An Extended Reality Simulator for Advanced Trauma Life Support Training

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Abstract. We describe the design and development of an Extended Reality Advanced Trauma Life Support (ATLS) simulator that incorporates several ATLS scenarios. ATLS is a training program developed by the American College of Surgeons for teaching medical practitioners a systematic approach to treating trauma patients. The ATLS simulator is based on case-level data, which helps create reusable medical training scenarios. The simulation consists of three components, namely, incident history, initial assessment and resuscitation, and a secondary survey. It provides several scenarios for medical practitioners to perform the tasks from the ATLS checklist and practice diagnosing patients. The simulator can also predict the requirement of an ICU room, ventilator and the length of stay for a given trauma patient based on the type and severity of their injury. With our ATLS simulator we aim to provide medical practitioners a comprehensive training module for practicing emergency trauma response.

Keywords: Extended Reality · Medical simulation · Education and training · Machine Learning

1 Introduction

Extended Reality (XR) is an umbrella term used to describe immersive technologies that merge physical and virtual worlds. It comprises the entire spectrum of augmented reality (AR), virtual reality (VR), and mixed reality (MR). The recent advances in XR technologies and head-mounted display devices have resulted in several new educational, collaborative, and gaming applications. Medical training, however, is increasingly complex and imposes financial, ethical, and supervisory constraints. Digitizing training helps medical trainees with evidence-based solutions to enhance their skills and supplement the traditional curriculum.

In the ATLS simulator, the trainee is immersed in an XR environment and asked to correctly diagnose a virtual patient following the ATLS guidelines

J. Y. C. Chen and G. Fragomeni (Eds.): HCII 2022, LNCS 13318, pp. 31–44, 2022.
https://doi.org/10.1007/978-3-031-06015-1_3

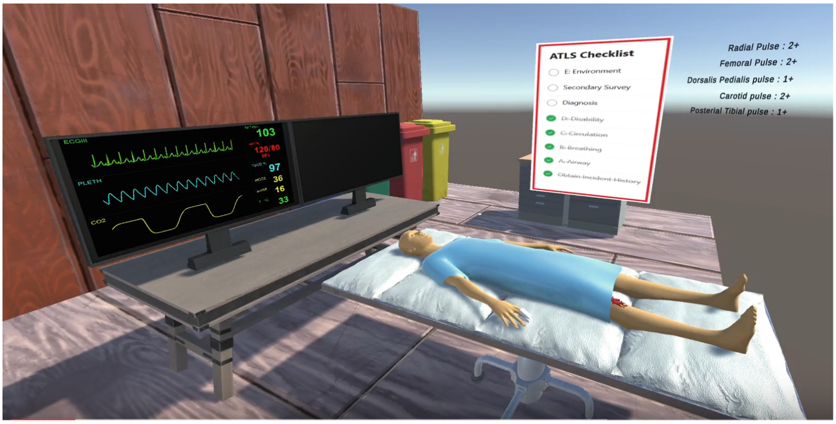

Fig. 1. Trauma room scene.

(Fig. 1). At the start of the simulation, the trainee is provided with a brief about the Mechanism, Injury patterns, Signs, and Preliminary Treatment (MIST) of the patient. The trainee then performs the Airway, Breathing, Circulation, Disabilities, and Exposure (ABCDE) steps of the ATLS procedure as listed on the checklist in the scene.

Sudden interruptions and stressful situations could lead to failure in following the ATLS guidelines. Therefore, we created a checklist in our XR simulator to facilitate adherence to the ATLS guidelines. The ATLS checklist in the XR simulator provides visual feedback about the trainee's progress in the scene and helps to ensure that all the ATLS steps are performed in the correct sequence. The steps in the simulation require the trainee to attach additional devices, like a pulse oximeter or a blood pressure cuff, for receiving and monitoring the patient's vitals. After completing a thorough examination of the patient, the trainee diagnoses them and makes appropriate arrangements for transferring them to Definitive Care. The MIST information of the patient and the outcomes of the ABCDE steps vary in each scenario, providing the trainee with several trauma cases to diagnose.

Artificial Intelligence (AI) and Machine Learning (ML) methods have been used to improve the interactions of XR users and evaluate their performance in training modules. The ATLS simulator includes a resource prediction model that supplements trainee medical diagnosis and can help manage hospital resources. The predictor model uses a random forest algorithm to predict the requirement of hospital resources like ventilators, ICU rooms and hospital beds for a trauma patient with a given set of injuries and vitals data.

