Objective Assessment of the Early Stages of the Learning Curve for the Senhance Surgical Robotic System

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OBJECTIVE: The purpose of this research is to study the early stages of the Senhance learning curve to report how force feedback impacts learning rate. This serves as an exploratory investigation into assumptions that fellows and faculty will adjust faster to the Senhance in comparison with residents, and that force feedback will not hinder skill acquisition.

DESIGN: In this study, participants completed the peg transfer and precision cutting task from the Fundamentals of Laparoscopic Surgery (FLS) manual skills assessment five times each using the Senhance while instrument motion was tracked.

SETTING: This study took place in the Surgical Education and Activities Laboratory at Duke University Medical Center.

PARTICIPANTS: Participants for this study were residents, fellows, and faculty from Duke University Medical Center in general surgery and gynecology specialties ($N = 16$).

RESULTS: Postulated linear mixed effects models with participant level random effects showed significant improvement with additional attempts for the peg transfer task after adjusting for surgical experience and force feedback respectively for the primary FLS score metric. The secondary metric of total instrument path length also showed improvement (significant decreases) in path length with additional attempts after respectively adjusting for surgical experience and force feedback.

CONCLUSIONS: This study investigates the early stages of the learning curve of the Senhance. Exploratory modeling indicates that residents, fellows, and faculty surgeons rapidly adapt to the controls of the Senhance regardless of experience level and force feedback engagement. The results from this study may serve as motivation for future prospective studies that achieve sufficient statistical power with a larger sample size and strict experimental design. (J Surg Ed 76:201−214. © 2018 Association of Program Directors in Surgery. Published by Elsevier Inc. All rights reserved.)

KEY WORDS: Fundamentals of Laparoscopic Surgery, Learning Curve, Motion Tracking, Robotic Surgery, Surgical Skill Transfer

COMPETENCIES: Practice-Based Learning and Improvement, Systems-Based Practice, Medical Knowledge

INTRODUCTION

Advances in laparoscopic surgery have greatly impacted how some general surgery, gynecologic, cardiothoracic, colorectal, and urologic procedures are performed. The benefits of laparoscopic surgery are well-documented as patients experience less post-operative pain, faster recovery, lower morbidity rates, and less trauma in comparison with open surgery.[1-4] However, there are several challenges the surgeon faces during laparoscopic surgery, including poor depth perception, challenging camera control, fewer degrees of freedom, poor ergonomics, and amplified tremors.[2,5-7] Surgical robots have aimed to assist with some of these issues by adapting 3D capable cameras, motion scaling, seated surgeon consoles for better ergonomics, and tremor dampening. Problems, including the lack of haptic feedback, still exist in commercial robots approved for use in the United States; however, a robot with force feedback technology, the Senhance Surgical Robotic System (TransEnterix, Inc., Morrisville, NC), is being used clinically in Europe and has recently been approved for clinical use in the United States.[8,9]

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 1931-7204/$30.00 https://doi.org/10.1016/j.jsurg.2018.06.026

Laparoscopic skills are amongst the most challenging to learn and develop for surgical trainees.[10,11] The transition from open surgery to laparoscopic surgery skills can be daunting as varying sensory cues are required due to a lack of depth perception and tactile feedback, as well as poor posture. Although there are set curriculums such as the Fundamentals of Laparoscopic Surgery (FLS) through the Society of American Gastrointestinal and Endoscopic Surgeons for conventional laparoscopic surgery, training for current surgical robots varies widely across medical centers. The Senhance mimics laparoscopic surgical motions, making the manual skills portion of the FLS an ideal curriculum for training on this robotic system.

Modern surgical training programs have moved from the traditional Halstedian model[12] to more data-driven, objective methods. Prior surgical training studies have made cases for more objective means of evaluating surgeon trainees.[5,13-16] One studied method for objectively critiquing surgical proficiency has been economy of motion through motion tracking of instruments to understand path length and smoothness.[17] Fard et al.[18] examined speed and smoothness of surgical instrument movements from a suturing task using a da Vinci Surgical System (Intuitive Surgical, Inc., Sunnyvale, CA), to train two classification algorithms: logistic regression and support vector machine. Using kinematic features, Fard et al. were able to distinguish between novice and expert surgeons with high classification accuracies. Novice surgeons have been shown to have greater path lengths in comparison to expert surgeons prior to robot training but quickly adapt and decrease path length in as few as 10 trials at pick and place, needle driving, and suturing tasks.[19] Other studies have shown that instrument and manipulator path lengths decrease with training in as few as five attempts at a surgical task.[20] Objective measures for proficiency, such as FLS scores and instrument motion tracking, have yet to be implemented as evaluative metrics for the Senhance.

The Senhance received its CE (European Conformity) marking in 2012, permitting its use in European hospitals. Researchers and clinicians in Europe have observed procedural-based learning curves for terms of operation time for hysterectomy, adnexal surgery, and pelvic lymphadenectomy. A significant decrease in operative time for hysterectomy and adnexal surgery between the range of 60−80 cases was found in Fanfani et al.[21] Although it is important to report surgeon performance in the operating room, it is necessary to first demonstrate surgeon proficiency on the Senhance using benchmarked laparoscopic tasks, such as the manual skills curriculum from the FLS. FLS manual skills are the ideal testbed for the Senhance since laparoscopic motions are used for controlling instruments.

The aim of this study was to establish a foundation for understanding the early stages of the learning curve of the Senhance for residents, fellows, and faculty surgeons. The force feedback capability was studied to motivate questions regarding the effect that the feature has on the rate of learning due to sensory overload. The primary metric of performance was the standardized FLS score for both tasks. In addition, we investigated how total path length of instruments correlate to FLS scores and whether the two measures are monotonically related for users of the Senhance.

MATERIALS AND METHODS

This study was approved by the Institutional Review Board at Duke University Medical Center. All experimental sessions occurred in the Surgical Education and Activities Lab at Duke University Medical Center, and subjects were recruited via email from Duke Medical Center and ranged in experiences from intern to faculty surgeon.

