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This is *First* Issue of Volume *Ten* of International Journal of Human Computer Interaction (IJHCI). IJHCI is an International refereed journal for publication of current research in Human Computer Interaction. Publications of IJHCI are beneficial for researchers, academics, scholars, advanced students, practitioners, and those seeking an update on current experience, state of the art research theories and future prospects in relation to applied science. Some important topics covers by IJHCI are affective computing, agent models co-ordination and communication, computer mediated communication, innovative interaction techniques and user interface prototyping for interactive systems etc.

The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Starting with Volume 11, 2022, IJHCI will appear with more focused issues related to human computer interaction studies. Besides normal publications, IJHCI intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

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Assessing Effectiveness of Information Presentation Using Wearable Augmented Display Device for Trauma Care

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Abstract

Technological intervention that supports data transfer of sending summary of the patient vitals through the transfer of care would be a great benefit to the trauma care department. This paperfocuses on presenting the effectiveness of information presentation on using wearable augmented reality devices to improve human decision making during transfer of care for surgicaltrauma, and to improve user experience and reduce cognitive workload. The results of this experiment can make significant contributions to design guidelines for information presentation on small form factors especially in time critical decision-making scenarios.This could potentially help medical responders in the trauma care center to prepare for treatment materials such asmedicines, diagnostic procedures, bringing in specialized doctors or consulting the advice of experienced doctors and calling in support staff as required, and so on.

Keywords: Transfer of Care, Wearable Augmented Reality, Information Presentation, Usability.

1. INTRODUCTION

Small screen devices are foreseen as ubiquitous in the medical field especially in the fields of surgery and trauma care (Glauser, W., 2013). In this era, where the Internet of Things (IoT) is believed to be the future, augmented reality allows interaction between the digital and real world. It can deliver rich and meaningful digital overlay on the real world. The abilities of this technology are well identified and research is being done in different domains such as education, medicine, aviation, and so on (Schmidt, G. W., & Osborn, D. B., 1995; Casey, C. J., 1999, Szalavári, Z., Eckstein, E., &Gervautz, M., 1998; Casey, C. J., & Melzer, J. E., 1991; Foote, B. D., 1998). The purpose of this study was to analyze the effects of information complexity and mental workload on trauma care providers/surgeons during emergency response scenarios for augmented display devices. Using heads-up displays for medical responders in hospital trauma care can optimize the communication channel and information flow. Wearable devices such asGoogle Glass™, being a small form factor, poses challenges in presenting information in such a small screen and at the same time making sure that there is no cognitive overload for the user. Other challenges in small form factor devices include low information density that can influence the user's readability and optimum navigation to access the different features of the applications. Previous study by Ho et. al. (2016), found that when the interface was less cluttered and left justified it resulted in better legibility.

2. BACKGROUND

2.1 Transfer of Care

Trauma surgeons treat patient injuries which include falls, motor vehicle crashes, motorcycle crashes, assaults, gunshot wounds, stab wounds, burns, and so on.

Once a trauma case is reported, the information reaches the emergency team in the hospital and then air and ground transfer are assigned according to what was asked by the person who reports at the scene. The first responder on scene decides the urgency of care required and; the present emergency response protocols involve the information sent by first responders to the most appropriate trauma center around. The first responders provide a brief summary of what they observed on the ground such as: vital signs that they manually noted, pictures taken, any changes in vitals during the transport, any signs of pain in the patient's body, any kind of care given during transport, the type of incident that had been reported by witnesses, and the duration of transport. Patient evaluation is done by assessing the scenario, severity of injury, the first responder's knowledge repository, and emergency protocol(Shen & Shaw, 2004). Quality and timely organization of treatment during transfer of care is given by prioritizing patients based on severity of their injuries. The trauma center receives the updates only when the patient reaches the emergency department. The present system is chaotic and requires a desperate need to reduce response time(Carr et al., 2006). This would also require the transport vehicle (air or ground) to be equipped with an appropriate sensor network and a medium to transfer data smoothly to the trauma care center. Study suggests that air transfer is significantly faster than ground transfer when it comes to distances greater than 50 miles but for distances less than 50 miles there is no significant difference(Diaz et al., 2005). Studies report different response times like on scene arrival, on scene time and total response time (Frykberg& Tepas, 1988). Research by Guise et al., (2015) states that EMS relies on the knowledge repository of the personnel on clinical assessment, decision making, and so it would be important to add the doctor in the training of the EMS personnel.

Mobile health monitoring systems have been used extensively for triage purposes. Van Halteren et al. (2004) developed MobiHealth System which explains the different pros and cons of wireless network transmission of patients' vitals data. The system can support sensors and is connected through a body area network.

2.2 Information Presentation

In spite of the growing adoption of wearable devices, there is a lack of research on user interface design solutions to enable successful multitasking without information overload. Information can be classified into several categories such as text information, picture information, and sound information. In the case of text information, past research highlights the importance of information being presented in the right place at the right time. Information presentation has been used to study complex task decision making (Speier, 2006) and in mobile phone form factor (Ganapathy et al., 2011). Resultsfrom previous studies suggest that the relationship between information presentation format and decision making is moderated by the task complexity. Technological intervention that supports data transfer, in this case sending vitals from the patients during the transfer of care, would be a great benefit to the trauma care department. This would help the medical responder, in the trauma care center, to prepare the necessary treatment materials like medicine, diagnostic procedures, bringing in specialized doctors, obtaining consultation from experienced doctors, and calling in support staff if required.

2.3 Visual Search

Information presented in the wearable augmented reality devices involves activities such as browsing, text messaging, route navigation, reading and gaming. All these activities involve visual search that helps the user find the information they require. Hasegawa et al. (2008) found by subjective evaluation that increasing character sizes (2.5 mm, 2mm and 1 mm in height) resulted in an increase in legibility in computer screens and there was no significant difference in search speed for the different character sizes. Van Schaik& Ling(2001) studied the effects of background contrast on visual search performance in web pages and mobile devices, and they did not find any significant difference in performance. To measure mobile user information processing abilities while walking, a conventional serial visual search paradigm was used. Participants were instructed to search for a target (“T” shape) among distractors (“L” shapes) in different rotated orientations. They reported that the presence vs. absence of an irrelevant color singleton distractor in a visual search task was not only associated with activity in the superior parietal cortex, in line with attentional capture, but was also associated with frontal cortex activity (Eglin et al., 1991).

2.4 Wearable Technology

Previous studies related to users’ attitude towards devices such as google glass shows that there are some concerns related to privacy and there is a curiosity towards access to information right then and there (Xu et. al, 2015). Google Glass has an optical head-mounted display, resembling eyeglasses; it displays information in a Smartphone-like manner, but provides a hands-free format that is controlled via voice commands and touch.The device is a wearable mobile computing device with Bluetooth connectivity to wireless internet access.The Glass display of 640 x 360 pixels rests above the line of sight such that the user’s vision is not interrupted. The device comes with a storage of 16GB and 1GB RAM of memory. Applications for the device are developed on Android version 4.4. The device includes the following features: real time hands free notification, hands-free visual and audio instructions, instant connectivity access, instant photography/videography, augmented reality.

The potential medical dangers of head-mounted displays have been documented by Patterson et al. (2006)and include: decreased awareness of physical surroundings, visual interference, binocular rivalry with latent misalignment of eyes and headaches. The authors performed intense tasks on the device and noted that the surface temperature rises by 90% in 10 minutes of usage.

3. METHODS

The primary objective of this study was to a) explore how wearable augmented reality devices, such as Google Glass, can improve human decision making during transfer of care and b) understand the design of information presentation on the wearable augmented reality device to improve user experience, reduce cognitive workload and aid decision making. Hence an empirical study was conducted to support the hypotheses. The experiment was designed to be tested on a Google Glass as the wearable device. The pool of participants included physicians and residents from the Department of Trauma and Surgery, Boonshoft School of Medicine, Miami Valley Hospital, Wright State University, Dayton. Six residents (three junior and three senior) participated as novice and six physicians as residents. The experiment was divided into two parts – visual search task and patient vitals simulation task.

- Visual Search Task: This included testing participants with a visual search task for addressing the research question of how the design of information presentation on the wearable augmented reality device improves user experience, reduces cognitive workload and aids decision making.
- Patient Vitals Simulation: This included testing participants on multi-tasking and viewing streaming patient vitals data and decision- making. The participants were asked to take ATLS (Advanced Trauma Life Support) as the secondary task.

Fig.1, shows the experiment setup as the participant was viewing the stimuli. EEG data was collected through the Emotiv device to understand the brain response to visual search tasks as the stimuli was presented.

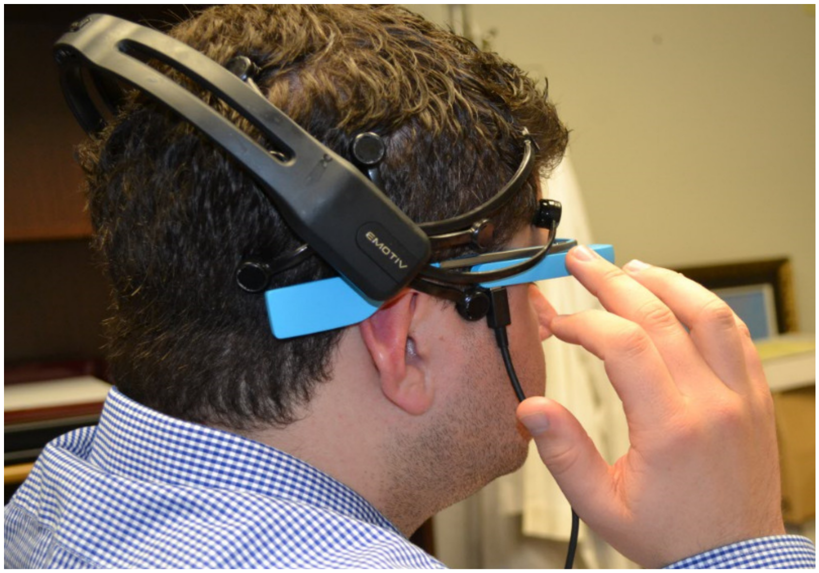


FIGURE 1: Participant wearing Google Glass and EmotivEpoc during the visual search experiment.

