Surgical flow disruptions during robotic-assisted radical prostatectomy

Christopher J. Dru, MD,[1] Jennifer T. Anger, MD,[1] Colby P. Souders, MD,[1] Catherine Bresee, MD,[2] Matthias Weigl, MD,[3] Elyse Hallett, MD,[4] Ken Catchpole, MD[5]

[1]Division of Urology, Cedars-Sinai Medical Center, Los Angeles, California, USA
[2]Cedars-Sinai Biostatistics & Bioinformatics Research Center, Los Angeles, California, USA
[3]Institute for Occupational, Social, and Environmental Medicine, Ludwig-Maximilians University, Munich, Germany
[4]Pacific Science and Engineering Group, San Diego, California, USA
[5]Department of Anesthesia and Perioperative Medicine, Medical University of South Carolina, Charleston, South Carolina, USA

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Introduction: *We sought to apply the principles of human factors research to robotic-assisted radical prostatectomy to understand where training and integration challenges lead to suboptimal and inefficient care.*

Materials and methods: *Thirty-four robotic-assisted radical prostatectomy and bilateral pelvic lymph node dissections over a 20 week period were observed for flow disruptions (FD) - deviations from optimal care that can compromise safety or efficiency. Other variables - physician experience, trainee involvement, robot model (S versus Si), age, body mass index (BMI), and American Society of Anesthesiologists (ASA) physical status - were used to stratify the data and understand the effect of context. Effects were studied across four operative phases - entry to insufflations, robot docking, surgical intervention, and undocking. FDs were classified into one of nine categories.*

Results: *An average of 9.2 (SD = 3.7) FD/hr were recorded, with the highest rates during robot docking (14.7 [SD = 4.3] FDs/hr). The three most common flow disruptions were disruptions of communication, coordination, and equipment. Physicians with more robotic experience were faster during docking (p < 0.003). Training cases had a greater FD rate (8.5 versus 10.6, p < 0.001), as did the Si model robot (8.2 versus 9.8, p = 0.002). Patient BMI and ASA classification yielded no difference in operative duration, but had phase-specific differences in FD.*

Conclusions: *Our data reflects the demands placed on the OR team by the patient, equipment, environment and context of a robotic surgical intervention, and suggests opportunities to enhance safety, quality, efficiency, and learning in robotic surgery.*

Key Words: robotics, technology, instrumentation, flow disruptions, radical prostatectomy

Introduction

Technological advances in the last century have met with unexpected effects. Increasing complexity requires specialized skills and increased integration with existing technologies and processes. These "ironies of automation"[1] often offset the intended benefits. It is useful to identify these challenges so that they can be addressed. The da Vinci Surgical System (Intuitive Surgical, Sunnyvale, CA, USA) likely represents the most prominent technological change in surgery in the last 15 years. A greater understanding of how the robot functions in relation to the operators may lead to evolving training, improved design, smoother processes, and better integration with existing infrastructures.

The technical complexity of robotic-assisted surgery in urology coupled with coordination of

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Address correspondence to Dr. Christopher J. Dru, 8635 West 3rd Street, Suite 1070, Los Angeles, CA 90048 USA

operating room and surgical personnel provide many opportunities for disruptions in patient care to occur.[2,3] Such disruptions have been studied in other fields to improve efficiency and risk management.[4,5] Understanding system failures allows for improvement in patient safety and care.[6] Flow disruptions (FDs) are deviations in patient care that can compromise safety and are correlated with surgical error.[7,8] The accumulation of FDs can lead to patient harm, while also frequently contributing to inefficiency, frustration, communication breakdown and longer operating time. They can be used to identify flaws or pitfalls in healthcare systems before serious accidents occur.[9] Identification of FDs in teamwork, communication, equipment, and various other factors can allow for improvement in the delivery of care.[10] In a previous multispecialty analysis of FDs in robotic surgery, technological problems, breakdowns in communication/coordination, and difficulties in maintaining vision in the operative field were commonly sited problems.[11]

Robotic-assisted radical prostatectomy is a frequently performed urologic surgery with 4 out of every 5 cases being performed with robotic assistance.[12] Robotics in urology, as a whole, continues to evolve with new models and systems rolling out every 3-5 years and novel surgical applications and uses being developed even more often. However, the technological, environmental and organizational challenges that lead to FDs in urological robotic surgery are not well-characterized. This investigation was a prospective observational study to identify and quantify FDs that occur during robotic-assisted radical prostatectomy and pelvic lymph node dissection using the da Vinci S and Si Surgical Systems. First, we explored the types of FDs specific to urological surgery. We hypothesized that coordination and equipment disruptions would be the most frequent problems. Second, we hypothesized that more advanced surgeon experience would translate into a lower frequency of FDs. Third, we hypothesized that different surgical phases – preparation, docking, console time, undocking – have specific demands that would be reflected in different rates and types of FDs. Overall, we sought to characterize the barriers to robotic operating efficiency, which ultimately could help to reduce costs, improve training and communication, and reduce barriers to adoption of this new technology.

