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PAPER

A New Highly Portable Simulator (SECMA) Based on Virtual Reality for Teaching Essential Skills in Minimally Invasive Surgeries

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ABSTRACT

This study presents a new minimal access surgery training system, SECMA, and its constructive validation to determine its usefulness for training basic laparoscopic skills. SECMA is an affordable, highly portable, mobile virtual reality training tool for laparoscopic techniques that integrates the Oculus Quest with a mechanical interface for surgeon simulation of forceps using the hand controllers of these devices. It allows the execution of structured activities (supported by virtual scenarios simulating operating rooms developed in Unity), performance evaluation, and real-time data capture. Two experiments were carried out: 1) coordination; and 2) capture and transport, with a total of 21 individuals divided into two groups: a novice group (inexperienced) of 10 participants and an expert group (>100 endoscopic procedures) of 11 participants. Total task time score, right-hand speed, path length, and other metrics from several consecutive runs on the simulator were compared between experts and novices. Data automatically recorded by SECMA during the experiments were analyzed using hypothesis tests, linear regressions, analysis of variance, principal component analysis, and machine learning-supervised classifiers. In the experiments, the experts scored significantly better than the novices in all the parameters used. The tasks evaluated discriminated between the skills of experienced and novice surgeons, giving the first indication of construct validity for SECMA.

KEYWORDS

laparoscopy, technical training, virtual reality (VR) simulator for minimal access surgery training system, constructive validation, statistical analysis, supervised machine learning (ML) classification, data analysis, basic motor skills learning in surgery, portable virtual reality (VR) simulator

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1 INTRODUCTION

Almost any abdominal or pelvic surgery can be performed with minimally invasive surgery (MIS) or laparoscopy. For example, currently, 93% of appendectomies and 94% of cholecystectomies are carried out with this technique [1]. This surgery produces fewer postoperative complications, favors prompt patient rehabilitation, and allows a short hospital stay [2].

Despite these apparent benefits, this type of surgery presents challenges and complications. MIS is an indirect surgery that requires the surgeon to use graspers and simultaneously monitor a flat image (without depth sensation) given by the laparoscopic camera. On the other hand, the length of the instruments and their pivot at one point cause a multiplying effect of the change in hand position, dangerously amplifying the surgeon's movements. The time required for a surgeon to gain skills for MIS is months to years. Currently, training is done with models (traditional box trainers) and animals. The models are relatively simple and inexpensive. However, they only allow familiarization with endoscopic procedures and the acquisition of basic skills. Although instruction with animals simulates surgical operations more realistically, it is more expensive, ethically questionable, and has environmental consequences associated with animal sacrifice. Both of the former mentioned teaching methods to get skills for MIS also lack automation and objective measurement of educational progress and require the involvement of highly trained tutors and expensive staff [3] [28].

Currently, the greatest expectations for MIS training are focused on virtual reality (VR) simulators. The VR simulator allows: (1) repeating surgical procedures many times (obviously, practices with animals do not allow undoing or repeating actions); (2) creating training in rare (infrequent) and/or complex pathologies; (3) performing automatic evaluations and capturing data of the practitioner's actions in the virtual environment; (4) analyzing progress data, among other advantages.

The use of VR-based simulators for healthcare training in general (see, for example, [42] [43]) and specifically for teaching surgical skills has been in development for several decades. The first clinical training with these simulators was reported in the nineties in the works of Delp and other authors [4] [5] on lower extremity orthopedic procedures. A notable advance in the use of VR simulators for MIS education was made in 1997 with the "Minimally Invasive Surgery Training Virtual Reality" (MIST-VR) [6–8]. MIST-VR used three-dimensional graphics to represent the real-time movements of the laparoscopic instruments in a virtual environment. On the other hand, computer-generated geometric surfaces were used to simulate organs to be manipulated during training. Versions "*classic*" and "*procedicus*" of the MIST-VR used at the Mentice Medical Simulation AB in Gothenburg demonstrated that, utilizing virtual environments of low engineering fidelity and high psychological fidelity, it is possible to transfer learned skills acquired in a simulator to the operating rooms [9].

