The Role of Active Engagement of Peer Observation in the Acquisition of Surgical Skills in Virtual Reality Tasks for Novices

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OBJECTIVE: Peer-assisted learning has been regarded as an adjunct to teaching modalities. It remains inconclusive regarding the benefits of peer observation in skills learning. Hence, we investigated whether the active engagement (AE) of peer observation in addition to expert demonstration would facilitate the performance in the virtual reality (VR) tasks.

SETTING/DESIGN: The programs involved 4 VR tasks including basic (camera targeting), intermediate (energy dissection and energy switching), and advanced (suture sponge) tasks in the da Vinci Skills Simulators, which were set up in the operating room at Taipei Medical University Hospital. Fifty medical students participated in the study. The AE of the participants was defined as the total number of peer observations in addition to expert observation before their performance. We assessed the correlations between AE and surgical task performance using Pearson correlation and the concept of learning analytics.

PARTICIPANTS: Medical students (sixth-year students in Taiwan, equivalent to fourth-year students in the US system) from Taipei Medical University were recruited.

RESULTS: AE was correlated with the energy dissection task ($r = 0.329$, $p = 0.02$) and marginally associated with the energy switching task ($r = 0.271$, $p = 0.057$). However, AE was not correlated with either task scores for camera targeting ($r = 0.096$, $p = 0.509$) or task scores for suture sponge ($r = -0.091$, $p = 0.529$).

CONCLUSIONS: Our findings suggest that AE of peer observation may facilitate learning energy dissection task, which is an intermediate-level task, but not in other basic or advanced tasks in a VR context. The study highlights the potential effect of AE of peer observation on surgical learning based on a distinct level of tasks. Tasks that fit the learners' level are recommended. Nevertheless, the effectiveness of peer observation on surgical training still has to be explored to ensure favorable results and optimal learning outcomes. (J Surg Ed 76:1655−1662. © 2019 Association of Program Directors in Surgery. Published by Elsevier Inc. All rights reserved.)

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ABBREVIATIONS: PAL, peer-assisted learning VR, virtual reality AE, active engagement dVSS, da Vinci skill simulator LA, learning analytics QR codes, quick response codes VG video game

KEY WORDS: collaborative learning, peer-assisted learning, observational learning, virtual reality, surgical simulation, robotic surgery

COMPETENCIES: Patient Care, Practice-Based Learning and Improvement

INTRODUCTION

Collaborative learning of clinical skills has been regarded as an efficient and cost-effective method in the simulated context.[1] Peer-assisted learning, which comprises peer tutoring, peer observation, peer feedback, and peer assessment, has been increasingly implemented as an adjunct to the learning methods in clinical contexts.[2] Observational learning is one of the nucleus methods for collaborative motor skills learning. Conventionally, observational learning has been one of the principal teaching approaches in surgical training.[3] In reality, surgical movements are somewhat difficult to articulate; therefore, observing an expert model is a well-established technique applicable in many circumstances.[4] However, research on peer observation, observing flawed demonstrations from nonexperts or novices, has led to considerable debate.[5-8]

Since the da Vinci Surgical System received Food and Drug Administration approval in 2000, the clinical application of robotic-assisted surgery has exponentially increased across multiple specialties.[9,10] Simulators in the acquisition of minimally invasive surgical skills, which do not imperil patient safety, have been considered a bridge between preclinical training (didactic lectures, dry lab training, and animal models) and hands-on operations.[11] Seymour et al. reported that virtual reality (VR) training had the opportunity to improve the operating room performance in surgical education.[12,13] Hence, we employed the da Vinci Skills Simulator (dVSS) platform for training sixth-year medical students to ensure safe practice and provide students with an opportunity to gain hands-on experience using state-of-the-art simulator technologies.

Digital technologies have become integrated into medical education, generating a multitude of data that can be used in learning analytics (LA).[14,15] The objective of the LA approach is to optimize learning and environments by measuring, collecting, analyzing, and reporting a large amount of process data.[16-18] It is of note that LA focuses on learning process data instead of outcome data.[19] Specifically, the learning process refers to how people acquire knowledge or skills that influence their attitudes, decisions, and actions.[20] With the emergence of LA and the advancement of technology, virtual learning environments such as dVSS allow us to collect real-time learning process for each student.[21] Therefore, the relationships between each aspect of teaching, learning, assessment, academic work, and administration can be elucidated by analyzing the learning process.[18] Although LA has become an emerging research method in the health professional education sector, research on the application of LA in medical education remains limited.

