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Step-specific CUSUM analysis of robot-assisted sacrocolpopexy

Akimasa Takahashi

akimasat@belle.shiga-med.ac.jp

Shiga University of Medical Science

Yuji Tanaka

Shiga University of Medical Science

Yutaka Yoneoka

Shiga University of Medical Science

Mari Deguchi

Shiga University of Medical Science

Akiko Nakamura

Shiga University of Medical Science

Tsukuru Amano

Shiga University of Medical Science

Shunichiro Tsuji

Shiga University of Medical Science

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Abstract

Background

Learning curves for robot-assisted sacrocolpopexy (RSC) are commonly evaluated using total operative or console time, although RSC consists of multiple technically distinct steps. We evaluated step-specific learning patterns using cumulative sum (CUSUM) analysis.

Methods

We retrospectively analyzed the first 29 consecutive RSC procedures performed by a single surgeon with approximately 100 prior robotic procedures and experience in robotic surgical instruction. Seven procedural steps were timed using prespecified video landmarks. CUSUM analysis and Spearman correlations were used to evaluate temporal efficiency patterns. Early and late phases were compared using the console-time CUSUM peak.

Results

Median operative and console times were 183 and 139 min, respectively, and both CUSUM curves peaked at case 14. Step-specific CUSUM peaks varied substantially. Hysterectomy, anterior and posterior mesh suturing, and peritoneal closure became significantly shorter with increasing case sequence, whereas bladder dissection showed greater variability and a later CUSUM peak. Despite significant shortening of several individual steps in the late phase, total operative and console times did not differ significantly between phases.

Conclusions

RSC demonstrated heterogeneous step-specific learning patterns that were not captured by total console time alone. Even for an experienced robotic surgeon, step-specific CUSUM analysis may identify procedure-specific technical bottlenecks and provide an objective framework for proctoring and surgical training.

Introduction

Sacrocolpopexy is a durable reconstructive procedure for apical and multicompartment pelvic organ prolapse [11]. Robotic assistance facilitates deep pelvic dissection, three-dimensional visualization, and intracorporeal suturing, and robot-assisted sacrocolpopexy (RSC) has become an established minimally invasive option. However, RSC is a composite procedure that combines dissection, suturing, mesh fixation, and peritoneal closure, each of which places different demands on the console surgeon.

The RSC learning curve has been studied using operative time, console time, complications, and cumulative sum (CUSUM) methods. Earlier studies reported improvement after the initial cases, whereas larger or risk-adjusted series suggested that stable efficiency or complication-based proficiency may require substantially more experience [1–5]. These reports have been important for defining global procedural learning, but a single total-time endpoint cannot determine which component of an operation is improving or which step remains a technical bottleneck.

Step-specific assessment is particularly relevant to robotic surgical education. Crane et al. established benchmark times for individual robotic hysterectomy and sacrocolpopexy components [6], and Catanzarite et al. incorporated individual RSC steps into a structured fellowship pathway [7]. Outside RSC, component-level analyses of robotic hysterectomy have shown that separate procedural stages can have different learning trajectories [8, 9]. More recently, CUSUM has also been used to characterize team-level maturation and operational efficiency in robotic gynecologic surgery [10].

The primary objective of this study was therefore to characterize step-specific temporal efficiency patterns during the introduction of RSC by a single surgeon using CUSUM analysis. We hypothesized that technically distinct components of RSC would demonstrate different learning patterns.

Materials and methods

Study design and patients

This retrospective single-surgeon cohort included the surgeon's first 29 consecutive RSC procedures. Before initiating RSC, the surgeon had performed approximately 100 robotic surgical procedures and had experience in robotic surgical instruction. The cohort included patients who underwent RSC for symptomatic pelvic organ prolapse at Shiga University of Medical Science between July 26, 2023 and July 27, 2026. Cases performed by another surgeon were excluded from the learning-curve analysis. Patient characteristics and perioperative variables were extracted from the clinical database, and step-specific durations were obtained from operative video review. The study was approved by the Ethics Committee of Shiga University of Medical Science (approval number R2022-042). The requirement for written informed consent was waived because of the retrospective design.

Preoperative prolapse severity was recorded using the Pelvic Organ Prolapse Quantification staging system. Variables used for descriptive and phase-comparison analyses included age, body mass index (BMI), parity, specimen weight, estimated blood loss, operative time, and console time.

