Review Article

Learning Curve of Robotic Gastrectomy: Lessons and Evidences

Min Seo Kim ,^{1,2} Sungsoo Park ³

¹Korea University College of Medicine, Seoul, Korea

²Cheongsan Public Health Center, Wando, Korea

³Division of Upper Gastrointestinal Surgery, Department of Surgery, Korea University College of Medicine, Seoul, Korea

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Correspondence to

Sungsoo Park

Division of Upper Gastrointestinal Surgery,
Department of Surgery, Korea University Anam
Hospital, Korea University College of Medicine,
73 Incheon-ro, Seongbuk-gu, Seoul 02858,
Korea.

E-mail: kugspss@korea.ac.kr

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ORCID iDs

Min Seo Kim

<https://orcid.org/0000-0003-2115-7835>

Sungsoo Park

<https://orcid.org/0000-0002-1779-8683>

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ABSTRACT

Understanding the etiology of the learning curve and elucidating factors that affect the slope and length of an individual surgeon's learning curve is essential. Cumulative evidence from previous studies and additive insights from the recent learning curve study of multicenter prospective trials has unveiled several valuable findings. Consecutive 10–25 cases are required to reach proficiency level and 88 cases to reach mastery level in robotic gastrectomy (RG). Empirical evidence does not support mandating a requirement for extensive experience performing laparoscopic gastrectomy (LG) prior to the initiation of RG training. The mode of training significantly affects the learning course, and self-learning with a mentoring system is better suited for the learning process of RG than solely relying on proctorship. A stepwise learning curriculum would facilitate novice practitioners in adapting to RG.

Keywords: Robot; Gastrectomy; Learning curve; Training; Stomach cancer

INTRODUCTION

Since robotic-assisted surgery was first approved by the U.S. Food and Drug Administration in 2000, its role has continued to expand in diverse surgical disciplines worldwide, and robotic surgery is now available at most major medical institutions [1]. Robotic surgery has become a standard of care in certain surgical fields such as urology, and robotics has penetrated general oncology fields including gastric cancer [2,3]. According to the U.S. National Cancer Database, the number of robotic gastrectomy (RG) procedures increased 4.4-fold from 2010 to 2014 [3]. The frequency of RG has also increased in East Asia, where the incidence of gastric cancer is high [4,5]. Despite its improved accessibility, RG is restrictively adapted in the oncologic field as cumulative evidence has revealed that RG does not provide better surgical outcomes than laparoscopic gastrectomy [6-8]. This situation is markedly different from the advent of laparoscopic gastrectomy (LG) 2 decades ago, where LG superseded open gastrectomy (OG) given its favorable recovery and surgical outcomes [9-12].

Despite a seeming lack of benefit of RG compared to LG at present, several promising features have led to the retention of robotic-assisted surgery in gastrectomy. Technical support with ergonomically friendly mechanisms [13,14], non-inferior long-term oncologic outcome to LG [15-17], and superior surgical outcome in D2 dissection [18,19] add value to

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RG. Above all, schematic incorporation with an imaging and navigating system is a unique strength of robotic surgery with a promising potential. The image data acquired through preoperative endoscopic, radiologic, and pathologic assessments and computed tomography (CT) or magnetic resonance imaging (MRI) can be incorporated into the surgeon's viewing console, while augmented reality (AR) could help a surgeon navigate a case-specific surgery [20-22]. Although high cost is still an issue for robotic surgery, the price is expected to reduce as the industry competes to invent alternative robotic systems [20]. Hence, the overall benefit and safety profile of RG is expected to outweigh the expenses at some point in future.

To prepare for the boom in the upcoming robotic surgery era, enhancing the accessibility of robotic platforms to surgeons by introducing high-quality learning opportunities and developing structured training would be crucial steps. In fact, previous studies have shown a relatively shorter learning curve for RG than for LG, with about 10–20 cases required to reach proficiency level in a group of surgeons [23-25]. However, the surgical community not only wants to know how many cases does it take to gain proficiency in general but also wants to know what factors determine the slope and length of a surgeon's learning curve. This has important implications for stratifying surgeons into training programs and creating more robust training models to minimize the on-patient learning curves. Recently, our learning curve study on RG has reported several novel factors differentiating the learning curve of individual surgeons and unveiled numerous insights that might help construct well-designed training opportunities [26]. In this review, we have summarized the current evidence on the learning curve for RG and introduced the latest findings.

METHODS

We searched and reviewed articles evaluating the learning curve and cumulative experiences with RG. All the reviewed articles were written in English and published between December 2003 and March 2020.

LEARNING CURVE METHODOLOGY

The conventional method of analyzing the learning curve for surgical performance primarily relies on the operation time and considers the learning curve accomplished when the operation time is stabilized. Previous studies that performed learning curve analysis for RG employed such a methodology and reported that 10–20 consecutive cases were needed to overcome the learning phase in terms of operation time [23,24,27]. Their results are consistent in terms of the number of cases to reach the proficiency, and using operation time as a proxy for the learning of RG seems reliable. However, using operation time as the primary endpoint of the learning curve may involve bias where short operation time resulting in poor surgical outcomes would still be considered a marker of proficiency. Analyzing surgical outcomes rather than operation time for the learning curve would be clinically relevant and even ideal.