In this study, we investigated whether an increasing number of observations of the flawed demonstration can improve learning of surgical skills. To investigate the learning process, we employed the concept of LA by recording the number of peer observation (defined as active engagement [AE]) using the Google form of the observation checklists (Supplementary Appendix Table 1) throughout the whole program. We highlighted the learning process of the participants by using LA to evaluate the learning effectiveness between AE and their performance. Furthermore, we did further analyses in the surgical tasks that would benefit most from peer observation.

MATERIALS AND METHODS

Study Participants

This study was approved by the Institutional Review Board of Taipei Medical University Hospital (TMUH). Medical students (sixth-year students in Taiwan, equivalent to fourth-year students in the US system) from Taipei Medical University were recruited voluntarily through advertisements on bulletin boards. The participants had no prior experience with robotic surgery, endoscopic surgery, or any form of surgical VR simulation.

Study Design

The dVSS platform, the da Vinci surgeons' console, and the simulator backpack were set up in the operating room at TMUH. The education and surgery department of TMUH organized the programs. Five instructors were attending surgeons from TMUH who had passed the surgery board and were qualified as surgeons by the Taiwan Association for Endoscopic Surgery. Prior to the tasks, each participant was provided with an informative overview of the da Vinci surgeon console and the dVSS platform.

All participants received the standardized instruction and observed experts' demonstration once at the beginning of the tasks. Five to six participants took turns to practice the tasks in 1 dVSS platform. Before performing the tasks, the participants were encouraged to observe and assess the flawed practice of their peers. Before the observation, students received the checklist, which was designed based on the metric definitions of the VR task of the dVSS (Supplementary Appendix Table 2). Observers recorded each item on the checklist using the quick response codes via the Google form system (Supplementary Appendix Table 1). The performance results of the peers were displayed on the screen immediately after each operation. Therefore, students can compare what they had observed in the checklists (Supplementary Appendix Table 1) to the operators' performance results analyzed by the dVSS.[22] It is of note that the numbers of observation would differ from person to person because the students operated on the da Vinci simulator in sequential order, and thus they did not have the equal opportunity to observe the peers for the same frequencies. Furthermore, while we encouraged students to record the checklists during the whole sessions, students were not forced to complete the checklists for each observation. To investigate the learning process, we defined AE as the number of observations (an observation was defined by completion of a checklist for an operator). We used the total scores from the dVSS to represent surgical performance (Fig. 1).

The dVSS can retain the detailed records of the movement skills for the trainers. Total scores of surgical performances were standardized by aggregating the following items: time to complete exercise (seconds), economy of motion (cm), instrument collisions, excessive instrument force (seconds), instruments out of view (cm), master workspace range (cm), and misapplied energy time (seconds). We also investigated whether observing flawed demonstrations from the peers affected the students' surgical task performance by evaluating the correlations between observation numbers and performance scores.

Task Description and Metrics for Evaluation

We selected specific simulator tasks from the dVSS module brochure according to the training purpose and the distinct degrees of difficulty (Supplementary Appendix Table 3): camera targeting (basic), energy dissection and energy switching (both intermediate), and suture sponge (difficult). First, camera targeting required participants to control the camera in a large, 3-dimensional workspace by manipulating the camera by positioning a light-blue sphere within the center of the camera target. Second, energy dissection required participants to use 2 arms to electrocauterize and sharply divide 6 blood vessels in order to minimize blood loss. Third, energy switching required participants to navigate the camera inside a cavity to identify dots that require the application of either monopolar or bipolar energy until they disappear. Finally, suture sponge required participants to drive a curved needle through multiple designated areas on a sponge from different angles by using either a forehand or backhand approach. These tasks were selected reflecting some surgical skills required for robotic proficiency; these skills include hand-eye coordination (camera targeting) while operating multiple instruments simultaneously, during electrocautery and cutting (energy dissection and energy switching), and during curved needle driving from a variety of angles (suture sponge). All tasks also incorporated other fundamental skillsets including camera clutching, efficient instrument utilization, and speed.

