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ORIGINAL ARTICLE

Flow disruptions in robotic-assisted abdominal sacrocolpopexy: does robotic surgery introduce unforeseen challenges for gynecologic surgeons?

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Abstract

Introduction and hypothesis The purpose of this study was to apply a human factors research approach to identify flow disruptions, deviations in the optimal course of care, in robotic abdominal sacrocolpopexy procedures with the ultimate goal of developing system interventions to improve the safety and efficiency of robotic surgery.

Methods Twenty-four robotic abdominal sacrocolpopexy procedures were observed for flow disruptions. Surgeries were divided into four phases: (1) patient arrival and induction of anesthesia; (2) port placement and robot docking; (3) console time; (4) undocking of robot, incision closure, and patient exiting the OR.

Results Flow disruptions were observed at a rate of 10.9 ± 5.1 per hour. The most frequently observed flow disruptions involved training issues (2.8 ± 2.4 flow disruptions per hour), equipment (2.2 ± 1.6 flow disruptions per hour), and poor coordination (2.0 ± 1.3 flow disruptions per hour). The rate of flow disruptions was highest in phase 2 (19.2 ± 14.4 flow disruptions per hour). Cases with more experienced surgeons involved shorter console times by 1.5 h (95% CI: 0.1, 3.0, $p = 0.033$) and 1.8 fewer (95% CI: 1.2, 2.6, $p = 0.001$) flow disruptions per hour. Surgeries were 1 h shorter on average (95% CI: 0.1, 1.9, $p = 0.034$) in cases in which the patient was > 65 years old. Da Vinci S console times were 0.8 h longer (95% CI: 0.01, 1.5, $p = 0.047$) than Si.

Conclusions Flow disruptions in robotic abdominal sacrocolpopexy surgery occur about every 6 min. Flow disruption rates are highest during the most complex portions of the surgery. More experienced surgeons have lower flow disruption rates and operate more quickly.

Keywords Da Vinci system · Flow disruptions · Human factors research · Robotic surgical procedures · Sacrocolpopexy

Introduction

Despite a relative lack of comparative effectiveness data, urologists and gynecologists rapidly adopted robotic surgery technology [1]. In fact, the rate of robotic hysterectomies increased from 0.5% in 2007 to 9.5% in 2010, and robotic-assisted abdominal sacrocolpopexies (RASCs) have increased at an exponential rate [1, 2]. However, this initial enthusiasm by gynecologists has decreased in recent years, especially for benign hysterectomies, as data from randomized controlled trials found no significant difference between laparoscopic hysterectomies and robot-assisted hysterectomies in terms of primary outcomes and quality of life, despite significant cost differences [2]. It is not expected, however, that the same trend will be seen for RASCs, given the wrist articulation and robot magnification provide a significant advantage in this case.

Introducing new technologies into the operating room can fundamentally change the requirements for teamwork, process, and individual skills [3, 4]. The introduction of surgical robots has changed many elements of the operating room (OR) work system. For example, the surgeon no longer operates at the table, the surgeon speaks through a microphone to the team, the robot needs to be docked to the patient, and the instrument changes need to be carefully managed—all of

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which change the intraoperative requirements for communication, coordination, equipment use, expertise, and training [5]. It is these changes in the system environment, and how humans interact with this modified system, that may cause flow disruptions (FD), or "deviations in the optimal course of care" [6]. Ultimately, the FDs may impact surgeon performance, patient outcomes, and OR efficiency [6]. Studies of non-robotic surgeries identified FDs at a rate of about one FD every 5 to 10 min [7].

Human factors research is the study of how humans interact with and perform in complex systems [3]. It is a commonly held belief that, if a surgical outcome is poor, then it is either the fault of the surgeon, due to an error or lack of skills/training, or the patient, due to their illness or comorbidities. However, human factors research postulates that it is a combination of factors in the work environment, such as communication, external distractions, teamwork, equipment, training, and ergonomics that ultimately contributes to error occurrence [8].

The purpose of this prospective observational study is to apply a human factors research approach to identify and characterize FDs in RASC procedures that may contribute to decreased efficiency, errors, and suboptimal patient outcomes. The ultimate goal of this work is to develop system interventions to improve the safety and efficiency of robotic surgery for urogynecologic procedures. This article is part of a larger group of work evaluating FDs across several types of robotic surgeries [3, 9].