We used the Pennsylvania State Trauma Registry as our dataset for training [2]. The trauma registry was created by the Pennsylvania Health Department to collect information about injured patients from all accredited trauma centers and to develop a mechanism to review the quality of care provided by the state's trauma system. The Pennsylvania Trauma Outcome Study (PTOS) registry has entries of more than one million trauma patients, including the demographic data, pre-hospital data, the process of acute care, clinical data, and outcomes data of the patient. Along with the advantages of creating reusable scenarios for medical training, our ATLS simulator with AI assistance will help medical trainees provide patients with more data-driven and personalized healthcare treatment.

2 Related Work

The advantages of using XR in healthcare training is immense and includes reduced training cost and repeatable standardized practice scenarios. These simulators typically have a one-time development and equipment cost, followed by minimal runtime cost per session [9]. Zweifach et al. discuss the needs and benefits of realistic XR simulation methods over the traditional training opportunities with real patients [33]. In their work, they also describe a framework to help medical schools adopt the mixed reality tools into their school's anatomy and procedural curricula. De et al. observed that the majority of students who attended online training sessions were satisfied with their virtual, interruption-free medical training experience and gave positive feedback to the perceived quality [8]. This suggests that virtual training modules can be successfully developed to enhance vocational training.

The examples of simulators for healthcare training include an ultrasound-guided vascular access simulator [4], a cardiac simulator [12], an orthopedic surgical training simulator [5] and ophthalmoscopy simulators [23] that help medical students improve their diagnostic skills and offer superior clinical findings. Sheik-Ali et al. investigated the role of these devices in the acquisition of technical skills during surgical education. They observed a positive correlation between the usage of XR in surgical education and improvement in procedural accuracy, hand-eye coordination, and the surgeon's ability to multitask [24]. Harrington et al. demonstrated validity criteria for a VR-based medical training simulator. Their simulator was successfully tested for its ability to distinguish decision-making skills between the different levels of expertise [16]. Handosa et al. similarly developed a mixed reality training program for CNA students [15]. These simulators indicate the feasibility of using XR for practical medical training.

2.1 Intelligent XR Simulators

AI and XR are two prominent and growing fields of Computer Science with different focus areas and applications. However, these two fields can be synergistically combined to create advanced training modules for various disciplines. Studies have been conducted to understand and investigate the AI-XR continuum applications, including training AI, conferring intelligence to XR, and interpreting XR-generated data [7,22].

ML models have recently been seeing increased use in supporting medical diagnoses. Stanney et al. observe that XR simulators driven by AI offer a unique opportunity to decrease time to proficiency and extend trainee retention significantly [26]. ML models can be used to predict hospital admission from patient medical history and triage data [17]. Patient mortality, hospital stay duration, and readmission likelihood can also be predicted using patient information at admission [6,18,29].

Adding Natural Language Processing (NLP) and ML helps improve XR experiences. For example, Talbot et al. created an AI Dialogue system to integrate XR models with the ability to understand human speech and hold a conversation. Such ML models are trained on large datasets consisting of patient hospital data [28]. In addition to this, ML models can be trained to teach XR simulators to make decisions by identifying patterns and analyzing historical data. In this paper, we present an approach to using ML algorithms to augment medical trainee diagnosis in an XR ATLS simulator. Hospital data from the Penn State trauma unit was used as the training data.

2.2 Advanced Trauma Life Support

Patients with trauma injuries are not easy to manage and can cause anxiety even for expert clinicians. The ATLS course was developed to solve this issue. All trauma surgeons and ED physicians working at trauma centers are reuired to complete this course. Several studies show the importance of the ATLS courses in emergency rooms. Williams et al. reviewed the value of ATLS training for medical staff in a major incident situation [32]. 13 simulated casualties were treated by eight doctors with different experience levels. Williams et al. awarded scores to these doctors based on whether they took the critical treatment criteria into account while making their diagnoses. Their research shows that medical staff who had undertaken ATLS training scored higher than those who had not. Wang et al. compared the severe trauma care effect before and after the ATLS training [31]. From their experiment, they observed that the mortality of the patients in the emergency department decreased significantly post-ATLS training.