The VR simulator has become a valuable tool for learning basic motor skills in surgery [26]. Moreover, many studies have shown that these learned skills can be transferred to operating rooms [10–14]. However, given its high cost and associated infrastructure, it is not easily accessible, especially in low- and middle-income countries [26–30]. Consequently, it is necessary to develop and validate low-cost portable VR simulators for MIS [15–17].

To address this problem, our research group from the Faculty of Engineering of the Universidad del Desarrollo (which has experience in the development of teaching technologies [41]) developed a highly portable, inexpensive Training System for Minimal Access Surgery based on a VR simulator (SECMA), which incorporates a management system for the training activities and recording and visualization tools of the generated data. SECMA has a high degree of interactivity and sense immersion by presenting a scenario simulating a surgical operating room and incorporating essential activities for psychomotor coordination. It allows psychomotor skills assessment in laparoscopic basic procedures by capturing data on student interactions with the simulator instruments, reporting the advances in training through a Web application, and providing feedback to the trained subjects. These characteristics give SECMA the potential to be accessible and helpful for training surgeons and medical personnel in general.

Table A1 in Appendix shows a basic comparison between SECMA and other commonly used MIS training simulators.

Constructive validation is used for testing an instrument based on the degree to which the test items identify the quality, ability, or trait it was designed to measure [35]. This is typically accomplished by measuring performance in two groups that are hypothesized to exhibit differences in the skill being measured by the instrument (e.g., experienced surgeons and novices). In this study, we present a constructive validation of SECMA already used in training experiences at the Surgical Skills Training Center of the University of Chile, the Hospital del Salvador, and the San Borja Arriarán Hospital in Chile. We do this by demonstrating that the metrics and variables registered by this simulator during the training activities (the total task time, right-hand velocity, the path length, etc.) can be used to discriminate between novice surgical residents (no prior experience) and experts (more experienced surgeons) under the assumption that more experienced surgeons already have the basic psychomotor skills being measured [18].

Measurements during experiments were performed automatically using the simulator's real-time data capture capabilities. We use various statistical and machine learning methods to demonstrate that activities designed with SECMA discriminate between individuals with unequal levels of essential skills in laparoscopic surgery. To our knowledge, this is the first time that supervised classifiers have been used for this task. A flexible data processing workflow was also implemented for data analysis and visualization production during the experience.

2 MATERIALS AND METHODS

2.1 Brief description of the SECMA – VR simulator

SECMA (see Figure 1) includes our software application for a virtual reality headset developed by Oculus, *Oculus Quest*, which incorporates a surgical ward scenario for carrying out exercises where the movements of the surgeon's instruments are simulated. A mechanical interface for the surgeon's laparoscopic graspers is incorporated, and the device controllers are adapted for use. All parts are included in a suitcase for easy transport of the simulator.

a)  b) 

Fig. 1. Image (a) shows the Minimum Access Surgery Training System (SECMA), a VR simulator based on the Oculus Quest lens that incorporates a mechanical interface to simulate laparoscopic forceps and is integrated into a case for portability. Image (b) shows the use of SECMA in the training of resident surgeons

SECMA captures three types of data during the simulations. (1) Learning data: Records from student interactions with the virtual environment. These data are sent to an on-premise server in real-time and include timestamps using the e-learning xAPI standard. (2) Activity participant data: metadata for registration and connection identification; (3) Simulation data (simulator variables): These data include records of metrics and variables such as total time in the execution of the task, total distance traveled by the virtual instruments (virtual markers), and the number of errors during the execution of the training routines, among other variables. The data is automatically sent to the server at the end of the simulation. The registered data from the simulations is stored in a database on the server, and reports are automatically generated through a Web application for the follow-up and control of the subject's progress during training routines.