Statistical Analysis

All analyses were conducted using SPSS version 19.0 (IBM Corp., Armonk, New York). We performed descriptive statistical analysis for background information and VR practice scores including frequency (n), minimum, maximum, median, interquartile range, mean, and standard deviation (SD). We conducted an independent-sample t test to compare the mean and SD of observations, suture sponge scores, camera targeting scores, energy switching scores, and energy dissection scores between women and men and between video game (VG) players and nonplayers. We used Pearson correlation to evaluate the correlations between observations and VR practice scores. The p values of <0.05 were regarded as statistically significant.

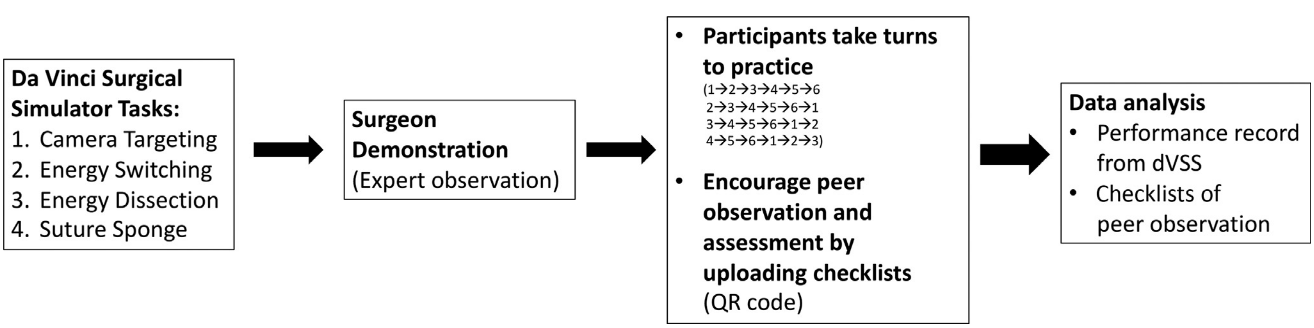


FIGURE 1. Process flow diagram.

RESULTS

Table 1 presented the study demographics. A total of 50 participants were recruited (31 male students and 19 female students). Thirteen participants had experience of playing VG, whereas 37 participants did not. The mean number of total observations was 7.0 ± 4.2 (max: 14, min: 0). The mean scores for camera targeting, energy dissection, energy switching, and suture sponge were 70.9 ± 12.5 (max: 95, min: 30); 67.1 ± 15.5 (max: 96, min: 33); 54.2 ± 15.8 (max: 79, min: 17); and 17.9 ± 23.8 (max: 72, min: 0), respectively. Concerning the degree of difficulty, the tasks (from easiest to the most difficult) were as follows: camera targeting, energy dissection, energy switching, and suture sponge (Supplementary Appendix Table 3). Supplementary Appendix Table 4 presented the mean differences (±SD) in the number of observations and task scores by sex. No significant differences in the number of observations were noted (men: 6.3 ± 4.3 vs women: 8.2 ± 3.7 times, $p = 0.11$) between the sexes. Moreover, there were no significant differences in scores for the 4 tasks between the sexes. Supplementary Appendix Table 5 displayed the differences in the number of observations and surgical task scores based on prior experience of playing video games (VG) among the participants. No differences in the number of observations (with VG experience: 7.2 ± 4.2 vs without VG experience: 7.0 ± 4.2 times, $p = 0.89$) and scores for the 4 tasks were observed between the students with and without prior experience of playing VG.

AE and Performance

The AE of the participants was assessed from the total number of observations of flawed demonstrations by novices in addition to the observations of flawless demonstrations by experts prior to their performance (Fig. 2). A significant correlation was found between AE and task scores for energy dissection ($r = 0.329$, $p = 0.02$; Fig. 2d). The relationship between AE and task scores for energy switching was marginal related ($r = 0.271$, $p = 0.057$; Fig. 2c). However, AE was not correlated with either task scores for camera targeting ($r = 0.096$, $p = 0.509$; Fig. 2b) or task scores for suture sponge ($r = -0.091$, $p = 0.529$; Fig. 2a).