Study Participants

A total of 16 participants responded to a recruitment e-mail from Duke University Medical Center. The median age of the cohort was 33.5 years (interquartile range: 31−36.2), and the majority of the participants were male (68.8%). Ten of the participants were residents (62.5%), and the rest were either fellows or faculty. The majority of the participants were right hand dominant (75.0%), and the cohort had a median of 11 laparoscopic surgery cases performed per month (interquartile range: 5−20). Half of the participants were randomized to "disengaged" force feedback and completed the peg transfer and precision cutting tasks without haptic assistance, while the other half of participants completed the tasks with the force feedback capability engaged. Complete participant information is shown below in Table 1.

Senhance Surgical Robotic System

The Senhance Surgical Robotic System, previously known as the Telelap ALF-X,[8] was developed by a robotics division at SOFAR S.p.A., an Italian pharmaceutical company, in collaboration with the European Commission's Joint Research Centre.[22] The Senhance was acquired by TransEnterix, Inc. in the Fall of 2015 and in October 2017 received Food and Drug Administration 510(k) clearance for clinical use in United States hospitals. The Senhance maintains robot-assisted laparoscopic capabilities including 3D vision, tremor filtering, seated ergonomics, and instrument clutching for improved dexterity.[23] Additional features novel to robotic-assisted laparoscopic surgery include camera movement via eye tracking, force feedback from the instruments to the surgeon manipulators, four separate, exchangeable instrument arms with individual mobile bases, trocar fulcrum detection and reusable

TABLE 1. Subject Baseline Characteristics

	Total (N = 16)
Age, Median (IQR)	33.5 (31–36.2)
Range	28–48
Gender (Male)	11 (68.8%)
Surgical Experience	
Resident	10 (62.5%)
Fellow/Faculty	6 (37.5%)
Number of Laparoscopic Surgery Cases Per Month, Median (IQR)	11 (5–20)
Range	0–30
Dexterity	
Left/Ambidextrous	4 (25.0%)
Right	12 (75.0%)

instruments that do not have a predetermined limited number of uses.[8,22-24]

Tasks

Two tasks based on the laparoscopic surgery (FLS) manual skills assessment were used for evaluating the early stages of the learning curve for the Senhance.[7,25,26] FLS assesses and critiques the psychomotor abilities that are necessary for laparoscopic surgery.[26] Trainees have been historically evaluated on time and precision (number of errors made) metrics; however, economy of motion has been gaining interest, particularly for robotic-assisted surgery.[2,14,17,27,28] For this study, FLS scoring was measured using the below equation,

$$Score_{FLS} = Time_{max} - Time_{taken} - Errors \tag{1}$$

where $Score_{FLS}$ is the standardized FLS score, $Time_{max}$ is the maximum amount of time (seconds) allowed for each task, $Time_{taken}$ is the total time taken (seconds) to complete the task, and $Errors$ are precision measures that vary between tasks.[7,29] Economy of motion was measured using total path length from both instruments to determine if the metric is monotonically correlated with calculated FLS Scores.

The peg transfer task was performed in concordance with FLS standards. Penalties were assessed for objects that were dropped outside the field of view or outside the Senhance joint limits. The penalty score for the peg transfer task was calculated as the percent of objects that fell outside of the field of view and were not able to be retrieved. The maximum time permitted for this task was 300 seconds. Eq. (2) gives an adaptation of (1) to the peg transfer task.

$$Score_{FLS,\ peg} = 300 - Time_{taken,\ peg\ transfer} - 100 * \frac{Number\ of\ Objects\ Not\ Transferred}{Total\ Number\ of\ Objects} \tag{2}$$

Similarly, the precision cutting task was performed in line with FLS instructions. However, the FLS training gauze was used for the first four attempts which consists of two concentric circles compared with the single circle utilized for testing. For the final attempt, the FLS single circle gauze was used in which subjects were instructed to cut along the marked circumference of the circle. The change from the two circle training gauze in the first four attempts to the single circle gauze on the fifth attempt was used to emulate training for the precision cutting task as surgical trainees are only permitted to use the single circle gauze during the exam. The maximum time permitted for this task was 300 seconds. A digital single-lens reflex camera, placed at a fixed distance above a table, was used to take images of each gauze after it was cut. Images were then uploaded to Adobe Photoshop CC 2015 (Adobe Systems Inc., San Jose, CA), and the deviated area (number of pixels) was measured using the lasso tool. Penalties were calculated as the percent area cut that deviated from the gap between circles for the first four attempts, and were calculated as the percent area cut that deviated from the marked circumference on the single circle gauze in the final attempt. Eq. (3) gives an adaptation of (1) to the peg transfer task.

$$Score_{FLS,cut} = 300 - Time_{taken,\ precision\ cutting} - 100 * \frac{Deviation\ from\ Circle\ Area}{Circle\ Area} \tag{3}$$

Experiment Design

Subjects were randomly assigned to complete the experiment with force feedback capabilities from the Senhance engaged or disengaged. Force feedback randomization was initially balanced within surgical experience groups. Each subject was instructed on how the system operates and were allowed to adjust the Senhance chair for ergonomic purposes but not told about


(a)

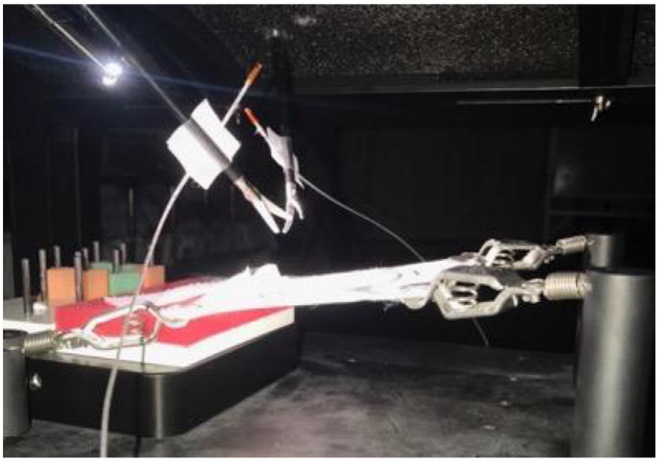

(b)

FIGURE 1. (a) Experimental setup showing the Senhance arms and surgeon console. Three arms were used for this study with two holding instruments and one holding the endoscopic camera. Instruments are inserted through trocars that have been inserted into ports on a training dome. (b) trakSTAR Model 180 motion tracking sensors are affixed 1 inch (2.54 cm) above the tip of the instrument and aligned 1 inch (2.54 cm) away from the instrument shaft to reduce metallic distortion.