Surgical procedure

The procedural concept was standardized throughout the series: hysterectomy when applicable, anterior vesicovaginal dissection, posterior rectovaginal/Douglas pouch dissection, fixation of posterior and anterior mesh arms to the vagina, fixation of the mesh to the sacral promontory, and peritoneal closure.

Definition of surgical steps and video-based time measurement

The following procedural components were timed from operative videos using prespecified video landmarks: (1) hysterectomy, from the first incision for hysterectomy to retrieval of the suture used for vaginal cuff closure; (2) bladder dissection, from the first incision initiating vesicovaginal dissection until withdrawal of the camera after completion of the dissection; (3) Douglas pouch dissection, from the first incision initiating posterior dissection until withdrawal of the camera after completion of the dissection; (4) anterior mesh suturing, from the first appearance of the mesh in the operative field until retrieval of the final suture used for mesh fixation; (5) posterior mesh suturing, from the first appearance of the mesh in the operative field until retrieval of the final suture used for mesh fixation; (6) promontory fixation, from introduction of the fixation suture into the operative field until retrieval of the suture after completion of sacral fixation; and (7) peritoneal closure, from introduction of the closure suture into the operative field until retrieval of the suture after completion of peritonealization. Step-specific time was recorded only when both start and end landmarks could be identified reliably. When a step could not be determined from the video or was not applicable, such as hysterectomy in a patient with prior hysterectomy, the value was left missing. Missing values were not imputed; each step-specific analysis therefore used all available observations for that component.

CUSUM analysis

For each time-based outcome, the mean duration across all available observations was calculated. The CUSUM after case n was defined as $CUSUM_n = \Sigma(i = 1 \text{ to } n)(x_i - \mu)$, where x_i is the observed duration for case i and μ is the overall mean duration for that outcome. An upward CUSUM slope indicates a sequence of cases longer than the overall mean, whereas a downward slope indicates a sequence shorter than the overall mean. The case at which the maximum positive deviation occurred was recorded as the descriptive CUSUM peak. The peak was interpreted as a potential transition in temporal efficiency, not as definitive proof of competency or proficiency.

CUSUM curves were generated for total operative time, total console time, and each procedural component. The total console-time CUSUM peak was used as the transition point for an exploratory post hoc comparison between the early and late phases. Thus, cases 1–14 comprised the early phase and cases 15–29 comprised the late phase.

Statistical analysis

Continuous variables are reported as median (interquartile range [IQR]) unless otherwise specified, and categorical variables as number (percentage). Spearman rank correlation was used to evaluate monotonic relationships between chronological case sequence and each operative-time outcome. Early-versus-late comparisons used the Mann–Whitney U test for continuous variables. Because of the small sample size, multiple correlated endpoints, and exploratory nature of the analysis, p values are descriptive and were not adjusted for multiplicity. Two-sided $p < 0.05$ was considered statistically

significant. Statistical analyses were performed using IBM SPSS Statistics version 29 (IBM Corp., Armonk, NY, USA).

Results

Patients and operative characteristics

Twenty-nine consecutive procedures performed by the study surgeon were analyzed. Median age was 71 years (IQR 65–76), median BMI was 23.7 kg/m² (IQR 21.6–26.0), and median parity was 2 (IQR 2–3). POP-Q stage was II in 8 patients (27.6%), III in 14 (48.3%), and IV in 7 (24.1%). Median operative time was 183 min (IQR 163–203), and median console time was 139 min (IQR 125–151) (Table 1).

Table 1
Patient and operative characteristics

Variable	Overall cohort (n = 29)
Age, years	71 (65–76)
BMI, kg/m²	23.7 (21.6–26.0)
Parity	2 (2–3)
POP-Q stage II / III / IV, n	8 / 14 / 7
Specimen weight, g	41 (34–52); n = 24
Estimated blood loss, mL	0 (0–0)
Operative time, min	183 (163–203)
Console time, min	139 (125–151)

Values are median (interquartile range) unless otherwise specified. POP-Q, Pelvic Organ Prolapse Quantification.

Step-specific median times were 27.2 min for hysterectomy (n = 27), 8.7 min for bladder dissection (n = 29), 7.1 min for Douglas pouch dissection (n = 28), 15.4 min for posterior mesh suturing, 14.5 min for anterior mesh suturing, 3.6 min for promontory fixation, and 13.3 min for peritoneal closure.