Before the use of cumulative sum (CUSUM) analysis to assess surgical performance, which was formerly used for quality control of manufactured products in the industry [28,29], there were limited methods to incorporate binary outcomes such as complication rate into the function and algorithm of learning curve analysis. However, as the CUSUM method allowed

the use of binary data as endpoint outcome, obtaining the learning curve with important surgical outcomes such as complication rate [26,30], open conversion [31,32], and survival rate [33] become possible. The CUSUM method can be used with continuous variables as well such as operation time [24,31,34,35] and blood loss [31]; this further renders CUSUM analysis highly flexible and usable in learning curve analysis. Our recent study used CUSUM analysis and depicted the first complication learning curve for RG [26]. Such an approach minimized the effect of “short operation time-poor surgical performance” bias and enabled us to focus on the proficiency that represents the true manageability of case complexity and technical maturity.

MULTIPHASIC LEARNING CURVE: THE INITIAL LEARNING PHASE, PROFICIENCY PHASE, REBOUND PHASE, AND MASTERY PHASE

The learning curve of RG depicts a multiphasic pattern (**Fig. 1**) [24,26]. Operation time and complication rate do not continuously reduce during consecutive cases, but they fluctuate until surgeons finally reach the mastery level [26]. Most of the previous learning curve studies have consistently indicated that approximately 10–25 consecutive cases are required to achieve proficiency level, warranting stabilized operation time [23,24,26,27] and low complication rate [26]. In addition, a recent study has examined the mastery level in RG by subdividing the measure of learning phases with complication rate [26]; the initial learning phase (1–25 cases, complication rate [CD $\geq$ grade II]: 20%), proficiency phase (26–65 cases, complication rate [CD $\geq$ grade II]: 10%), rebound phase (66–88 cases, complication rate [CD $\geq$ grade II]: 26.1%), and mastery phase (89–125 cases, complication rate [CD $\geq$ grade II]: 6.4%) were identified.

Fig. 1. The comprehensive learning curve of robotic gastrectomy. The X-axis indicates the percent (%) progression of the learning process, and the Y-axis indicates the relative change of surgical outcomes (complication rate and operation time) from the initial learning phase. The horizontal lines represent the average complication rate and operation time of the individual learning phase.

The rebound phase is a key step that involves many implications and lessons in understanding the etiology of the learning curve of RG. Surgical outcomes paradoxically begin to deflate at 66 cases after a long stable period of having reached the proficiency level (26–65 cases) [26]. The moderate and major complication outcome in this period is worse than that of the initial cases (1–25 cases, initial learning phase). The extension of indications and increased attempts at a technically demanding procedure may explain this rebound phase [26]. Surgeons are careful with patient selection in their initial experiences with RG. However, as they get accustomed to robotic platforms and gain confidence from stress-free cases and stabilized surgical outcomes, they begin to extend surgical indication to more complicated cases such as obese elderly cases [26]. Moreover, the frequency of demanding and stressful procedures of the full intra-corporeal approach paired with D2 dissection is considerably increased in this period [26].

The moderate and major complication rates eventually subside to 6.4% and 2.7%, respectively, after approximately 20 serial cases of experience in the rebound phase and the surgeons subsequently enter the mastery phase [26]. The key difference between the proficiency and mastery phases would be the manageability of high case complexity and technical maturity. Since the rebound phase is placed between the proficiency and mastery phases, understanding the etiology of the rebound phase and reflecting such learning dynamics into training programs or curriculum is crucial.

IMPACT OF PREVIOUS EXPERIENCES ON LAPAROSCOPIC GASTRECTOMY

How previous experience in laparoscopic surgery affects the learning curve of robotic surgery has been a longstanding question in diverse surgical disciplines. Studies from the field of urology and colorectal surgery suggest that robotic surgery can be easily adopted by surgeons with extensive experience in laparoscopic surgery [36,37]. However, this does not hold true for RG as cumulative studies have revealed that the learning of RG does not necessarily require extensive prior experience in LG [23,26,27]. Park et al. [23] have reported that while the degree of reduction in the operation time is the largest for a surgeon with extensive laparoscopy experience, the number of cases to reach the stabilization point is smaller and time to overcome the learning curve is shorter for surgeons with less experience. A recent study has also revealed that surgeons with more experience in LG ironically take more time to reach the proficiency level in RG, perhaps because of difficulties in reorganizing a familiar procedure into a new procedure [26]. Although extensive LG experience is not a prerequisite for RG, solid experience in open surgery has proved to be helpful [27], while familiarization with the laparoscopic surgery algorithm may make it easier to operate robotic systems since the two techniques share many handling maneuvers and procedures. Therefore, experience with open gastrectomy as well as LG to overcome the initial learning curve might constitute the basis for novice surgeons to initiate RG training.