Materials and methods

After Institutional Review Board approval (Cedars-Sinai IRB Pro00028833), six research staff underwent operating room observation training with experts in human factors research. Thirty-four robotic-assisted radical prostatectomies were observed over a 20 week period at Cedars-Sinai Medical Center in Los Angeles, CA. All six operating urologists had received fellowship training in robotic surgery. FDs were recorded and classified into pre-determined categories and then stratified by surgical phase. The established categories of FDs included communication, coordination, instrument changes, surgeon decision-making time, external/extraneous, training/supervisory, equipment issues, environment, and patient factors, Table 1.

The four phases of surgical care were identified. Phase one (Induction/Pre-Robot) began with the patient entering the operating room and ended with trochar placement, representing the preoperative set up process. Phase two (Robot Docking) encompassed docking of the robot. Phase three (Robot-Assisted Surgery) started with the urologist sitting at the console and ended with completion of the robotic portion of the surgery, representing the main interaction with the console. Phase four (Post-Robot and Exit) began with the surgeon leaving the console, and ended with the patient being transferred out of the OR, representing undocking, closure, and transfer from the OR table.

The number of FDs and rates (number/time) at which FDs occurred were calculated for each surgical phase. These data were further stratified by physician experience, the presence of trainees, the robot model (S versus Si), patient age, patient body mass index, and patient American Society of Anesthesiologists (ASA) physical status classification system (low risk: ASA 1-2; and high risk: ASA 3-4). Obesity was defined as a body mass index (BMI) > 30 kg/m^2. Physician experience was categorized into three groups (low experience < 250 cases (n = 2), medium experience 250-700 cases (n = 1), and high experience > 700 cases (n = 3)). Patient age was grouped into two categories (younger, ≤ 62 years of age; older, > 62 years of age), based on previous classifications.[12]

Surgical time was tested in a linear regression model. The rate of FDs was modeled using Poisson regression methods. Time was included as a covariate in modeling of FD rate to test for the association of the length of surgery in predicting FD counts. Fit statistics were used to assess appropriateness of the modeling. Residuals were inspected to assess the presence of any influential outliers, and no outliers were identified. Statistical significance was set at $p < 0.05$. Data are presented as counts, percent or means, and standard deviations unless otherwise noted. All data were analyzed using SAS v9.3.

TABLE 1. **Characteristics of flow disruptions (FD))**

FD category	Definition	Example
Communication	Disruption involving a verbal transition between team members	Bedside assistant could not hear directions from the surgeon because of other people talking
Coordination	Disruption involving an interaction with a piece of equipment and a team member	Circulating nurse could not find an additional piece of equipment needed for surgery
External interruption	Disruption impacting the procedure originating from an outside source, which may include persons and/or telecommunications, that did not pertain to the procedure directly	Surgeon needed to answer a phone call from his or her office
Training	Disruption involving training of residents or fellows for their educational benefit	Surgeon had to repair a mistake made by a resident while operating on the console
Equipment	Disruption involving a malfunctioning piece of equipment essential to the surgery	A Maryland forcep would not adequately grasp tissues and needed to be exchanged
Environment	Disruption affecting the surgeon or OR staff through auditory or visual means that is not directly related to the surgery	The temperature in the OR was too hot to keep the surgeon comfortable
Patient factors	Disruption involving patient-related factors	Body habitus required use of extra-long trochars which then had to be located and opened
Instrument changes	Disruption due to unanticipated changes in robotic instruments or camera	Surgeon caused excessive bleeding requiring need for replacement of needle drivers with Maryland forceps and endoscopic scissors
Surgeon decision-making	Disruption due to an unanticipated need to consult with another physician or staff member due to an unforeseeable circumstance	Surgeon caused a small bowel injury requiring intraoperative consultation with a general surgeon

Results

Cronbach's α found research staff inter rater reliability to be excellent at 0.95 (Phase One, $\alpha = 0.90$; Phase Two, $\alpha = 0.79$; Phase Three, $\alpha = 0.97$; Phase Four, $\alpha = 0.86$). Average total operating room time was 302 (SD = 76) minutes with an average of 9.2 (SD = 3.7) FDs recorded/hr. Phase three accounted for the greatest amount of operating room time; on average 178 (SD = 57) minutes. However, the greatest number of FDs/hr occurred during phase two (robot docking); on average 14.7 (SD = 4.3) FDs/hr. These data are represented in Figure 1.