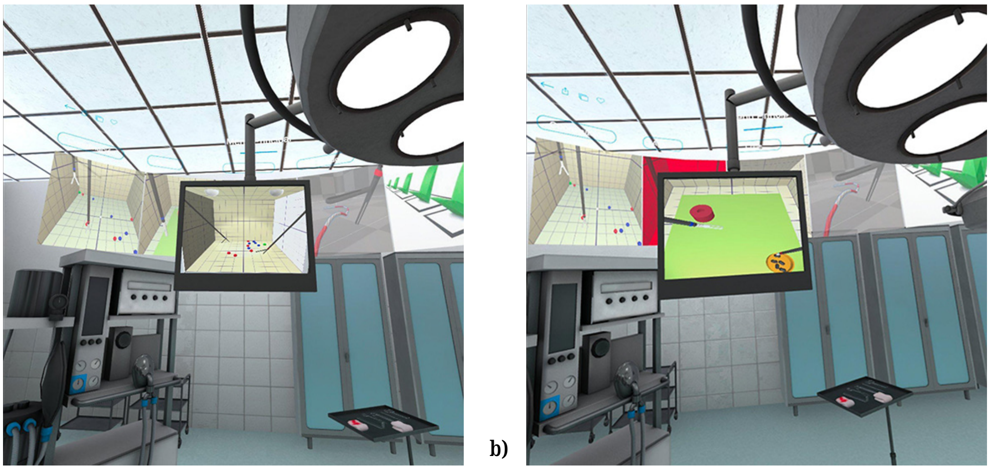
To simulate the trajectories of the laparoscopic instruments, the mechanical interface considers all the grasper's degrees of freedom. Thus, the entry of the trocar into the cavity (for example, the abdominal cavity) is taken as the pivot point. The grasper`s movements are decomposed into three rotations given by the roll, pitch, and yaw angles (rotations are achieved using a ball joint) and three longitudinal displacements through the axes. The longitudinal displacement of the graspers is accomplished by an adaptation made to the controllers of the oculus. Thus, each of the two controllers runs along the axis of a cylindrical rod, to which they are connected through a cylindrical union. These rods are, in turn, connected to the ball joint at the trocar, which acts as a pivot point. To achieve the simulator's portability, the rods of the graspers must have a limited length (so that the entire simulator fits in the suitcase), which requires significant innovation in modifying Oculus controllers. Thus, the introduction or advancement of the graspers into the cavity is achieved virtually through simulation, running the Oculus controllers along the rods, and calibrating the depth in the virtual environment. In this way, the depth required for the surgical operation is achieved without needing to excessively increase the length of the rods in the physical world.

The simulator application software was created with C# in Unity [31], and the three-dimensional models of the virtual environment were created with Maya [32] and Blender [33]. Additionally, various Oculus Quest plugins [34] were used for the virtual tweezers.

2.2 Constructive validation of SECMA

We present a comparative, cross-sectional study for the constructive validation of SECMA. A total of 21 individuals, divided into two work groups, were evaluated: a novice group of 10 participants and a group of experts of 11 participants. The performance of each of the participants was measured through the variables used by SECMA in training with two different activities in the virtual environment.

1) *Coordination:* This activity allows the student to work synchronously with the hands in one direction and the vision in another. In the scene, a box contains five randomly placed blue and five red spheres. The blue spheres must be touched with the left grasper (marked with a blue ring) and the red ones with the right grasper (marked with a red ring). Also, in the scene, a randomly positioned green sphere touched with any of the tweezers produces an error (Figure 2a).
2) *Catch and transportation:* This activity simulates a typical exercise in training with models, but now in a virtual environment. In the virtual scene, a box with five virtual beans is at a starting point. The virtual beans inside must be grabbed and transported to another box located at a destination point (Figure 2b).



a) b)

Fig. 2. Virtual scenes corresponding to the coordination activity (a) and the capture and transport activity (b)

Before starting these activities with SECMA, each participant in the experiment received a description of the system and its functions, including the graphical interface and the controllers that imitate laparoscopic graspers. Before each of the previously described activities (coordination and catch and transportation), they were allowed to perform a familiarization exercise that was not used for statistical analysis. Subsequently, three valid exercises were performed for each activity and participant. The data generated from the activities was recorded and stored in a database for further analysis.

3 RESULTS

3.1 Analysis of the execution time for coordination activity with SECMA

In the coordination activity, the time (in seconds) the participant takes in its complete execution is measured. Recorded execution times are labeled according to whether they correspond to experts or novices. The time distributions differentiated by this label are illustrated in Figure 3, which shows histograms and density lines (frequency polygons) representing the execution times of the coordination activity among experts (panel A) and novices (panel B). The distributions are different. For example, the time distribution (histogram) in the case of experts shows right (positive) skewness (≈ 0.84), and the time distribution for novices appears as multimodal and more symmetrical (skewness ≈ 0.25). The differences between the execution time distributions can be considered indicators of different behaviors during the execution of the coordination activity between novice and expert participants.

