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Operative-time learning curve in robotic-assisted reverse shoulder arthroplasty: a component analysis of the first 50 cases in a single-surgeon series

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Keywords: Robotic shoulder arthroplasty, reverse shoulder arthroplasty, learning curve, operative time, surgical workflow, surgical efficiency

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Operative-time learning curve in robotic-assisted reverse shoulder arthroplasty: a component analysis of the first 50 cases in a single-surgeon series

Running title: Operative-time phases in robotic shoulder arthroplasty

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Ethics approval

This analysis of de-identified intra-operative timing data was approved via the exemption pathway by the University of the Sunshine Coast (Research Ethics and Integrity Team, Office of Research; project number E26048) under the National Statement on Ethical Conduct in Human Research (2025). Individual consent was not required under the approved exemption. The study was conducted in accordance with the Declaration of Helsinki.

Acknowledgments

None.

Author contributions

Joseph Coory conceived the study, performed the procedures, and contributed to the data analysis. Nicholas Ralph contributed to the data analysis and to drafting, writing and revising the manuscript. Philip Norris contributed to drafting, writing and revising the manuscript. Jacob Symes contributed to data collection and to revising the manuscript. All authors read and approved the final manuscript

Abstract

Background: Total operative time in robotic-assisted reverse total shoulder arthroplasty has been shown to converge toward a conventional benchmark after approximately two dozen cases, but the operation has been treated as a single interval. The purpose of this study was to dissect it into its component phases to determine which parts drive the operative-time learning curve and where residual time lies.

Methods: We analysed prospectively recorded timing for 50 consecutive primary robotic-assisted reverse total shoulder replacements by a single fellowship-trained surgeon at one institution. Total operative time (skin incision to start of closure) was partitioned into three mutually exclusive phases (pre-registration, the robotic step, and humeral preparation) and two sub-intervals within the robotic step (registration and glenoid preparation). Cumulative sum analysis and segmented regression located the inflection, and phase durations were compared between cases 1 to 10 and 34 to 43.

Results: Mean total operative time was 52.2 minutes. Between phases the robotic step contracted from 14.8 to 8.1 minutes, while pre-registration fell proportionally least (33.7 to 26.4 minutes). Registration stabilised at a median of two minutes. At proficiency the robotic step accounted for only about one-fifth of operative time, whereas pre-registration remained the largest and least-reduced component. The cumulative sum inflection occurred at case 23 (95% CI, cases 15 to 33).

Conclusion: The operative-time learning curve in robotic-assisted reverse shoulder arthroplasty reflects both robotic and non-robotic phase dynamics, with the robotic step showing the largest proportional reduction. Residual operative time at proficiency lies predominantly outside the robotic interval.

Level of Evidence: Level IV; Case Series.

Keywords: Robotic shoulder arthroplasty; reverse shoulder arthroplasty; learning curve; operative time; surgical workflow; surgical efficiency

Introduction

Robotic assistance has recently entered routine practice for reverse total shoulder arthroplasty, with the aim of improving the accuracy and consistency of glenoid component positioning [9]. The robotic workflow adds steps that are not part of conventional surgery, including equipment setup, registration of the scapular anatomy and robotic preparation of the glenoid, and these added steps prolong operative time during early adoption.

Operative-time learning curves have been characterised across orthopaedic robotic surgery, and consistently show a learning curve for operative time but not for implant positioning, which is platform-mediated from the first case [12,14,15]. For the shoulder application specifically, a recent single-surgeon series using the same platform reported that total operative time falls with experience and converges toward a conventional benchmark after approximately two dozen cases 4 (its 100-case extension found that efficiency continued to improve beyond case 30, chiefly through fewer prolonged cases [11]), and contemporary technique reviews describe the operative workflow [10]. Computer-assisted navigation, an earlier glenoid-guidance technology, has been adopted rapidly in shoulder arthroplasty [17], and closely analogous navigation platforms show similar early operative-time learning, with reported inflections in the same range [2,13,16]. In a further early series on the same platform, surgeon cognitive workload showed a breakpoint after three to five cases, whereas operative time correlated poorly with case number [3].