FIGURE 2: Participant taking the ATLS test during the patient vitals application simulation.

3.1 STIMULI

The system was designed based on Android Google Glass design guidelines (Google developers, 2015). The user interface design elements in the patient vitals simulation was developed after assessing and prioritizing the triage information by observing various patient monitoring tools in the trauma care department. Triage information was verified and evaluated by experts and the software was developed using Android Studio for Android version 19. The system design for the mobile interface was based on a flat navigation hierarchy with three levels of display as shown in Fig.4. The Navigation Design includes three different levels of information presentation.

a) Home screen: Home screen is the first screen users will see when launching the app.

b) Menu Page: Section Page is the second level of the app and represents the various applications in the device. Users need to select on the Patient Vitals app or the Visual Search task app depending on the experiment.

c) App page: Detail Pages are the third level of the Application. In the case of patient vitals application the details of each patient was presented. If any component has active criticality, the color of the component tile will change to yellow or red; yellow indicating low criticality and red indicating high criticality. The visual search task included presenting the first slide and the user navigating to the next screen by swiping or tapping.

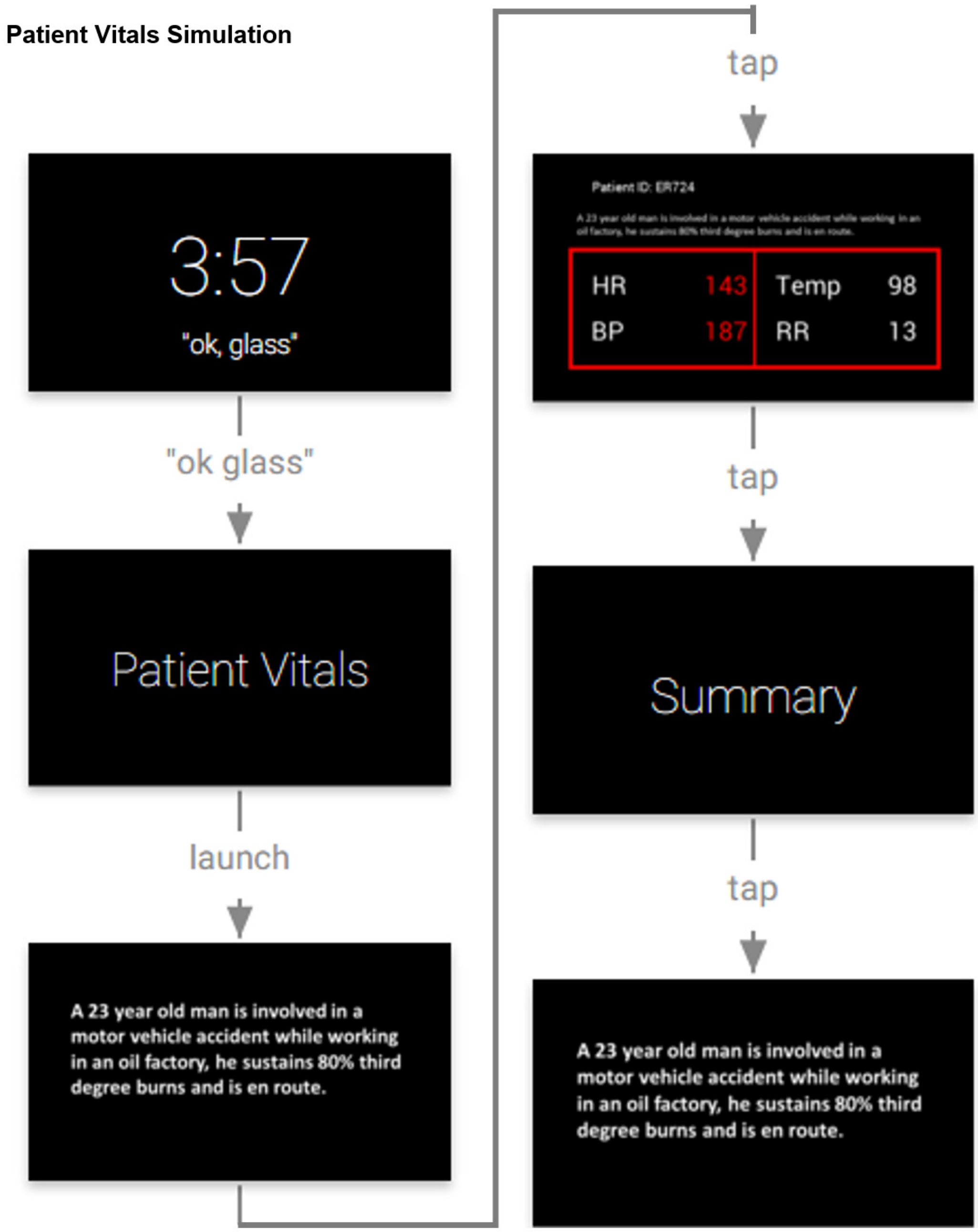


FIGURE 3: Navigation design of the Patient Vitals application.

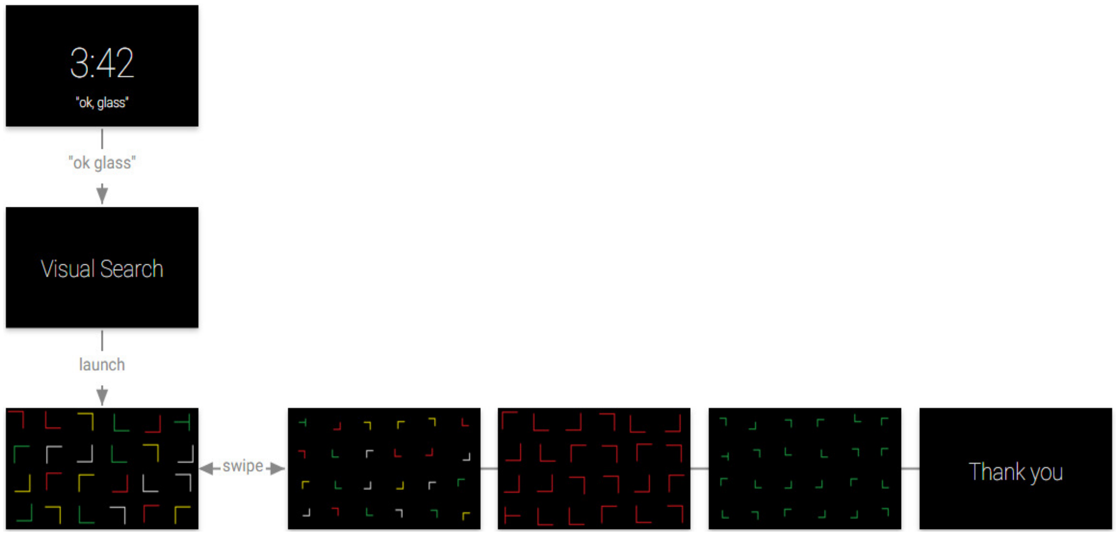


FIGURE 4: Navigation design of the Visual search task application.

3.2 Experimental Design and Procedures

Participants were introduced to the Google Glass device and were trained on the different gestures, which could be used to operate it, navigate between and within the applications. The training modules were untimed sessions and participants were encouraged to practice until they were familiar with the system. Familiarity was based on a subjective measurement of the participant's level of comfort in interacting with the interface and successful completion of a scenario similar to the testing scenarios.

3.2.1 Patient Vitals Simulation

The experiment conducted was a repeated measures design, with two within-subjects independent variables: type of User Interface (UI1 vs. UI2 vs. UI3) and frequency of data visualization (2 seconds vs. 6 seconds). The experiment was counterbalanced using Latin square with respect to the order of scenarios being tested and the type of system. Twelve different scenarios were tested to collect the appropriate metrics across the three different UIs and the two data visualization frequencies. All the scenarios involved monitoring the vital signs and user responses. All scenarios were presented with a summary for 8 seconds and patient vitals for 30 seconds. The scenarios were developed from observing emergency scenarios in Miami Valley hospital, Dayton and were evaluated by subject matter experts.

3.2.2 UI1

UI 1 consists of Patient ID at the top of the screen, below this the screen was divided into two halves, the left half contains the summary and the right half contains the three most important vital signs for the physician's evaluation.

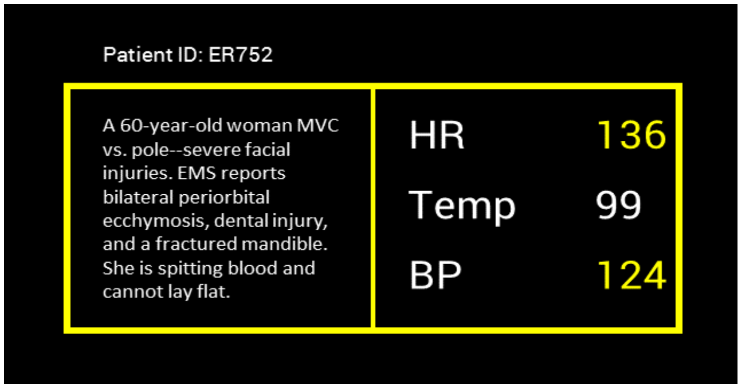


FIGURE 5: Screen layout of user interface 1.

3.2.3 UI2

UI 2 consists of Patient ID at the top of the screen followed by a summary, below this the screen is divided into two halves, the four most vital(Heart rate, BP, temperature and RR) patient information are presented in this area in a 2x2 matrix form.

