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ORIGINAL RESEARCH

Effect of an artificial-intelligent chest radiographs reporting system in an emergency department

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Abstract

Though chest radiography is a first-line diagnostic tool in the emergency department (ED), interpretation has a high error rate. We aimed to evaluate the usability and acceptability of deep learning-based computer-aided detection for chest radiography (DeepCADCR) in an ED environment. We conducted a single-institution survey of emergency physicians (EPs) who had used DeepCADCR (Lunit INSIGHT Chest Xray (CXR), version 3.1.4.1) as part of their ED workflow for at least three months. We developed 22 questions that assessed the subscales of effectiveness, efficiency, safety, satisfaction, and reliability. A seven-point Likert agreement scale was used to rate the responses. A total of 23 EPs who completed the survey was enrolled in the study. When averaged by subscale, satisfaction scores were highest (mean 4.71, standard deviation (SD) 1.43), and safety scores were lowest (mean 4.3, SD 0.72). When scores were converted to acceptability, the total average acceptance of DeepCADCR was 86.0%, with higher scores in ED residents than ED specialists for all subscales. Use of DeepCADCR in the ED workflow was well accepted by EPs.

Keywords

Artificial intelligence; Deep learning; Chest radiography; Emergency department; Survey; Computer-aided detection

1. Introduction

Chest radiography is a first-line diagnostic tool in the emergency department (ED) [1, 2]. However, interpretation has a high error rate (up to 22%) [3]. Moreover, interpretation of Chest xray (CR) images of patients requiring immediate procedures, such as pneumothorax or large pleural effusion, is often delayed [4, 5]. Although it is recommended that radiologists interpret all diagnostic radiology images in the ED [6, 7], coverage by radiologists is limited, especially on nights or weekends [8].

Recently, there have been major breakthroughs in the development of deep learning-based computer-aided detection of chest radiography (DeepCADCR) [6, 9–11]. Several studies have demonstrated that DeepCADCR can contribute to prompt and accurate interpretation as well increased work efficiency [12–15]. These benefits have been studied mostly in simulated studies with radiologists [14, 16, 17]. Implementation of DeepCADCR by non-radiologists in a real clinical environment has only been investigated by a single study [18].

Although promising, the impact of DeepCADCR for EPs in real practice remains unclear [19]. Patients present various symptoms and signs in the ED environment, and timely interpretation of all CRs and prompt decision-making can be difficult [20, 21]. Moreover, CR conducted in the ED generally was interpreted by radiologists after ED care was complete and was not used for ED decisions. Implementation of DeepCADCR in the ED has been expected to result in more accurate and prompt interpretations, but its usability and acceptability have not been evaluated. Therefore, we aimed to evaluate the usability and acceptability of DeepCADCR in the clinical workflow of EPs.

2. Methods

2.1 Study design

We conducted a survey study of EPs in a tertiary academic center ED in Seoul, Korea. The survey was carried out after the EPs had used DeepCADCR in their ED workflow for three months.

2.2 Study settings

The ED of a tertiary academic hospital in a metropolitan area with an average of 250 ED visits per day implemented DeepCADCR from June 2022 to September 2022. When patients visit this ED, EPs examine the patient and then transcribe initial laboratory orders, including CR if indicated. The EP interprets the CR images and consults with a radiologist if necessary. Radiologists are stationed in the hospital 24–7 and interpret CR images for ED patients, but it usually takes hours for specific consults.

2.3 Radiology, Picture archiving and communication system (PACS) and the DeepCADCR system

Chest radiographs were obtained with the patients in the posteroanterior projection or in the supine position according to condition. All CRs were obtained using an XGEO GC80 (Digital Radiography System, Samsung Medison, Seoul, South Korea) or GM60A-32 (Mobile Digital Radiography System, Samsung Medison, Seoul, South Korea) digital radiography system.

DeepCADCR (Lunit INSIGHT CXR, version 3.1.4.1) was implemented to assist the interpretation of ED CRs with a focus on nine abnormal findings: pulmonary nodules, calcification, fibrosis, pneumothorax, pleural effusion, atelectasis, pneumothorax, cardiomegaly, and consolidation. The system provides a probability score between 0% and 100%, with a heat map of each original chest radiograph to identify the location of the abnormality when the probability score is 15% or greater.

Routine ED practice during the study period is illustrated in Fig. 1. When CR was performed, the DeepCADCR system received the image from PACS storage and presented results in the electronic medical records (EMR) integrated view within a few seconds. Results were presented in the form of an INSIGHT map and/or INSIGHT report. Location(s) of abnormalities and abnormality scores were provided in the heat map of each chest radiograph. The INSIGHT report includes the anatomical location of the detected lesion along with information about the INSIGHT map.

Original CRs were examined side by side with INSIGHT maps by EPs to receive assistance from DeepCADCR in real time. An example image of a DeepCADCR INSIGHT map is provided in Fig. 2.

2.4 Participants

Fig. 3 describes the inclusion flow of study participants. ED residents and board-certified ED specialists affiliated with the ED were enrolled as participants. Only EPs with clinical experience with DeepCADCR during the study period were included; EPs who were on rotation in other clinical departments were excluded.

