuracy of assessing a surgeon's improvement or diminishment in efficiency over time*.*

DISCUSSION

Our study presents a novel methodology for the adjustment and monitoring of surgical metrics, specifically operative efficiency. Surgery is a technical specialty, improving with volume and experience. Consideration of surgeon-specific factors may seem intuitive, but remains poorly investigated. Our findings quantitatively demonstrated that such adjustment significantly altered the interpretation of operative efficiency monitoring – at times resulting in an inversion of perceived trends in efficiency relative to consideration of patient-adjustment alone. Although we investigated operative time, this methodology can be applied to any surgical outcome.

Fully-adjusted control charts were shown to offer an accurate and perceptive means of interpreting trends in a surgeon's efficiency, identifying outlying or anomalous units and providing early warning of divergence from the cohort mean. We believe such factors may prove particularly advantageous in the context of surgeon monitoring and performance tracking.

Limitations

efficiency relative to consideration of patient-adjustment alor
rative time, this methodology can be applied to any surgical out
control charts were shown to offer an accurate and perceptive me
argeon's efficiency, identif These implications must be considered in the context of this study's limitations. First, this investigation was performed at a single academic medical center, retrospectively, which may limit the representativeness of our sample. It should be noted, however, that the retrospective nature of our investigation removed any Hawthorne bias with regards to performance and therefore may provide a truer depiction of procedural dynamics than could have been ascertained through prospective methods. Importantly, our database covered a substantial time period and it is possible that operative technique and technology may have changed during this. Second, our focus on operative time did not implicitly incorporate considerations related to patient outcomes. Studies, however, have indicated that faster completion of the TKR procedure is associated with better

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lised years of training as a proxy for surgical experience, rather
This limitation is a reflection of the fact that a number of surge-
appear in clinical practice prior to the implementation of our surg
of training, howeve outcomes [29]. Indeed, in a variety of work both within surgery and outside, time of task completion has been used as a robust indicator of learning and outcome [17, 30, 31, 32, 33, 34]. Further, longer operative times and increased use of the operating theatre, as discussed below, expose patients to greater risks of surgical site infection, whilst also entailing larger financial costs and reduced efficiency, that amidst rising costs in health care, are of clear importance. Third, our investigation utilised years of training as a proxy for surgical experience, rather than number of cases performed. This limitation is a reflection of the fact that a number of surgeons included in the dataset had been in clinical practice prior to the implementation of our surgical tracking application. Years of training, however, has been utilised as an acceptable substitute for surgical experience in prior published studies [15, 16, 17]. Finally, although we adjusted control charts for patient characteristics and surgeon individual experience, there may be other factors, such as non-technical skills, teamwork and resident involvement which need to be accounted for to enable better interpretation of performance.

Policy Implications

Monitoring operative times with the aim of improving operative efficiency has strong financial implications. Theatres, excluding day surgery, have been shown to account for approximately 6% of NHS Trust budgets, equating to running-costs per theatre per year of £1.5 million [35, 36]. In the U.S., the cost of an operating theatre has been estimated at approximately \$130 per minute [37]. Strategies that can improve operative efficiency and reduce operative costs are therefore of importance.

nce. Thus, use of surgeon-specific, experience-adjusted charts
young trainees to be accurately and equitably monitored relation
ying bias. This could give rise to appraisals based upon perform
y or volume of cases alone, p The impact of surgeon-specific adjustment itself, also has implications both within and outside the sphere of individual performance-tracking. In the context of training, it is arguably inequitable to compare the performance of less and more experienced trainees; indeed it would be inappropriate to expect a surgeon who has just started their training to perform as well as a surgeon who is about to complete their training, rather, trainees must be compared to cohorts of the same level of experience. Thus, use of surgeon-specific, experience-adjusted charts will permit the performance of young trainees to be accurately and equitably monitored relative to a relevant benchmark, removing bias. This could give rise to appraisals based upon performance rather than career chronology or volume of cases alone, potentially ensuring progression only upon acquisition of sufficient expertise. The tools outlined in this study could furthermore be used to establish minimal competency requirements for operators and permit important contributors to training to be quantitatively identified. In the context of experienced surgeons, fully-adjusted control charts provide a sensitive and timely means of identifying deviations from expected benchmarks, permitting prompt investigation or intervention to improve the respective surgeon's performance. Recent work has also shown that performance may decline as surgeons approach seniority [38]; patient- and surgeon- adjusted control charts have the capacity to identify this deterioration and supplement the implementation of continuing education programs. In the broader context of outcomes research, any studies investigating the impact of an intervention on performance could gain interpretational benefit from surgeon-factor adjustment. Where groups of surgeons or departments are being compared, it is intuitive that adjustment for the respective experiences, or 'surgeon-mix' of these groups are adjusted for, in parallel with patient-mix adjustment, to improve the transparency of results.

We present this research as a proof-of-concept that i) patient- and surgeon-adjusted control charts can be utilised to inform ongoing professional development and feedback for individual surgeons, and ii) surgeon-specific adjustment is necessary for correct assessment of operative efficiency and performance outcomes; failure to do so exposes metrics to statistically significant misinterpretation. We believe this should be considered in developments regarding surgical monitoring, to permit equitable and accurate performance assessment, addressing concerns of patients, surgeons and policy-makers alike.

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Figure 1. Performance curve for individual surgeon TKR operative efficiency. The graph illustrates how operative time within the cohort changed with surgeon experience. 132x90mm (300 x 300 DPI)

Figure 2. Individual performance curves for surgeons A-D. The graph illustrates the patient-risk adjusted operative times of the 4 surgeons selected to test the control charts, with respect to the expected 'benchmark' performance curve. 123x90mm (300 x 300 DPI)

Figure 3: Patient-risk vs. fully- adjusted control charts for surgeons A-D

Figure 3. Patient-risk vs. fully- adjusted control charts for individual surgeons. For each surgeon a patient-risk adjusted chart, and fully-adjusted (patient-risk and surgeon-experience adjusted) chart is displayed. The horizontal axes indicate the experience of the surgeon in years and the blue curve his/her adjusted performance over time. The central black dotted line represents the expected operative time over the course of surgeon's career. The upper red and lower green lines illustrate poor and high performance limits, set at two standard deviations (dotted warning limits) and three standard deviations (continuous control limits) around the central line. Poor and high performers are defined as those breaching the upper and lower limits, respectively. Average performers are those with operative time around the central line, without crossing the limits. 66x90mm (300 x 300 DPI)

Table 1. Overview of study participants

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Table 2. Number of total knee replacements performed by each surgeon.

*Testing dataset, **Training dataset

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Table 3. Agreement between patient-risk adjusted and fully-adjusted charts in detecting indicator variations.

Fire Primer * Each unit in the table represents the position of a data point on a control chart, according to 5 ordinal levels based on Warning Limits (2SD) and Control Limits (3SD), as follows: <LCL (below the lower control limit), LCL-LWL (between the lower control and warning limits), LWL-UWL (between the lower and upper warning limits), UWL-UCL (between the upper warning and control limits), >UCL (above the upper control limit).

FIGURE LEGENDS

Figure 1. Performance curve for individual surgeon TKR operative efficiency. The graph illustrates how operative time within the cohort changed with surgeon experience.

Figure 2. Individual performance curves for surgeons A-D**.** The graph illustrates the patient-risk adjusted operative times of the 4 surgeons selected to test the control charts, with respect to the expected 'benchmark' performance curve.

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Figure 3: Patient-risk vs. fully- adjusted control charts for surgeons A-D

Experience (years) Experience (years) For peer review only - http://bmjopen.bmj.com/site/about/guidelines.xhtml