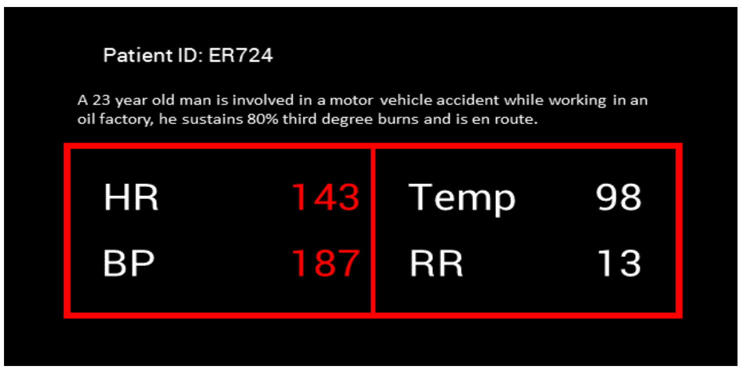


FIGURE 6: Screen layout of user interface 2.

3.2.4 UI3

UI 3 consists of Patient ID at the top of the screen, below this the screen is divided into two halves, the five most vital patient information (Heart rate, BP, spO2, temperature and RR) with age are presented in this area in a 3x2 matrix form.

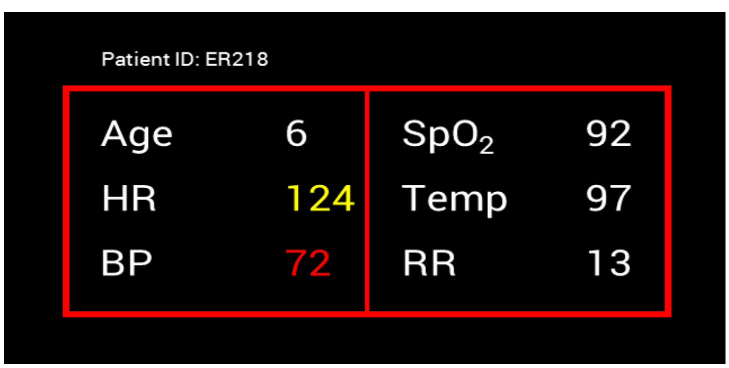


FIGURE7: Screen layout of user interface 3.

3.2.5 Visual Search Task

The experiment conducted was a repeated measures design, with four within-subjects independent variables: target and distractor color (Monochromatic vs. Polychromatic), size of the font (Large vs. Small), position of the target (Right half vs. Left half of the screen) and area in which the target is present (Inner vs. Outer area). The Google Glass screen displayed the target "T" shape in either of the two orientations; the top of the "T" shape faced either right or left. There were multiple "L" shapes as distractors in four different orientations; the top of the "L" shapes faced top, right, bottom, and left. Every slide had one target and 23 distractors in a 4 by 6 grid screen.

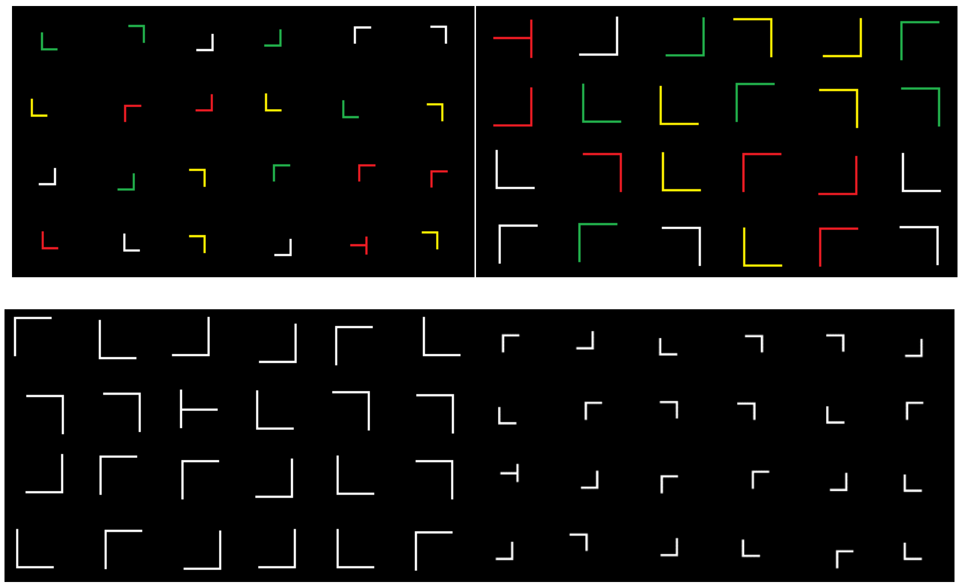


FIGURE 8: Types of screen layout for the visual search task with varying size, color, and target location: polychromatic small (Top left), polychromatic large (Top right), monochromatic large (Bottom left), monochromatic small (Bottom right).

3.3 Dependent Measures and Analysis

3.3.1 Patient Vitals Simulation

In order to evaluate the performance of the system several measures such as cognitive workload, ease of use, and performance times were collected. NASA TLX was used to measure the cognitive workload of the participants when performing a task and is an aggregate of six subscales: mental demand, physical demand, temporal demand, performance, effort and frustration (Hart &Staveland, 1988). Ease of use was measured using System Usability Scale (SUS) score. SUS provides a quick reliable tool to measure usability and learnability. It consists of a standardized ten item questionnaire with five response options. SUS was followed by a general questionnaire about the performance index of the device, application and the user interface. Performance time was measured using a stopwatch to measure the time taken by the participant to respond to each of the scenarios. This was calculated using the difference in the time taken by the participant to start writing their response and the time when the patient vitals scenario started. ATLS test response was collected to see the number of questions answered by the participants. This would help in evaluating the multitasking ability while using the augmented wearable device.

3.3.2 Visual Search Task

In order to evaluate the performance of the system a general questionnaire was used to evaluate the user interface design elements and the response time was collected using a stopwatch to measure the time taken by the participant to find the target in a particular slide. This was calculated using the difference between the time when the participant taps/swipes after finding the target from the current slide and the previous slide.

4. RESULTS

Results indicate that there was significant difference in the response time for doctors and residents (F (5,141), p-value < 0.001, ηp2= 0.031).There was no significant difference in response time for the different user interfaces and there was no interaction effect. Mean response time and standard deviation were 12.027 sec and 3.406 sec for doctors and 14.43 sec and 4.949 sec for residents. The mean response times with respect to the user interface were 13.6 sec for UI1, 13.31 sec for UI2 and 12.77 sec for UI3 with standard deviation of 4.59 sec, 4.34 sec and 4.31 sec respectively. When residents were further analyzed based on their experience, the response time was significantly different for Junior residents when compared to Senior residents and doctors (F (2,141), p-value < 0.001, ηp2= 0.211) Mean response time and standard deviation were 12.027 sec and 3.406 sec for doctors, 16.722 sec and 4.79 sec for junior residents and 12.139 sec and 3.994 sec for senior residents.

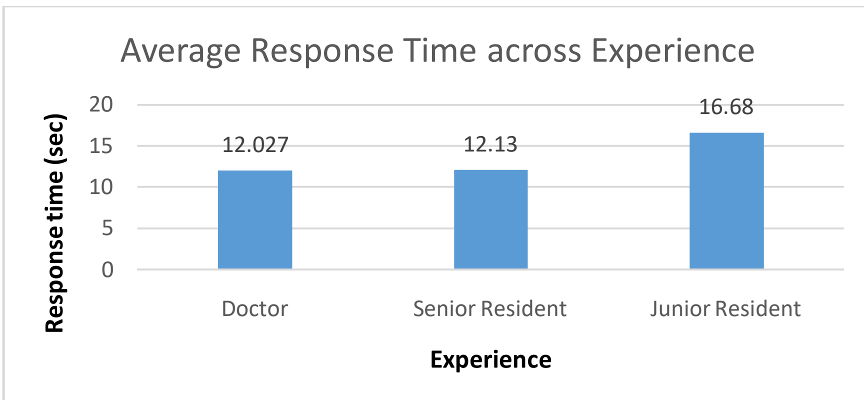


FIGURE 9: Average response time with respect to experience.

Analyzing the number of questions answered in the ATLS test, we found that there was no significant difference between doctors and residents in the number of questions answered. The mean number of questions answered was 4.5 by doctors, 3.67 by senior residents and 1 by junior residents.There was no significant difference in response time for the UI elements; color, size, left/right half of the screen and inner/ outer area of the screen, and there was no interaction effect.