Trauma-related injuries are extremely common. They are a leading cause of death in children and adults below 45 years. Severely injured patients are resuscitated by a trauma team, who perform a predefined set of tasks in a sequence determined by the ATLS. Stressful situations can make it difficult to correctly follow through with the ATLS protocol. In order to address this issue, a checklist was created to help medical practitioners adhere to ATLS guidelines. Maarseveen et al. reviewed the effects of applying a checklist during the resuscitation process of trauma patients [30]. They observed that the average adjusted time to task completion was 9 s faster with the application of a checklist.

Several studies have been conducted to evaluate the effects of a checklist during trauma resuscitation. Smith et al. developed a standardized pre-procedural checklist to assist clinicians in ensuring adequate preparation for intubation [25]. They also studied its effectiveness for reducing intubation-related complications in emergency department (ED) trauma patients. For this study, 141 patients were considered, including 76 patients in the pre checklist period and 65 in the post checklist period. A 7.7% absolute risk reduction of intubation-related complications was observed from the pre checklist period to the post checklist period. There was only a 12 s decrease in the time associated with the process of intubation, which may not directly result in the improvement of patient outcomes.

3 Problem Definition

The ongoing pandemic has also reinforced the importance of healthcare training and education. Typically, training is conducted by having actors enact certain conditions that medical trainees need to diagnose. Physically recreating each reuired training scenario with actors and equipment can cost institutions around $63,000 per trainee [1]. This expense can be brought down significantly with XR-based training modules.

The medical field demands accurate and precise procedures to be performed by doctors, with no room for error. Traditional training methods involve the trainer demonstrating the technique and the student repeating it, which increases the risk of medical errors [21]. The memory recall, ease of use, and novel learning modality offered by immersive environments benefit the using XR technologies in medical education. XR also provides risk-free, immersive, reproducible environments that help improve physicians' performances for various surgical and medical tasks.

The majority of the existing simulators are in VR. VR being fully-immersive leads to a phenomenon called VR sickness. In VR sickness, the users often forget where they actually experience a visually induced perception of self-motion that leads to disorientation, discomfort, headache, and nausea [10].

Lastly, having the ability to place the user within an augmented world, with the option to interact with both physical and digital objects simultaneously, has many advantages. The inclusion of MR will also make it possible for physicians and educators to incorporate real-world medical instruments into training modules. Using tools like Vuforia [11], or Microsoft's Mixed Reality Toolkit [20], physical objects can be detected in MR applications and made to interact with virtual content. This will provide realistic training environments for new medical trainees to practice the ATLS curriculum.

4 Proposed Approach

In this section, we present an XR ATLS training simulator that is developed in conjunction with Penn State Health. Our goal is to create reusable training modules for medical students to practice trauma diagnosis. These modules can be designed to simulate several different trauma scenarios, including accidental injury, poisoning, drowning, and burn injuries. These scenarios can be used not only for training but also for evaluating medical student performance as part of their educational curriculum.