Overall CUSUM analysis

CUSUM curves for both total operative time and total console time reached their maximum positive deviation at case 14 (Fig. 1). The corresponding peak CUSUM values were 97.0 min for operative time and 72.6 min for console time. However, neither total operative time nor total console time demonstrated a significant monotonic relationship with chronological case sequence (operative time: $\rho = 0.045$, $p = 0.815$; console time: $\rho = 0.028$, $p = 0.885$). These findings indicate substantial case-to-case variability despite a common descriptive CUSUM transition point.

Step-specific CUSUM analysis

Step-specific CUSUM curves showed clearly heterogeneous patterns (Table 2; Fig. 2). Anterior mesh suturing reached its maximum CUSUM at case 8, peritoneal closure at case 13, posterior mesh suturing at case 14, and hysterectomy at case 18. All four components showed significant negative correlations between case sequence and step duration: hysterectomy ρ=-0.503 (p = 0.007), anterior mesh suturing ρ=-0.534 (p = 0.003), posterior mesh suturing ρ=-0.443 (p = 0.016), and peritoneal closure ρ=-0.492 (p = 0.007).

Table 2
CUSUM summary and temporal trend by operative component

Outcome	n	Median time, min (IQR)	CUSUM peak case	Spearman ρ	p value
Total operative time	29	183.0 (163.0–203.0)	14	0.045	0.815
Total console time	29	139.0 (125.0–151.0)	14	0.028	0.885
Hysterectomy	27	27.2 (21.8–29.8)	18	-0.503	0.007
Bladder dissection	29	8.7 (6.3–12.9)	27	0.515	0.004
Douglas pouch dissection	28	7.1 (5.2–8.4)	3	0.169	0.390
Posterior mesh suturing	29	15.4 (13.0–17.5)	14	-0.443	0.016
Anterior mesh suturing	29	14.5 (12.5–18.0)	8	-0.534	0.003
Promontory fixation	29	3.6 (3.1–4.1)	5	0.057	0.770
Peritoneal closure	29	13.3 (12.0–16.3)	13	-0.492	0.007

CUSUM peak case indicates the chronological case number at which the cumulative sum reached its maximum positive deviation from the overall mean. Missing step-specific values were not imputed.

Bladder dissection demonstrated a different pattern. Its CUSUM peaked late, at case 27, and step duration increased with chronological case sequence (ρ = 0.515, p = 0.004). Douglas pouch dissection and promontory fixation peaked early (cases 3 and 5, respectively) and showed no significant temporal trend. Thus, the components most clearly showing shorter duration with accumulated experience were hysterectomy and the suture-dominant steps, whereas dissection-related steps were more variable.

Early-versus late phase comparison

Using the console-time CUSUM peak, the early phase comprised cases 1–14 and the late phase cases 15–29. Median operative time decreased from 193 min (IQR 166–213) to 172 min (IQR 160–194; p =

0.169), and median console time from 147 min (IQR 130–157) to 135 min (IQR 122–144; p = 0.206), but neither difference was statistically significant (Table 3; Fig. 3).

Table 3
Early-versus-late comparison based on the console-time CUSUM peak

Variable	Early phase (n = 14)	Late phase (n = 15)	p value
Age, years	70 (60–74)	74 (68–76)	0.137
BMI, kg/m²	23.3 (22.1–25.8)	23.8 (21.5–25.3)	0.983
Parity	2 (2–3)	2 (2–3)	0.423
Specimen weight, g	40 (35–53)	47 (33–52)	0.883
Estimated blood loss, mL	0 (0–0)	0 (0–0)	0.180
Operative time, min	193 (166–213)	172 (159–194)	0.169
Console time, min	147 (130–157)	135 (122–144)	0.206
Hysterectomy, min	29.4 (28.0–33.4)	22.3 (17.8–24.3)	< 0.001
Bladder dissection, min	6.4 (4.6–8.6)	12.7 (8.7–14.9)	0.005
Douglas pouch dissection, min	7.1 (5.4–8.3)	7.0 (5.2–8.5)	0.982
Posterior mesh suturing, min	17.7 (15.2–20.9)	14.0 (12.5–15.7)	0.003
Anterior mesh suturing, min	17.0 (14.7–21.0)	12.9 (11.9–14.8)	0.006
Promontory fixation, min	3.4 (3.1–4.1)	3.7 (3.1–4.2)	0.727
Peritoneal closure, min	16.6 (13.5–19.1)	12.3 (10.0–13.2)	< 0.001

The number of available observations varied for specimen weight and selected step-specific durations because missing or non-applicable values were not imputed. Continuous values are median (interquartile range). Mann–Whitney U tests were used for continuous variables. P values are descriptive.

