Development of a BLS Self-Training Support System using MR and Sensor Devices

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Abstract. We have developed a system using Mixed Reality (MR) and sensor devices to aid Basic Life Support (BLS) self-training. Our system can provide BLS trainees with the real-time feedback of training score and post-training score visualization. It combines visual information provided by a MR device and physical input data such as chest compression depth and recoil obtained from sensor devices. Our system was utilized by a group of nurses (from novices to experts) to evaluate its usability and effectiveness. The result shows that it assists BLS trainees with consistent self-training and offers valuable feedback, especially through score visualization, though we found that there were problems with the visibility and usability of real-time feedback elements. This study suggests that our system can complement conventional On-the-Job Training (OJT) based BLS training and has potential for broader application in clinical education.

Keywords: Basic Life Support, Mixed Reality, Sensor Devices, Raspberry Pi

1 Introduction

Learning BLS (Basic Life Support) is important for nurses, since BLS requires no specialized equipments and the patient survival rate is improved by expeditious and adequate chest compression [1].

Frequent BLS drill is recommended but difficult in actual due to a substantial burden on supervisors. The early, periodical and continuous BLS practices are recommended for newly hired nurses to build skills and confidence [2][3]. In typical clinical settings, training for BLS is conducted in the form of OJT (On-the-Job Training) using manikins, supervised by mentor nurses (Fig.1). Hence, repeated hands-on training places a heavy burden on supervisors, making it difficult to carry out regularly.

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Fig. 1. An example of traditional BLS OJT training: "Pacific Partnership 2022 Facilitates Basic Life Support Training in Phu Yen 220621-N-YL073-1416" by NavyMedicine is marked with Public Domain Mark 1.0. To view the terms, visit https://creativecommons.org/publicdomain/mark/1.0/?ref=openverse.

Our research focuses on developing a BLS self-training support system to resolve conflicts described above. Our approach aims to reduce instructor workload while helping novice nurses improve their BLS skills through self-guided simulation. It allows spaced and repeated BLS self practices for nurses.

We integrate a manikin, an MR (Mixed Reality) device, a cloud service and sensor devices into a BLS training system. The manikin is equipped with physical sensors on the chest to collect quantitative data such as compression depth and tempo. The sensor data is sent to a cloud server in real time. The data is processed statistically and the summarized score is visualized through an MR device worn by the trainee. The visual feedback helps the trainee with intuitive understanding and reflection.

2 Related Works

2.1 Traditional Training in Clinical Nursing Fields

A typical BLS training program in clinical nursing fields consists of theoretical and practical components.

The theoretical part includes lectures, video instructions and discussions on the series of action to keep a patient alive. Nurses are trained to recognize Sudden Cardiac Arrest, understand the protocol to call for help, and learn CPR (cardiopulmonary resuscitation) and the use of an AED (automated external defibrillator) device.

The typical practical component is simulation based education using a manikin. This training is conducted as OJT (Fig.1). It requires experienced nurses as the supervisors. This OJT places a burden on the supervisors.

The traditional BLS training has been effective but its limitations are recognized these days. JRC (Japan Resuscitation Council) resuscitation guideline proposes a lot of improvement method candidates including use of more realized manikins, spaced learning[4], AR (Argument-ed Reality) and VR (Virtual Reality) [4].

2.2 Application of AR and VR to BLS Training

AR and VR are expected to be effective methods to enhance training outcomes as mentioned above[4]. These techniques could provide trainees with more reality in simulation and training environment unrestricted by time or geography.

There are several study[5][6] on application of virtual reality to BLS training but research on application of AR to BLS one remains largely under-explored.

Hasumi et.al. developed an AR based training system to resolve the gap between CPR training and real scenarios[7]. Trainees are able to see agonal breathing, hematemesis and circulation of blood within the human body in CG (computer graphics) and check the statistics for the chest compression. It looks it could provide a high sense of presence but its usability and the effects derived from its feedback mechanisms have not been thoroughly investigated.