2.5 Survey development

There is as no consensus on standards for assessing deep learning-based clinical decision support systems. We developed a systematic questionnaire format based on review of previous studies [18, 19]. A total of 22 questions was developed to assess effectiveness, efficiency, safety, satisfaction and reliability. A 7-point Likert agreement scale was used to rate the responses as “Strongly disagree = 1”, “Disagree = 2”, “Somewhat disagree = 3”, “Neither agree nor disagree = 4”, “Somewhat agree = 5”, “Agree = 6”, or “Strongly agree = 7”. Averages of scores were calculated to determine the overall user experience, along with the system usability scale (SUS). More specific questions were developed for each feature of the DeepCADCR to assess the level of agreement among EPs and the impact of the CAD system on clinical practice.

2.6 Statistical analysis

All continuous variables are reported as mean (SD) or median (IQR). Categorical variables are described as number and percentage. We calculated Cronbach’s alpha to measure the internal consistency of the developed questions. We defined a score of 4 or higher as an “acceptable” response. For all statistical analyses, $p < 0.05$ was considered statistically significant. Statistical analyses were performed using R software (version 4.1.2, R Foundation for Statistical Computing, Boston, Messachusetts, USA).

3. Results

3.1 Participants

A total of 31 EPs used DeepCADCR during the study period. We excluded 8 EPs who left or who rotated to other departments. Finally, 23 EPs were enrolled and completed the survey. Table 1 describes the baseline characteristics of participants. Average age of the participants was 33.2 years, and 12 (52.2%) participants were female. Fifteen (65.2%) participants were emergency residents, and 10 (43.5%) participants had more than 5 years of work experience.

3.2 Chest radiograph interpretation by DeepCADCR

A total of 19,649 patients visited our ED during the study period. Of these, 2882 (14.7%) were younger than 19 years and 5373 (27.3%) did not undergo CR. As a result, a total of 14,745 CR images from 11,394 ED patients were collected during the study period.

The DeepCADCR interpreted 6138 (41.6%) CR images as normal and 8607 (58.3%) as abnormal. The proportions of specific abnormal findings are shown in **Supplementary Fig. 1**. The most common abnormal finding was pulmonary nodule (24.5%), followed by consolidation (22.8%), fibrosis (16.4%), and pleural effusion (13.2%).

3.3 User experience with DeepCADCR

The full survey questions are listed in Table 2. Response distribution for each subscale of user experience with DeepCADCR is presented in **Supplementary Fig. 2**. When averaged by subscale, satisfaction scores were highest (mean 4.71, SD 1.43), and safety scores were lowest (mean 4.3, SD 0.72). Average user experience scores for each subscale are presented in Fig. 4.

Survey questions and acceptance level of DeepCADCR by participants are presented in Table 2. When scores were converted to acceptability, the total average acceptance was 86.0%.

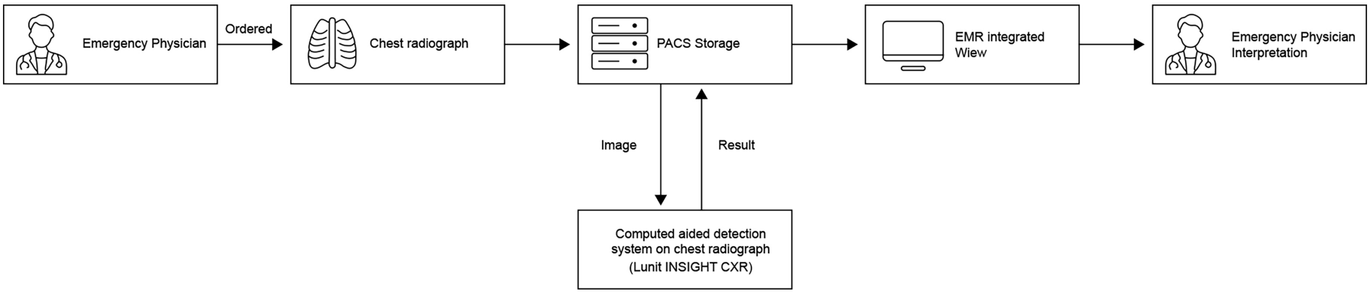

FIGURE 1. Implementation of computer-aided detection system on chest radiograph into emergency department workflow. PACS, picture archiving and communication system; EMR, electronic medical records; CXR, chest Xray.