The score items of the dVSS training systems encompass various facets of performance, such as time to complete a specific task, motion and efficiency characteristics, and errors. In the energy dissection task, we found a significant correlation between AE and score items such as "time to complete exercise" ($r = -0.383$, $p < 0.01$) and "blood loss" ($r = -0.402$, $p < 0.01$; Table 2). Thus, the higher the number of observations of flawed demonstrations from novices (AE), the faster the participants completed the task with less blood loss in the energy dissection task. In the energy switching task, a moderate correlation between AE and the score item "excessive instrument force" ($r = -0.385$, $p < 0.01$) was noted (Table 2). Thus, the higher the number of observations of flawed demonstrations from novices (AE), the less-excessive instrument force was applied by participants in the energy switching task.

DISCUSSION

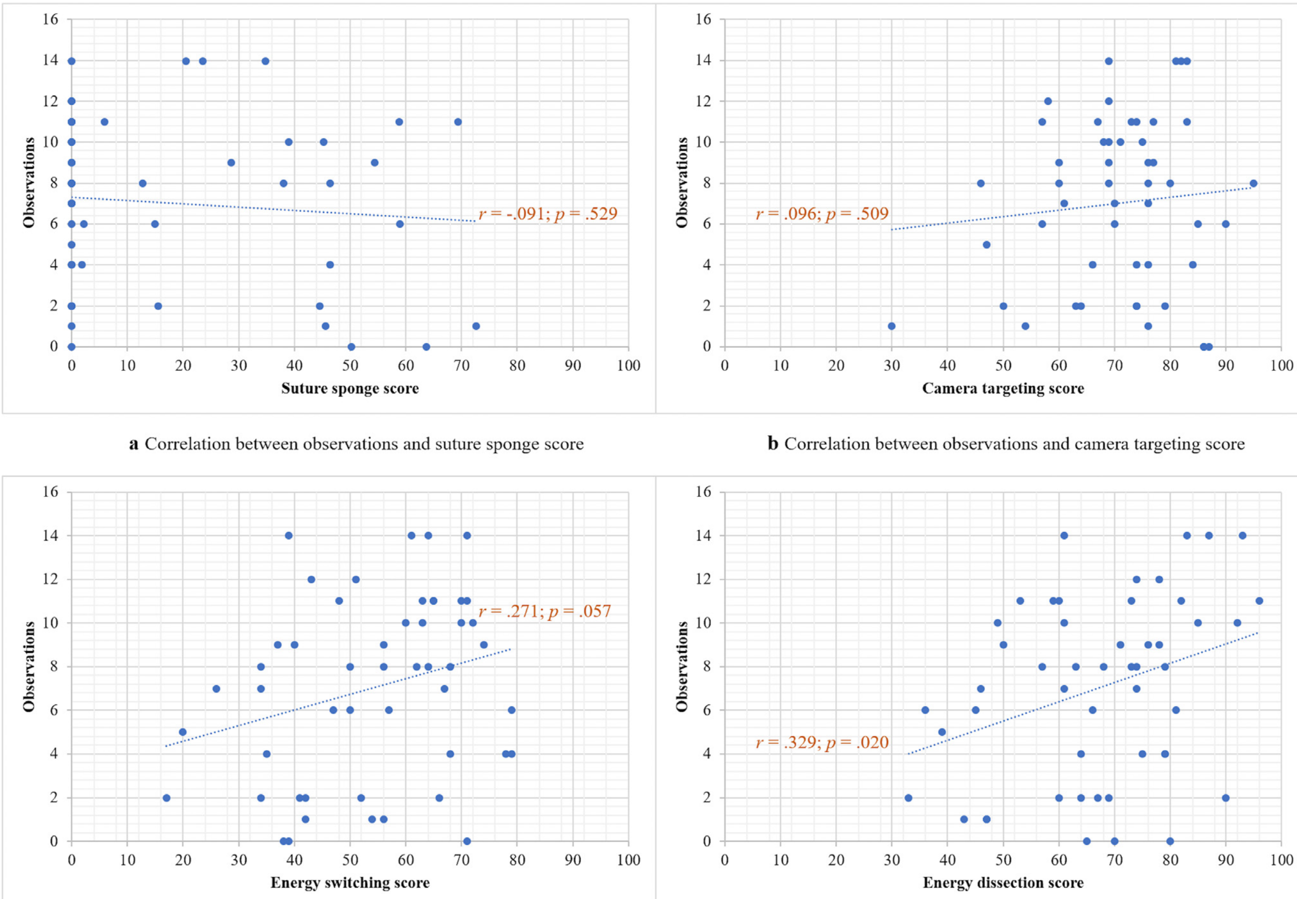
We found that performance in the energy dissection task was positively correlated with the AE of the participants. Furthermore, we found a moderate association between performance in the energy switching task and the AE of participants, with marginal significance. However, no significant correlations were revealed between the AE of participants and their performance in the camera targeting and suture sponge tasks.