To highlight the differences, we will use some statistical tests. But first, we transform the data using $y = \log(Time)$ to make the distribution of values more normal.

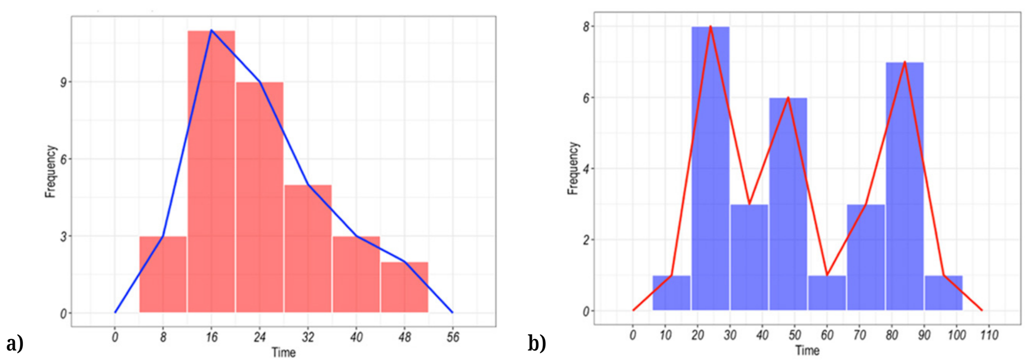


Fig. 3. Histograms for the distribution of the execution times (seconds) for the coordination activity separated by experts (Panel a) and by novices (Panel b)

The Shapiro-Wilk normality test for y gives a p-value = 0.07. A p-value > 0.05 (95% confident interval) implies that the distribution of the data (log(*Time*)) is not significantly different from the normal distribution. In other words, we can assume approximate normality for the transformed data.

Analysis of variance (ANOVA). We want to answer whether the variable "*Classification*" (being an expert or a novice), as a whole, influences the execution time for the coordination activity. In other words, we want to test the null hypothesis: E(Y|Classification = Expert) = E(Y|Classification = Novice). For this, we use an F-test with the proper variances in the F-statistic ratio for one-way ANOVA (F = Between-Groups Variance/Within-group variance). The procedure calculates the means for each group (experts and novices). The further the groups' means are from the overall mean, the greater the F-statistic numerator (Between-group variance). On the other hand, as the data points within each group move further away from their group mean, the denominator in the F-statistic (Within-group variance) increases. The Within-group variance represents the variance that the model does not explain. As this variance increases, the observed differences between group means are more likely to be due to errors rather than actual differences at the population level. The ANOVA Table 1 summarizes the F-test. This result (***Pr*(>*F*)** = p-value ≈ 0) indicates that we should reject the null hypothesis. That is, the variable *Classification* is statistically significant in differentiating between the mean execution times of experts and novices.

Table 1. Result for one way ANOVA test for the log(*Time*) depending on the classification in novice and expert

	Df	Sum Sq	Mean Sq	*F* statistic	*Pr*(>*F*)
Classification*	1	7.976	7.976**	34.69	1.79×10^{-7}
Residuals	61	14.024	0.230***		

Notes: * The variable Classification contains the values "novice" and "expert". ** Between-Groups Variance. *** Within-group variance.

Two sample *t*-test. Another way of showing the difference between the sample means is by using a hypothesis test. We consider the null hypothesis H_0: $\mu_N - \mu_E = 0$, and the alternative hypothesis, H_α: $\mu_N - \mu_E > 0$. Here, μ_N is the Novice mean execution time, and μ_E is the Expert mean execution time. Given the size of the samples, we used on-side Welch Two Sample *t*-test.

Table 2 shows the result of the Welch Two Sample *t*-test for the execution time samples of the coordination activity for experts and novices.

Table 2. Welch Two Sample *t*-test for execution times of the coordination activity

Variable	Novice (n = 10)	Expert (n = 11)	95% Confidence Interval	*P*-value
Time(sec)*	52.73	24.76	19.44 – Inf	1.284×10^{-6}

Note: * Time is the duration time in seconds for the coordination activity.