These reports analysed total operative time, and could not identify which components of the procedure drive the learning effect or where time remains once the curve has resolved. The initial 30-case report of that series explicitly identified granular per-step timing as the key outstanding question [4]. Whether the operative-time learning curve reflects acquisition of the robotic workflow specifically, or improvement in the conventional phases of the operation, is unknown, and the answer has direct implications for how surgeons and institutions target efficiency during early adoption.

We therefore dissected a single surgeon's first 50 consecutive robotic-assisted reverse shoulder replacements into their component phases, to determine which phases drive the operative-time learning curve, how quickly the robotic step itself stabilises, and where the residual operative time lies.

Materials and Methods

Study design and setting

This is a retrospective analysis of prospectively recorded intra-operative timing data from a consecutive single-surgeon series, reported in accordance with the STROBE guideline for observational studies. Fifty consecutive primary robotic-assisted reverse total shoulder replacements were performed by a single experienced shoulder surgeon with fellowship training, at two institution betweens August 2025 and February 2026. These were the surgeon's first 50 robotic-assisted cases, all of which were included, with no exclusions; the surgeon performs approximately 1,200 procedures per year, including approximately 100 reverse total shoulder arthroplasties and 20 other shoulder arthroplasties. A stable theatre nursing team and a single robotically trained operator were maintained across the series. Only the de-identified case sequence and intra-operative timings were retained. This analysis of de-identified intra-operative timing data was approved via the exemption pathway by the University of the Sunshine Coast (Research Ethics and Integrity Team, Office of Research; project number E26048) as meeting the requirements of the National Statement on Ethical Conduct in Human Research (2025); individual consent was not required under the approved exemption, and the study contains no patient-identifiable information. It was conducted in accordance with the Declaration of Helsinki.

Robotic total shoulder application

All procedures used a robotic total shoulder application (Mako, Stryker, Kalamazoo, Michigan, United States), with pre-operative computed tomography and three-dimensional planning of glenoid baseplate version, inclination, lateralisation and screw trajectory. Intra-operatively, scapular registration was performed using an array fixed to the lateral coracoid and a probe-based bone-surface acquisition workflow. A robotic burr prepared the glenoid within the planned envelope; baseplate placement and screw insertion were performed manually. Procedures were undertaken in the beach-chair position under interscalene block and general anaesthesia. A different humeral stem from the same manufacturer was introduced at case 44 for component matching; the robotic glenoid workflow was held constant across the entire series.

Variables

For each case, intra-operative times were recorded contemporaneously by a circulating nurse on a clock; the nurse was not aware of the study. Total operative time was defined as skin

incision to start of skin closure and partitioned into five intervals: three mutually exclusive phases: pre-registration (incision to probe insertion, encompassing patient positioning, draping, surgical approach, and coracoid array fixation), the robotic step (probe insertion to baseplate implantation), and humeral preparation (baseplate implantation to start of skin closure). Two sub-intervals were recorded within the robotic step: registration (probe insertion to completion of scapular surface acquisition) and glenoid preparation (robotic burring to baseplate implantation). The remainder of the robotic step, from completion of registration to the start of burring, was not timed directly and is reported as a derived interval (robotic step minus registration and glenoid preparation); during this interval the robot was positioned beside the patient and the surgeon completed a verification step by tracing a square with the robotic arm. Pre-registration, the robotic step, and humeral preparation sum to total operative time. Glenoid preparation was not sub-timed in the first nine cases and is reported for 41 cases; all other intervals are reported for 50.