Materials and methods

Institutional Review Board (IRB) approval (Pro00028833) was obtained from Cedars-Sinai Medical Center to allow the direct observation of robotic surgeries to identify and characterize FDs. A waiver of informed patient and staff consent was granted by the IRB, given that no identifiers were to be collected.

A data collection tool was developed in a collaborative effort between surgeons and human factors research experts. The data collection tool was divided into four sections to reflect four basic phases to robotic surgery: (1) patient arrival and induction of anesthesia; (2) port placement, abdominal insufflation, and robot docking; (3) console use time; (4) undocking of robot to patient exiting the OR [3]. The data collection tool had fields to record times and, when appropriate, time intervals for FDs. In addition, there were text fields for the observers to note the details of each FD and categorize them into seven categories as defined by Parker et al. 2010: communication, coordination, external factors, training, equipment, environment, and patient factors (Table 1) [10].

Medical student observers were trained in human factors research by a field expert (KC), and their observation recordings were reviewed by the expert for several cases to ensure accuracy. The observers were also trained to understand the surgical steps of an RASC. All RASCs were observed, including those with concomitant procedures such as hysterectomy that were performed at a single institution.

Twenty-four surgeries were directly observed. Observers were present in the operating room at the time of patient entry to the OR until the patient exited the OR. They used laptop computers to continuously annotate FDs, their times, descriptions, and categories throughout the surgery. Data on the robot type (da Vinci S versus Si ± training console) were recorded. Observers were unaware of the physician robotic experience level, which was defined as low < 250 cases, medium 250–700 cases, and high > 700 cases.

Table 1 Flow disruption definitions and examples

Categories	Definition	Examples
Communication	Any miscommunication that impacts surgery progress	Examples: Surgeon on console is unable to hear bedside assistant, who has to repeat communication. Nurse does not hear surgeon suture request
Coordination	Any lapse in teamwork to prepare for/conduct surgery that affects surgery flow	Example: Surgeon always uses a specific piece of equipment, but staff fails to retrieve item prior to when it is needed during the surgery
External factors	Any interruption that is not relevant to the current case or surgery	Examples: Resident enters room to ask attending about another patient. Surgeon receives cell phone call or text message
Training	Any instruction by the attending surgeon to fellows, residents, or medical students	Example: Surgeon instructing resident on where to place the ports
Equipment	Any equipment issue that affects surgery progress	Example: Robotic arm malfunctions requiring consult with da Vinci tech support
Environment	Any room conditions that impact surgery progress	Example: Music is too loud, making it difficult for staff to hear surgeon requests
Patient factors	Any patient characteristic that impedes efficient surgery progress	Example: Obesity making port placement difficult

In addition to FDs, de-identified data about the patients including the American Society of Anesthesiologist (ASA) physical status classification system, body mass index (BMI), and age were recorded.

Surgical times were tested in a linear regression model to include testing of factors simultaneously. The rate of FDs was modeled on the parameters of interest using Poission regression methods. Time was included as a covariate in modeling of the FD rate to test for the association of the length of surgery in predicting FD counts. Fit statistics were used to assess the overall appropriateness of the modeling. Residuals were inspected to assess the presence of any influential outliers. Statistical significance was set at $p < 0.05$. Data are presented as counts and percent or means and standard deviations unless otherwise noted. All data were analyzed using SAS v9.3.

Our calculations accounted for all of the covariates captured in the study. We separately analyzed impact of variables on both overall time and rates per hour.

Results

Twenty-four RASC cases were observed, 13 of which had a concomitant supracervical hysterectomy. The surgeries had a mean duration of 4.7 h, standard deviation (SD) of 0.9 h (Table 2).

Overall, 1195 FDs were observed. The mean number of FDs per case was 49.8 (SD: 21.7, range 18–116) and mean FD rate was 10.9 disruptions per hour (SD: 5.1, range 4.6–17.4). The most frequent FDs were training [2.8 FDs/h (h) and 24.4% of total disruptions], equipment (2.2 FDs/h, 20.5% of total disruptions), and coordination-related disruptions (2.0 FDs/h, 18.6% of total disruptions), which together accounted for 63.6% of the FDs.