In contrast, step-specific differences were pronounced. Median hysterectomy time decreased from 29.4 to 22.3 min (p < 0.001), posterior mesh suturing from 17.7 to 14.0 min (p = 0.003), anterior mesh suturing from 17.0 to 12.9 min (p = 0.006), and peritoneal closure from 16.6 to 12.3 min (p < 0.001). Bladder dissection increased from 6.4 to 12.7 min (p = 0.005). Baseline age, BMI, parity, specimen weight, and blood loss were not significantly different between phases.

Discussion

Principal findings

This single-surgeon study examined the surgeon's first 29 consecutive RSC procedures and demonstrates that temporal efficiency during RSC is not uniform across procedural components. Importantly, the operator had already performed approximately 100 robotic surgical procedures before initiating RSC and was involved in robotic surgical education as an instructor. The observed curves should therefore be interpreted as procedure-specific learning during adoption of a new robotic operation by an experienced robotic surgeon, rather than acquisition of fundamental robotic console skills. Although both total operative and console-time CUSUM curves peaked at case 14, global times did not show significant monotonic improvement across the 29-case series. In contrast, hysterectomy, anterior mesh suturing, posterior mesh suturing, and peritoneal closure showed clear negative correlations with case sequence and shorter late-phase durations. Bladder dissection behaved differently, with a late CUSUM peak and longer durations in later cases. These findings support the central premise that total console time alone can obscure meaningful, and sometimes opposing, changes at the level of individual surgical tasks.

Comparison with previous learning-curve studies

Published RSC learning-curve studies have reported a wide range of transition points because they used different endpoints and included surgeons with differing baseline robotic experience. Akl et al. described early reduction in operative time [1], Myers et al. used complication-based CUSUM for sequential performance monitoring [2], and Linder et al. reported risk-adjusted proficiency after substantially greater experience when complications were used as the endpoint [3]. van Zanten et al. reported stabilization of operative time after approximately 24–29 cases and proficiency after 78 cases [4], whereas Park et al. evaluated RSC performed by an experienced gynecologist and identified time-based phases at approximately 9 and 35 cases [5]. These differences underscore that a learning curve is endpoint-dependent and also influenced by the operator's pre-existing robotic skill set rather than being defined by a single fixed number of procedures.

Our results extend these reports by decomposing the operation into individual components. The concept is consistent with robotic hysterectomy literature: Seamon et al. concluded that individual components of robotic hysterectomy and lymphadenectomy have separate learning curves [8], while Tang and Tsai showed different stabilization requirements for docking, main console surgery, and suturing [9]. In RSC specifically, Crane et al. reported benchmark times for anterior and posterior dissection, mesh attachment, sacral fixation, and peritoneal closure [6], and Catanzarite et al. used six individual RSC steps within a graduated fellowship training pathway [7]. The present study adds sequential CUSUM analysis at the level of those individual technical steps.

Interpretation of step-specific patterns and training implications

The most consistent temporal shortening occurred in suture-dominant components. This finding is particularly informative because the operator entered the series with approximately 100 prior robotic procedures and established experience in robotic surgical instruction. Fundamental robotic psychomotor

abilities such as wrist articulation, bimanual coordination, camera control, and needle handling were therefore already well established before the first RSC. The subsequent improvement is more likely to represent transfer and adaptation of pre-existing robotic skills to the specific geometry, tissue targets, sequence, and workflow of sacrocolpopexy. Peritoneal closure and mesh attachment may therefore represent procedure-specific tasks that can be standardized even in an experienced robotic surgeon. Hysterectomy also shortened, which may reflect maturation of RSC-specific procedural flow, exposure, team coordination, and transitions between operative steps rather than acquisition of basic console proficiency.

By contrast, bladder dissection did not behave as a simple learning endpoint. Dissection time may be heavily influenced by prior pelvic surgery, tissue planes, cervical elongation, prolapse configuration, adhesions, and the extent of dissection required for mesh placement. A longer duration in later cases therefore should not be interpreted as deterioration in skill. Rather, it highlights a limitation of time-only performance metrics for anatomy-dependent tasks. Future work should combine step duration with case-difficulty measures and video-based technical quality scores, such as global robotic skill assessments, to distinguish deliberate careful dissection from inefficiency.