TABLE 2. Linear Estimates and 95% Confidence Intervals for Fixed Effects When Modeling "Attempt Number" and "Surgical Experience" on FLS Scores for Both Tasks

	Estimate	95% Confidence Interval	*T*-statistic	p-value
Peg Transfer				
Intercept	16.03	(−12.14, 44.20)	1.09	0.28
Surgical Experience	36.88	(−9.12, 82.88)	1.54	0.13
Attempt Number	**20.12**	**(14.34, 25.89)**	**6.82**	<**0.001**
Surgical Experience*Attempt Number	2.53	(−6.91, 11.96)	0.53	0.60
Precision Cutting				
Intercept	**49.22**	**(9.63, 88.80)**	**2.38**	**0.02**
Surgical Experience	26.36	(34.11, 86.83)	0.83	0.41
Attempt Number	6.65	(−4.06, 17.36)	1.22	0.23
Surgical Experience*Attempt Number	3.48	(−12.88, 19.84)	0.42	0.68

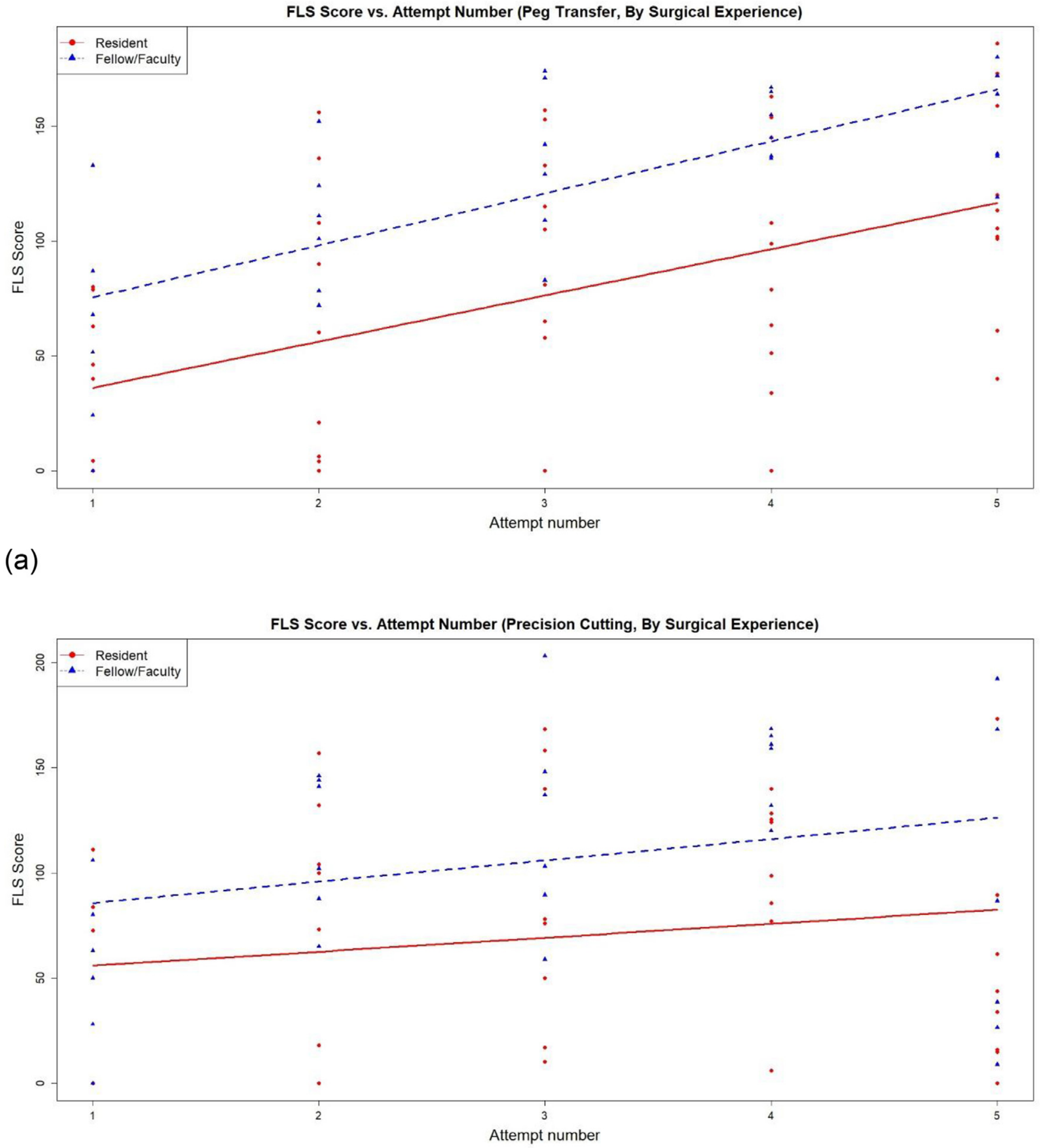


FIGURE 2. FLS score vs. attempt number for the (a) Peg transfer task and (b) Precision cutting task, grouped by surgical experience.

the force feedback capability (Fig. 1 (a)). Subjects were given the ability to control two Senhance robotic arms equipped with surgical instruments assigned for each task, but the third arm, which held the endoscopic camera, remained fixed to emulate conventional FLS procedures. As the camera was static, the eye tracking capability was not used as a parameter in this study.