2.3 Application of MR to BLS Training

AHA (American Heart Association) recommends the use of visual feedback in CPR training[1]. From the point of view on interaction between real and virtual spaces, MR (Mixed Reality) is expected to show the potential to enhance BLS training outcomes.

Research on MR application to BLS training is extremely limited. Studies combining sensor devices and HMD (Head Mounted Display) virtually not exists.

3 Design and Implementation

In this section, we describe details of design and implementation of our system.

3.1 Overview

We have developed a system using MR and sensor devices to aid BLS self-training. Our system is composed of a manikin, an MR device, a cloud service and sensor devices. The features can be summarized as follows

[4] Spaced learning is an effective learning method based on the principle that learning is enhanced when information is retrieved multiple times rather than once. It is one of the most effective methods for enhancing learning outcomes, as supported by educational psychology [8]

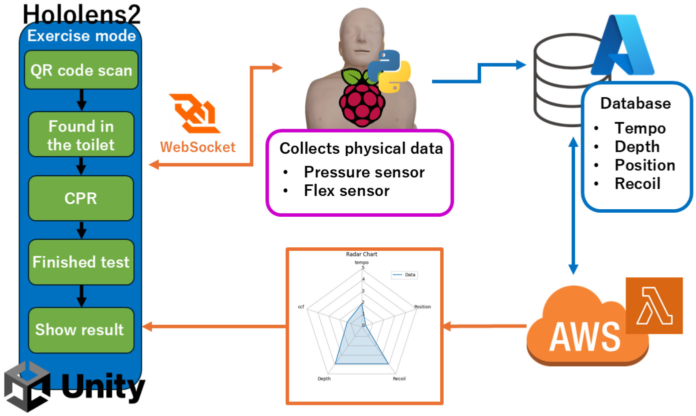

Fig. 2. A schematic diagram of our system for measurement and visualization. The data is exchanged among an MR device, a cloud service and sensor devices attached to the manikin. The left column shows our scenario where the whole set of the training is processed along it. See Fig. A1 for more details on the flow chart of the scenario.

1. implementation of a self training system that simulates a traditional set of BLS training exercises.
2. direct measurement via sensor devices attached to the manikin.
3. visual feedback in real-time.
4. display of the training score in both real-time and after the whole set ends.
5. a prototype implementation that superimposes facial expressions onto the manikin.

The BLS self-training content is based on a demonstration video provided by Japan Lifesaving Association and JRC Resuscitation Guidelines 2020[4]. We also refer to the standard BLS training program of Japanese Association for Emergency Nursing, which is commonly used for conventional OJT in hospitals. Fig. 2 shows a schematic diagram of our system for measurement and visualization. The whole set of the training is processed along a scenario shown in the left column in Fig. 2. See Fig. A1 for more details on the flow chart of the scenario.

Our system displays feedback data in front of the trainee's eyes within the virtual space illusion-ed by a MR device. The shown feedback is statistically processed data based on the physical input data such as chest compression depth and recoil obtained from sensor devices.

We use Microsoft HoloLens 2 as the MR device and a Raspberry Pi 3A+ (Unix/Linux device) as the platform which manages sensor devices. Precisely speaking, sensor devices are attached to our system via the Raspberry Pi 3A+. Raspberry Pi 3A+ manages the data retrieval from sensor devices, processes the data statistically and transmits the processed data to the MR device and a cloud service (Microsoft Azure). See sections below for more details.

In conventional BLS training, it is difficult for trainees to obtain real-time feedback and review quantitatively their performance after a session since trainees

Fig. 3. Manikin's internal configuration (side view). In the actual BLS training, this body is covered with a vinyl cover that simulates the texture of human skin (the cover can be seen in the left side in Fig.4). The Raspberry Pi under the chest cannot be seen (not seen in Fig.4, too).