Step-specific monitoring also has potential value beyond an individual procedure and beyond novice training. Contemporary robotic training increasingly emphasizes staged curricula, objective performance assessment, and team-level learning [7, 10]. Our findings suggest that even an experienced robotic surgeon entering a new procedure may have distinct learning needs at the level of individual operative steps. This is directly relevant to proctoring and faculty development: prior robotic expertise should not be assumed to translate uniformly across all components of a new operation. A CUSUM framework can be applied to repeated components shared across specialties—dissection, suturing, reconstruction, and closure—and may support individualized feedback for both trainees and established surgeons adopting new robotic procedures. Instead of judging performance only by total operative time, step-specific monitoring can identify whether the limiting component is exposure, dissection, suturing, or closure and direct targeted video review, simulation, or proctoring accordingly.

Strengths and limitations

The principal strength of this study is the video-based decomposition of a complex robotic operation into clinically meaningful components across the surgeon's first 29 consecutive RSC cases. Because the surgeon had already completed approximately 100 robotic procedures and had an instructional role before beginning RSC, the series provides a focused view of procedure-specific learning after transfer of established robotic skills to a new operation. This distinction is important from an educational perspective: the present study evaluates how an experienced robotic surgeon acquires a new procedure, rather than how a novice learns robotic surgery itself. The consecutive design reduces selection based on perceived procedural difficulty, while the single-surgeon design minimizes between-surgeon variability and allows the global learning curve to be interpreted in terms of specific technical tasks. Missing or non-applicable video measurements were retained as missing rather than imputed, preserving transparency about available observations.

Several limitations are important. First, the sample size was small and derived from a single surgeon and institution; therefore, external generalizability is limited. In particular, because the surgeon entered the series with approximately 100 prior robotic procedures and established instructional experience, these results should not be extrapolated directly to surgeons who are new to robotic surgery. Conversely, this design intentionally isolates learning related to adoption of RSC itself and may be most applicable to experienced robotic surgeons expanding their procedural repertoire or to faculty development settings. Second, CUSUM peak locations are descriptive and depend on the series mean; they should not be interpreted as validated competency thresholds. Third, operative time is an efficiency metric rather than a complete measure of technical quality or safety. Fourth, case complexity may have evolved during the series and was not captured by a validated RSC difficulty score. Finally, video-derived timings depend on identifiable procedural landmarks and were unavailable for some steps.

Conclusions

In the first 29 consecutive RSC procedures performed by a surgeon with approximately 100 prior robotic procedures and established instructional experience, step-specific CUSUM analysis revealed heterogeneous patterns of procedure-specific learning that were incompletely represented by total operative or console time. Hysterectomy and suture-dominant steps showed the clearest shortening with accumulated RSC experience, whereas bladder dissection remained highly case-dependent. These findings suggest that even experienced robotic surgeons may benefit from step-specific monitoring when adopting a new robotic procedure. Step-specific CUSUM may provide a practical framework for identifying technical bottlenecks and tailoring proctoring, faculty development, and robotic surgical education. Larger multi-surgeon studies incorporating case-difficulty adjustment and validated video-based skill scores are needed before step-specific thresholds can be used for credentialing or competency decisions.

Declarations

Conflict of interest:

The authors declare no conflicts of interest.

Ethics approval:

This study was approved by the Ethics Committee of Shiga University of Medical Science (approval number R2022-042).

Consent to participate:

The requirement for written informed consent was waived owing to the retrospective nature of the study.

Consent for publication:

Not applicable.

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Author Contribution

All authors made substantial contributions to the study design, data interpretation, and critical review of the manuscript. Data collection and analysis were performed by A.T., Y.T., Y.Y., M.D., A.N., and S.T.. The initial draft of the manuscript was prepared by A.T.. S.T. supervised the study and contributed to project administration and critical revision of the manuscript. All authors reviewed and approved the final version of the manuscript for publication.

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Data availability:

The data that support the findings of this study are available from the corresponding author on reasonable request, subject to institutional and ethical restrictions.