The highest rates of FDs were attributable to coordination disruptions (1.4 (SD = 0.7) FDs per case), followed by equipment problems (1.3 (SD = 0.7) FDs per case) and communication breakdown (1.0 (SD = 0.6) FDs per case). Physician experience had a significant effect on the phase-specific surgical time but minimal effect on the rate of FDs/hr. Physicians with a higher level of robotic experience spent less time during phase two than lower volume robotic surgeons (11 (SD = 4) versus 18 (SD = 8) minutes, $p = 0.003$). There was a statistically significant decrease in the amount of time spent in phase one when the surgeon had a higher level of robotic proficiency as compared to lower level robotic

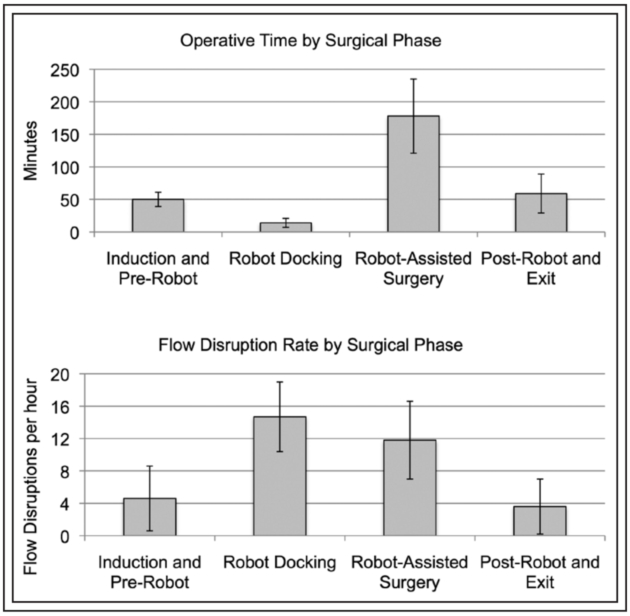

Figure 1. Operative rate and rate of flow disruptions by surgical phase. Standard deviation errors bars.

surgeons (46 (SD = 10) versus 57 (SD = 10) minutes, p = 0.028). This is represented in Figure 2. In addition, physicians with a higher volume of robotic experience had a significantly lower FD rate in most categories, Figure 3. Trainee involvement in the cases did not have any significant effect on total or phase-specific surgical time but did impact the rates of FD occurrence. Trainee involvement was associated with a statistically

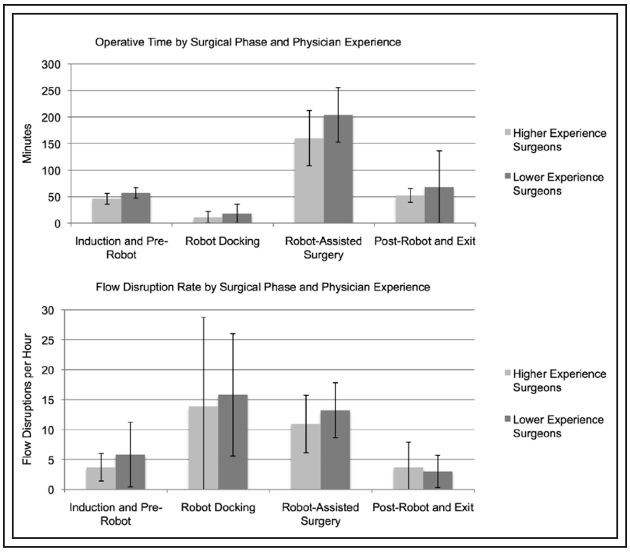

Figure 2. Comparison of lower experience and higher experience robotic surgeons with regard to operative time and rate of flow disruptions by surgical phase.