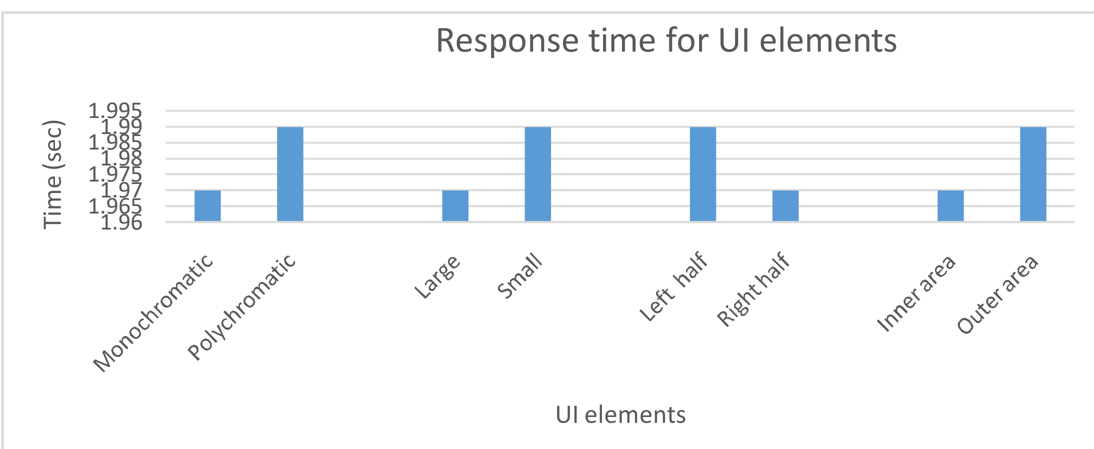
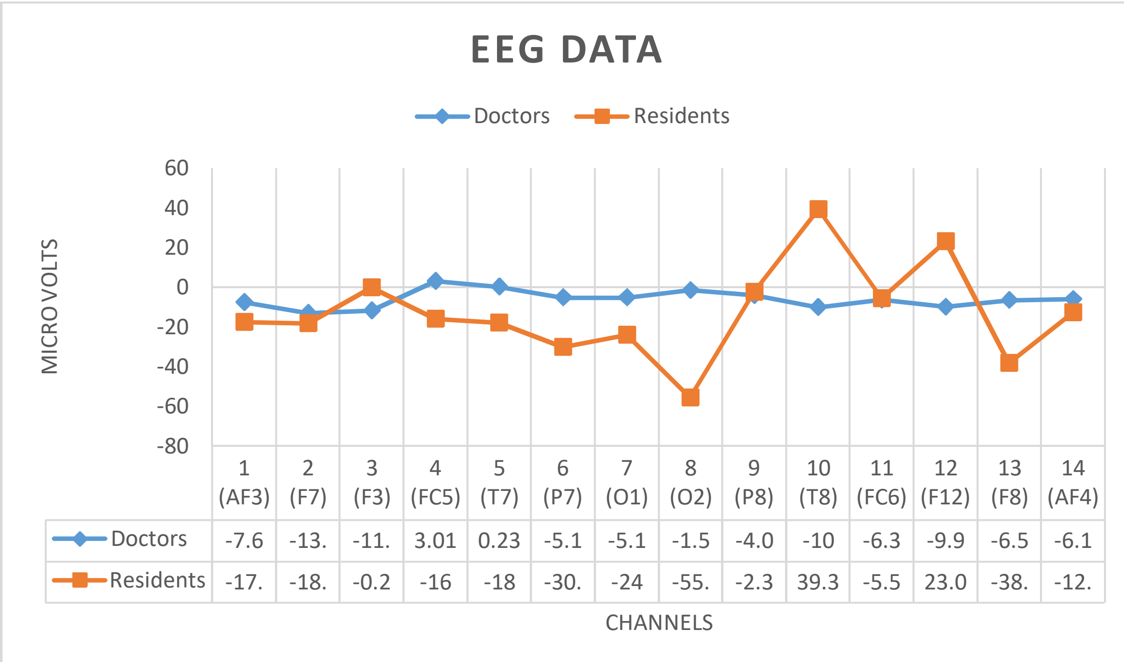


FIGURE 10: Response time for different UI elements.

The following chart shows the difference in brain signal amplitude averaged for doctors and residents in terms of microvolts. The table shows a comparison of these microvolt values against the respective channels.



	1 (AF3)	2 (F7)	3 (F3)	4 (FC5)	5 (T7)	6 (P7)	7 (O1)	8 (O2)	9 (P8)	10 (T8)	11 (FC6)	12 (F12)	13 (F8)	14 (AF4)
Doctors	-7.6	-13.	-11.	3.01	0.23	-5.1	-5.1	-1.5	-4.0	-10	-6.3	-9.9	-6.5	-6.1
Residents	-17.	-18.	-0.2	-16	-18	-30.	-24	-55.	-2.3	39.3	-5.5	23.0	-38.	-12.

FIGURE 11: Average electric data in microvolts against each EEG channel.

The EEG heat map, Figure 12 and 13, shows activity in the brain color coded ranging from red to blue, where the area marked in red is where the brain was most active and the area marked in blue is where it was least active. The figure shows that there were two areas of the brain that were most active for the visual search task. Figure 12 shows the brain activity of a participant whose temporal region of the brain was active. Figure 13 shows that there was more activity in both temporal and the frontal area of the brain.

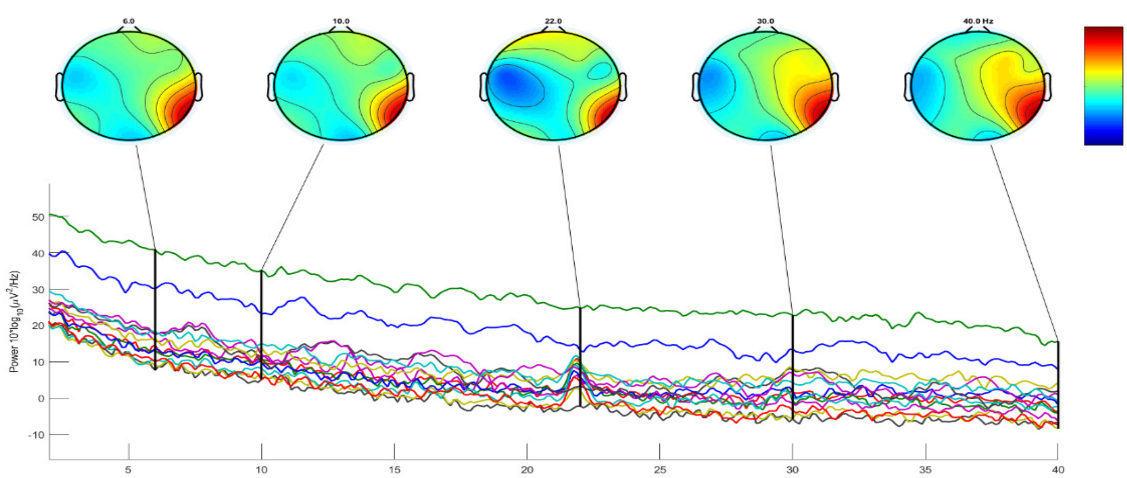


FIGURE 12: Heat map showing activity in the superior parietal cortex.

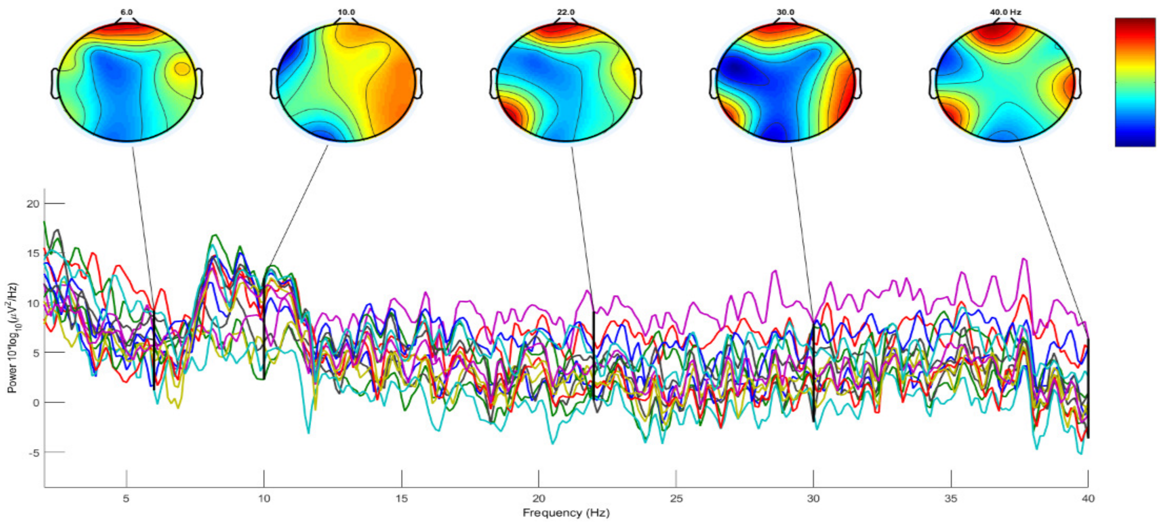


FIGURE 13: Heat map showing activity in the superior parietal and prefrontal cortex region.

User response for color, size, left/right position and inner/outer area of the screen did not have significant effect on the response time but experience had significant effect on the response time and there was no interaction effect ($F(31,1131)$, p-value > 0.69, $\eta p2= 0.023$). The mean response time for Doctors was 1.88 seconds per slide and for Residents was 2.08 seconds per slide with a standard deviation of 0.96 and 1.04 respectively.The NASA TLX mean score, given by Doctors was 42.93 and for Residents was 51.26 with standard deviation of 15.87 and 14.67 respectively.

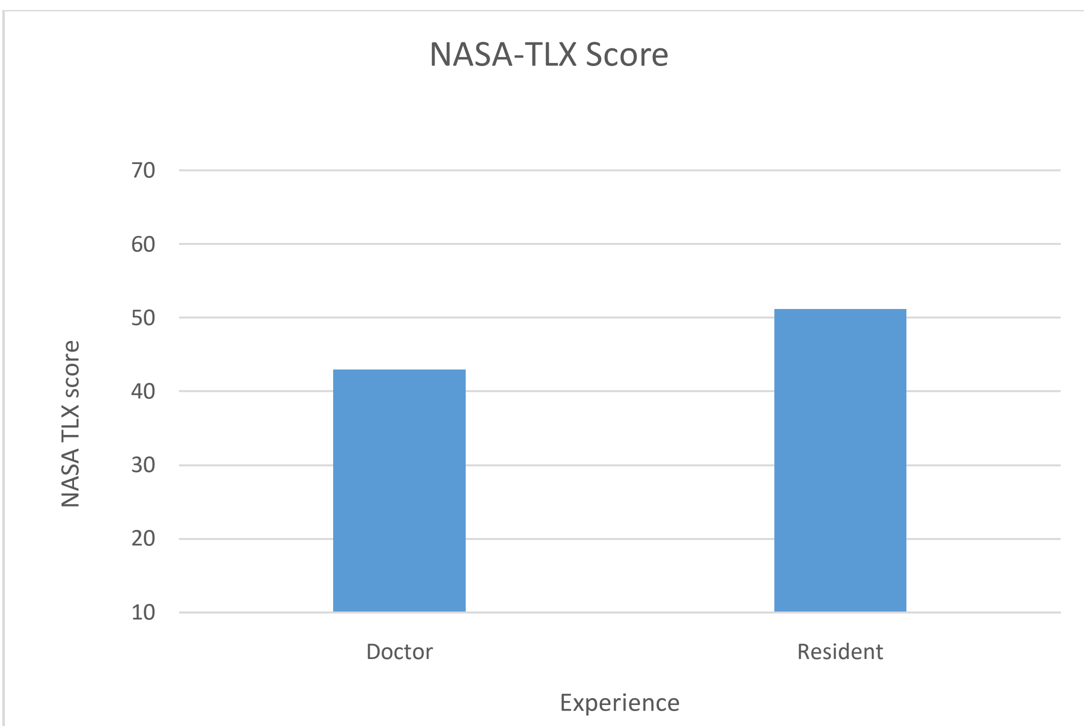


FIGURE 14: NASA TLX score across experience.