Subjects were assigned to start with the peg transfer or precision cutting task based on a random number generator. Each subject completed four training repetitions of the task. For the fifth attempt, subjects were first read the formal FLS script and informed of the cutoff time. They were also informed that they were being evaluated on this fifth, and final attempt, based on FLS standards.

Surgical instruments were equipped with Model 180 trakSTAR electromagnetic motion tracking sensors (Ascension Technology Corporation, Northern Digital, Inc., Shelburne, VT). Sensors were offset 1 inch (2.54 cm) from the tip and 1 inch (2.54 cm) away from the instrument shaft such that metallic distortion would be minimized (Fig. 1 (b)). Data from the sensors was initially passed through an adaptive low-pass filter to

TABLE 3. Linear Estimates and 95% Confidence Intervals for Fixed Effects when Modeling "Attempt Number" and "Force Feedback" on FLS Scores for Both Tasks.

	Estimate	95% Confidence Interval	*T*-statistic	p-value
Peg Transfer				
Intercept	18.65	(−16.15, 53.44)	1.03	0.31
Force Feedback	22.43	(−26.77, 71.63)	0.88	0.39
Attempt Number	**22.35**	**(15.89, 28.80)**	**6.78**	<**0.001**
Force Feedback*Attempt Number	−2.56	(−11.70, 6.57)	−0.55	0.59
Precision Cutting				
Intercept	**76.23**	**(28.50, 123.95)**	**3.05**	**0.004**
Force Feedback	−27.50	(−90.63, 35.64)	−0.83	0.41
Attempt Number	1.98	(−10.21, 14.18)	0.32	0.75
Force Feedback*Attempt Number	10.77	(−5.36, 26.90)	1.31	0.20

eliminate any high frequency noise from electrical sources in the instrument surroundings. For analytical preparation, the Cartesian points and time stamps collected were further filtered using MATLAB 2017a (MathWorks, Inc., Natick, MA). The points were passed through an outlier detection algorithm that flagged points falling outside of the laparoscopic trainer box. These points were treated as noise and eliminated since the instruments could not reach those positions. Data were then smoothed using a moving average filter, and total path length was then calculated by summing each of the segments from the sampled points.

Statistical Analysis

For each task, linear mixed effects models were postulated to evaluate the effect of surgeon experience and force feedback respectively on outcome variables (FLS score and path length) as a function of the number of attempts. Subjects were taken as a random effect to account for repeated measures on the same subject. Interaction terms were included to assess the presence of a difference between the fit curves. In addition, Spearman's rank-order correlation was performed to analyze the relationship between FLS scores and total instrument path lengths. In all cases, the threshold for assessing statistical significance was set at the alpha = 0.05 level. Analyses were conducted using R version 3.4.3 (Vienna, Austria).

RESULTS

Fourteen subjects were able to successfully complete both the peg transfer and the precision cutting task within the allotted time. Two resident subjects with force feedback disengaged did not complete the precision cutting task. A Mann-Whitney U-Test of the subject survey data revealed that subjects from the fellow/faculty cohort had a statistically greater laparoscopic surgery case volume per month than subjects from the resident cohort ($p < 0.05$). On average, learning curves indicate improvement with additional attempts after respectively adjusting for surgical experience (resident vs. fellow/faculty) or force feedback (disengaged vs. engaged). The primary metric of success used for this study was the FLS Score as this measure is standardized across the tasks used. Total instrument path length was taken as a secondary metric and was tested alongside FLS Scores to determine if the two measures were correlated. It was hypothesized that FLS Score and total instrument path length was linearly correlated based on evidence of prior studies. This hypothesis was tested by conducting a Spearman's rank-order correlation test between the two metrics.

FLS Scores

To assess whether the pattern of change in FLS score across attempts differed between the different surgical experience groups for each task, a mixed effects model was postulated. Table 2 shows the relevant regression fixed effects estimates with corresponding p-values for the peg transfer task. In this model, after adjusting for random individual effects, the intercept represents the estimate of the average FLS score in the "resident" surgical experience group at baseline. The surgical experience estimate gives the change in FLS score when comparing the average FLS score in the "fellow/faculty" surgical experience group to the "resident" surgical experience group at baseline. The attempt number estimate gives the average change in FLS score for an additional task attempt in the "resident" surgical experience group. The "surgical experience*attempt number" estimate describes the additional change in FLS score for an additional task attempt when comparing the "fellow/faculty" surgical experience group to the "resident' surgical experience group.

For the peg transfer task, "attempt number" was the only fixed covariate associated with a significant p-value