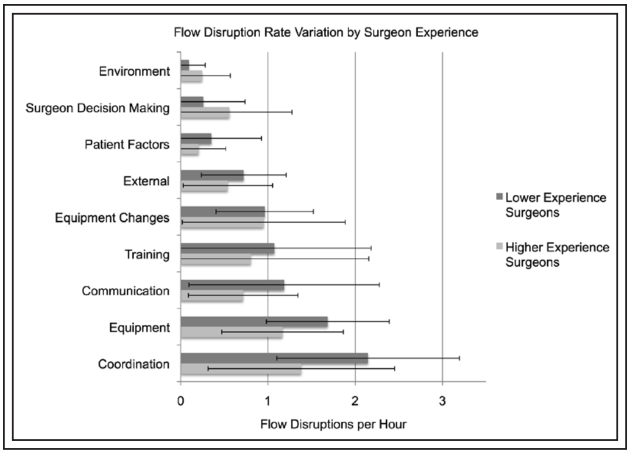

Figure 3. Comparison of lower experience and higher experience robotic surgeons with regard to the types of flow disruptions that occured. Standard deviation errors bars.

significant increase in FDs/hr in total (10.6 (SD = 3.6) versus 8.5 (SD = 3.6) FDs/hr, p < 0.001) and in phase three (13.4 (SD = 4.7) versus 11.1 (SD = 4.8) FDs/hr, p = 0.016) compared to the absence of trainee involvement. This is represented in Tables 2 and 3.

Use of the da Vinci model Si was associated with a statistically significant increase in FDs/hr in total (9.8 (SD = 4.0) versus 8.2 (SD = 3.2) FDs/hr, p = 0.002) and in phase three (12.8 (SD = 5.2) versus 10.5 (SD = 3.9) FDs/hr, p < 0.001) compared to use of the da Vinci model S, Figure 4. BMI had significant effects on the rate of FDs but not on total or phase-specific surgical time. Obesity (BMI > 30 kg/m^2) was associated with an increase in FDs/hr in phase one (8.6 (SD = 6.7) FDs/hr, p = 0.011)

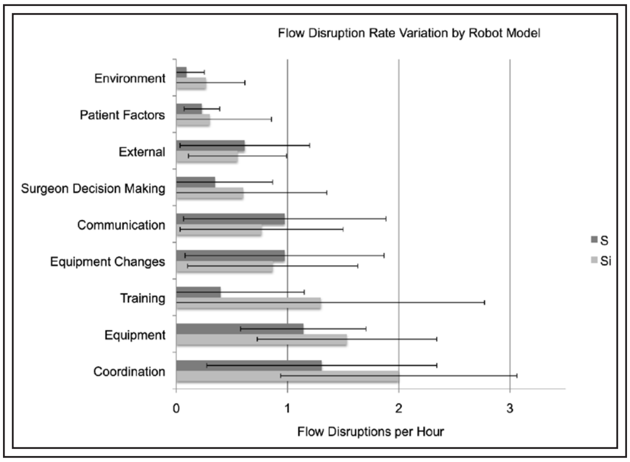

Figure 4. Comparison of the robot model utilized (S Versus Si) with regard to the types of flow disruptions that occured. Standard deviation errors bars.

TABLE 2. **Analysis of surgical times**

Factor	N	Total			Phase 1			Phase 2			Phase 3			Phase 4		
		Mean	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***
Physician experience																
Lower	14	348	83	0.083	57	10	0.028	18	8	0.003	204	51	0.373	68	44	0.329
Higher	20	269	53		46	10		11	4		160	52		52	13	
Training case																
No	23	278	56	0.281	49	13	0.947	14	7	0.223	160	52	0.152	55	21	0.891
Yes	11	351	91		54	8		15	6		215	49		66	45	
Robotic model																
S	14	302	63	0.806	50	9	0.676	14	5	0.484	179	53	0.587	59	24	0.898
Si	20	301	86		51	13		15	8		178	61		58	35	
Patient age																
<= 62	12	296	49	0.994	54	13	0.168	15	8	0.719	168	45	0.762	58	25	0.995
> 6 2	22	305	89		49	10		14	6		184	62		59	34	
Patient body mass index																
< 25	14	291	76	0.482	51	13	0.851	16	9	0.257	163	60	0.513	62	32	0.228
25 to 30	14	294	42		50	11		13	5		183	35		48	10	
>= 30	6	344	128		51	12		13	5		204	85		76	50	
Patient ASA																
Lower risk	21	283	58	0.712	49	12	0.460	14	7	0.379	167	55	0.891	54	20	0.522
Higher risk	13	331	94		52	10		15	7		197	57		67	42	