The following graph shows user preference response for color, size, left/right position, inner/outer area of the screen.

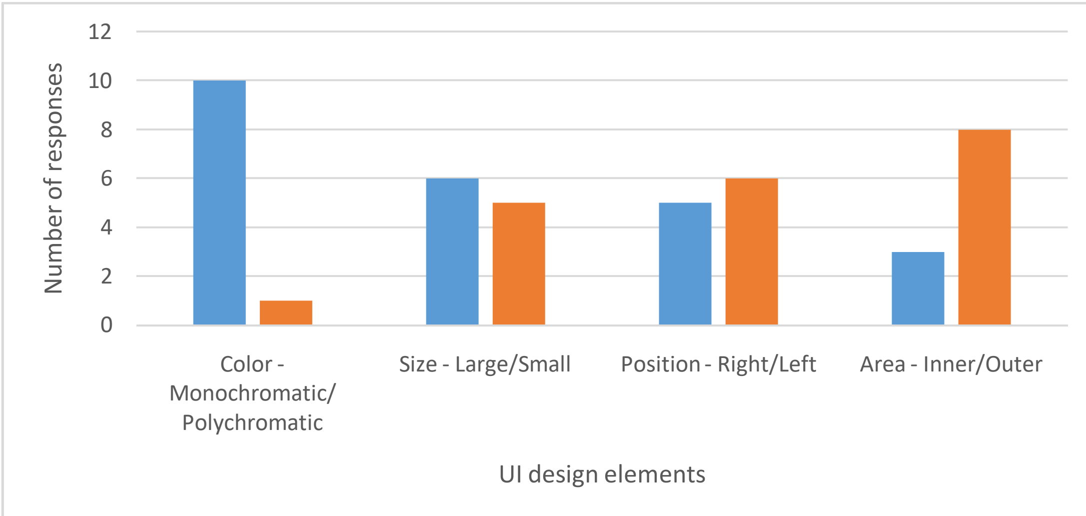


FIGURE 15: User response for preference of UI elements.

The System Usability Scale (SUS) results showed that there was no significant difference between the three User Interfaces. When compared between doctors and residents, there was no significant difference for UI1 and UI3, whereas for UI2 the SUS for junior residents was significantly lesser (F (2, 12), p-value = 0.0203, ηp2= 0.579) with mean and standard deviation values of 61.667 and 10.104 than senior residents and doctors with mean and standard deviation values of 77.5 and 4.33 and 72.5 and 3.16 respectively.

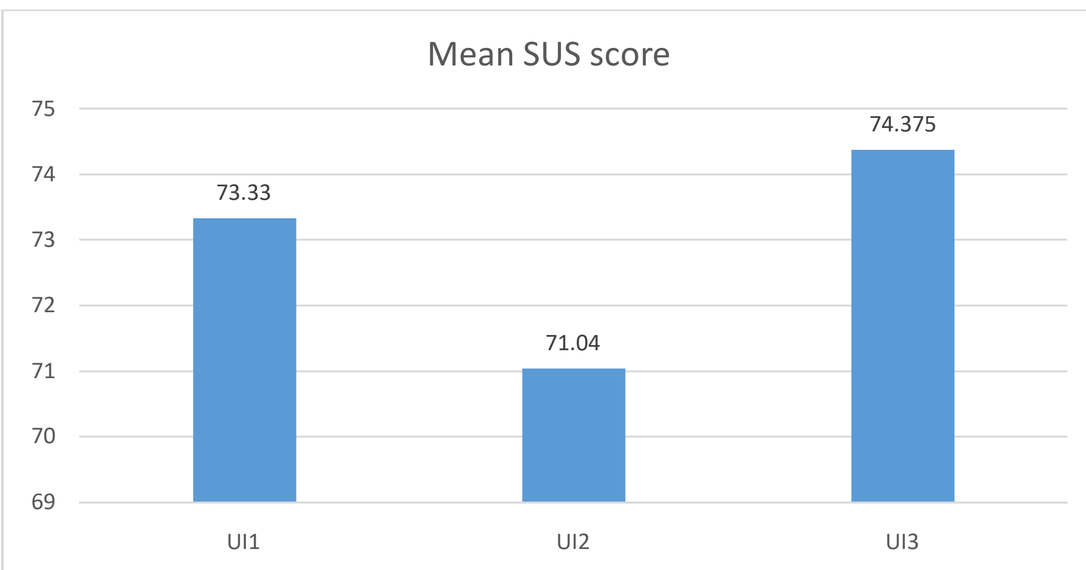


FIGURE 16: SUS scores for the 3 UIs.

The user response for the questionnaire was analyzed and the tables below show the average response for the questions in a scale of 1 through 5; where 1 is strongly disagree, 2 is disagree, 3 is neutral, 4 is agree and 5 is strongly agree.

#	Question	Response
1	Device Comfort	2.91
2	Application load time for the device	2.167
3	The use of heads-up display to improve patient monitoring and decision making	3.08
4	Device usefulness in trauma pre-hospital care	3.00

TABLE 2: User response for device.

#	Question	Response
1	Navigation through the application	3.667
2	Clarity and understandability of the application	3.833
3	Flexibility of the application	3.333
4	Application ease of use	3.75
5	Learnability of the application	4.167
6	Ability to accomplish task with the help of this application	3.41
7	Organization of information in the screen	3.75
8	Appropriate Content in the application	3.667

TABLE 3: User response for Patient Vitals application.

#	Question	Response		
		UI-1	**UI-2**	**UI-3**
1	Optimum number of elements within the screen across the 3 UIs	3.58	3.00	3.167
2	Design of screen layout across the 3 UIs	3.83	2.91	3.33

TABLE 4: User response for User Interface.

5. DISCUSSION

Upon analyzing the patient vitals simulation data it was found that junior residents took a longer time to process than when compared to senior residents and doctors. It is also evident from the ATLS test that the average number of questions answered was less compared to senior residents and doctors.

The user response shows that UI1 was comparatively better in the design of screen layout and the optimum number of elements than UI3 and UI2. The difference in the screen layout between UI1 and UI2 was the patient summary presentation which shows that the participants preferred the summary above the vital signs over no summary at all. The difference in the number of elements (Heart rate, blood pressure, temperature, etc.) in the screen is that UI1 has 4 and UI2 has 3. So, participants recognize that in the same screen space, when summary was presented UI1 had more information presented on the screen and it did not affect the attention levels compared to UI2.

For the visual search task it was found that there was no significant difference in size, color, right/left position and inner/outer area of the screen but the response time was significantly less for doctors than residents. However, the questionnaire results showed that monochromatic search was easier than polychromatic search, and additionally the targets in the outer area were easier to find when compared to targets in the inner area. This showed that participants visually scanned the outer area first and then the inner area.

The EEG data showed that there was more activity in the T8 channel area which included the temporal region as well as the temporal-parietal area and parietal area. Past research shows that the superior parietal lobe was associated with visual search. Hence the use of augmented devices for information presentation is useful for people such as surgeons who do multitasking during patient monitoring. Results indicate that participants experienced discomfort using the device and the application took less time to load. The users felt discomfort due to the heat generated when the Google Glass was used for a long time (greater than 30minutes); which included the learning phase before the experiment began. Future work should focus on evaluating other wearable form factors.

6. CONCLUSION

This study analyzed cognitive stress by using EEG and compared with the perceived cognition using NASA-TLX. By doing so this approach shows more insight into the trauma care physician's cognition. From the results, we can imply that wearable augmented display devices can enhance visualization for emergency response without additional mental workload and aid in decision making. Wearable augmented devices provide ubiquitous information especially in multitasking scenarios where users can have access to information on an "as needed" basis. The mean channel data shows that for residents the prefrontal area was active and all participants had temporal cortex active. This shows that the participants were not under high stress or in other words we can say that wearable augmented reality devices can aid human decision making during transfer of care. Understand the design of information presentation on the wearable augmented reality device to improve user experience and reduce cognitive workload. This study showed that there is no significant difference in the different screen layouts which can help design adaptive UI for emergency response. Adaptive UI shows relevant information based on the needs and creates less confusion to new users.Using NASA-TLX for the user's perceived cognition and at the same time comparing it with brain signals give research insight and help developers in designing future products. So future devices should use these evaluation techniques to move towards better usability.

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Development of an Integrated Catheter Insertion Training Simulator and Performance Monitoring System

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Abstract

Catheters are used in a wide range of procedures such as insertion of stents or drains and are increasingly utilized. Currently experience or judgement is used in intravenous catheter selection and, while this can be a reasonably successful approach, it is felt that improvements could be made by utilizing a combination of historical data analysis and machine learning algorithms and Artificial Intelligence (AI) to improve catheter selection performance and assessment in early-stage catheterization training.

Current training lacks consistency, is expensive, and requires access to a both surgeons and test cadavers. There is therefore a requirement for research to cover means to improve and standardize catheter selection and catheterizationassessment methods, especially in emergency situations. An system with automated wall-hit detection and evidence-based catheter selection could provide additional practice time to medical students in their initial training. Combining this performance tracking to give consistent, qualitative feedback to students and instructors can potentially reduce training times and subsequently improve catheterization performance and patient outcomes.