Analysis

The primary analysis was the phase decomposition. Mean durations of each interval in the first 10 cases (the learning phase) were compared with those in a proficiency phase, defined as the 10 consecutive cases immediately preceding the humeral component change at case 44 (cases 34 to 43), the latest run of 10 cases with an unchanged implant system and robotic glenoid workflow; both windows were chosen after data collection and the comparison is descriptive; absolute and relative changes were calculated. To locate the operative-time inflection, cumulative sum analysis of total operative time and of the robotic step was performed [12], with the case at the cumulative sum peak taken as the inflection, and two-segment (step-change) regression, with the breakpoint chosen to minimise the residual sum of squares, provided a sensitivity check. A 10-case rolling mean and the cumulative running mean of total operative time were used to describe stabilisation. Comparison with conventional surgery was treated as a secondary, exploratory endpoint, defined as a 10-case rolling mean of total operative time at or below the lower bound of the published range for skin-to-skin conventional reverse shoulder arthroplasty performed by experienced surgeons (60 to 90 minutes [1,8]); because that range is measured to completion of closure, whereas this series was timed to the start of closure, the comparison is indicative only. Analyses were performed in Python (version 3.11).

Total operative time and robotic step duration were compared between the learning and proficiency phases with Welch's t-test, with the Mann-Whitney U test as a check, and mean differences are reported with 95% CI. The linear trend in each was estimated by least-squares

regression on case number and is reported in minutes per case with its 95% CI. Uncertainty in the step-change breakpoint was estimated by residual bootstrap (2,000 resamples, breakpoints constrained to cases 5 to 45), taking the 2.5th and 97.5th percentiles as the 95% CI. Sensitivity to outliers was examined by replacing cases with residuals more than two standard deviations from the linear trend with the series median, and separately case 22, and repeating the cumulative sum and step-change analyses. Two-sided $p < 0.05$ was considered significant; with two primary comparisons, no adjustment for multiple comparisons was made.

Results

Fifty consecutive cases were performed across 20 operating days. Mean total operative time was 52.2 minutes (median 51.5, range 34 to 91, standard deviation 11.0). Summary statistics for every interval are presented in Table I.

The decomposition of operative time between the learning and proficiency phases is shown in Table II and Figure 1. Every interval contracted, but not evenly. Total operative time fell from 62.2 to 44.4 minutes (difference −17.8 minutes, 95% CI −28.8 to −6.8; $p = 0.004$). The robotic step more than halved, from a mean of 14.8 to 8.1 minutes (difference −6.7 minutes, 95% CI −10.4 to −3.0; $p = 0.002$), whereas pre-registration fell proportionally least, from 33.7 to 26.4 minutes (21.7%). At proficiency the robotic step accounted for approximately 18% of total operative time (8.1 of 44.4 minutes), pre-registration for approximately 59%, and humeral preparation for the remainder. Within the robotic step at proficiency, registration (2.3 minutes) and glenoid preparation (1.7 minutes) together accounted for 4.0 of the 8.1 minutes; the remaining 4.1 minutes, approximately half of the robotic step, fell in the derived interval between completion of registration and the start of burring, which covered robot positioning and the square-tracing verification step. The robotic interval was the smallest component at proficiency but showed the largest proportional reduction; residual operative time was concentrated in the non-robotic phases.

The robotic step and its sub-intervals stabilised rapidly (Figure 2). Registration settled at a median of two minutes (mean 2.3 minutes in the proficiency phase) from the second decile of cases and remained tightly clustered across the whole series (standard deviation 1.1, range 1 to 6). Glenoid preparation, sub-timed from case 10 onward, contracted to a median of two minutes, with no proficiency-phase case exceeding five minutes. The 10-case rolling mean of the robotic step remained at or below 10 minutes from case 32 onward, and the cumulative sum

of the robotic step peaked at case 22 (step-change breakpoint, case 22; bootstrap 95% CI, cases 19 to 29). With the four outlying cases (1, 11, 22 and 44) replaced by the median, both estimates moved to case 20. Robotic step duration fell by 0.18 minutes per case across the series (95% CI 0.11 to 0.26; $p < 0.001$).

Total operative time showed a single learning curve consistent with the component analysis (Figure 3). The cumulative sum of total operative time peaked at case 23, identifying this case as the point estimate of the inflection of the operative-time learning curve; two-segment regression placed the optimal breakpoint after case 23, with cases 1 to 23 averaging 58.4 minutes and cases 24 to 50 averaging 46.9 minutes. The bootstrap 95% CI for the breakpoint spanned cases 15 to 33, and total operative time fell by 0.36 minutes per case across the series (95% CI 0.17 to 0.56; $p < 0.001$). Replacing the two outlying cases (cases 1 and 10) left both estimates at case 23, but replacing case 22 (72 minutes) with the series median moved the cumulative sum peak to case 20 and the step-change breakpoint to case 12; a breakpoint at case 12 fitted almost as well as one at case 23 (residual sum of squares 4,444 versus 4,436 min^2). The inflection is therefore best described as lying approximately between cases 12 and 33 rather than at a single case.