We found that AE of peer observation has divergent effectiveness depending on task difficulty. The performance of the medical students did not correlate with AE in the basic task camera targeting task, which might be

TABLE 1. Descriptive Statistics

Variables	*n*	Minimum	Maximum	Median	IQR	Mean	SD
Background information							
Gender (male/female)	31/19	NA	NA	NA	NA	NA	NA
Video game (yes/no)	13/37	NA	NA	NA	NA	NA	NA
Body height (cm)	50	146	187	170	14.8	168.4	8.6
Observations	50	0	14	8	7.3	7.0	4.2
Scores of virtual reality tasks							
Camera targeting	50	30	95	73.5	15.5	70.9	12.5
Energy dissection	50	33	96	68	20.5	67.1	15.5
Energy switching	50	17	79	56	26.5	54.2	15.8
Suture sponge	50	0	72	0	40.4	17.9	23.8

n, number; IQR, interquartile range; SD, standard deviation; NA, not applicable.



a Correlation between observations and suture sponge score

b Correlation between observations and camera targeting score

c Correlation between observations and energy switching score

d Correlation between observations and energy dissection score

FIGURE 2. Correlation between active engagement (AE) and performance in 4 respective tasks: (a) suture spongy; (b) camera targeting; (c) energy switching; (d) energy dissection.

TABLE 2. Further Analysis of Various Facets of Performance

No.	Items	$M \pm SD$	Observations ($n = 50$)
Energy switching			
	Time to complete exercise (s)	180.76 ± 62.63	−0.015
	Economy of motion (cm)	272.68 ± 92.27	−0.098
	Instrument collisions (times)	0.68 ± 2	−0.227
	Excessive instrument force (s)	11.81 ± 29.65	−0.385**
	Instruments out of view (cm)	0.02 ± 0.14	−0.001
	Master workspace range (cm)	11.42 ± 2.01	−0.006
	Misapplied energy time (s)	8.02 ± 5.42	−0.245+
Energy dissection			
	Time to complete exercise (s)	207.62 ± 63.44	−0.383**
	Economy of motion (cm)	215.88 ± 70.66	−0.262+
	Instrument collisions (times)	2.26 ± 3.35	−0.192
	Excessive instrument force (s)	2.4 ± 9.78	−0.241+
	Instruments out of view (cm)	0.1 ± 0.46	−0.202
	Master workspace range (cm)	7.32 ± 1.62	−0.098
	Misapplied energy time (s)	20.6 ± 10.79	−0.214
	Blood loss (cc)	93.56 ± 87.26	−0.402**
	Broken vessel	0.02 ± 0.14	−0.035

$p < 0.10$; *$p < 0.05$; **$p < 0.01$; +$p < 0.01$.

attributed to the fact that participants could learn effectively only after observing the demonstration from experts. A potential reason might be that the camera targeting task, the fundamental skill in robotic training, is relatively simple and it takes less time and technique to achieve the competency even for novices. As shown in Figure 2b and c, the performance score clusters of camera targeting (64.5-78.5; 25-75 percentile) were in a relatively narrower range than that of energy switching score (41.3-66.8; 25-75 percentile), which might partially explain the weaker correlation observed for the camera targeting score. Moreover, participants' performance and AE were not related in the suture sponge advanced-level task. The possible reason might be that suture sponge was a demanding task with a steep learning curve despite expert demonstration and increased numbers of peer observation. Although observational learning can aid understanding regarding the steps of a procedure, much more practice is required to achieve free-flowing movements, especially for those requiring complex or advanced surgical skills. Thus, learning through observation of flawed performance might be restricted with advanced tasks. However, we noted that in the energy dissection task, participants with a higher AE exhibited significantly higher performance. Further analyses may elucidate what learning processes AE could facilitate in the intermediate tasks. An increased number of observations of flawed demonstrations from novices (i.e., AE) resulted in participants completing the energy dissection task faster and with less blood loss. Besides, AE resulted in participants using less-excessive instrument force in the energy switching task. This result suggests that AE may help achieve more effective performance, such as shorter completion time, less blood loss and less-excessive instrument force, especially in the intermediate tasks.