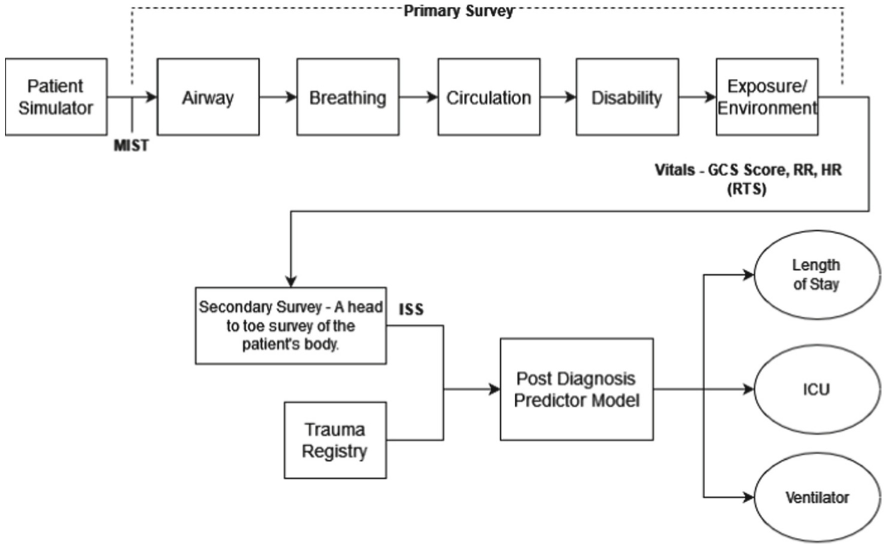

Fig. 2. System flow diagram

4.1 ATLS Scenario

Our ATLS simulator was developed for the Microsoft HoloLens 2 using the Unity Game Engine. ATLS protocol dictates that students perform a medical evaluation of trauma patients in a specific sequence, scanning for injuries in areas of importance first and then proceeding to lower priority areas. The ATLS procedure consists of two assessments, a primary survey and a secondary survey (Fig. 2). The primary survey is the most important part of assessing a trauma patient where life-threatening injuries are identified and resuscitation steps are taken. After completing this survey, patient vitals are recorded, and a secondary survey is conducted. The secondary survey is a head-to-toe examination of the trauma patient, including a complete physical inspection and reassessment of all vital signs.

We created a practice scenario involving a young male patient injured in an automobile accident. The patient is rolled into the trauma bay, and the trainee student (HoloLens 2 user) is provided with the MIST (Mechanism, Injury, Signs, Treatment) information. This information is provided in audio format to the user and varies with each trauma scenario. After receiving background MIST information about the patient, the medical student performs the ATLS procedure. A checklist is provided to the student to help them identify the correct sequence of actions to perform.

Primary Survey: The primary survey comprises of 5 ABCDE steps namely Airway, Breathing, Circulation, Disability and Exposure:

1. **Airway**: The first step of the primary survey is to assess the airway. If the patient is able to state their name clearly, the airway is considered to be patent.
2. **Breathing**: In the second step, the chest of the trauma patient must be examined by inspection, palpation, percussion and auscultation.
3. **Circulation**: In the next step, the trainee connects the cardiac monitor and pulse oximeter to the patient. The goal of this step is to identify all possibilities of hemorrhage, as it the predominant cause of preventable trauma-related deaths. After connecting the devices, the trainee notes the vitals of the patient which includes Blood Pressure (BP), heart rate (HR), respiration rate (RR) and oxygen saturation (Sp02).
4. **Disability**: In this step, the patient's level of consciousness is assessed by using the Glasgow coma scale (GCS), pupil size and reaction, and lateralizing signs.
5. **Exposure**: The last step of the primary survey is to ensure that no physical injuries were missed. Body temperature and critical skin conditions must be examined.

The checklist contains all the steps of the ATLS guidelines in sequential order. Each step of the primary survey is marked completed on the checklist after successfully executing the tasks involved.

Secondary Survey: A secondary survey is performed once the patient has been resuscitated and stabilized. After the primary survey, the patient is examined head-to-toe to identify significant but not immediately life-threatening injuries. The purpose of the secondary survey is to evaluate and treat injuries not found during the primary survey. It helps prioritize continued evaluation and management. In our ATLS simulator, the medical trainee examines the head, neck, chest, abdomen, and musculoskeletal system of the patient. Additionally, radiographs might be requested depending on the observed injuries.

4.2 Hospital Resource Management

Currently, in the COVID-19 pandemic, hospital resources like ICU rooms, ventilators, and hospital beds are severely strained. Increased patient volumes make the allocation of these resources a grave problem. This has direct consequences on hospital costs and patient satisfaction. To address this issue, we developed a NLP-based ML model for predicting the requirements of ICU rooms, ventilators, and patient length of stay based on the MIST information of the patient and diagnosis made by the trainee.

For training the model, we considered the Pennsylvania State Trauma Registry. The registry contains records of all trauma patients from January 2018 to July 2021 reported at the trauma centers in Pennsylvania. A random forest algorithm was used to make predictions as it is simple to implement, fast in operation, and has proven to be successful in various domains (Fig. 3).

Fig. 3. Left: Participant wearing HoloLens 2. Right: Participant's point of view.