As an exploratory secondary endpoint, the 10-case rolling mean of total operative time first fell to or below the lower bound of the published conventional range (60 minutes) with the window ending at case 11 (59.6 minutes), and remained there from the window ending at case 13 onward; 41 of the 50 cases were at or below 60 minutes. The cumulative running mean first came within 0.1 minutes of its eventual value at case 43 and remained within 0.3 minutes of it thereafter, indicating the point at which cumulative experience was sufficient to characterise the surgeon's steady-state operative time. The inflection of the learning curve at case 23 and the stabilisation of the cumulative mean at case 43 are distinct milestones and should not be conflated.

Discussion

The principal finding of this single-surgeon series is that the operative-time learning curve in robotic-assisted reverse shoulder arthroplasty reveals two parallel observations. First, the robotic step, the only interval unique to this platform, showed the largest proportional reduction (45.3%) and stabilised within approximately the first 20 to 30 cases, with registration showing little variability. Second, at proficiency the robotic step accounted for less than one-fifth of

total operative time, and the residual operative time was concentrated in the non-robotic phases. Within the robotic step, approximately half of the time at proficiency fell outside registration and burring, in robot positioning and verification.

This decomposition extends recent work. A single-surgeon series using the same platform reported that total operative time converges toward a conventional benchmark after approximately two dozen cases, and identified granular per-step timing as the key outstanding question [4]. Its 100-case extension has since shown that efficiency continues to improve well beyond case 30, with mean operative time falling from 88.6 minutes (cases 1 to 30) to 64.3 minutes (cases 71 to 100), largely through elimination of prolonged cases rather than shortening of the typical case [11]. Our component analysis addresses part of that question: in this series the early convergence was driven by rapid stabilisation of the robotic workflow rather than by sustained improvement across the whole operation, and the residual operative time is conventional rather than robotic. The early time cost of robotic assistance is therefore real but transient and specific to the added robotic steps, which are quickly routinised. Because the present series ends at case 50, later gains of the kind reported in the extended series cannot be excluded, and the learning curve should not be regarded as complete.

The pattern of sub-step learning is consistent with that described for robotic knee and hip arthroplasty, in which operative time follows a learning curve but implant positioning is platform-mediated from the first case [12,14,15]. The magnitude of the operative-time gain in this series, a reduction of 17.8 minutes or 28.6% from the learning to the proficiency phase, is of the order reported during the learning phase of robotic knee and hip arthroplasty (for example, an additional 12 minutes over a 16-case learning curve in robotic total knee arthroplasty) [5,14], and is therefore platform-typical rather than specific to the shoulder.

The practical implication follows directly from the decomposition. This study did not instrument the specific processes within the non-robotic phases, and the sources of their variability and potential for reduction cannot be determined from these data. Future work incorporating granular sub-step timing across the full operative workflow would be required to identify specific efficiency targets. For surgeons and centres adopting the platform, the expectation should be that the robotic workflow itself is rapidly mastered; the non-robotic phases represent the larger share of operative time and merit further study.