The difference in means between experts and novices is statistically significant (*p*-value ≈ 0). The null hypothesis (equality of the sample means) is rejected. The observation samples contain evidence that this difference is statically significant. Moreover, the novice mean execution time is greater than the expert mean execution time. In other words, SECMA distinguishes the different behaviors between experts and novices using the execution times in the coordination activity.

By using a regression model, we can get more details about the implication of being an expert or a novice on the execution time for the coordination activity with SECMA. To consider the linear relationship between the variables *Classification* and execution *Time* of the coordination activity, we build the following linear model:

$$\log(Time_i) = \beta_0 + \beta_1 \text{Classification}_i + \varepsilon_i,\ i = 1 \dots N \tag{1}$$

Where N is the number of observations and ε_i is the residual for the observation i. Using ordinary least square algorithm (OLS) the following result is obtained:

Table 3. Results for the regression model (1)

	Estimate	Std. Error	*t*-value	*Pr*(>|*t*|)
β_0	3.12290	0.08347	37.41	$<2 \times 10^{-16}$
β_1: Classification-Novice	0.71245	0.12096	5.89	1.79×10^{-7}
R-squared: 0.3626	*Adjusted R-squared:* 0.3521		*p*-value: 1.786×10^{-7}	

This result (Table 3) shows that the *Classification* variable influences (is statistically significant) the execution times of the coordination activity with SECMA. Specifically, it is obtained that, on average, the experts execute the coordination activity in 22.71 seconds ($\exp(\beta_0)$) while the novices on average add 2.039 seconds more to this mean ($\exp(\beta_1)$). In addition, the variable *Classification* explains 36% of the execution time variance of the coordination activity.

3.2 Analysis of the execution time and speed for catch and transport activity with SECMA

In the catch and transportation activity, each subject makes several attempts that are recorded as observations. Each observation is characterized by the variables or characteristics as represented in Table 4.

Table 4. Variables registered in catch and transport activity

Variable	Explanation
LeftDist	Distance traveled by the end of the left rod
RightDist	Distance traveled by the end of the right rod
LeftSpeed	Speed of the end of the left rod (a measure of the speed of the left hand)
RightSpeed	A measure of the right-hand speed
Errors	Number of errors made during the task
Time	Activity duration time
Classification	Expert or Novice

The distributions of speeds of the right-hand *RightDist* and of the execution times *Time* of the activity are shown in Figure 4 in the left and right panels respectively.

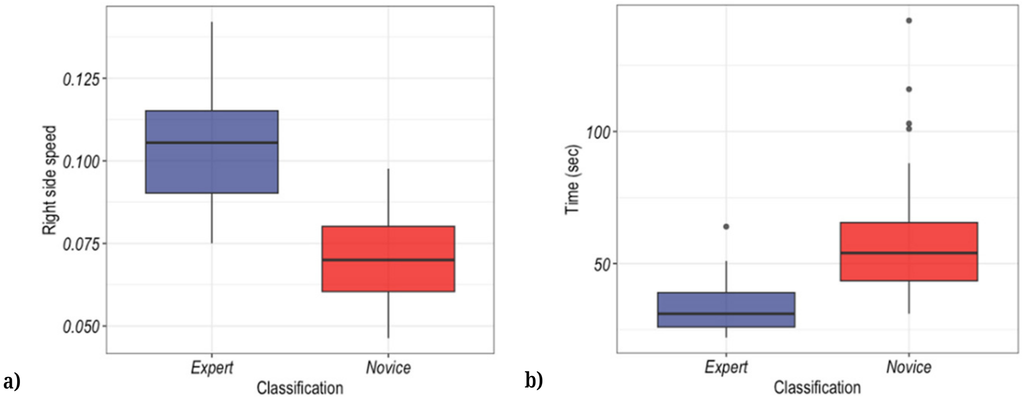


Fig. 4. Box and whisker plots to differentiate experts and novices according to right-hand speed distributions (Panel a) and execution times distributions (Panel b) for catch and transportation activity. Points represent outliers

As we did in section 3.1, we use a *t*-test to establish the statistical differences in mean execution times between experts and novices for the capture/transport activity. We consider the null hypothesis H_0: $\mu_N - \mu_E = 0$, and the alternative hypothesis, H_α: $\mu_N - \mu_E > 0$. Here, μ_N is the Novice mean execution time, and μ_E is the Expert mean execution time in the capture and transport activity.