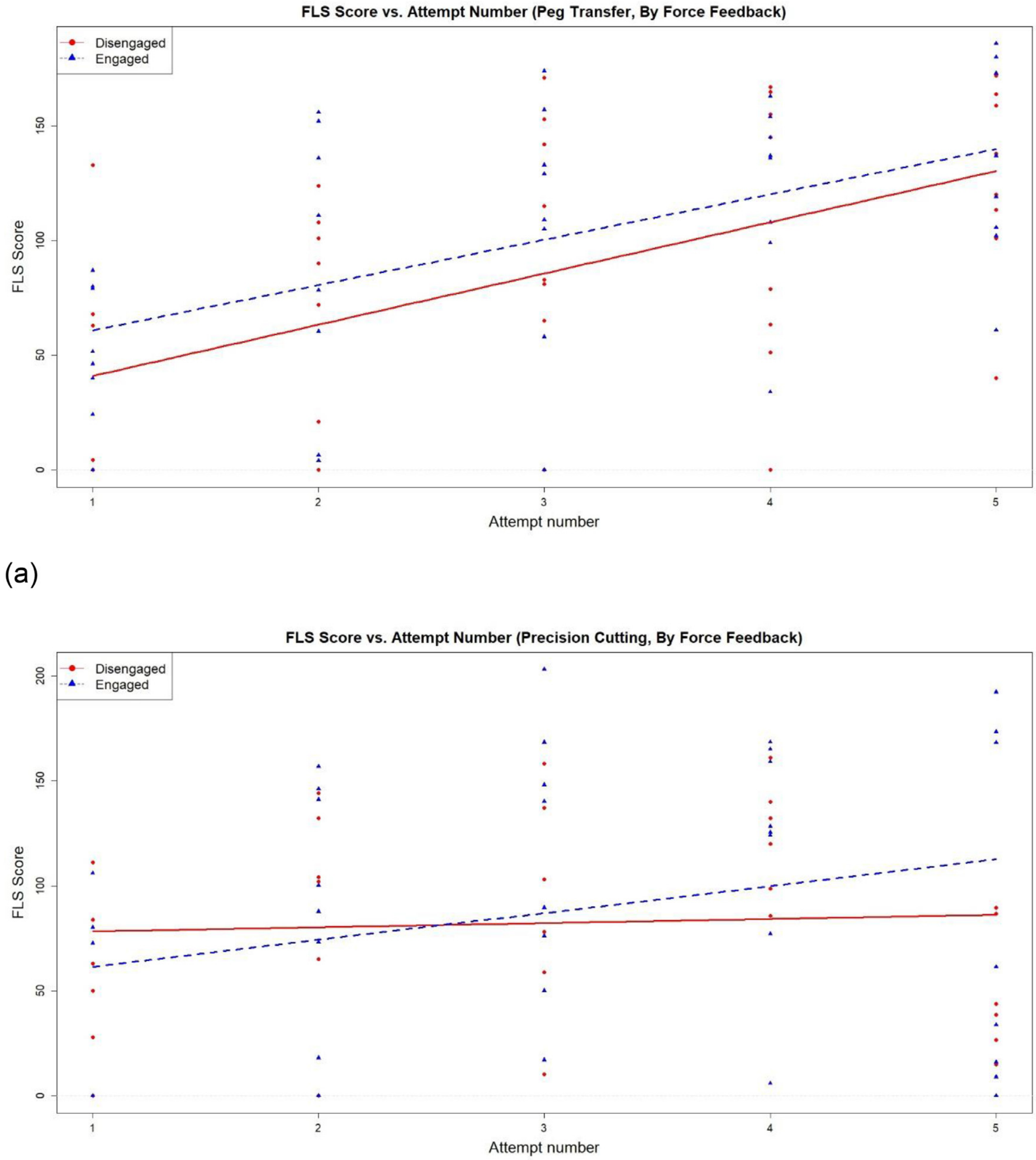


FIGURE 3. FLS score vs. attempt number for the (a) Peg transfer task and (b) Precision cutting task, grouped by force feedback groups.

($p < 0.001$), indicating that learning improved (a 20.12 average increase in FLS score with each additional attempt). Non-significant p-values for the remaining variables suggest that baseline FLS scores, and the rate of learning may not differ statistically between the surgical experience groups. A graphical representation is shown in Fig. 2(a).

A similar analysis was completed for testing the linearity for the precision cutting task (Table 2). In this model, none of the variables of interest were associated with significant p-values; this indicates that the FLS score might not change significantly with successive attempts for this task. It also demonstrates that for the precision cutting task, baseline FLS scores, and the rate of learning may not differ statistically between the surgical experience groups. A graphical representation is shown in Fig. 2(b).

To investigate if the pattern of change in FLS score across attempts differed for the force feedback feature,

TABLE 4. Linear Estimates and 95% Confidence Intervals for Fixed Effects when Modeling "Attempt Number" and "Surgical Experience" on Path Length in Centimeters for Both Tasks.

	Estimate	95% Confidence Interval	*T*-statistic	p-value
Peg Transfer				
Intercept	**3709.81**	**(2942.81, 4477.47)**	**9.27**	**<0.001**
Surgical Experience	**−1359.02**	**(−2607.31, −111.42)**	**−2.09**	**0.04**
Attempt Number	**−338.13**	**(−500.33, −175.03)**	**−4.07**	**<0.001**
Surgical Experience*Attempt Number	243.79	(−21.24, 507.94)	1.80	0.08
Precision Cutting				
Intercept	**2905.45**	**(2320.53, 3490.37)**	**9.49**	**<0.001**
Surgical Experience	−215.82	(−1109.29, 677.66)	−0.46	0.65
Attempt Number	**−174.03**	**(−310.84, −37.22)**	**−2.49**	**0.02**
Surgical Experience*Attempt Number	−89.64	(−298.62, 119.34)	−0.84	0.40

the surgical experience variable is replaced in the previous mixed effects linear regression model. Table 3 shows the results for the peg transfer task after adjusting for random individual effects, where the intercept now represents the estimate of the average FLS score when the force feedback feature is "disengaged" at baseline. The force feedback estimate gives the change in FLS score when comparing the average FLS score in the "engaged" force feedback group to the "disengaged" force feedback group at baseline. The attempt number estimate gives the average change in FLS score for an additional task attempt in the "disengaged" force feedback group. The "force feedback*attempt number" estimate describes the additional change in FLS score for an additional task attempt when comparing the "engaged" force feedback group to the "disengaged" force feedback group.

Similar to the results in Table 2, for the peg transfer task, "attempt number" was the only fixed covariate associated with a significant p-value ($p < 0.001$), showing that learning improved (a 22.35 average increase in FLS score with each additional attempt). Non-significant p-values for the remaining variables suggest that baseline FLS scores, and the rate of learning may not differ statistically between the force feedback groups. A graphical representation is shown in Fig. 3(a).