This study has limitations. It is a single-surgeon, single-institution retrospective analysis. Implant positioning, complication rates and patient-reported outcomes were not evaluated, although the platform-mediated accuracy of these systems is established from cadaveric and bench work [9]. We did not collect operative times for the surgeon's own conventional reverse shoulder arthroplasty practice, which is a significant limitation of the time neutrality observation. Time neutrality was assessed against a published literature range (60 to 90 minutes) for experienced surgeons performing conventional reverse shoulder arthroplasty, not against this surgeon's own non-robotic cases in the same setting. This comparison is indicative only; absolute times are not directly comparable with series that define operative time to completion of closure rather than to the start of closure. Glenoid preparation was not sub-timed in the first nine cases, so a learning effect within that sub-interval before case 10 cannot be excluded. A different humeral stem was introduced at case 44, with a consequent change to the humeral preparation phase; the robotic glenoid workflow was unchanged, and the proficiency phase was defined to precede this change. The statistical inference is also limited: with one surgeon and 50 cases, the learning and proficiency phases each contain 10 cases, the confidence interval for the breakpoint is wide, and the cumulative sum was calculated against the series mean without control limits or a target time, so it describes rather than tests the learning curve. The comparison windows were chosen after data collection. Patient demographic and case-mix data (age, sex, body mass index, diagnosis and glenoid morphology) were not available, so case-mix effects on operative time could not be assessed; the order of cases within each operating day was not analysed, and the surgeon's prior conventional experience, which will influence the learning curve, is specific to this series. Timing by the nursing team may itself have influenced workflow, and the series ends at case 50, before the later gains described in longer series [11].

The improvement in pre-registration time across the series reflects a combination of general operative familiarity and team-level workflow learning rather than acquisition of a robotic-specific skill. Coracoid array fixation is included within the pre-registration phase; this is a platform-dependent step, and its individual contribution to the change in pre-registration time across the series cannot be disaggregated from other non-robotic steps without finer sub-interval timing. The reduction in humeral preparation time is best attributed to general case experience and workflow maturation, given that this phase does not involve the robotic system. These observations are reported descriptively and should not be over-interpreted. Within the IDEAL framework for the evaluation of surgical innovation, this single-surgeon series

represents an early development-stage (Stage 2a) evaluation [7]. Future evaluation should pair component-level timing with implant-positioning and clinical outcomes, and should test in multicentre cohorts, analogous to randomised robotic arthroplasty programmes in knee and hip surgery [6], whether the rapid stabilisation of the robotic workflow and the dominance of non-robotic time are general.

Conclusions

In this single-surgeon series, dissecting the operative-time learning curve in robotic-assisted reverse shoulder arthroplasty showed that the robotic step had the largest proportional reduction and stabilised within approximately the first 20 to 30 cases, contributing less than one-fifth of operative time at proficiency. Pre-registration remained the largest phase at proficiency; the sources of its residual time warrant further investigation. Further research is needed to confirm these findings and to link operative efficiency to clinical outcomes.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude (Anthropic) to assist with proofing the manuscript and checking compliance against the journal's submission guidelines. After using this tool, the authors reviewed and further edited the content as needed and take full responsibility for the content of the publication.

Declaration of conflicting interests

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Ethical approval and informed consent

This study was approved via the exemption pathway by the University of the Sunshine Coast (Research Ethics and Integrity Team, Office of Research; project number E26048) under the National Statement on Ethical Conduct in Human Research (2025). Individual consent was not required under the approved exemption.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Figure and Table Legends

Table I. Operative time and component intervals across 50 consecutive cases.

Interval	n	Mean (min)	Median	Minimum	Maximum	SD
Total operative time	50	52.2	51.5	34	91	11.0
Pre-registration	50	29.6	29	16	55	6.9
Registration	50	2.6	2	1	6	1.1
Robotic step	50	11.0	10	6	25	4.4
Glenoid preparation	41	2.2	2	1	5	1.0
Humeral preparation	50	11.6	10.5	6	25	4.0

SD, standard deviation. The robotic step is the interval from probe insertion to baseplate implantation and contains registration, glenoid preparation and an untimed interval between them. Glenoid preparation was not sub-timed in cases 1 to 9 (n = 41).

Table II. Phase decomposition: learning phase (cases 1 to 10) versus proficiency phase (cases 34 to 43). Values are mean (SD).