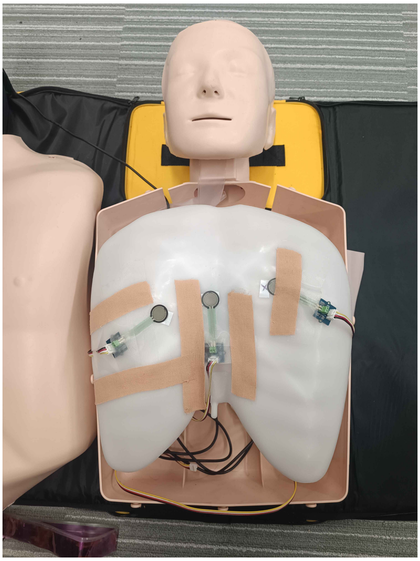

Fig. 4. Manikin's internal configuration (front view). We can see sensor devices on the chest plate of the manikin.

are advised by the supervisors after the whole set of each BLS training session. Our system can provide BLS trainees with the real-time feedback of training score (see section 3.3) and post-training score visualization (see section 3.4). The feedback consists of key metrics such as compression tempo, depth, position, and recoil. These values are scored according to the criterion mentioned above (See Appendix B for criterion details). After the training session, the system performs statistical analysis of the recorded sensor data and visualizes the score results. These visualizations enable trainees to review their BLS self training from the objective point of view.

3.2 Data Exchange among the MR Device and Sensor Devices

The communication between our MR device and the Raspberry Pi is bi-directional. The MR device receives the processed data from sensor devices in real time and shows it in the front of eyes of the trainee. The MR device transmits flags to the Raspberry Pi to change the system status since our system needs to change the behavior along the scenario.

Sensor devices are attached to our system via the Raspberry Pi 3A+, which is a platform and manages sensor devices. As shown in Fig.4, we embedded three GROVE pressure sensors using FSR402 and one Qwiic flex sensor using ADS1015 into the chest compression structure of the manikin. Both sensors are attached to the Raspberry Pi via GROVE interface.

The Raspberry Pi manages the data retrieval from sensor devices, processes the data statistically, scores them and transmits the processed data to the MR device. All data are also transmitted to a cloud service simultaneously. The scoring criteria is based on the recommended values specified in the JRC Resuscitation Guidelines 2020.

This setup allows us to evaluate the compression position and depth quantitatively. The analog signals from these sensors are digitized using an analog-to-digital converter (ADC: MCP3008). To reduce the data noise and prevent the data from reacting too sensitively to sudden signal fluctuations, especially when calculating BPM (beats per minute), we apply a simple moving average (SMA) filter to the sensor data.

$$\mathrm{SMA}_t = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i}$$
$$x_i \in \mathbb{R} \quad (i = 0, 1, \ldots, t)$$

Filtered values are transmitted every 125 milliseconds (approximately 8 Hz) where 8 Hz must be precise enough since the recommended chest compression rate is two times per second.

For data exchange between the Raspberry Pi and the HoloLens 2, we adopt Web-Socket, which supports bidirectional and asynchronous data exchange. This choice enables real-time transmission of sensor data and state requests from either side. Each set of sensor values is packetized and sent in JSON format, with an attached timestamp for proper data handling.

3.3 Real-Time Feedback in the Trainee's Virtual Space

The MR device receives and shows the scored data in real time, as mentioned in section 3.2. These metrics are displayed as a hand menu that follows the trainee's wrist movements, ensuring that feedback remains within the trainee's field of view during the exercise.

Fig.5 shows an example of what a trainee will see. The displayed metrics include compression tempo, position, depth, and recoil. Each metric is represented by an icon, and the evaluation results are color-coded: green indicates "appropriate", while red indicates "inappropriate". This design allows the trainee to intuitively recognize performance quality during chest compressions and make adjustments in real time.