The input parameters for training the model include:

1. **MIST information:** Standard NLP preprocessing techniques like removing stop words, lower casing, tokenization were applied to the MIST text to prepare the text data for the model building. The top 200 keywords from the entire corpus were selected using the TF-IDF (Term Frequency - Inverse Document Frequency) score.
2. **Injury type:** An integer value ranging from 1 to 4. The values represent the different categories of injury, namely: blunt, penetrating, burn, and skin disease. It helps medical practitioners identify the type of force applied to the body.
3. **Revised Trauma Score (RTS):** A physiological score ranging from 1 to 12 based on the GCS Score, Blood Pressure, Respiratory Rate of a trauma patient as recorded during the primary survey [14]. A patient with an RTS score of 12 is labeled delayed, 11 urgent, 3–10 immediate, and a score below 3 is declared dead.
4. **Injury Severity Score (ISS):** A medical score ranging from 3 to 75 that helps assess trauma severity [27]. It is based on the Abbreviated Injury Scale (AIS) severity code of the three most severely injured ISS body regions. It correlates with mortality, morbidity, and hospitalization time after trauma.

To predict the patient's length of stay, a KNN model was trained on the above-mentioned input parameters of the PTOS registry. The model identifies the 5 nearest cases (neighbors) to the test case and uses them to predict the length of the stay. After successfully completing the secondary survey, the model predicts the requirement of an ICU room, ventilator for the trauma patient and the length of stay of the patient. This prediction is based on the MIST information and the evaluation of the medical trainee.

4.3 Study Procedure

We conducted a pilot study with five participants to test our XR ATLS simulator. All participants were familiar with XR technology and Human-Computer Interaction concepts. Participants performed the ABCDE steps of the ATLS with minimal assistance.

For the pilot study, a situation was given, and participants followed the checklist to complete the simulation. At the start of the pilot study, the simulator states the background MIST information about the patient. Participants were asked to probe the patient's airway by having them state their name. Next, participants were asked to examine the patient's breathing sounds. Breathing sounds were heard using a virtual stethoscope. Blue bubbles were used to indicate locations where participants were required to measure breathing.

Following this, participants noted the patient's HR and pulse vitals from the cardiac monitor. They assessed the radial, femoral, posterior, tibial and dorsalis pedis pulses of the patient bilaterally. Pulse reading locations were indicated using yellow bubbles.

Next, in the Disability step, participants determined the patient's consciousness level and assessed the patient's motor control. This was done by making the patient blink their eyes, wiggle their toes, and state their current location.

The last step of the ATLS simulator involved examining the patient and ensuring that no physical injuries were missed during the previous stages. Participants assessed the right leg of the patient and observed deformity in the lower right leg. They also noted that no open wound was present. Participants asked for x-rays of the right knee, leg, and ankle, following which they applied a splint and requested an orthopedic consult.

5 Results

After completing the pilot study, the participants were asked to fill out a System Usability Scale (SUS) Questionnaire. The SUS was developed by John Brooke in 1986 [3]. It is a popular tool for evaluating the usability of software, websites and applications. It consists of a 10-item questionnaire. Each question is multiple choice with five answer choices ranging from "Strongly Agree" to "Strongly Disagree". Odd numbered questions corresponded to "positive affect" questions, while even numbered questions corresponded to "negative affect" questions. Participants were asked to respond to these ten questions based on their experience with the ATLS simulator. An additional free response question was also included in the questionnaire for participants to provide feedback.

5.1 SUS Results

All ten question item responses were assigned raw numeric values, with 1 = "Strongly Disagree" and 5 = "Strongly Agree". These raw scores were converted to weighted scores based on their effect. The weighted scores range from 0 to 4.