We also use a *t*-test to establish the mean differences for the Right-hand speed between experts and novices in the capture/transport activity. We consider the null hypothesis, H_0: $\mu_E - \mu_N = 0$, and the alternative hypothesis, H_α: $\mu_E - \mu_N > 0$. Here, μ_N is the Novice mean Right-hand speed and μ_E is the Expert mean Right-hand speed in the capture and transport activity.

Table 5 shows that the difference in the means between experts and novices is statistically significant for both measured variables (execution time and right-hand speed). The null hypothesis (equality of the sample means) is rejected in both cases. Moreover, the novice's mean execution time is greater than the expert's mean execution time, while the mean right-hand speed is greater in experts than in novices. SECMA distinguishes the different behaviors between experts and novices concerning the execution time and right-hand speeds during the catch and transportation activity.

Table 5. Welch Two-Sample *t*-test of execution times and right-hand speed for catch/transportation activity

Variable	Novice (n = 10)	Expert (n = 11)	95% Confidence Interval	*P*-value
Time(sec)*	60	33	20 – Inf	1.879×10^{-8}
Right-hand speed	0.11	0.07	0.03 – Inf	1.113×10^{-12}

Note: * Time is the execution time in seconds for the catch/transportation activity.

Figure 5 shows the results of the principal component analysis (PCA) with the variables measured during the catch and transportation activity. The right panel corresponds to the so-called *Graph of Variables*, which indicates that the first component mainly uses the differences between the *RightSpeed* variable and the rest of the other variables, in which the execution *Time* has greater weight, to distinguish between the observations. The second principal component considers the differences in speed, mainly *LeftSpeed* and execution *Time* to distinguish between the observations. The left panel of Figure 5 indicates that the observations corresponding to experts are mainly concentrated in the second quadrant, towards which *RightSpeed* points; that is, the experts have greater right-hand speed than the novices. The novices are scattered throughout the rest of the other quadrants. For example, observations in the fourth quadrant are characterized by longer activity execution *Times*, and in this quadrant, all graph points correspond to novices.

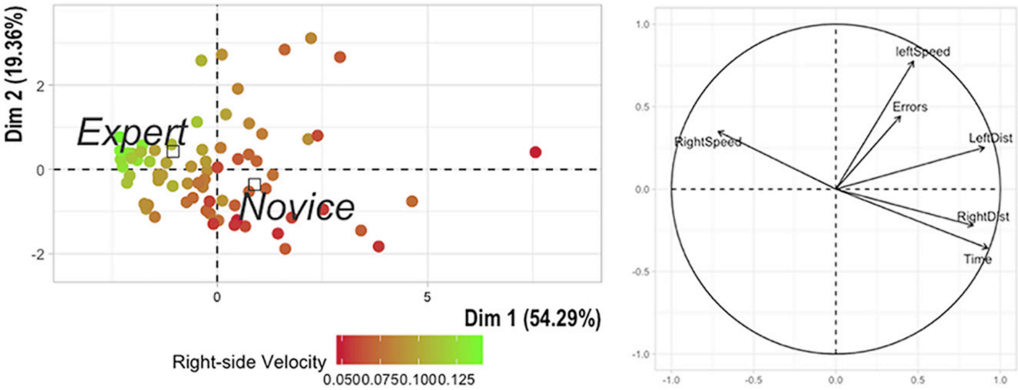


Fig. 5. PCA graph of observations (projection of the observations) in the plane of the first two principal components (left panel). Observations distinguish between experts and novices in the catch-transfer activity. The color is given according to the right-hand speed during the catch and transport activity. The PCA graph of variables is in the right panel

Furthermore, we use a regression model to get more details about the consequences of being an expert or a novice on the right-hand velocity for the catch and transportation activity with SECMA.

$$Velocity_i = \beta_0 + \beta_1 \text{Classification}_i + \varepsilon_i, i = 1 \ldots N \tag{2}$$

Where N is the number of observations and ε_i is the residual for the observation i. By using OLS we get the result as presented in Table 6.