3.4 Post-Training Feedback in the Trainee's Virtual Space

After a set of BLS training, our system shows the summary to enable trainees to quantitatively assess their performance and effectively reflect on their training. The summary is shown by the MR device (HoloLens2) in the trainee's view as a radar chart which covers typical metrics such as compression tempo and recoil. Trainees can see more details as a histogram for each metric if needed. Fig. 6 shows an example of a radar chart.

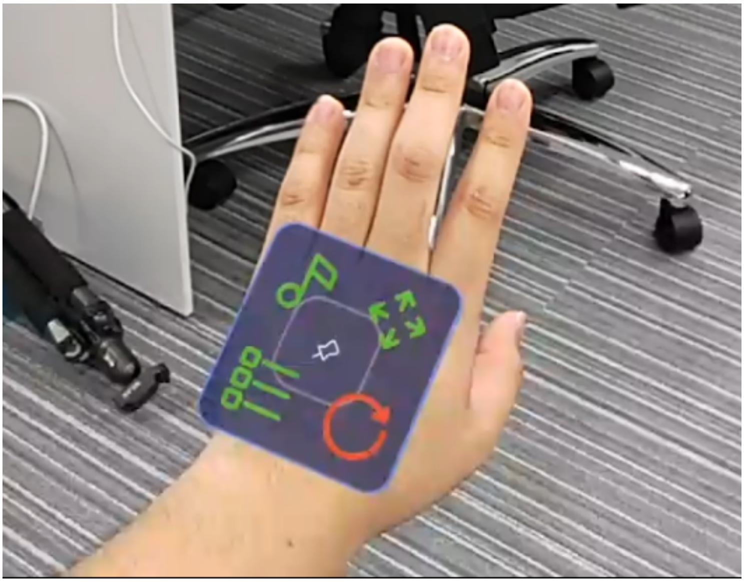

Fig. 5. An example of the real time feedback. It is shown in the front of the trainee's eyes in the virtual space. The hand menu shows the brief summary of the trainee's training score.

The Raspberry pi manages the data from sensors as described above but images such as radar charts and histograms are processed by cloud rendering to avoid the processing load of Raspberry Pi. During each session, various sensor data are recorded on the Raspberry Pi as time series on a per-session basis. Upon completion of the BLS training session, these data are uploaded to a cloud (Azure Table Storage). The session completion event triggers an AWS Lambda function, which automatically performs statistical analysis using Python. This analysis includes the distribution of compression tempo, variation in compression depth, reproducibility of recoil, and the chest compression fraction (CCF). Based on these calculated values, the system generates radar charts and histograms using the Matplotlib module and converts them into image files.

The generated images are then transmitted via HTTPS to the HoloLens 2. Their images are shown in the front of trainee's eyes. It is expected that this workflow allows trainees to review their performance objectively and supports data-driven reflection.

4 Evaluation and the Results (1)

A set of BLS self training exercises using our system was utilized by two "expert" nurses in hospital A and their feedback was subsequently assessed by a

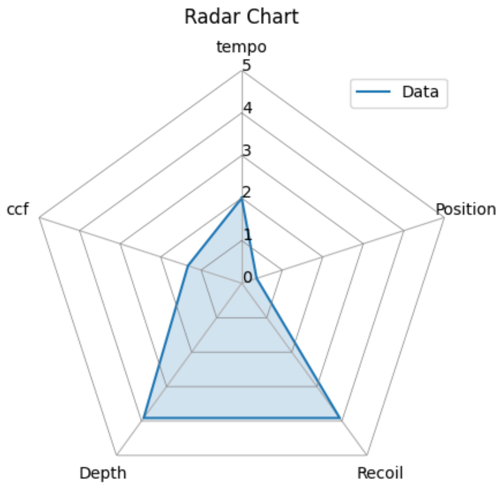

Fig. 6. An example of the radar chart showing evaluation results. It is shown in the front of the trainee's eyes in the virtual space after the whole set of BLS training.

post questionnaire. Both participants was classified as "expert" according to the Benner's novice-to-expert model[5][9].