Phase	Learning phase, mean (SD) (min)	Proficiency phase, mean (SD) (min)	Δ (min) (95% CI); p	Δ (%)
Total operative time	62.2 (14.6)	44.4 (6.6)	−17.8 (−28.8 to −6.8); p = 0.004	−28.6
Pre-registration	33.7	26.4	−7.3	−21.7
Registration	3.1	2.3	−0.8	−25.8
Robotic step	14.8 (5.1)	8.1 (1.5)	−6.7 (−10.4 to −3.0); p = 0.002	−45.3
Glenoid preparation	4.0 (n = 1)	1.7	n/a	n/a
Humeral preparation	13.7	9.9	−3.8	−27.7

Δ, change; CI, confidence interval; SD, standard deviation. Glenoid preparation in the learning phase represents the single available case (case 10), so its change is not computed (n/a). SD, 95% CI and p values (Welch's t-test) are given for total operative time and the robotic step, the intervals with case-level data shown in Figures 2 and 3.

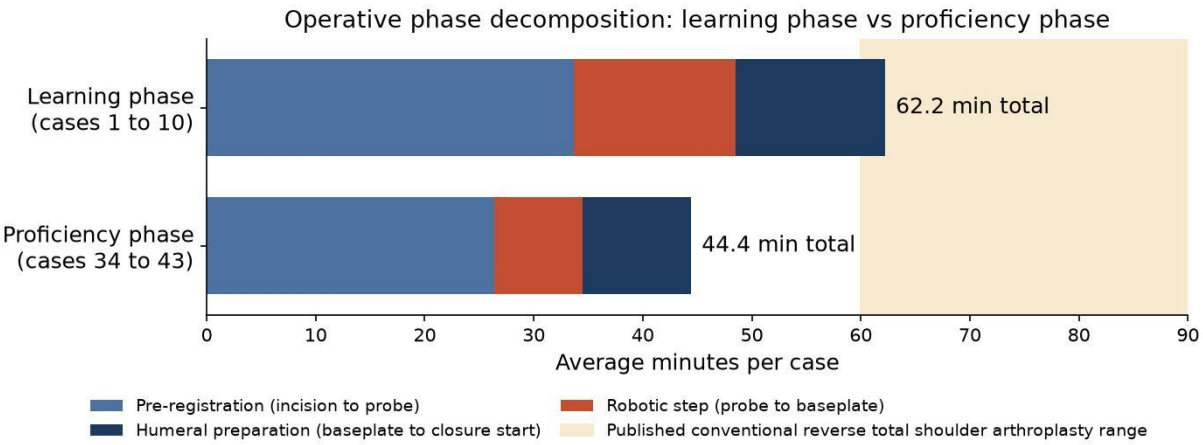


Figure 1. Operative phase decomposition for the learning phase (cases 1 to 10) and the proficiency phase (cases 34 to 43). The shaded band shows the published operative-time range for experienced surgeons performing conventional reverse shoulder arthroplasty, measured to completion of closure; times in this series end at the start of closure.