Observational learning approach has been reported to accelerate skill learning.[23,24] Furthermore, observing flawed performances had the opportunity to enhance skill acquisition in light of error detection and mitigation strategies.[25] The mechanism of observational learning is primarily based on the mirror neuron system discovered in the premotor cortex.[26] Rohbanfard and Proteau found that observing a mixed model from both experts and novices was more conducive to the learning process than observing either an expert model or a novice model alone.[27] In clinical skill training, Domuracki et al. reported the impacts of observing flawed and flawless demonstrations on the developments of inserting a central venous catheter, which revealed no difference in the checklist analysis.[6] LeBel et al. found that observing videos from nonexpert with errors might improve skills during simulation-based training in arthroscopy.[8] Harris et al. showed no difference in performance of a ring-carrying training task on a robotic platform between expert-observing and error-observing groups.[7] Those studies mentioned above employed all video-based observational practice with diverse research designs and outcomes, and they focused on 1 specific skill. Nonetheless, watching video performances did not seem to obtain the whole benefits of observational learning because effective observation practice entailed feedback throughout the learning process.[28] The key to learning through observation entails a process of AE in the activities being performed.[29,30] Therefore, we designed the observation checklists (Supplementary Appendix Table 1), which could facilitate achieving AE,[31] for the participants to record the observation process and perform assessment during the program. After observing the peer, the performance score of the operator was provided to have immediate feedback on the assessment difference between the robotic simulator and the observers. Furthermore, the leverage of observational learning relies on the learner's current level of performance.[32] Therefore, we categorized the tasks as basic, intermediate, and advanced level according to the mean scores of the participants' performance.

We used the concept of LA in VR activities with the dVSS platform to analyze the surgical learning process by evaluating the association between AE of peer observation and learning effectiveness. Through the analysis of the learning process, we sought to identify the optimal learning approaches for students. To achieve this, we investigated robotic surgical performance and the associated learning process among medical students by analyzing data from the dVSS. This system can document the learning process of medical students in VR tasks. These data included not only the completion time but also the efficacy of movements such as instrument collision, excessive instrument force, motion economy, blood loss, and instrument out of view. These are all crucial indicators of surgical performance; however, recording them during real surgeries in operating rooms is laborious.

The present study had some limitations. First, we had a relatively small sample size. However, the study had sufficient sample size to detect the correlation of >0.16 between the number of observation and virtual task score, with at least 80% of statistical power. Second, the study was conducted at a single academic institution, which might limit the generalizability of the findings to other institutions and countries. Third, all participants observed the expert demonstration once at the beginning of the study. We employed the concept of LA to observe and analyze the learners' behavior and engagement during the program without conducting a randomized controlled trial. Lastly, we used correlation to measure the outcomes between the performance and AE of peer observation, which might have restrictions in explaining the results.

In conclusion, AE of peer observation had diverse effectiveness in different tasks. AE of peer observation may be related to better performance in the energy dissection task, which is an intermediate-level task in a VR context. Nevertheless, AE may have restrictions on learning basic or advanced tasks. As such, AE of peer observation is not a panacea, and its effectiveness might be contingent on the level of tasks. Hence, we suggest that educators need to select the appropriate tasks that fit the learners' level while we apply the learning method of peer observation. Furthermore, the effectiveness of peer observation in new technologies on surgical training still has to be explored to ensure favorable results and optimal learning outcomes.

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Ethical Requirement: This study was approved by the Institutional Review Board of Taipei Medical University Hospital.

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SUPPLEMENTARY INFORMATION

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