We designed the questionnaire to verify how effectively our proposed system could function as an integrated BLS self training platform. This questionnaire consisted of 14 questions, each answered on a 6-point Likert scale (1: very dissatisfied, 2: dissatisfied, 3: slightly dissatisfied, 4: slightly satisfied, 5: satisfied, 6: very satisfied). These questions ware composed of the following four perspectives(Table 1):

1. Overall process and user satisfaction (Q1-Q3)
2. Usability related to MR operations (Q4-Q7)
3. Effectiveness of real-time feedback (Q8-Q12)
4. Usefulness of post-training data visualization (Q13-Q14)

4.1 Overall Process and Satisfaction (Q1-Q3)

Both participants rated their satisfaction as 4 (slightly satisfied) to Q1 and Q2. This indicates that there are no major concerns on the overall process.

[5] Patricia Benner's 5-stage model[9] is a theory that describes the progression of nurses from novices (beginners) to experts through a five-stage process. This model is based on the Dreyfus model of skill acquisition[10].

Fig. 7. An image showing a nurse using our system. Data is exchanged among an MR device, a cloud service, and sensor devices attached inside the manikin.

Table 1. Summary of evaluation results for each questionnaire item. Numbers in parentheses indicate years of nursing experience.

Q#	Evaluation Item	Nurse A (30)	Nurse B (18)
Q1	Overall system process	4	4
Q2	Satisfaction with training scenario	4	4
Q3	Ease of overall operation	4	3
Q4	MR panel visibility	5	3
Q5	Ease of pressing buttons	4	3
Q6	Panel position	5	3
Q7	Ease of menu operation	4	3
Q8	Tempo feedback	2	1
Q9	Position feedback	2	1
Q10	Depth feedback	2	1
Q11	Recoil feedback	2	1
Q12	Icon synchronization with motion	2	1
Q13	Usefulness of radar chart visualization	4	4
Q14	Usefulness of histogram visualization	4	4

4.2 Usability Related to MR Operations (Q4-Q7)

Nurse A provides positive ratings to Q4-Q7 but Nurse B rated Q5 (ease of pressing buttons) and Q6 (panel position) as 3 (slightly dissatisfied). These results in Table 1 suggest that the user experience varies considerably from person to person and it would be necessary to improve UI (user interface) design and operability.

4.3 Effectiveness of Real-time Feedback (Q8-Q12)

Both participants assign low ratings to Q8-Q12 on visual feedback details. We introduce the open-ended survey question in the questionnaire, below. Nurse B commented: "The icons are not visible unless I change the angle of my wrist, and I rarely look at my wrist during chest compressions." Nurse A commented: "My gaze is directed slightly forward rather than toward my wrist. During CPR, nurses often look at the patient's face or a monitor" [6]. Therefore, the current feedback display position is suboptimal from the actual workflow perspective. This indicates the need for UI design to incorporate principles of gaze guidance and ergonomics.

4.4 Usefulness of Post-Training Data Visualization (Q13-Q14)

Both participants assigned positive ratings to Q13-Q14. The summary of training score, shown after the set of BLS training, is visualized as a radar chart in the front of trainee's eyes (Fig. 6). They confirmed that visualization of metrics such as compression depth, tempo, and recoil was useful for reflection. This suggests that our system has the potential for BLS trainees to promote data-driven review.

Table 2. Summary of evaluation results for each questionnaire item. Each question is same as Table 1 though the third column in Table 1 is omitted for space cosmetics to avoid the overflow. Numbers in parentheses indicate years of nursing experience.