Table 6. Results for the regression model (2)

	Estimate	Std. Error	*t*-value	$Pr(>\|t\|)$
β_0	0.105011	0.002736	38.386	$<2 \times 10^{-16}$
β_1: Classification-Novice	–0.034212	0.003717	–9.204	1.12×10^{-13}
R-squared: 0.55	*Adjusted R-squared:* 0.54		*p*-value: 1.12×10^{-13}	

Table 6 shows that the variable *Classification* (being an expert or a novice) influences (is statistically significant) the right-hand speed during the catch and transportation task. Specifically, it is obtained that the experts execute the activity with a mean speed of 0.105455, and the novices show less right-hand speed by subtracting 0.033916 from the expert's mean. In addition, the variable *Classification* explains 55% of the variance of right-hand speed in the catch and transportation activity.

3.3 Machine learning analysis for constructive validation of SECMA

The previous analysis clearly shows a relationship between execution times, right-hand speed, and ranking in experts and novices. In this subsection, we take a different approach to confirm this relationship.

By using supervised machine learning (ML) classifiers, we seek to demonstrate that the variables used by the virtual simulator during the capture and transportation activity allow for novice and expert classification. To do this, we used the following classifiers: *Linear Discriminant Analysis* (LDA) [19], *Logistic Regression* (GLM) [20], *K-nearest neighbors* (KNN) [21], *Support Vector Machine linear* (SVMLinear) [22], and *Support Vector Machine radial kernel* (SVMRadial) [23], *XGBOOST* (XGBTREE) [24], and *Random Forest* (RF) [25].

With the data registered from the activity, we applied cross-validation (number of resamples: 35). Thus, the data is partitioned into seven parts. One of the parts is taken as testing data, and the other six parts are used to train the classifier. The trained classifier is applied to the testing data, and the classifier's performance metrics are calculated. The entire classification process is repeated five times.

The calculated classifiers' performance metrics were: accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (ROC). The results are shown in Table 7.

Table 7. Accuracy for classifiers in binary classification of expert and novices

Accuracy	Min	Q1	Median	Mean	Q3	Max
LDA	0.6666667	0.8000000	0.9000000	0.8721789	0.9090909	1
GLM	0.6666667	0.8000000	0.9000000	0.8523810	0.9090909	1
KNN	0.7000000	0.7777778	0.8181818	0.8316595	0.9000000	1
SVMRadial	0.7000000	0.8090909	0.8888889	0.8607504	0.9045455	1
SVMLinear	0.6666667	0.8000000	0.9000000	0.8641270	0.9090909	1
XGBTREE	0.6666667	0.8000000	0.8888889	0.8518615	0.9090909	1
RF	0.7000000	0.8000000	0.9000000	0.8737374	0.9090909	1

All classifiers show an accuracy greater than 80% and a ROC greater than 90% (see Figure 6). These results indicate that the variables measured with the simulator in the catch/transportation activity can distinguish between experts and novices.

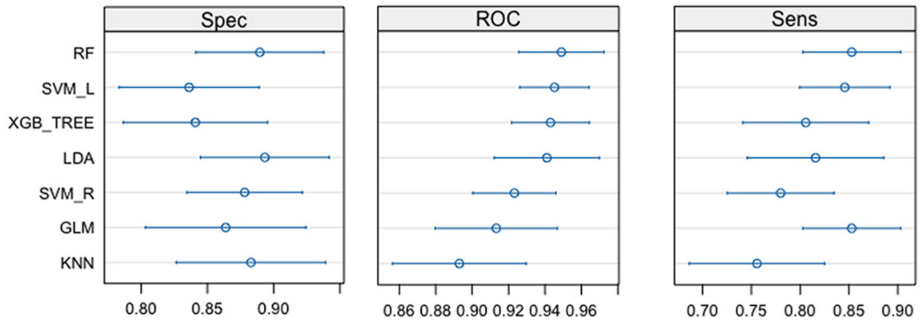


Fig. 6. Classifier performance metrics: Specificity, ROC and Sensitivity in binary classification in experts and novices during catch/transport activity with SECMA. The 95% confidence interval is also shown

4 CONCLUSIONS AND DISCUSSION

The VR simulator has become a valuable tool for learning basic motor skills in surgery. Skills that can be transferred to operating rooms. But commercial VR simulator packages for specific surgical practices can be expensive and not portable [19–23]. So, developing and validating low-cost VR simulators for MIS, especially for low- and middle-income countries, is mandatory.