TABLE 3. **Flow disruption rates per hour**

Factor	N	Total			Phase 1			Phase 2			Phase 3			Phase 4		
		Mean	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***	**Mean**	**SD**	**p***
Physician experience																
Lower	14	10.2	3.2	0.378	5.8	5.4	0.134	15.8	10.2	0.415	13.2	4.6	0.732	3.0	2.7	0.038
Higher	20	8.5	3.9		3.7	2.3		13.9	16.8		10.9	4.8		3.7	4.2	
Training case																
No	23	8.5	3.6	< 0.001	4.2	4.3	0.929	13.3	15.7	0.359	11.1	4.8	0.016	3.5	4.0	0.129
Yes	11	10.6	3.6		5.4	3.1		17.6	10.9		13.4	4.7		3.3	2.7	
Robotic model																
S	14	8.2	3.2	0.002	4.2	3.0	0.230	14.7	12.9	0.687	10.5	3.9	< 0.001	3.2	3.2	0.892
Si	20	9.8	4.0		4.8	4.6		14.7	15.5		12.8	5.2		3.5	3.9	
Patient age																
<= 62	12	8.9	2.6	0.996	4.7	5.7	0.097	11.6	6.8	0.782	12.0	4.0	0.250	3.2	3.1	0.241
> 62	22	9.3	4.2		4.5	2.8		16.4	17.0		11.7	5.3		3.5	3.9	
Patient body mass index																
< 25	14	9.5	4.7	0.070	4.0	2.7	0.011	14.6	18.1	0.468	12.8	6.0	0.004	3.8	4.9	0.207
25 to 30	14	8.9	3.3		3.5	2.5		14.1	10.3		11.5	4.0		2.8	2.6	
>= 30	6	9.1	2.1		8.6	6.7		16.3	14.8		10.2	3.4		4.1	2.0	
Patient ASA																
1 or 2	21	9.3	4.0	0.079	3.3	1.9	0.002	13.2	15.6	0.325	12.6	5.0	0.004	3.7	4.2	0.509
3	13	9.0	3.2		6.6	5.5		17.2	12.2		10.6	4.3		3.3	2.5	

as compared to BMI 25-30 kg/m^2 (3.5 (SD = 2.5) FDs/hr) and BMI < 25 kg/m^2 (4.0 (SD = 2.7) FDs/hr). However, obesity (BMI > 30 kg/m^2) was associated with a decrease in FDs/hr in phase three (10.2 (SD = 3.4) FDs/hr, p = 0.004) as compared to BMI 25-30 kg/m^2 (11.5 (SD = 4.0) FDs/hr) and BMI < 25 kg/m^2 (12.8 (SD = 6.0) FDs/hr). Patient ASA physical classification had significant effects on the rate of FDs but not on total or phase-specific surgical time. In phase one, higher risk ASA classification was associated with a higher rate of FDs (6.6 (SD = 5.5) versus 3.3 (SD = 1.9) FDs/hr, p = 0.002). In phase two, lower risk ASA classification was associated with a higher rate of FDs (10.6 (SD = 4.3) versus 12.6 (SD = 5.0) FDs/hr, p = 0.004). Age was not a contributing factor on total surgical time by phase or the rate of FDs/hr.

Discussion

We found a range in number and type of FD across the four phases of surgical care, with robotic docking experiencing the highest frequency of FDs. Pre- and post-robot phases showed fewer FDs. Coordination disruptions occurred most frequently, followed by disruptions of equipment and communication. Several contextual variables, most notably the surgeon robotic experience level, played a significant role in the overall time spent on and rate of FDs. We found significant effects of physician experience on OR time during the preparation and docking phases; and significant effects of resident training and robot models on the overall FD rate and FD rate during the robotic surgical intervention phase. Patient BMI and ASA also demonstrated significant effects during the surgical intervention and robot docking. This reflects the variety of demands placed on the surgeon and the OR team by the patient, equipment, environment and context of a robotic surgical intervention. A highly skilled urological team, with reliable equipment who communicate and coordinate well, will conduct smoother, faster, safer surgery.