This study covers the conceptualization, initial modelling, and requirements definition for such an application. Key to this is establishing performance metrics and a means to assess them. There are two critical performance measures in catheter insertion: ‘wall-hits’ or the number of times the catheter tip hits the side of the vein and procedure time. Establishing feedback loops in the training system reinforces learning by enabling real-time awareness and faster correction of mistakes.

While the application would initially be aimed at monitoring performance during training, this could be expanded to monitor performance throughout medical use of intravenous catheters. Several risks and challenges remain in the development of a solution, and are subject to ongoing research.

Keywords: Catheterization, Training, Artificial Intelligence, Medical Simulation.

1. INTRODUCTION

1.1 Background

Intravascular catheterization is a complex, time-critical medical technique that underpins minimally invasive procedures from angiographic imaging to angioplasty and stent fitting. Typically, the procedure involves the placement of a substance or device in the patient’s vascular system by means of a catheter and guidewire combination, introduced via a cannulation site typically via the femoral or subclavian vein, described in detail by Goldmann and Pier (1993).This task requires selection of a catheter and guidewire combination that best suits a given procedure, patient, and surgeon and is a particularly complex procedure (Myler, Boucher, Cumberland, & Stertzer, 1990).

Trainees in cardiac catheterization program must follow specific steps delineated in the Core Cardiovascular Training Statement (COCATS) 4 training requirements (King et al., 2015) to gain appropriate experience in the cardiac catheterization lab. COCATS 4 Taskforce 10 (King et al., 2015) outlines a structured, three phase framework for training in cardiac catheterization and is endorsed by the Society for Cardiovascular Angiography and Interventions. The framework outlines milestones in knowledge and skill requirements in a detailed timeline. The ability to perform a Right Coronary Artery (RCA) Catheterization is a requirement of the first phase of COCATS 4 (King et al., 2015), expected to be complete after 24 months of medical training. This procedure is the focus of this study, and we believe supporting early phase training can improve performance.

While there is a training framework for catheterization, there is currently no defined catheter selection procedure or framework in place at Miami Valley Hospital and literature searches did not discover any such standards in place in the wider angiographic community. The current catheter selection process is largely down to the experience of the Surgeon and their familiarity with certain shapes and sizes of catheter which can lead to inconsistencies in performance and localization of best practice.

Catheterization training is either conducted on cadavers or simulation-based in the initial stages and highly reliant on expert mentors to assess performance. The requirement for expert oversight limits the amount of time available for training, even in the early stages. Barsuk et al. (2009) demonstrated that Cardiac Catheterization simulation training can increase both the skill and self-confidence of trainees. In a subsequent study Barsuk et al. (2010) also investigated the long-term effect of simulation on training with between 82.4% to 87.1% of trainees maintaining their performance up to one year after training.In addition, catheterizationtraining using ultrasound guidance was shown to improve catheterizationperformance in emergency technicians to 0.970 (95% confidence interval, 0.956–0.983), which was close to the level expected of surgeons (Duran-Gehring et al., 2016)

Throughout related literature, Right Coronary Arterial (RCA) Angioplasty is highlighted as a particularly complex procedure from the perspective of catheter selection with several consideration influencing the choice (Myler et al. 1990). Understanding the nature of the tasks involved in the process is an important aspect to design a useful training system. As such, it is important to understand the factors that relate to successful catheterization.

There are limited examples of research into improved catheterization training in the literature. Wang et al. (2018) focus on the implementation of a VR catheterization training system to mitigate problems arising from the use of additional x-ray shielding by surgical teams. In 2020, Guo et al., demonstrated a machine learning approach for the assessment of difficulty levels in a specific catheterization task. This approach utilized machine learning to classify the aortic arch geometry to establish a difficulty associated with performing the required catheterizationon the patient. In 2009 Sarkar and colleagues. studied the problem of Catheter Selection, specifically considering coronary angiography and intervention in anomalous Right Coronary Arteries (RCA). Based on the 24 interventions included, this study defined a catheter selection framework for anomalous RCAs for 4 different takeoff types. The study also suggests that characteristics of the angiographic procedure, such as the initial trajectory, angle at takeoff, aortic root dimensions, configuration of the ostium, and the location of the procedure are important aspects that influence the selection of a guide catheter (Sarkar et a., 2009).

While Sarkar et Al. show that historical data can predict optimal catheter selection for a given procedure, they only highlight the successful catheter and give both a procedure time and list the number of attempts. This analysis does not consider other factors such as 'tip strikes', which could be another important factor in catheter selection. In their 2011 paper, Riga and colleagues define the Imperial College Complex Endovascular Cannulation Scoring Tool (IC3ST) to assess catheterization performance, defining seven elements to be scored by an expert observer. The IC3ST catheterization scoring framework is shown in Table 1.

Catheter Use	**1** Inappropriate use of catheter, failure to recognize catheter unsuitability	**2**	**3** Inappropriate catheter use initially but recognizes and rectifies error within a reasonable timeframe	**4**	**5** Correct catheter use to full advantage
Wire and catheter manipulation	**1** Excessive & uncontrolled	**2**	**3** Makes clumsy movements on occasion	**4**	**5** High degree of finesse
Contact wit the vessel wall/vessel trauma (wall hits)	**1** Excessive force and multiple dragging of the catheter tip along the vessel wall	**2**	**3** Some contact with the vessel wall but swift correction	**4**	**5** Minimal contact with the vessel wall, careful placement of wire and catheter
Areas of specific embolic potential	**1** No respect for areas of danger – embolization risk HIGH	**2**	**3** Recognition of potential areas of danger – embolization risk MODERATE	**4**	**5** Full awareness of areas of danger – embolization risk LOW
Vessel cannulation	**1** Failure to cannulate and maintain position>3cm into target vessel	**2**	**3** Successful wire cannulation but inability of the catheter to follow	**4**	**5** Successful cannulation with wire and catheter >3m into target vessel
Overall time and motion	**1** Slow, makes many unnecessary movements	**2**	**3** Efficient but some unnecessary movements	**4**	**5** Maximum efficiency and clear economy of movement
Flow of procedure	**1** Stops frequently and needs to discuss the next move	**2**	**3** Demonstrates some forward planning	**4**	**5** Has obviously planned course with efficiency
General Score	**1 Poor**	**2**	**3 Competent**	**4**	**5 Clearly Superior**

TABLE 1: Imperial College Complex Endovascular Cannulation Scoring Tool (IC3ST), reproduced from (Riga et al., 2011).

The IC3ST represents a baseline performance metric that has credible historical use and although its current implementation requires assessment by a 3rd party expert could provide the basis for catheterization assessment within an automated or non-expert training system.

Understanding catheter deflection and the potential space envelope achievable is a key aspect of any system to predict optimal catheter selection for a given patient and procedure. A finite element method for predicting the shape of any given catheter and guidewire combination as function of the relative position of the two elements is described by Li et al. (2011). This method is detailed but also requires accurate information on the mechanical properties of the catheter and may be less accurate given any variability in shape due to temperature changes.

A computational, predictive approach to catheter selection is described by Rauf, et al. (2016), where, again, the RCA is scanned by means of a pre-procedural MRI to determine the dimensions of the RCA geometry. This information is then combined with deflection predictions for specific catheters to make a prediction as to the optimal catheter for a given RCA geometry and procedure. Rauf et al. (2016) continue to define the significant parameters of the RCA as: Coronary Arteries Curve Angle (CACA), Distance of the Ostium from the Aortic Valves (DOAV), and Aorta Diameter (AD) and conclude that the calculation of the dimensions of the aortic arch curve were found to be important factors in optimized catheter selection.

Zhang, et al. (2017) took a different approach to improving catheterization performance, detailing a system that utilizes a braking system on detection of a potential wall hit. This approach has the potential to mitigate wall-hits but does not provide a means to improve catheter selection and would potentially slow procedures down in order to achieve success.

To achieve a catheter selection and wall-hit classification system requires access to existing data on the outcomes of catheterization procedures and ground-truth of wall-hit situations to train the image classification system. There are significant challenges in the design, build and implementation of such a system. This problem has the potential to be both computationally intensive and require analysis of large datasets to deliver optimal catheter selections, robust and credible performance assessment, and timely and precise feedback to improve training outcomes and therefore improve performance and patient outcomes in the long term. Artificial Intelligence can provide the means to interpret big data and provide useful insights that otherwise would not be realized (Najafabadi et al., 2015). We believe that utilizing AI and Machine Learning (ML) to analyze performance and provide real-time feedback to improve training outcomes, decision-making and reinforce best practice. In addition to this, there is a need to implement the performance assessment in a training environment that may not have access to expert oversight.

There is clearly a research gap in the area of catheterization selection training, especially for emergency situations and where pre-existing MRI scans are not available. Catheterization training also requires expert oversight to classify wall-hits which is both costly and a highly limited resource. This paper conceptualizes an approach to bridge these research gaps and details elements of a prototype system that could be implemented to standardize catheter selection training. In addition to improving training by providing a standardized means to guide catheter selection in an evidence-based approach, the system could replace the need for expert oversight to assess wall-hits, allowing trainees time to practice without expensive senior surgeons to be present. The AI-based wall hit detections system would enable the performance of trainees to be tracked and qualitative performance metrics could be established in line with the requirements defined in COCATS 4 (King et al., 2015). Neither of these approaches have been considered in literature and their implementation could benefit trainee physicians undertaking early-phase catheterization training. Additionally, improving catheter selection and insertion performance through improved training has the potential to deliver a range of benefits to patients and surgeons. These could range from reducing complications arising from wall hits to reducing the procedure time and hence reduce the radiation exposure for the surgical team. In addition to these performance improvements, there is potential for cost savings, with Miami Valley Hospital alone performing approximately 3000 endovascular procedures each year the reduction in wasted time and materials, as well as secondary treatment required due to complications could lead to significant cost reductions.