Table 2 Summary of surgical cases observed

Sacrocolpopexy cases		
($n = 24$)		
	Mean	SD
Patient age, years	62.1	11.6
Patient BMI	26.2	6.1
Total time, hours	4.7	0.9
Phase 1	0.7	0.4
Phase 2	0.4	0.2
Phase 3	2.3	0.8
Phase 4	1.2	0.5
FD rate/hour	10.9	5.1
Phase 1	5.5	3.8
Phase 2	19.2	14.4
Phase 3	15	7.6
Phase 4	4.7	4.4

When evaluating FDs by operation phase, the highest rate of FDs was in phases 2 and 3. The four phases were defined as: (1) patient arrival and induction of anesthesia; (2) port placement, abdominal insufflation, and robot docking; (3) console use time; (4) undocking of robot to patient exiting the OR. There was a significant mean FD rate difference between phase 1 and phase 2 (mean difference 13.7; 95% CI 7.5 to 19.8; $p < 0.0001$). There was a significant mean FD rate difference between phase 1 and phase 3 (mean difference 9.5; 95% CI 6.0 to 12.0; $p < 0.0001$). There was a significant mean FD rate difference between phase 2 and phase 4 (mean difference 14.4; 95% CI 8.2 to 20.6; $p < 0.0001$). Finally, there was a significant mean FD rate difference between phase 3 and 4 (mean difference 10.3; 95% CI 6.7 to 13.9; $p < 0.0001$). However, there were no differences between phases 1 and 4 ($p = 0.5$), 2 and 3 ($p = 0.2$).

Increased physician experience with robotic surgery is associated with a decreased overall FD rate (Table 3). After covarying for all other factors, more experienced physicians have an estimated rate that is 1.8 FD/h (95% CI: 1.2, 2.6) lower than the FD rate during the entire surgery of less experienced physicians. In addition, during the operative phase of the procedure (phase 3), less experienced physicians have a rate that is 1.9 FD/h (95% CI: 1.1, 3.3) higher than their more experienced colleagues. Increased physician experience with robotic surgery was also associated with shorter operative times in phases 1 and 3. After covarying for all factors, the estimated time difference for more experienced surgeons was 1.07 h faster (95% CI: 0.48, 1.63) in phase 1. For phase 3, the operative phase, more experienced surgeons were also faster. After covarying for all factors, the estimated difference between physician groups for phase 3 is 1.53 h (95% CI: 0.13, 2.95) longer for less experienced physicians.

Overall, there was a negative correlation of the flow disruption rates with the length of surgery (Table 4). For each hour of the total surgery, there was an estimated decrease of 0.90 FD/h (95% CI: 0.83, 0.98). In phase 3, for each hour the FD rate decreased by 0.75 FD/h (95% CI: 0.65, 0.87). In phase 4, for each hour of surgical time, the FD rate decreases by 0.33 FD/h (95% CI: 0.20, 0.54). Training cases with a resident had longer surgical times in phase 1 of the surgery, and, after covarying for all factors, the estimated difference in phase length between training groups for phase 1 was 0.65 h (95% CI: 0.01, 1.31). The presence of a trainee did not seem to affect the surgical times in phases 2–4.

Using the da Vinci S robot (vs. the newer Si model) resulted in slightly longer surgical times during the operative phase of the procedure (phase 3, Table 4). After covarying for all factors, the estimated difference between robotic models in phase 3 was 0.76 h longer using the S model (95% CI: 0.01, 1.51) compared with the Si. Increasing patient age was