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Figures

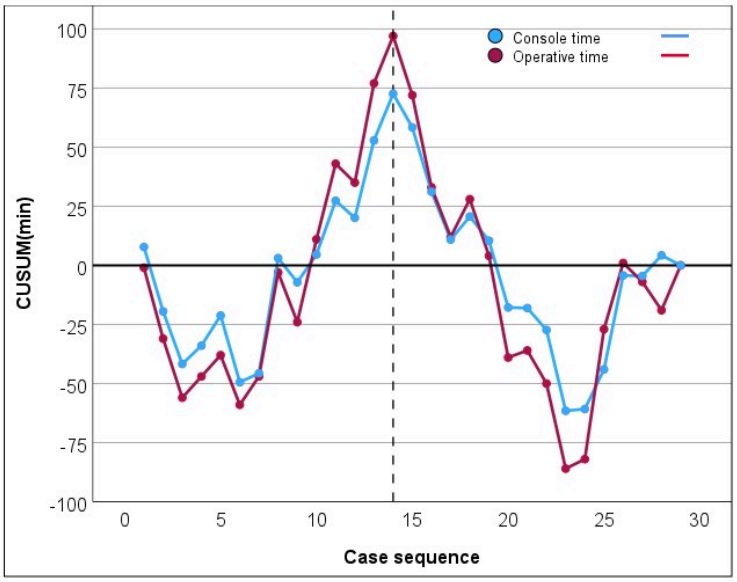


Figure 1

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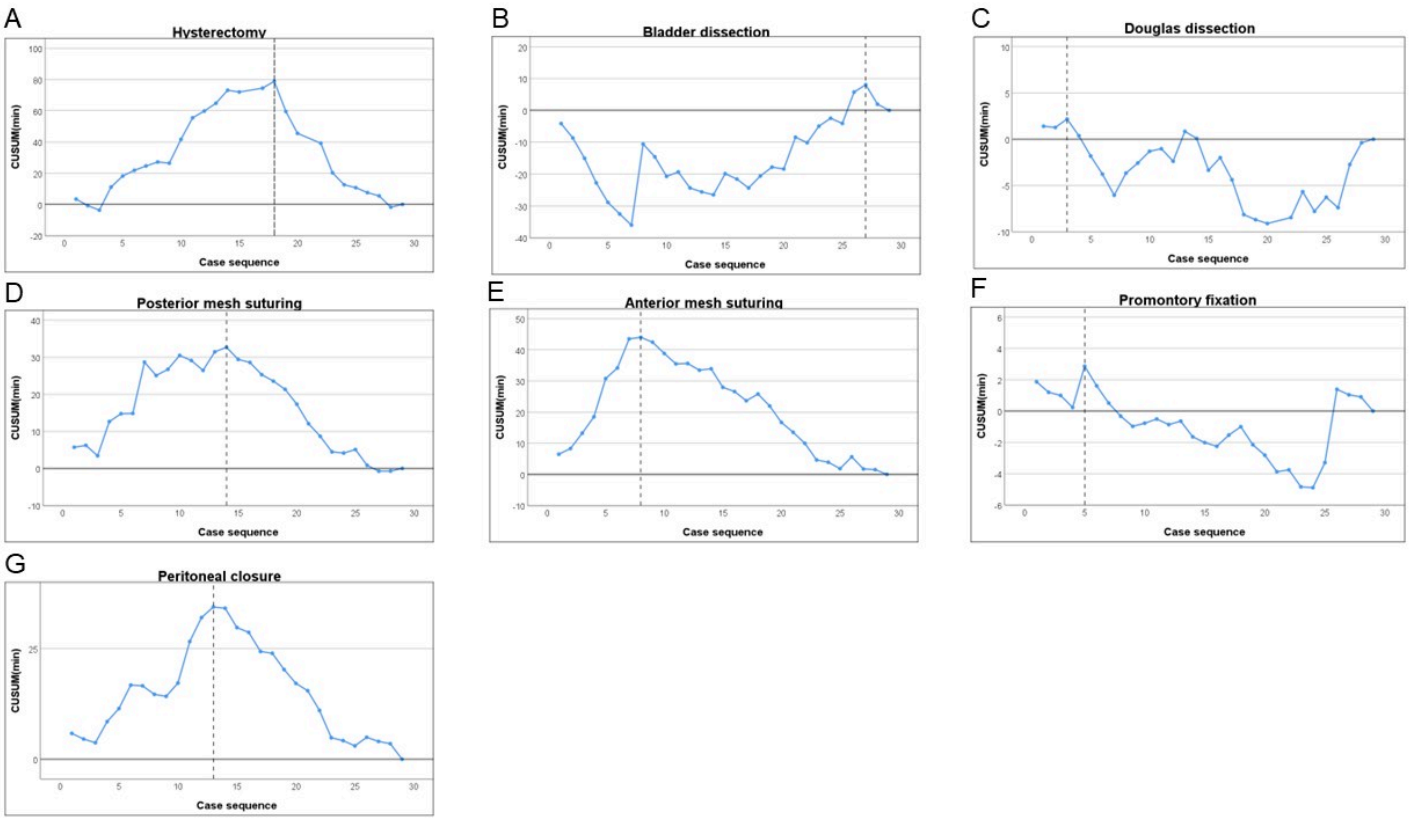