There is a dearth of published information available describing interactions of the operating room team during robotic surgery. A previous study explored a total of 89 robotic surgical cases encompassing multiple surgical disciplines to analyze system performance and FDs.[11] Our study, a urology-specific analysis of one type of surgery, finds similar effects. Thus, it would appear that the present observations are not specific to urology – and therefore that they suggest more general effects of the robot and the wider hospital infrastructure. In fact, issues with robotic equipment occur at a higher frequency than has been previously described in non-robotic surgery.[13-16] For example, exchanging a broken suture in a robotic case requires several coordinated steps and elements of communication as opposed to a laparoscopic or open case where haptic feedback makes broken sutures potentially less frequent, and where recovery from this minor problem requires less communication and coordination. However, the ease and speed of suturing with the assistance of the robot offsets any lost time, especially when compared to traditional laparoscopy or open surgical approaches. Additionally, shorter patient hospital length of stay and decreased need for transfusion of blood products after robotic-assisted/laparoscopic approaches compared to open surgical techniques has been definitively shown to reduce cost, an important factor in the current healthcare climate.[17]

It appears that the FD rates – and thus the demands on the team – are highest in the docking and surgical intervention phases. A successful and smooth docking process requires a running dialogue between the surgical scrub technicians, the robot staff, and the surgeons. There are multiple, overlapping conversations occurring in close proximity. A missing piece of equipment can not only delay the case but also disrupt the flow of communication. During the main surgical intervention, the dynamic of the surgery changes as the surgeon sits down at the robot console. This limits direct interactions between the surgeon and the rest of the team. Instead, the surgeon's voice is projected through the robot audio system for the scrub technician, bedside assistant, and robot staff to hear. They do not have reciprocal microphone communications, and rely on speaking more loudly and observing the laparoscopic monitors. With the Si model, we observed a frequent problem with the surgeon's microphone, which experienced frequent audio feedback interference, further limiting communication. The Si model has two robot consoles, and thus more equipment to account for and manage. This explains the difference in FD rates between S and Si models in the console phase. Robotic surgery places particular the demands on team communication and equipment maintenance, reliability and operation. It is not surprising that disruptions of communication, coordination, and equipment were the most common types of FDs, occurring during these more demanding phases and differing with different robot design and functionality.

Technical and non-technical simulation training is being explored to improve the progress of robotic surgical training for both physicians and operating room staff.[18] Given the stepwise progression of robotic-assisted radical prostatectomy, an opportunity exists to compartmentalize the phases of care, in a fashion similar to our study, to allow for operating room simulation training. Additionally, postoperative care can be streamlined with defined nursing pathways as described in the Robocare program.[19] Many nurse postoperative pathways are tailored to surgical laparoscopy and minimally invasive techniques that could be easily modified specifically for robotic prostatectomy including urinary catheter care, intermittent or continuous bladder irrigation, and awareness of the effect of per-rectum suppository medications.

Pre-robot surgical preparation was 11 minutes faster with experienced surgeons, and robot docking another 7 minutes faster, accounting for a total of 18 minutes in the first 60-80 minutes of surgery. While this addition does not reflect a likely effect on clinical outcomes, there are implications for increased costs. It is worth noting that the difference between higher and lower experience surgeons in terms of total operating time was approaching significance ($p < 0.083$) and represents a 79 minute difference. This has clear efficiency and cost implications, with longer anesthetic time also potentially having clinical implications. FD rate was higher in training cases, but this did not translate into higher operative time. More work is needed to understand expertise, training, and skill acquisition. Our observations provisionally support the previous studies that surgeons performing robotic-assisted radical prostatectomy did not achieve comfort and confidence until after performing more than 250 cases, and physician experience correlated with positive margin status.[20,21] However, this may not be the case moving forward in the future as the vast majority residents get substantial robot console time during their training and many dedicated urology robotic fellowships already exist. Additional studies are needed to compare older generation versus younger generation urologists in terms of robotic surgical skill and efficiency.

Direct observation has advantages over other safety and efficiency metrics but there are limitations.[22,23] The data collection required the utilization of six observers, so it is inevitable that observational variation occurred, even though they demonstrated good inter-rater reliability. A disadvantage of collecting data at this level of detail is the challenge in correlating FDs to long term clinical outcomes, requiring a larger sample size. Nevertheless, our results demonstrate the everyday challenges faced by operating teams in delivering quality robotic care. Many of these have been unrecognized until now.

We identified a range of flow disruptions across the perioperative course of robotic-assisted radical prostatectomy. This reflected problems with coordination, communication, equipment and training, and, by implication, the demands on the operating team. Surgeon experience, resident training, robot model, and patient factors variously affected these disruptions, which also varied across the operation. These findings suggest opportunities to enhance safety, quality, efficiency, and learning associated with surgical robotics. The model championed in Robocare and use of robotic-specific simulation training of technical and non-technical skills development will translate well into compartmentalized modules to help streamline patient care not only during surgery and but also postoperatively. □

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