Q#	C (0)	D (0)	E (4)	F (11)	G (13)	H (23)	I (23)
Q1	4	2	2	4	5	3	3
Q2	5	5	4	6	6	3	5
Q3	4	5	4	5	4	2	5
Q4	4	5	4	6	6	2	5
Q5	3	4	3	3	4	2	5
Q6	4	5	4	4	5	3	3
Q7	5	5	4	4	5	3	3
Q8	5	5	4	4	5	3	3
Q9	5	5	4	4	5	3	3
Q10	5	3	5	5	5	3	3
Q11	5	6	4	5	6	6	4
Q12	5	6	3	5	5	5	4
Q13	5	6	3	2	5	5	4
Q14	5	5	4	5	6	5	3

[6] "monitor" is as per the original text. This comment appears a generalized one since BLS requires no specialized equipments. It may mean that ideally, nurses would perform CPR while simultaneously monitoring the electrocardiogram (ECG).

5 Evaluation and the Results (2)

We performed another evaluation in hospital B. The participants ranged from nurse novices to nurse experts. See Table 2 for the result summary.

The general trend was similar to that in the previous section 4, but the real-time feedback was more favorable than in the previous section. It is possible that the feedback of young participants, digital native e.g. Z generation, can explain the trend.

6 Discussion

Our system is designed for professional use, with the primary objective of facilitating the self training of nurses which ranges from novices to experts. In this regard, to some extent, the system appears to be successful.

However, there seem to be some issues with the UI design, particularly concerning real-time feedback (see section 4 and 5). This comes from the condition we had to infer the actual work of professional nurses theoretically. It is mandatory to improve the UI design by following the evaluation results.

In the UI design issues, the evaluation varies from novice nurses to expert nurses. This may simply be due to age-related differences e.g. younger participants is more familiar with new technologies, such as virtual reality. Considering this, it might be beneficial to explore age-specific UI optimizations.

In the training, it is important to use more realized manikins as JRC proposes (section 2.1). The visual quality of our system is somewhat poor, compared to an AR-based research[7]. While, this was a our strategic decision. We decided that the visual quality could be considered a secondary priority, since our system is intended for professionals. To create a sense of realism, for example, our system can provide superimposed facial expressions as a prototype, though this feature is still in the prototype phase and requires improvement.

Spaced learning JRC recommends (section 2.1) is expected to promote BLS training outcomes. The feedback indicates that our system cloud be used as a self training system. Hence, our system could provide nurses with spaced learning, a BLS self training environment unrestricted by time.

Our research is unique in its use of MR (Mixed Reality) and sensor devices on Unix operating systems. This combination seems unprecedented in this field. On the other hand, a potential limitation is that our research may be overly focused on technical aspects. Therefore, we suggest the necessity of re-aligning our system with the training scenario and the evaluation.

The critical issue is the price of MR devices. We utilized the HoloLens 2 as it was readily available in our laboratory. Our system does not rely on any specialized features of the XR device and can therefore function with lower-cost XR devices. While it is true that current MR devices are expensive, we can anticipate a future decrease in price. In the nascent stages of the semiconductor industry, there were examples where prices plummeted to one-tenth of their original value in just three years[11]. We can see that computer prices fall to one-hundredth of their initial price over about two decades in 1950s-1970s[12]. If only there are a chance, a rapid decrease in prices can be initiated. Therefore, there is no need to be concerned about the current high prices.

7 Conclusion

Our BLS self-training support system, which utilizes Mixed Reality (MR) and sensor devices, has been successful in facilitating self-guided training for nurses, from novices to experts. The system effectively complements conventional, supervisor-led On-the-Job Training (OJT).

Our evaluation showed that the system provided valuable feedback, particularly through the post-training visualization of scores. However, we can find some concerns with the visibility and usability of the real-time feedback elements. These issues suggest the need for further refinement in UI design based on principles of ergonomics and gaze guidance.

Despite these challenges, the unique combination of MR and sensor devices in our system looks a novel approach in this field. While the cost of current MR devices is high, we anticipate a future decrease in price, making this technology more accessible for broader use in clinical education.