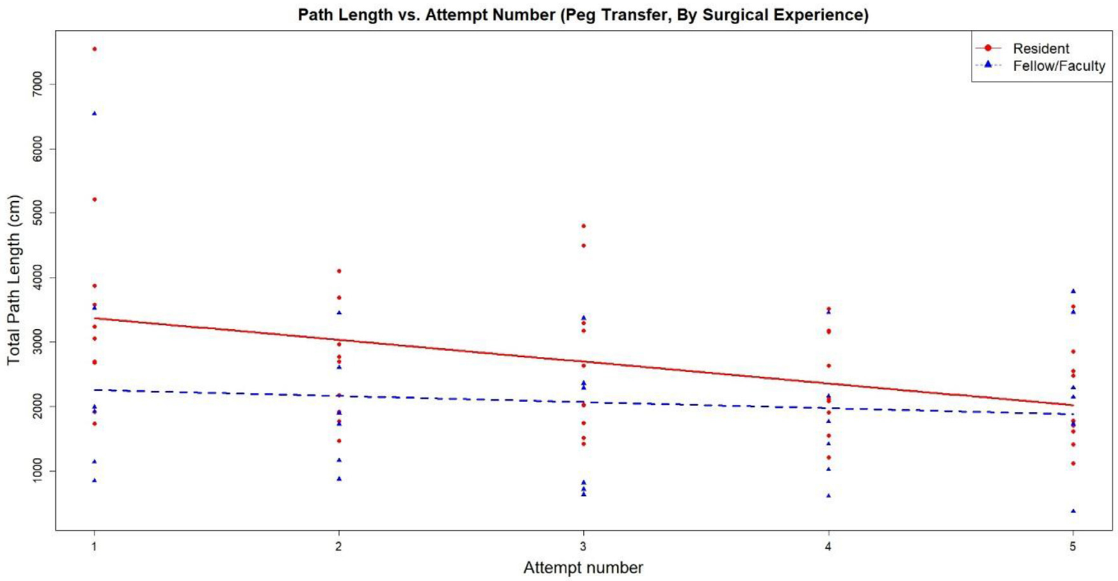
None of the variables of interest in this model for the precision cutting task were associated with significant p-values (Table 3); this indicated that the FLS score may not change significantly with successive attempts for this task. It also implied that for the precision cutting task, baseline FLS scores, and the rate of learning may not differ statistically between the force feedback groups. A graphical representation is shown in Fig. 3(b).

Total Instrument Path Length

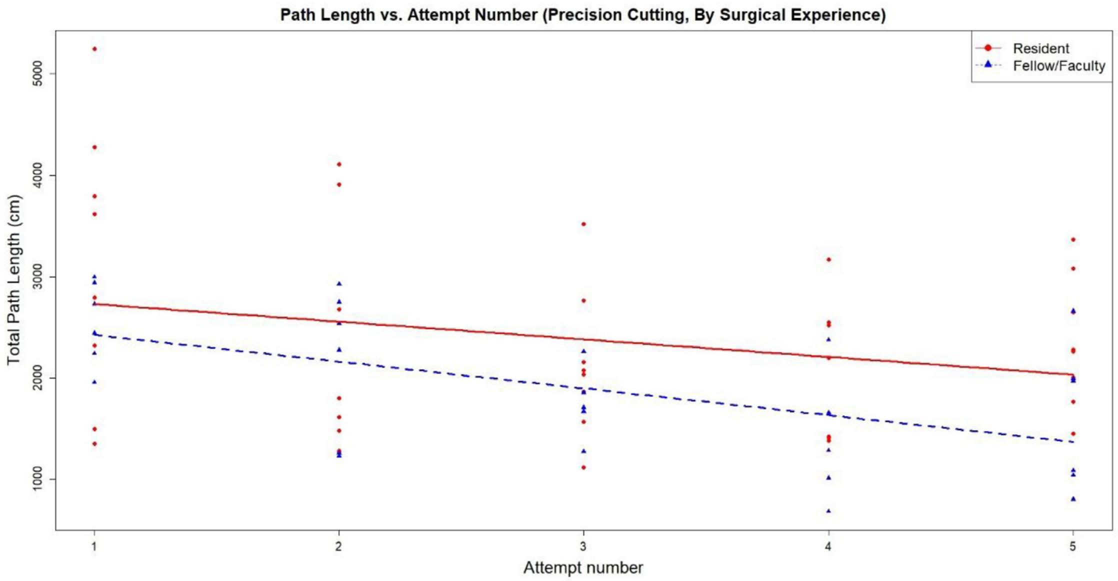
The respective set of covariates in the four previous mixed effects models were also regressed on path length, the secondary outcome of interest. Table 4 examines whether the pattern of change in path length across attempts differed between the different surgical experience groups for the peg transfer task. Here, the fixed "surgical experience" and "attempt number" covariates are associated with significant p-values. This indicates that the "fellow/faculty" surgical experience group had a 1359.02 cm decrease in mean path length at baseline compared with the "resident" surgical experience group, and that learning improved with attempt number; there is a 338.13 cm decrease in path length with each additional attempt. A non-significant p-value for the "surgical experience*attempt number" interaction term ($p = 0.08$) indicates that the rate of learning may not differ statistically between the surgical experience groups. A graphical representation is shown in Fig. 4(a).

Linear mixed effects results for the precision cutting task can also be found in Table 4 for "attempt number" and "surgical experience." Here, "attempt number" is the only fixed covariate of interest associated with a significant p-value ($p = 0.02$). This indicates that learning improved (a 174.03 average centimeter decrease in path length with each additional attempt). Non-significant p-values for the remaining variables of interest indicate that baseline path lengths and the rate of learning may not differ statistically between the surgical experience groups. A graphical representation is shown in Fig. 4(b).

Table 5 examines if the pattern of change in path length across attempts differed for the force feedback feature after adjusting for random individual effects. Similar to the results in Table 4 for peg transfer, "attempt number" is the only fixed covariate of interest associated with a significant p-value ($p = 0.002$), showing that learning improved (a 307.29 average centimeter decrease in path length with each additional attempt). Non-significant p-values for the remaining variables of interest indicate that baseline path lengths, and the rate of learning may not differ statistically between the force feedback groups. A graphical representation is shown in Fig. 5(a).



(a)



(b)

FIGURE 4. . Path length vs. attempt number for the (a) Peg transfer task and (b) Precision cutting task, grouped by surgical experience.

For the precision cutting task, Table 5 indicates that "attempt number" is the only fixed covariate of interest associated with a significant p-value ($p = 0.04$), showing that learning improved (a 171.51 average centimeter decrease in path length with each additional attempt). Non-significant p-values for the remaining variables of interest indicate that baseline path lengths, and the rate of learning may not differ statistically between the force feedback groups. A graphical representation is shown in Fig. 5(b).