Figure 2

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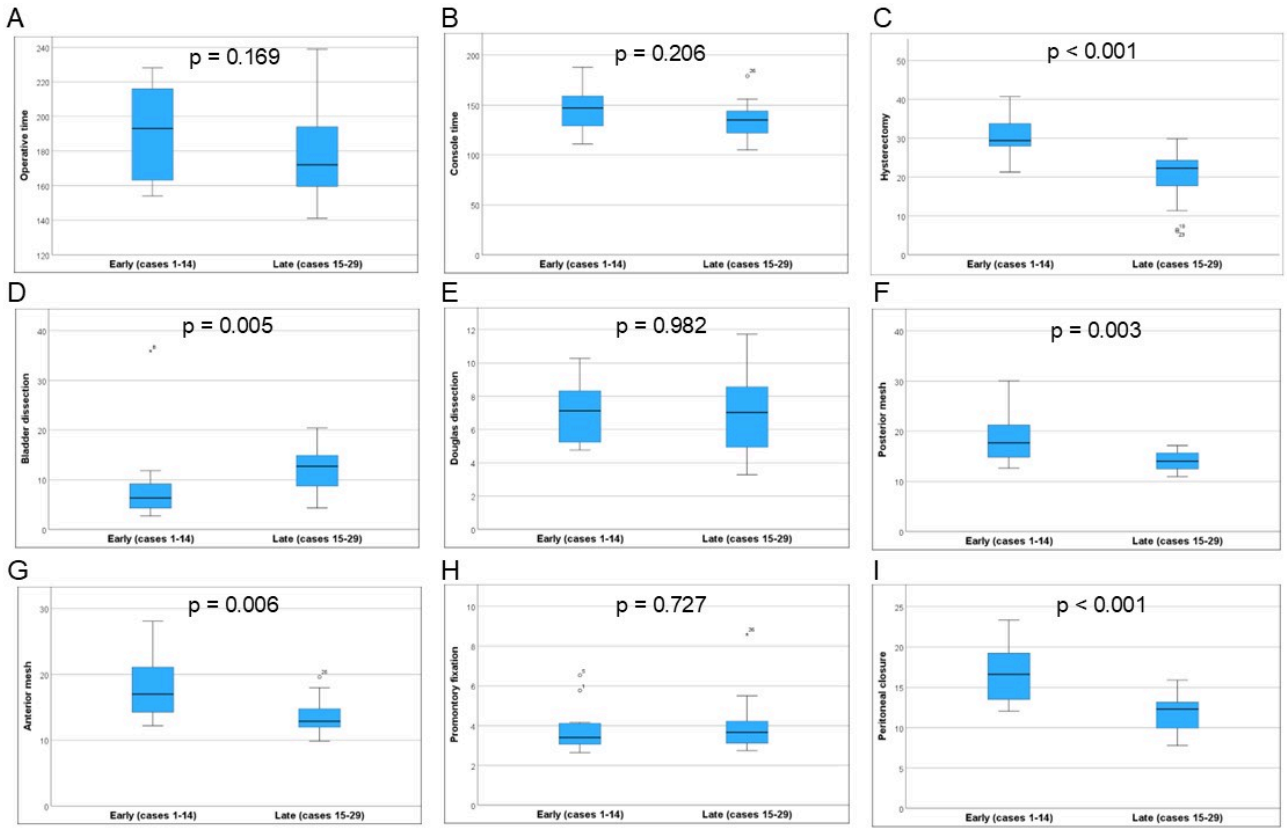


Figure 3

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