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Appendix

A Flow Chart of Our BLS Training Scenario

This flow chart (Fig. A1) describes the details of our BLS training system. It is the minimum BLS training scenario based on a typical JRC one[4], which is extended to contain our system specific extensions (e.g. "Start" in the top left implies starting our devices). The outline of the CPR procedures in the training are same as JRC ones but there may be some differences from the JRC scenario such as in the patient's location, whether they have injuries.

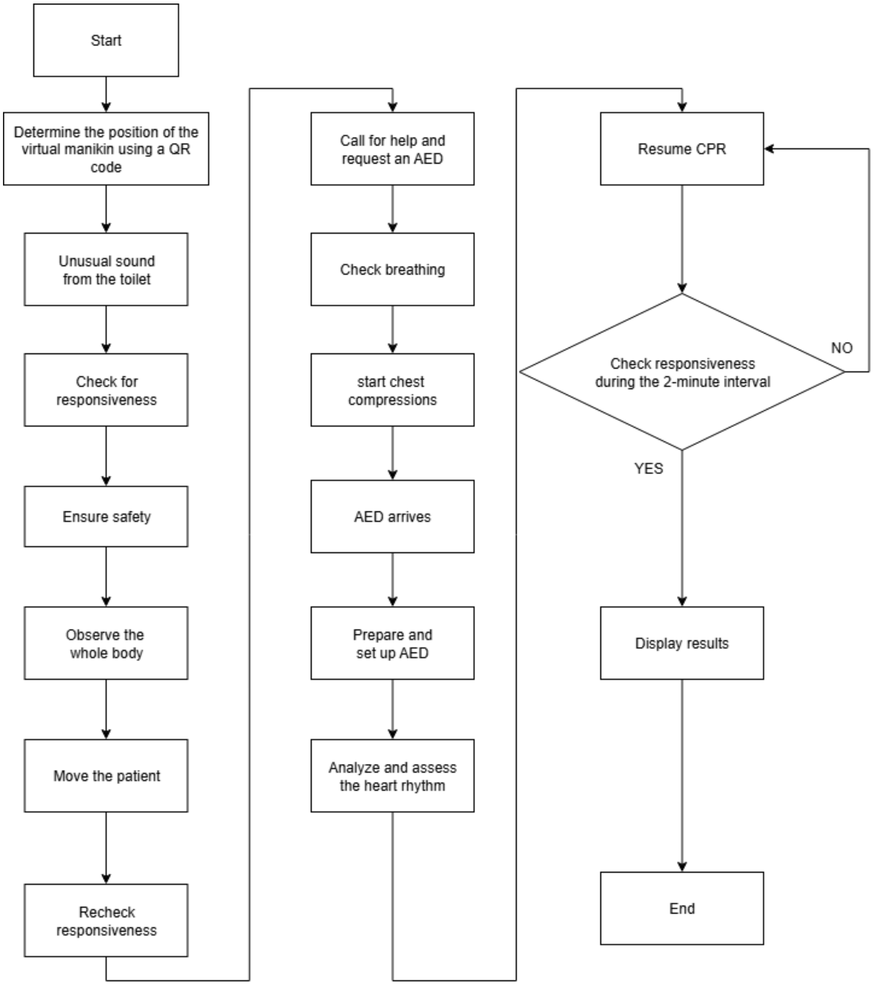

Fig. A1. Our BLS training scenario details shown as a flow chart

B Score Criterion Metrics

Table B1 shows critical metrics for evaluating the quality of chest compressions during CPR. These five metrics are monitored in our BLS training. The first four metrics are assessed and provided as in real-time score, while the Chest Compression Fraction (CCF) is included only in the final score.

Table B1. criterion metrics to evaluate the training score.

Metric	**Guideline / Target Range**
Rate	100 to 120 compressions per minute
Location	Lower half of the sternum, center of the chest
Depth	Approximately 5cm (for adults), not to exceed 6cm
Recoil	Complete chest wall recoil following each compression,
	but avoid leaning on the chest between compressions
CCF	Proportion of resuscitation time spent performing compressions. Target: $>$ 80%