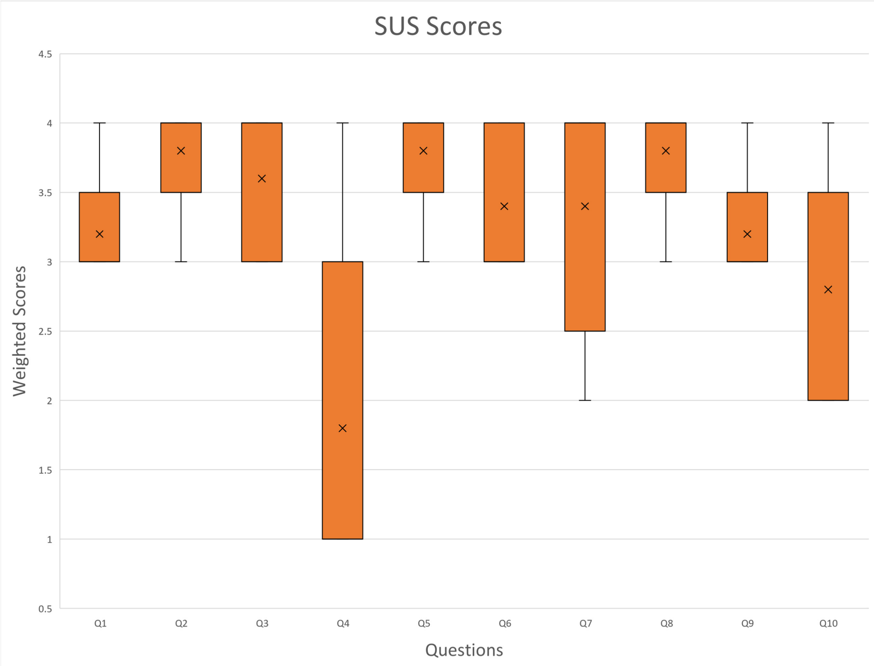

Fig. 4. Pilot study SUS scores

Each participant's weighted score was added, and the total was multiplied by 2.5 to get a composite score out of 100. A score of over 68 is considered to indicate good usability [19]. The average SUS score we observed through our pilot study was 82. It indicates that the participants considered our ATLS simulator to have high usability. The SUS scores for all 5 participants can be seen in Fig. 4.

Limitations of the ATLS Simulator: Our pilot study also highlighted certain limitations of the ATLS simulator that we need to improve on in future iterations. Two of these limitations can be observed in the SUS scores graph (Fig. 4). The score for Question 4 is significantly lower than the scores. This question corresponds to the "I think that I would need the support of a technical person to use this system." prompt of the SUS questionnaire. We believe that participants gave low scores in response to this prompt because of their inexperience with real-world ATLS scenarios and unfamiliarity with the ATLS protocol.

The second lowest score was given in response to the "I needed to learn a lot of things before I could get going with this system" prompt (Question 10). This could also be attributed to the participant's lack of experience with ATLS terminology. Testing our ATLS simulator with actual medical practitioners would help us re-evaluate these two usability scores.

During the study, a participant found it difficult to pick the virtual stethoscope using the default hand-interaction technique (select-and-drag). The participant also commented that the voice commands used in our ATLS simulator were too specific and could be improved further.

5.2 Model Prediction Results

The models predict three hospital resource values. Two of the predicted values (ICU bed requirement and ventilator requirement) are binary, and one value (the length of stay of the patient in days) is numeric. We use Accuracy and F1 scores as metrics to evaluate the binary predictions. To evaluate the predictions for the numeric values of the model, we use Mean Absolute Percentage Error (MAPE). The dataset was split in the following manner: 70% of the data was used for training, and 30% of the data was used to test the random forest model. The metrics used to evaluate the classification problem were accuracy and F1 score. The F1-score combines the precision and recall of the classifier into a single metric by taking their harmonic mean. We performed a 5-fold evaluation of the trained models and observed the following results (Table 1):

Table 1. ML model prediction results.

Patient requirement	Accuracy	F1 score
ICU	0.907	0.790
Ventilator	0.974	0.915

Similarly, to predict the length of stay of the patient, a KNN model was trained on the same input parameters of the dataset. The patient's length of stay varies from 0 days to 365 days. The model was evaluated using the MAPE metric. MAPE is the average percentage error and measures how accurate a forecast system is.

$$MAPE = \frac{1}{n} * \sum_{t=1}^{n} \left| \frac{PredictedValue - ActualValue}{ActualValue} \right|$$

A prediction model with MAPE value between 10% to 20% is considered good, and this varies with the type of industry and application. [13] The average MAPE value calculated over 5-fold cross-validation of the model is 0.129, which implies that the average difference between the predicted value and the actual value is 12.9%. The percentage error also indicates that the trained model is effective and acceptable.

6 Conclusion

Medical training is expensive and laborious to set up. To address this problem, we developed an XR medical training application for ATLS. In addition to this, we also used ML models to predict the requirement of hospital resources by incoming trauma patients.

We conducted a pilot study with five participants to evaluate our ATLS simulator. The System Usability Scale was used to evaluate the usability of our simulator application. We observed an average SUS score of 82, indicating that most of our participants found the XR ATLS simulator easy to use. However, additional improvements to the user interface and interaction modes can help further increase the usability of our ATLS simulator.

Our future work will include making the simulator more realistic by incorporating real-world objects in it and conducting a more comprehensive user study with healthcare professionals. Lastly, we also plan to add haptic feedback to enhance the realism of the ATLS simulator.

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