Table 3 Analysis of FD rates per hour

Factor	*N*	Total			Phase 1			Phase 2			Phase 3			Phase 4		
		Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*
Physician experience																
Low	22	11.3	5.1	**0.001**	5.7	3.9	0.110	19.7	15	0.789	15.6	7.6	**0.015**	5.2	4.3	n/a
High	2	6.3	0.4		3.8	2.9		13.2	1.7		8.7	4.6		0.0	0.0	
Training case																
No	2	8.2	3.0	0.553	3.6	2.6	0.210	14.7	0.4	0.168	8.9	4.9	0.897	3.6	5.1	0.343
Yes	22	11.1	5.2		5.7	3.9		19.6	15		15.6	7.6		4.9	4.4	
Robotic model																
S	7	11.6	8.4	0.093	6.8	3.7	0.250	23.7	21	0.082	13.2	12.5	0.917	6.8	4.2	0.390
Si	17	10.6	3.2		5.0	3.9		17.3	11		15.7	4.7		3.9	4.3	
Patient age																
≤ 62	10	9.7	3.8	0.429	7.0	4.3	0.064	15.5	9	**0.018**	12.5	4.5	0.111	4.5	4.3	0.602
> 62	14	11.7	5.8		4.5	3.3		21.8	17		16.8	8.9		4.9	4.5	
Patient BMI																
< 25	11	12.3	6.7	0.129	6.1	3.4	0.718	20.5	19	0.190	17.1	10.1	0.106	6.9	4.9	**0.001**
25 To 30	9	8.6	2.8		3.4	2.4		15.3	9		11.5	3.8		3.3	2.9	
≥ 30	4	12.1	0.5		8.5	5.6		24.3	8.2		17.2	2.5		2.1	3.3	
Patient ASA																
1	3	8.0	2.5	0.198	2.8	2.3	0.236	14.4	7.5	0.540	10.5	1.6	0.269	3.8	3.6	**0.031**
2	19	11.2	5.5		5.6	3.8		18.3	14		15.6	8.3		5.1	4.6	
3	2	12.7	1.1		8.7	5.2		34.8	28		16.5	3.2		2.8	3.9	
Duration, hours		*Rs* = −0.125		**0.011**	*Rs* = 0.239		0.09	*Rs* = −0.042		0.777	*Rs* = −0.434		**<0.001**	*Rs* = −0.120		**<0.001**

Bolded values indicate statistical significance ($p < 0.05$)

Rs Spearman rank correlation; negative values indicate negative association between time and rate (longer times have significantly fewer FDs/h)

**P* values computed from the full linear regression model while covarying simultaneously for all factors

associated with decreased total surgical time. After covarying for all factors, the estimated difference in total surgical time was 1.00 h shorter for older patients (> 65 years old vs. ≤ 65) (95% CI: 0.09, 1.93). In addition, a shorter operative portion of the procedure (phase 3) for older patients was observed. After covarying for all factors, the estimated difference in surgical time in phase 3 was 0.87 h shorter for older patients (95% CI: 0.22, 1.502).

Discussion

During RASCs, we found that FDs occurred about once every 6 min. This rate is consistent with findings from studies that evaluate flow disruptions in non-robotic surgery, including pediatric surgery, orthopedics, vascular, trauma, and general surgery [11–15]. The most common FDs were training, followed closely by equipment and coordination FDs.

Training specifically affected the first phase of the surgery. After controlling for other variables, training added about 40 min to that portion of the surgery. This is consistent with the observation that this phase of surgery heavily involves residents (as long as the case was a training case) and therefore was the phase in which many or most of the training FDs were observed. However, even without residents this phase involved the most flow disruptions, likely due to the complexity of the docking process. Depending on the resident skill level, time spent on the console (phase 3) was extremely variable. Hence, minimal training FDs observed during phase 3 of the surgery may have been due to the fact that residents simply were not spending a significant amount of time on the console. A larger sample size would help us to distinguish whether the training FD rate was higher with more senior residents, who were more likely to spend more time on the surgical console. Moreover, the presence of a surgical trainee did not seem to affect the FD rates and surgical times in phases other than phase 1.

Overall, the highest FD rates were in phases 2 (patient arrival and induction of anesthesia) and 3 (surgeon on console to surgeon off console), consistent with the fact that these are the most complex portions of the surgery and require the most interaction with and use of the robot, team coordination, communication, and equipment transitions. It follows that more experienced surgeons have a statistically significantly lower FD rate than less experienced surgeons, especially during these critical and complex phases. Less experienced surgeons have an FD that is almost two times that of the more experienced surgeon. It is important to note, however, that the number of highly experienced robotic surgeons in this cohort was low.