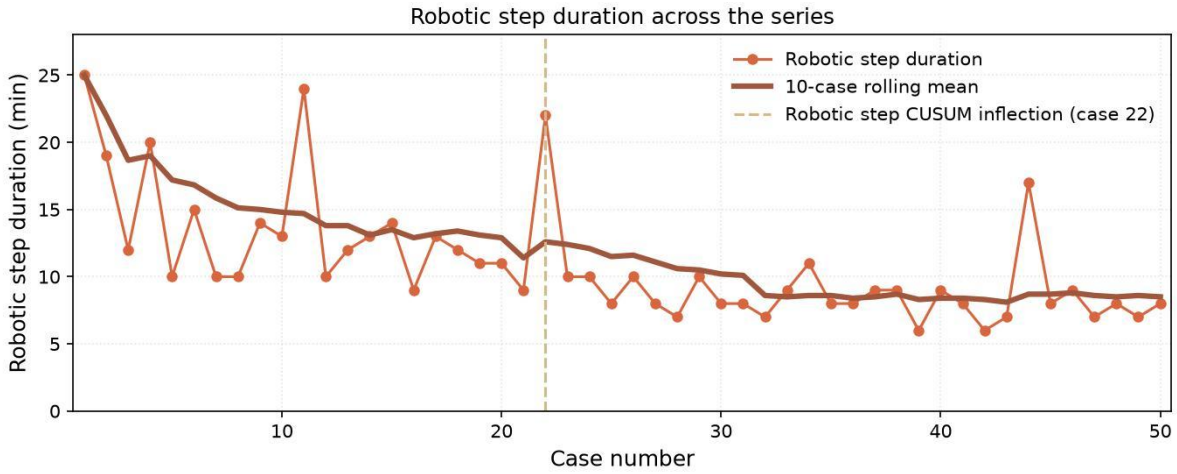


Figure 2. Robotic step duration (probe insertion to baseplate implantation) across the series, with a 10-case rolling mean (calculated over the available cases for cases 1 to 9). The cumulative sum inflection of the robotic step occurred at case 22 (bootstrap 95% CI for the step-change breakpoint, cases 19 to 29).

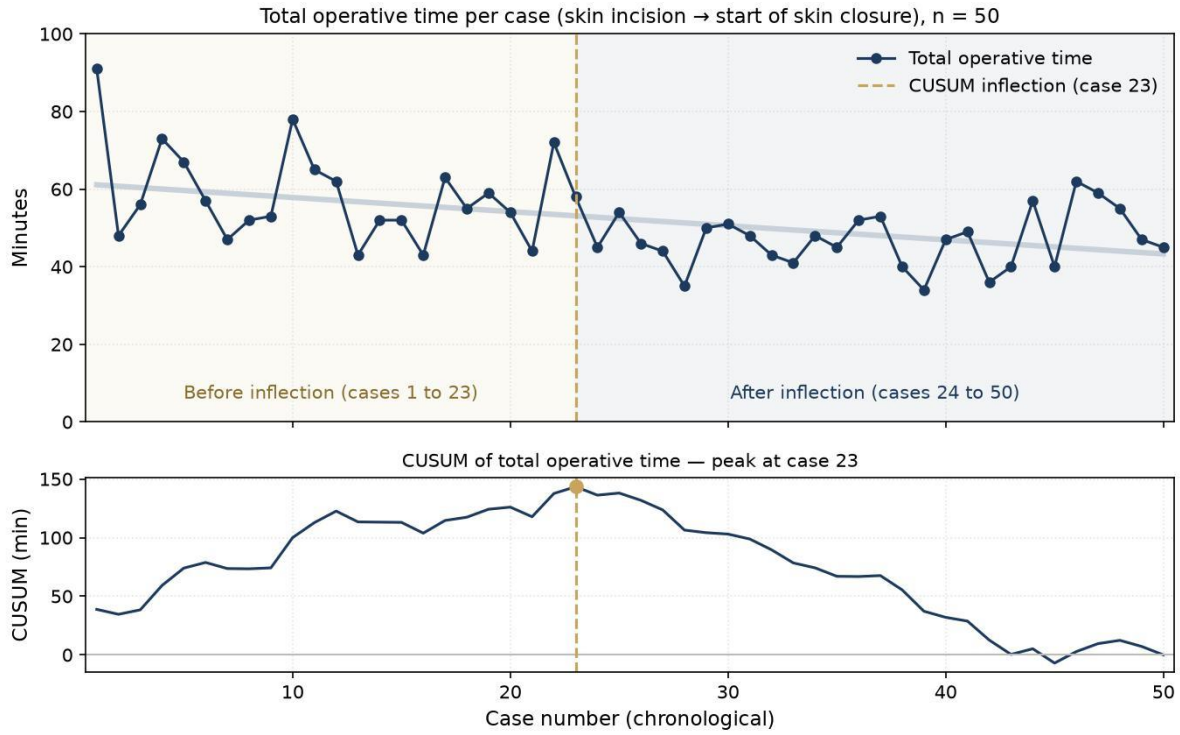


Figure 3. Total operative time per case (upper panel) and the corresponding cumulative sum curve (lower panel). The cumulative sum peak at case 23 marks the point estimate of the operative-time inflection (bootstrap 95% CI for the step-change breakpoint, cases 15 to 33). Shading distinguishes cases before (1 to 23) and after (24 to 50) the inflection; these are not the learning (cases 1 to 10) and proficiency (cases 34 to 43) phases used in Table II and Figure 1.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- STROBEchecklist.docx