While there are other approaches to catheterization training and assessment detailed in the literature, these focus on the use of virtual reality or difficulty assessment. Our approach focuses on improved catheter selection in the early stages of catheterization and using image classification to identify wall-hits in a catheterization simulator. In can be used in conjunction with existing training and assessment methods, as described in the literature. Alternative approaches for catheter selection improvement have been put forward (Rauf, et al., 2016) but these require pre-existing MRI scans of the patient. While this solution is potentially more accurate, the reliance on the MRI scan precludes this approach from use in emergency situations and does not include a means to assess wall-hits, in simulation or in a catheterization procedure.

1.2 Aim

The specific aim of this study was to determine the design requirements for a dynamic decision support and training tool for use in cardiovascular education and practice. A key goal of this study was the analysis of the requirements for all system elements such that a credible, usable, human-centered experience can be developed. This process includes broad consideration of the human-system interaction elements both in terms of the computer-based and physical interactions with the training system. The specific aim was to define the top-level design rules and requirements for low-cost, medium fidelity training applications.

1.3 Scope

This paper covers the conceptualization and development of initial design requirements and rules for the system. There are two main elements in the proposed training system. Firstly, the physical simulator and secondly the partner application. The interaction between the user and both these elements will be key to the implementation of a successful training system, however this paper focuses on the design of the Human Computer Interface (HCI) elements. This paper will examine the design of these elements and interactions from a Human Factors (HF) perspective from concept development to initial design requirements.

It is important for the credibility of the system that both the physical simulator and training application are representative of the tasks, protocols, and environment that the simulator will be used in. As such this study considers the goals and processes defined in the COCATS4, Task force 10 training framework (King et al., 2015)and specific design elements will utilize the language and appearance of similar medical training applications where possible.

2. CONCEPT

As stated in the scope, this study focuses on design requirements for a low-cost simulator with the Catheterization of the RCA as a testbed procedure. The purpose of the simulator is to be both a low-cost, low-fidelity training system and a decision support tool for practitioners. Although these uses might at first seem to require entirely different approaches, the fundamental task being performed is the same in both cases. Within these two applications there are two main functions of the proposed catheter selection and performance assessment tool: To provide catheter selection advice, and to assess practitioner performance.

These are somewhat easier to conceptualize as separate applications but much of the functionality is common. As a decision support tool, the key function is to provide the practitioner with advice on the best catheter for a particular task, while as a training tool, both this and the performance feedback are required functionalities. These concepts are summarized in Figures 1 and 2.

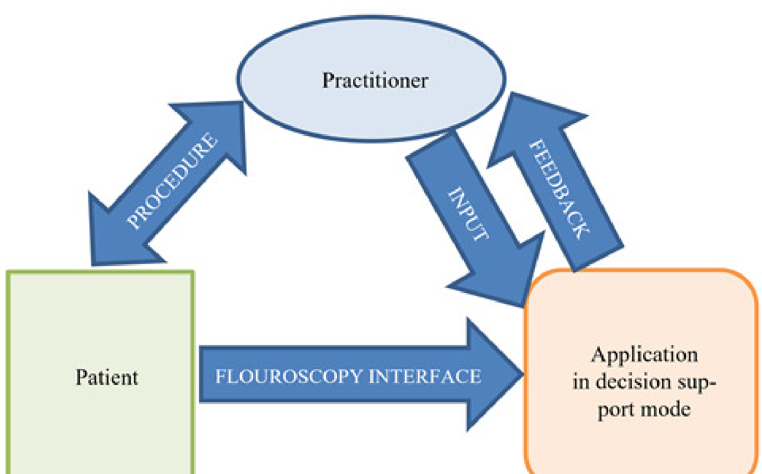

FIGURE1: Catheterization Training Simulator Concept Diagram.

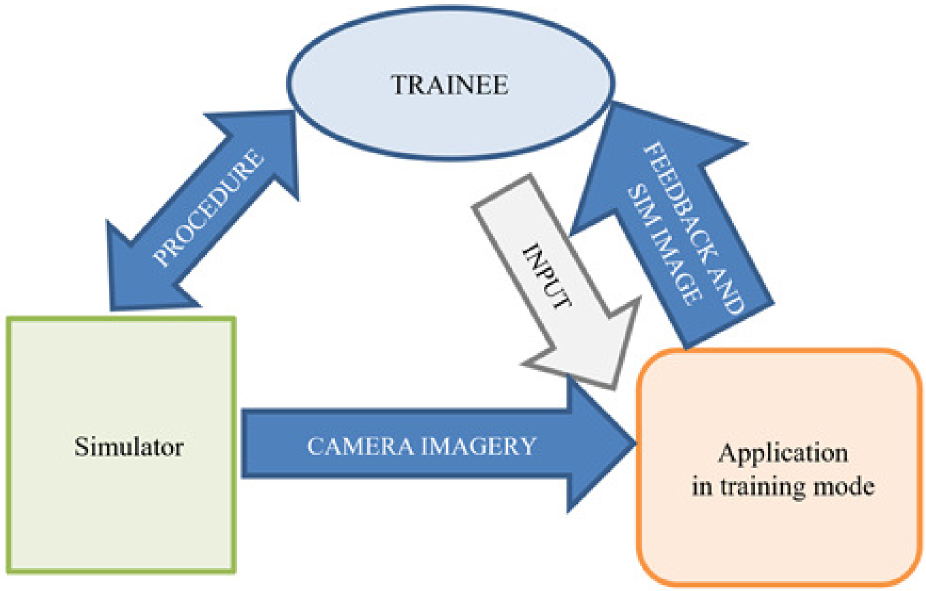

FIGURE 2: Catheterization Decision Support Concept Diagram.

As these two diagrams illustrate, although there are differences in the functional elements of the system in either configuration, the system design and driving requirements are common. The key differences of the concept as a training aid and as a decision support tool is the need to simulate as close as possible to the fluoroscopic display in the training mode and a need to integrate the fluoroscopic display to assess performance in the decision support mode. The Trainee input is shown in grey, as in a more complex simulator, parameter inputs would be required but for our testbed, only the RCA procedure is being conducted by the. A such, there is limited scope for varying the parameters of the 'patient' as it is difficult to vary the geometry of simulated vascular elements and other aspects such as age, criticality and catheter entry location cannot be varied, especially in a low cost simulator. As a result, no catheter selection output advice is required from the application.

Additionally, the nature of the performance feedback given to professional practitioners by adecision support tool will need to be different to that given to trainees in the training mode. This is key to establishing trust and eventually continuing use of such a tool by the practitioner community. The commonalities between these modes are defined in the unified training concept interaction model as shown in Figure 3. This combines all the system interaction requirements that were then analyzed further to develop design rules.

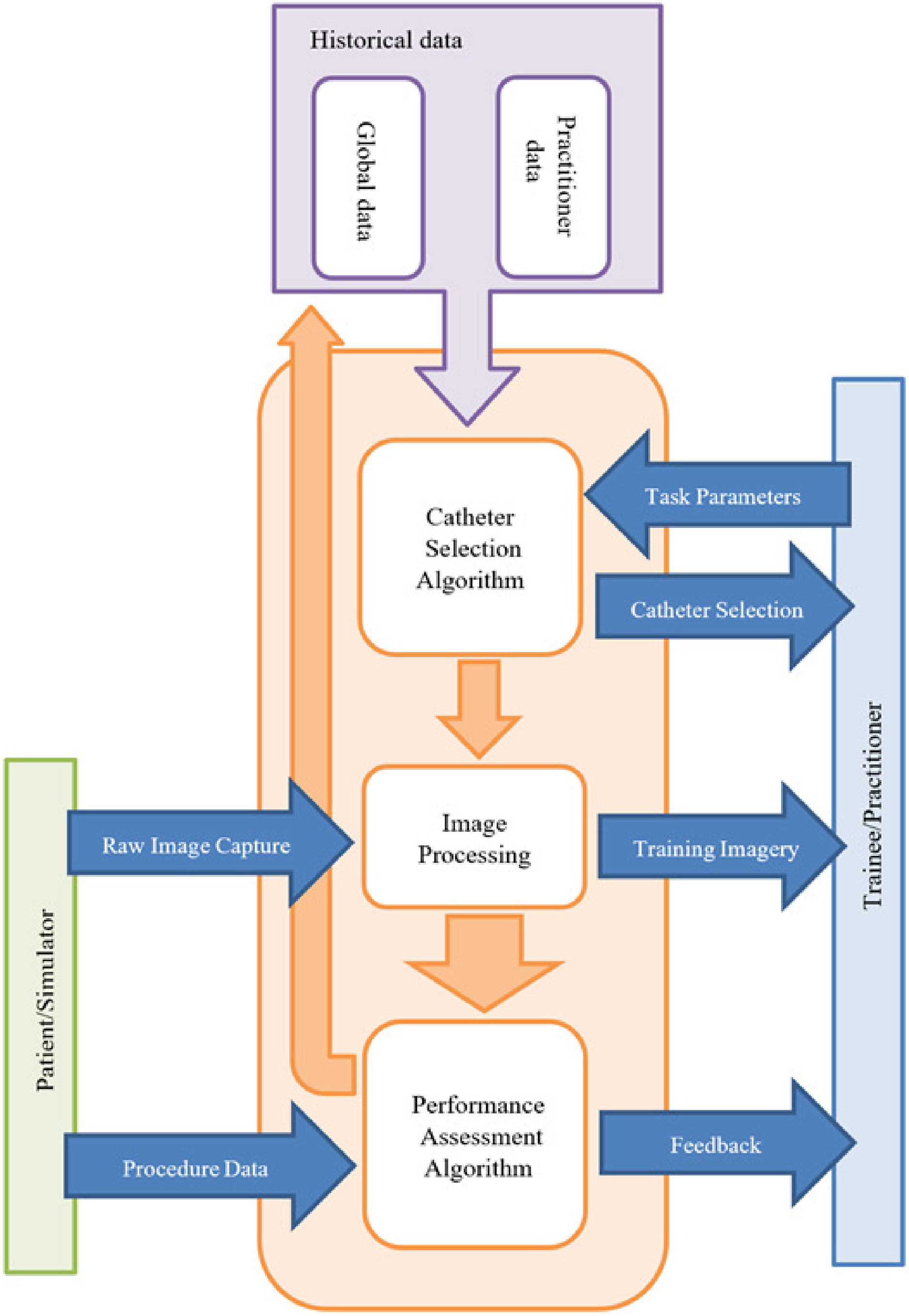

FIGURE 3: Catheterization Decision Support Concept Diagram.