Interestingly, after controlling for other variables, FD rates decrease with each hour of additional surgery. This is

Table 4 Analysis of surgical times, in hours

Factor	*N*	Total			Phase 1			Phase 2			Phase 3			Phase 4		
		Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*	Mean	SD	*p* value*
Physician experience																
Low	22	4.67	0.92	0.314	0.67	0.20	**0.001**	0.42	0.18	0.680	2.37	0.73	**0.033**	1.22	0.50	0.459
High	2	4.45	0.50		1.32	1.07		0.63	0.30		1.88	1.47		0.63	0.20	
Training case																
No	2	5.02	0.30	0.274	0.55	0.02	**0.047**	0.62	0.30	0.283	2.83	0.12	0.17	1.02	0.75	0.399
Yes	22	4.62	0.92		0.73	0.35		0.42	0.18		2.28	0.80		1.18	0.50	
Robotic model																
S	7	4.93	0.97	0.543	0.68	0.18	0.671	0.47	0.20	0.619	2.88	0.87	**0.047**	0.90	0.42	0.069
Si	17	4.53	0.85		0.73	0.40		0.42	0.20		2.10	0.63		1.28	0.52	
Patient age																
≤ 65	10	5.08	0.90	**0.034**	0.88	0.45	0.319	0.45	0.23	0.273	2.62	0.92	**0.012**	1.13	0.28	0.701
> 65	14	4.35	0.77		0.43	0.17		0.42	0.18		2.12	0.63		1.20	0.63	
Patient BMI																
< 25	11	4.62	0.82	0.991	0.65	0.15	0.366	0.37	0.13	0.289	2.38	0.78	0.448	1.22	0.63	0.489
25 To 30	9	4.62	0.93		0.73	0.53		0.50	0.27		2.32	0.83		1.05	0.43	
≥ 30	4	4.83	1.22		0.85	0.18		0.47	0.0		2.22	0.90		1.32	0.25	
Patient ASA																
1	3	5.00	0.22	0.790	0.65	0.08	0.502	0.37	0.07	0.157	2.67	0.30	0.323	1.32	0.30	0.81
2	19	4.53	0.97		0.72	0.38		0.45	0.20		2.20	0.80		1.17	0.55	
3	2	5.18	0.07		0.83	0.32		0.30	0.15		2.98	1.05		1.08	0.52	

Bolded values indicate statistical significance ($p < 0.05$)

**P* values computed from full linear regression model while covarying simultaneously for all factors

somewhat counterintuitive, as one would expect that longer surgeries are associated with more flow disruptions. This may be explained by the fact that, since RASC has relatively few steps, there is a relatively fixed number of possible FDs that may occur in RASC. It is also possible that the sample we observed, which was relatively small, did not include any major complications.

After controlling for other variables, including ASA, if a patient was > 65 years old they were more likely to have a shorter surgery than a patient that was < 65 years old. This may be due to the possibility that the surgeon worked more quickly because they knew the patient was older and there was concern about anesthetic length and associated risks.

Several of the surgeries observed were performed on an older robot model—the da Vinci S—which had a specific impact on phase 3, the console phase of the surgery. In fact, the average length of the operative phases, after controlling for all other variables, was about 45 min longer on the S model than those performed on the Si model. One may actually expect the Si operative phase to be longer, given that it has a training console and is more likely to involve residents. However, the expected increase of operative time associated with an increase in trainee time on the console was not observed. No specific flow disruption type was increased on the S model, so it is unclear exactly what is contributing to the increased operative time for phase 3.

While this study has many strengths, there are some limitations to this work. First, the sample size of RASCs observed was relatively small; therefore, the sample was slightly unbalanced especially regarding surgeon experience and training versus non-training cases. More surgeons were classified as have less robotic surgery experience, and a majority of the cases were teaching cases. Finally, we did not analyze FDs in non-robotic surgeries using this same methodology. As part of future work, we plan to obtain these data to determine whether the FD rate in phase 1 (which does not involve the use of the robot) is affected by whether the case is performed robotically versus non-robotically. Furthermore, we hope to evaluate whether the modified OR configuration for robotic surgeries affects the surgical team dynamic and ability to raise concerns about patient safety.

FDs in the operating room can impair progress, increase team workload, operating time, and reduce efficiency and safety. Defining and understanding the FDs that occur during a robotic surgery will assist us in identifying interventions that can help improve OR efficiency and patient safety. Understanding the fundamentals of FDs in the OR may help identify means to make the introduction of new OR technologies more safe, seamless, and efficient, thereby improving the overall quality of patient care.

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Compliance with ethical standards

Conflicts of interest None.

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