Results between the FLS Scores and total instrument path length metrics seemed to correspond both quantitatively and visually. For statistical analysis, Spearman's rank-order correlation was used for determining monotonic dependence between total path lengths of the instruments and FLS scores (Table 6). For the peg

TABLE 5. Linear Estimates and 95% Confidence Intervals for Fixed Effects When Modeling "Attempt Number" and "Force Feedback" on Path Length in Centimeters for Both Tasks

	Estimate	95% Confidence Interval	*T*-statistic	p-value
Peg Transfer				
Intercept	**3209.59**	**(2333.59, 4085.48)**	**7.03**	<**0.001**
Force Feedback	−30.82	(−1274.10, 1213.36)	−0.05	0.96
Attempt Number	**−307.29**	**(−491.66, −122.92)**	**−3.26**	**0.002**
Force Feedback*Attempt Number	123.57	(−137.63, 385.87)	0.92	0.36
Precision Cutting				
Intercept	**2480.27**	**(1791.36, 3169.18)**	**6.88**	<**0.001**
Force Feedback	582.21	(−329.13, 1493.55)	1.22	0.23
Attempt Number	**−171.51**	**(−329.85, −13.16)**	**−2.12**	**0.04**
Force Feedback*Attempt Number	−71.65	(−281.12, 137.82)	−0.67	0.51

transfer task, statistically significant values were measured for the resident and force feedback disengaged groups. The precision cutting task analysis resulted in significant values for the resident, force feedback engaged, and force feedback disengaged groups.

DISCUSSION

The application of robotics to various procedure types and surgical specialties has grown in recent years. With the expansion of surgical robotic use, there is a need for additional capabilities and methods for training and evaluation. In addition, as an increasing number of surgical robots emerge from research labs, it is important to ensure that skill transfer and rapid learnability for new systems can be attained. The Senhance is one such example of technology new to the United States clinical market offering true robotic laparoscopic control and manipulation. As such, the learning curve for surgeons of various expertise, new capabilities, and ability to transition from conventional laparoscopic surgery to robot manipulation should be evaluated to determine how fast skills can be acquired or if skill transfer is possible from conventional laparoscopic surgical training.

In this study, it has been shown that adaptation to the Senhance occurs rapidly for residents, fellows, and faculty surgeons. The rapid acquisition of skills on the Senhance suggests that previously developed conventional laparoscopic skills may translate to the Senhance controls. Additional findings reinforce the assumption that the force feedback capability of the Senhance does not hinder early learning as both force feedback engaged and disengaged groups demonstrated comparable learning rates; the absence of the presence of a significant difference between force feedback groups (Tables 3 and 5) motivates future research and further testing. Because of the small sample size and experimental design, the results from the postulated mixed effects models serve as an exploratory analysis. Therefore, results can serve as motivation for future inferential studies under adequate power and stricter design.

As expected, participants in the fellow/faculty group outperformed participants in the resident group across both tasks and each task attempt. A major component of this study was that all participants, regardless of surgical experience, were novice users of the Senhance; however, on average, all subjects were able to improve performance on the two FLS tasks over as few as five attempts. Typically, learning curves follow an exponentially plateauing or sigmoid function.[30] Determining the number of attempts to reach this plateauing juncture is beyond the scope of this current study and is left for further work to determine what the expected training time is for novice users to reach a skill plateau.

To our knowledge, this is the first scholarly study to evaluate the force feedback capability of the Senhance. Historically, one of the requests from surgeons using robots has been the addition of haptic feedback.[31,32] The benefit of haptic feedback on surgical robots has not been defined in terms of patient outcomes. In this study, we have attempted to establish the foundation for understanding how a form of haptics, force feedback, impacts learning and adaptation for novice users on basic laparoscopic surgery tasks. Our findings suggest that for the early stages of the Senhance learning curve, force feedback did not decrease the rate of learning. It is worth noting that this claim stands for these specific FLS tasks, and further evaluation is warranted for additional tasks. Moving forward, it will be important to further analyze the force feedback capability of the Senhance for performance on more complex tasks that depend on applied force including suturing, knot tying, and tissue palpation.

Surgical skills training has been moving toward more objective methods for evaluation over recent years. The most common objective features for critiquing surgical skills has been time and precision, but motion tracking of surgeon's hands and surgical instruments has yet to be implemented outside of a research setting. Tausch et al.[28]