Our first contribution is the construction of SECMA, a versatile, low-cost, and highly portable VR simulator that has already become an accessible tool for training surgeons in MIS. Indeed, SECMA was already used in training experiences at the Surgical Skills Training Center of the University of Chile, the Hospital del Salvador, and the San Borja Arriarán Hospital in Chile.

Achieving high portability and easy handling of the simulator were fundamental objectives in the design of SECMA. The importance of these features is brilliantly expressed in the following ad hoc quote from Levine [40]: "… *I learned that the biggest technology shortfall was that the simulator was anchored to the table. An early driving philosophy and the strategic goal was to make the simulator more flexible and mobile. I wanted to take the technology to the learner, not make the learner come to the technology* …."

We prove that the data and metrics/variables registered by SECMA during specially designed training activities (Coordination and Catch and Transportation) allow discrimination between novice surgical residents with no prior experience and experts or experienced surgeons, thus providing constructive validation of this instrument.

Our second contribution was to create a workflow for data manipulation to demonstrate SECMA's ability to discriminate between experts and novices, using not only the statistical tools commonly used for constructive validation but also a mixed set of machine learning (ML) classifiers. Data automatically recorded by SECMA was analyzed by hypothesis testing, linear regressions, analysis of variance (ANOVA), principal component analysis (PCA), and various ML-supervised classifiers. The methodology used, especially with the supervised classifiers, can be replicated in other experiences to classify the subjects who use the simulator according to their level of instruction. This is the first step to include artificial intelligence (AI) during training and thus enhance the teaching-learning processes of MIS with virtual simulators such as SECMA.

SECMA allows for the design of various training activities while recording various metrics and features that can be analyzed with machine or deep learning in real time. So, in future works, we will use the data recorded in real-time, from the trajectories of each virtual element during the practices with SECMA, to, through the AI, analyze the progress of the subject in training and offer real-time guidance in the instruction of MIS procedures.

We will also continue designing activities and benefits to improve the simulator's educational impact on the technical skills acquisition of undergraduate training in minimal access surgery. We will include a study to assess the concurrent validity and training effectiveness of SECMA to acquire specific technical skills and to compare it to other instructional methods that have been shown to train these same skills.

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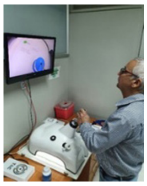
7 APPENDIX

Table A1. Comparative table of the SECMA with common-type MIS training simulators*

Attribute	SECMA	FLS Box Trainer	SIMBIONIX
Reference image			
Portability	High portability. The simulator fits in a small lightweight suitcase.	Low portability, it is designed to be in a fixed place (e.g., laboratories)	Low portability. It is designed to be used in a fixed place.
Commissioning	It does not use cables. Arming/disarming is intuitive.	Its commissioning is cumbersome. It uses power and video cables and requires additional accessories.	It has cumbersome commissioning using power and video cables
Automation	VR software automates the exercises and the assessment in real time through an Android device on the lens.	There is no automation in the execution of exercises.	It automates the exercises through VR and is controlled with a computer system.
Feedback on training	Real-time capture of data and performance reports generation through a Web application.	It does not capture training data and does not generate reports.	Generate reports of student training activities.
Self-management	The practitioner can work without an instructor.	An instructor is required for the evaluation and time record in the activities.	It does not require an instructor, but given the system's complexity, it is advisable.
Dynamic scenes	It uses dynamic and deformable elements that imitate surgical procedures.	It does not use dynamic elements. The deformable elements can be rendered useless at the end of the exercise.	It can use exercises with dynamic and deformable elements.
Price	Around US $ 2000.	US $75 – US $1280	US $2000 – US $100,000. US $25000 of annual maintenance.

Note: * See reference [36–39].

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