The proposed concept for the training and decision support algorithm centers on the catheter selection and performance assessment algorithms. It is proposed that ML algorithms that can take input parameters as well as historical data for both the practitioner and global procedure data and predict one or more potentially optimal catheters.

This model shows the information in a sequential manner ,although there is potential for catheterization to be a dynamic procedure requiring this to have more complex interactions with practitioner decision making, this simplified model outlines the basic requirements that are needed at any point in that dynamic process. This conceptual model combines the display simulation/fluoroscopy integration elements for simplicity, but these concepts are explored separately in the detailed design requirements section. The inputs and outputs detailed in this model are further examined to determine detailed system requirements for the catheter training and decision support application.

3. DETAILED DESIGN REQUIREMENTS

The following requirements are initial estimates of the requirements and may be subject to change during design development and evaluation.

3.1 Catheter Selection Algorithm

Task Parameter Input: To enable the application to select a suitable catheter for a given procedure, that procedure must be parameterized to enable user input into the application. The initial parameterization process was conducted with subject matter experts at the Miami Valley Hospital, Dayton, Ohio and resulted in the following high-level requirements for input data in the application:

- Type of procedure.
- Entry point.
- The location of the procedure.
- The size of the patient(length, mass).
- Age of the patient.
- Sensitivity to wall hits.
- Sensitivity to time (emergency situation or otherwise).

Catheter Selection Output: In both the Decision Support mode and the Training mode, when implemented on complex training scenarios, the application will provide a minimum of one or more potential catheter guidewire combination matches for a specific procedure. This will include a selection derived from the global data and, in the event of a discrepancy, a supplemental option derived from the practitioner specific data. To support these selections and provide additional information to the practitioner, a success probability will be given. As well as providing an estimate of the potential difficulty of the procedure, this approach provides a delta between global performance and the preferred option of the individual. As there are many different catheter manufacturers, producing many different models, it may be necessary to have parametric output as well as a specific catheter selection, the application will provide information to enable the nearest match in the available stock to be determined by the practitioner. The following parameters should be provided upon interrogation of the selected catheter option:

- Tip length.
- Shape description (imagery).
- Radius of shape elements.
- Thickness of catheter.
- Stiffness of catheter and guidewire.

3.2 Data Requirements

There are potential issues regarding the storage and use of procedural and individual data that may require additional security considerations in the implementation of such an application. In addition to this, there are specific functional requirements for input data to be used by the application.

Global Data: In order to build a ML algorithm capable of predicting suitable catheters for a given procedure, historical data is required to train the model. The eventual aim would be to utilize the high-fidelity data available within the application to update and refine the model. In the absence of this data, the initial model will be trained using data from the Mid Atlantic Group Interventional Cardiology (MAGIC) database. If possible, this will be supplemented with high fidelity data from partner organizations as the application is developed.

Practitioner Data: To account for practitioner preferences and skills, some account of the specific performance of the individual users, the application will maintain a record of the procedures, catheters used, and outcomes. This will be used to tune the suggestions and provide long term analytics to the application user. There are important trust considerations with such performance tracking data that may impact the trust of users and potentially the success of the product.

These are the manuscript preparation guidelines used as a standard template. Author must follow these instructions and ensure that the manuscript is carefully aligned with these guidelines including headings, figures, tables, and references. Manuscripts with poor or no typesetting are not preliminary approved and consider for review.

3.3 Image Processing

The training mode of the application requires image processing and display manipulation to ensure the training experience is as close as possible to a real catheter insertion procedure. The position of the catheter in the simulator will be relayed to the trainee through a video screen and various transforms will be applied to ensure the view is as representative as possible. This will not be required for the Decision Support mode of the application. The image capture and display are important components of the training system. An example of the raw image data from the low-cost simulator that will be available to the application is shown in Figure 4. The image output from the application should attempt to mimic, as far as possible fluoroscopic imagery in terms of frame rate, display resolution, field of view and contrast. The raw visual images captured in the simulation are very different to greyscale, low-resolution (spatial and temporal) fluoroscopic images available in surgery and as such, additional processing will be required to achieve a representative display and ensure credibility of the simulation.

FIGURE 4: Example simulator image.

3.4 Performance Assessment

Parametric Procedure data. The performance assessment algorithm will compare the procedural data with historical data to establish not only if the procedure was successful but also how it compared with both global and practitioner specific procedures. The IC3ST framework (Riga et al, 2011) was developed to assess catheterization success but this tool is reliant on the presence of a subject matter expert. The application will utilize quantitative data from the procedure, which is a subset of the initial metrics of the IC3ST (Riga et al, 2011), as follows:

- Wire and catheter manipulation – total movement (mm)
- Contact with vessel wall (number of hits)
- Vessel Cannulation – was the procedure successful (yes/no)
- Overall time of procedure (seconds)

While the Vessel Cannulation success and time of procedure can be recorded by the application or input by the practitioner respectively, the wire and catheter manipulation, and contact with vessel wall metrics are harder to determine. It is proposed that these are assessed by use of a ML algorithm that can determine the total distance of movement of the wire and catheter, and the number of catheter contacts with the vessel wall. To do this, the algorithm requires access to the image data from the procedure.

The proposed system will utilize a ML algorithm to assess wall hits and total movement of the wire and catheter. A transfer learning approach, based on the VGG16 image classification model (Simonyanet al., 2013), fined tuned on catheterization wall-hit image data using a process outlined by Rosebrock (2012) and the Keras ML library (Chollet, 2015) was implemented in python by the authors. This model was developed using a set of 320 images (160 'hit', 160 'no hit') captured on the low-cost simulator. The images data were split into a training set (60%), validation set (20%) and evaluation set (20%).The model training resulted in a mean training accuracy of 97.9% with an associated validation accuracy of 88%. The model was then tested using set aside test images and the associated image classification results are presented in Table 2.

N=64	Predict Hit	Predict No Hit	Total
Actual Hit	**30**	**2**	**32**
Actual No Hit	**3**	**29**	**32**
Total	**33**	**31**	**64**

TABLE 2: Confusion matrix of catheterization image classification.

This shows the successful training performance generalized well to the test data with a 93.8% True Positive rate and a 90.6% true negative rate, and a testing accuracy of 92.2%. This translates to a precision of 0.94 and a recall of 0.91, along with an f-1 score of 0.92 on test data from the catheterization simulator. This study demonstrates that vascular wall hits can be detected using a deep learning classification model. These results are in line with the expected performance of the VGG16 model and broader state-of-the-art for image classification. Although comparable to other image classification models requires comparison to the success rate of human assessors to determine if this approach will be suitable for such an application or if an alternate method for vessel contact assessment, such as reverting to human assessment, is required.

The application will require output assessment feedback specific to each user type. While both require some level of comparison to both global and individual historical data, the content and frequency of the feedback will be user specific.

In the case of the trainee, the feedback can be a direct comparison to required performance criteria for cannulation success, and to historical data for vessel contact and time performance. In addition to this, the trainee would be provided with trend analysis on their own performance specific to the procedure parameterization.

When used as a decision support tool by professional practitioners, there are further considerations when giving performance feedback. Surgeons may be unwilling to use such an application if it is highlighting areas of weakness, which they may be directly assessed against. It may seem that this is a desirable function of the application, but such information may result in resistance or resentment among the potential user community, which must be avoided if such an application is to be successful.

4. DISCUSSION

This study has defined a conceptual model and initial information requirements for a catheterization training and decision support application. The information requirements themselves can be met with available historical data and further developed as the application produces data. Although this study defines a design framework and associated requirements, there are still significant risks and challenges that need to be reduced and mitigated to develop the application.

Firstly, there is a visual difference between the raw simulator imagery and the fluoroscopy imagery. While ensuring a representative frame rate, field of view and resolution is achievable through commercial video processing methods, the contrasts between tissue areas and blood vessel maybe somewhat harder to achieve. This will require contrast adjustments and potentially localized image manipulation;however, any solution must be compatible with near real time image processing.

The second major risk is the ability of ML algorithms to select a suitable wire-catheter combination given the parameters defined. There is no standard performance metric for catheter selection as this is currently conducted based on individual preference and without rigorous training or selection requirements. As such the performance of the application needs to be compared to the success rate of historical data. For this reason, it is important that a scalable development process is used, starting on low fidelity simulators to ensure the advice given results in performance at least as good as existing procedure results, subject to the same assessment criteria. The development application should always be defined as an advisory system as the predictive ability of the algorithm will only ever be able to be successful if the procedure involved is representative of existing data in the historical database. In addition, the system should be fully compliant with all guidance in COCATS 4 (King et al., 2015).

There are additional risks associated with automation in the performance assessment elements of the application. Both the total wire-catheter movement and the vessel wall hit count are dependent on ML algorithms. To some extent, the initial research into the wall hit algorithm has somewhat reduced this risk, although this initial use of a 2D CNN did not generalize well and as a result, further development is required.

The final challenge involved with the application development is the need to store information and provide feedback that might be sensitive and subject to specific security requirements, especially in the case of professional practitioners who will be primarily using the application as a decision support tool. While these risks and challenges are not insignificant, the initial results are promising and there are potential alternative solutions that may be employed if successful resolutions cannot be achieved.

Future research will ideally include the design and build of a prototype training system with integrated AI-based catheter selection model and wall-hit image classifier. Once working prototype is available, a between-subjects, repeated measures experiment to test if the simulator improves performance in a representative population is proposed. A control group will conduct an initial training based on traditional methods, while the experimental group will use the training simulator. A final one-way ANOVA performance assessment against a suitable baseline test will be used to judge any variation due to the catheter insertion simulator.

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