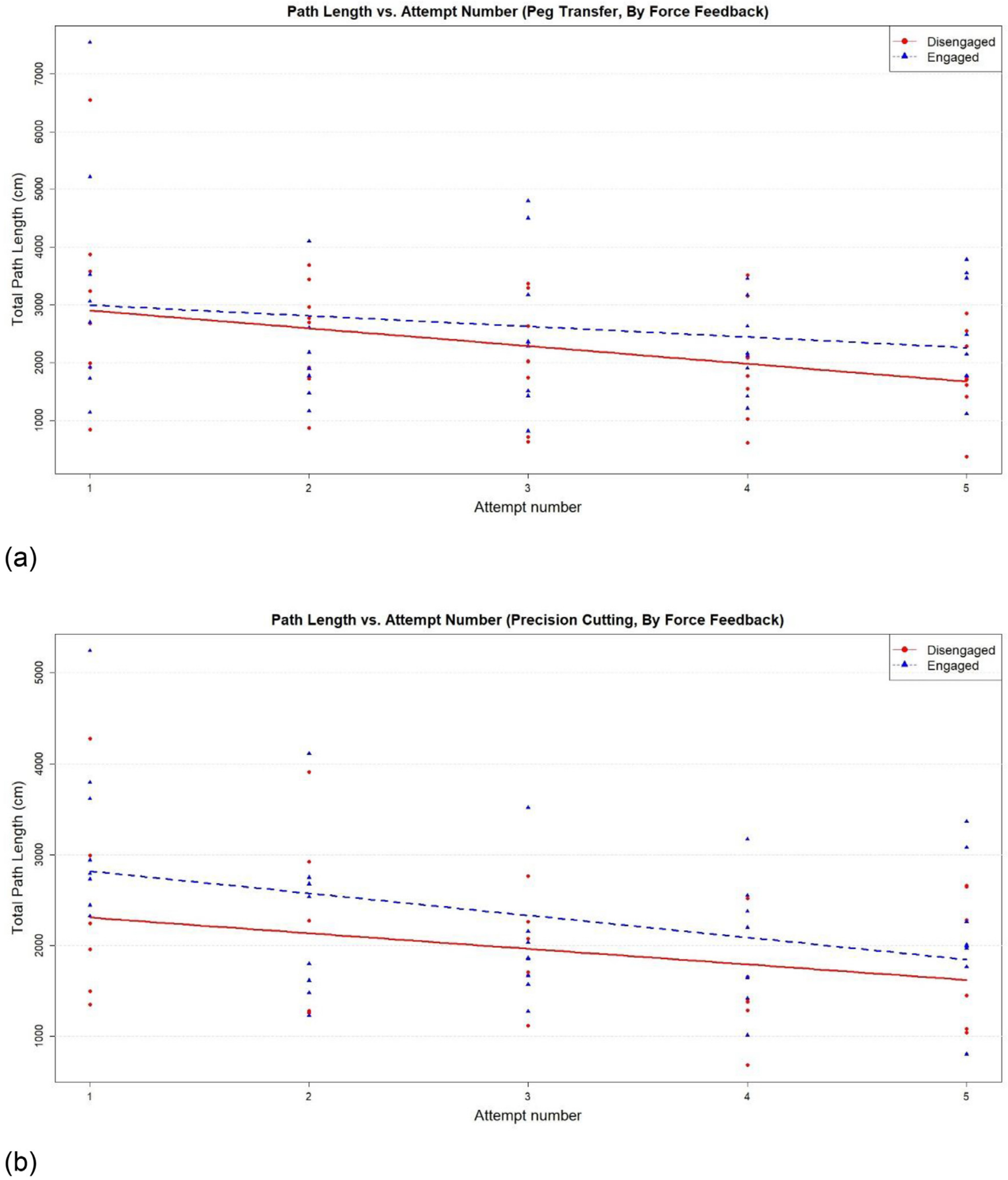


FIGURE 5. Path length vs. attempt number for the (a) Peg transfer task and (b) Precision cutting task, grouped by force feedback groups.

defined motion economy in terms of average velocity while the current study defines motion economy as total path length and compare this with a FLS score based on FLS standards instead of only a time metric. Findings from this study support the notion the FLS scores and instrument path length are monotonically related, providing evidence that path length could serve as a metric for proficiency for the Senhance and could be applied to the FLS manual skills curriculum for conventional laparoscopic surgery training. Although the relationship found for the early stages of the learning curve is linear, which would call for Pearson's product moment correlation, we know that learning curves plateau upon reaching proficiency. Thus, it was important to be general for future learning curve studies and use Spearman's correlation.

Limitations to this study include the limited number of subjects ($N = 16$) and the number of training attempts. Because of the small sample size, there is a possibility that

TABLE 6. Spearman's Coefficient and p-values for Comparing Monotonic Relationship of the FLS Scores and Total Path Lengths for Each Task and Subject Group

	Spearman's Coefficient (ρ)	p-value
Residents vs. Fellows/Faculty		
Peg Transfer		
Residents	**−0.665**	**<0.001**
Fellows/Faculty	−0.276	0.14
Precision Cutting		
Residents	**−0.583**	**<0.001**
Fellows/Faculty	−0.330	0.08
Force Feedback Engaged vs. Disengaged		
Peg Transfer		
Engaged	−0.302	0.06
Disengaged	**−0.806**	**<0.001**
Precision Cutting		
Engaged	**−0.512**	**<0.001**
Disengaged	**−0.468**	**0.009**

significant differences between force feedback and surgical experience groups across attempts are present, but not observed. Under these sampling conditions, the two subjects that did not complete the precision cutting task also affected the balance of the experiment design, as both individuals were residents with the force feedback disengaged. Because of the email recruitment method, there is a risk of selection and response bias, which may also impact results. More subjects, from all surgical tenures, are needed across all surgical specialties that perform robotic-assisted procedures to account for unmeasured confounding while providing additional statistical reinforcement. As this study only addressed the early stages of the learning curve for the Senhance, a more comprehensive study is necessary to understand the full learning curve and how many training attempts and training time is necessary to reach a proficiency plateau. A greater number of tasks, including suturing and camera control and manipulation is necessary to understand the learning curve for the Senhance for its full range of capabilities. The significant improvement for the precision cutting task when considering the FLS score metric could be attributed to the final attempt being performed using a single-circle gauze instead of the previously used double-circle gauze. It can be argued that the task increased in difficulty and led to a poorer performance for the final attempt. It was important, however, to use the double-circle gauze patterns during the training attempts as this is precisely how training is conducted for the standardized FLS curriculum.

CONCLUSIONS

This study has shown that surgeon learning and adaptation to the Senhance controls is rapid, regardless of experience level and force feedback engagement. The force feedback capability was found to not hinder skill acquisition as linear mixed effects models did not present significant results for differences in learning rates, though future studies with larger samples are needed to confirm this finding. Path length and FLS scores were found to be monotonically related across a majority of the groups. Further work is currently being planned to compare the learning curve for the Senhance to conventional laparoscopic surgery and other surgical robots. A further understanding of how surgeon performance is impacted by introducing another robotic platform into the operating room is also warranted. Robotic platforms have varying control mechanisms; therefore, it is pertinent that we ensure control confusion is minimized when moving between platforms to ensure optimal patient care.

ACGME COMPETENCIES

This study is an addition to the literature pertaining to *practice-based learning and improvement*. From a robotics perspective, this is particularly important as new devices are approved for clinical use.

ACKNOWLEDGMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We would like to acknowledge TransEnterix, Inc. for loaning the Senhance to Duke University for this study.

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