TRAINING FOR ROBOTIC GASTRECTOMY

Currently, there are numerous modes of training that can facilitate novice surgeons to acquire robotic skills such as proctorship, mentoring, dry lab, animal training, and simulator-based virtual training [36]. These modes of training are well integrated into a training program and

provide as a structured curriculum for robotic urology [36], but such a structured learning scheme is lacking in the field of RG. The development of a training program should be an evidence-based process. However, collective knowledge on the etiology of the learning curve and effectiveness of each training mode on surgical outcomes of RG has not been sufficiently accumulated. To address this shortcoming, we collected the training experience of five surgeons and reported the influence of training mode on their learning curves [26].

Mentoring (lectures, standardized laboratory training with videotape analysis, and case observation) helped surgeons to shorten their complication learning curves, while proctorship did not [26]. This may imply that encouraging self-learning is a vital element in shortening the learning curve for RG. The study also noted that surgeons who started with mentoring (self-learning through online and laboratory training) overcame the learning curve more promptly than surgeons who skipped the extensive self-learning process and began with proctorship. The results suggest that RG should be learned in a step-by-step curriculum—stepwise initiation with self-learning, lecture, dry lab assistance, and subsequently, experience in the operation room with proctorship.

COMPARISON OF LEARNING CURVES OF ROBOTIC SURGERY AMONG SURGICAL SPECIALTIES

Table 1 shows all available studies investigating the CUSUM-based learning curves of surgeons performing robotic surgery across different surgical disciplines including robotic gastrectomy [26], robot-assisted Roux-en-Y gastric bypass [38], robotic segmentectomy [39], robotic colectomy [40], robotic distal pancreatectomy [41], robotic transabdominal preperitoneal ventral hernia repair [42], robot-assisted kidney transplantation [43], robotic thyroidectomy [44], robotic esophagectomy [45], robotic sacrocolpopexy [46], and robotic low anterior resection [47]. Learning curves were drawn using operation time or surgical performance (i.e., surgical outcome and postoperative complication rate) as the measure of surgeon proficiency. The operation time and surgical performance learning curves showed different patterns; specifically, it usually required more cases to reach surgical performance proficiency than to reach stable operation time.

Robotic abdominal surgeries, including robotic gastrectomy, require approximately 20–50 cases for surgeons to attain proficiency, while other surgical disciplines performed in

Table 1. Summary of CUSUM learning curves of different robotic surgery disciplines with at least 60 cases

Field	Operation	No. of cases (range) required to achieve stable operation time	No. of cases (range) required to achieve adequate surgical performance*
Abdominal surgery	Robotic gastrectomy [26]	20–30	20–30 (proficiency), 80–90 (mastery)
	Robotic assisted Roux-en-Y gastric bypass [38]	40–50	-
	Robotic segmentectomy [39]	20	40–50
	Robotic colectomy [40]	25–30	25–30
	Robotic distal pancreatectomy [41]	40	-
Peritoneal surgery	Robotic transabdominal preperitoneal ventral hernia repair [42]	40–50	60
Transplantation	Robot-assisted kidney transplantation [43]	-	30–40
Thyroid surgery	Robotic thyroidectomy [44]	50	70–80
Esophageal surgery	Robotic esophagectomy [45]	-	80
Urologic surgery	Robotic sacrocolpopexy [46]	60	80–90
Rectal surgery	Robotic low anterior resection [47]	40–50	70–80

CUSUM = cumulative sum.

*Adequate surgical performance is defined as a satisfactory surgical outcome or sufficiently low postoperative complication rate.

narrower anatomical spaces (e.g., esophageal, urologic, rectal) require more than 70–80 cases to attain tolerable surgical performance (**Table 1**). This tendency may imply that the degree of freedom for maneuvering afforded by the anatomic space in which the surgery is performed may affect the learning curve for robotic surgery, while spatial availability might be inversely associated with learning curve length. It may take fewer cases to reach the proficiency level at which a surgeon is able to perform sound abdominal surgery using the robot, but the flexible and spacious abdominal cavity might dispel the unique strength of a robotic surgical system, i.e., the greater maneuverability in limited space provided by the multiple joints of the surgical robots' arms. This may partially explain the longstanding predominance of laparoscopic surgery over robotic surgery for gastrectomy.

CONCLUSION

The current review addressed the basic etiology of learning curve of RG and diverse factors determining the slope and length of a surgeon's learning curve. Consecutive 10–25 cases are required to reach proficiency level and 88 cases to reach mastery level in performing RG. The mode of training significantly affects the learning course. Promoting self-learning with the mentoring system would be better suited for the learning process of RG than solely relying on proctorship. A stepwise learning curriculum would facilitate novice practitioners to adapt to RG.

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