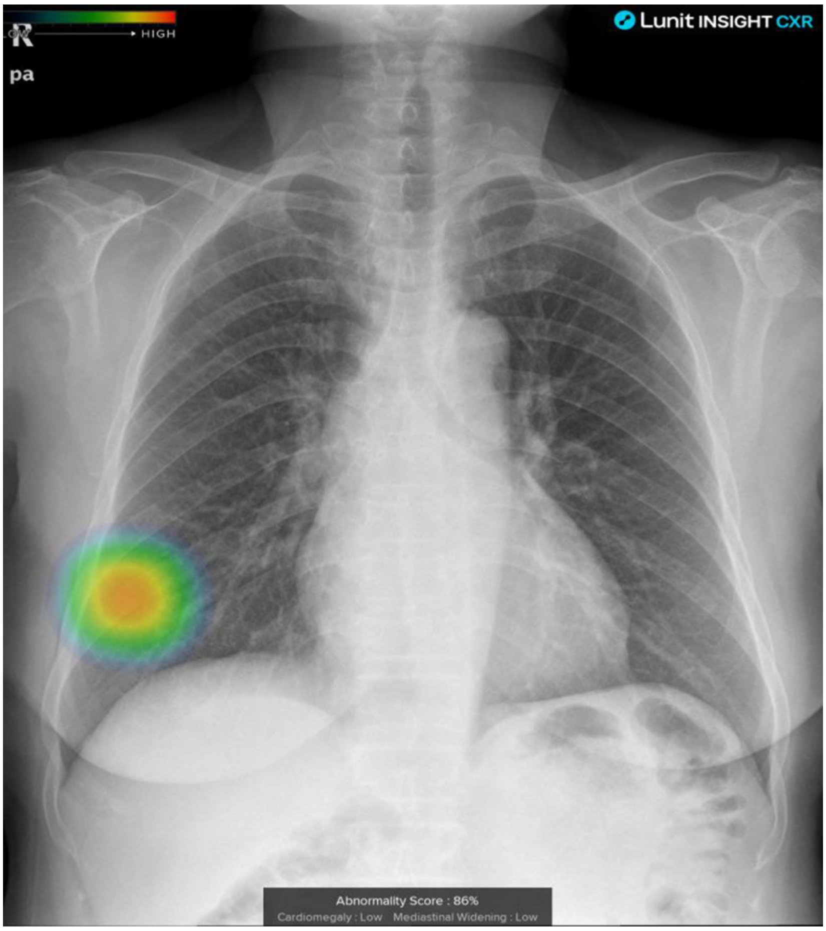

FIGURE 2. Example images of the computer aided detection system on chest radiograph. Heat map on abnormal findings. The system provided abnormality score below the chest radiograph with probability score. When probability score as 15% or greater, the system interpreted a chest radiograph as an abnormal.

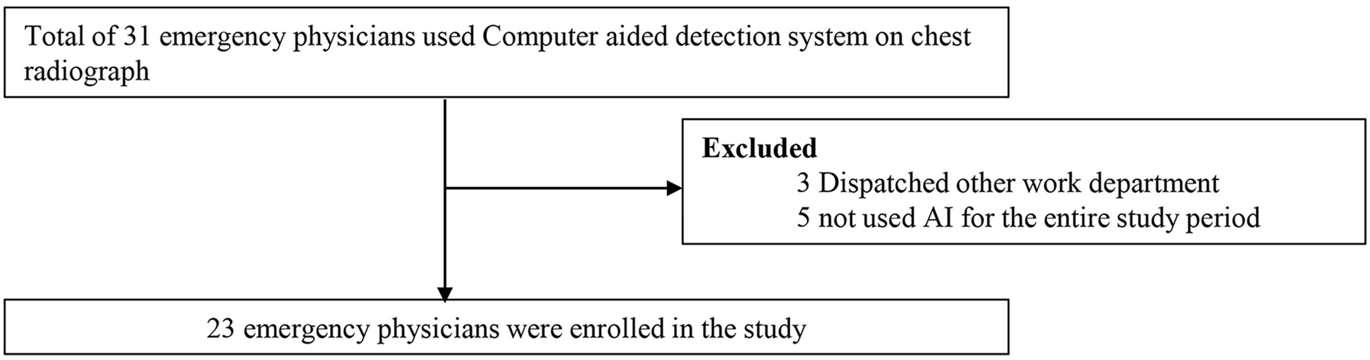

FIGURE 3. Flow diagram of study participants. AI, artificial intelligence.

TABLE 1. Baseline characteristics of the study participants.

Variables	Participants (N = 23)
Age, mean (SD)	33.2 (7.4)
Sex, n (%)	
Male	11 (47.8)
Female	12 (52.2)
Physician experience, n (%)	
Resident	15 (65.2)
Specialist	8 (34.8)
Work years, n (%)	
≤5	13 (56.5)
>5	10 (43.5)
Experience with AI clinical decision support system, n (%)	
Yes	11 (47.8)
No	12 (52.2)
Experience with attending a lecture or seminar regarding medical AI, n (%)	
Yes	9 (39.1)
No	14 (60.9)

AI, artificial intelligence; SD, standard deviation.

TABLE 2. Acceptability of DeepCADCR for chest radiograph interpretation.

Survey questions	Acceptability (%)
Effectiveness	80.4
Q1. My chest CR interpretation improved after CADCR implementation.	69.6
Q2. DeepCADCR helped plan future diagnoses and treatment of ER patients.	78.3
Q3. DeepCADCR made me more confident in my reading.	91.3
Q4. Overall, CADCR helped me interpret chest images of ER patients.	82.6
Efficiency	72.8
Q5. It is convenient that the DeepCADCR reading is shown along with the image.	91.3
Q6. It took more time to read the CR after DeepCADCR implementation.	26.1
Q7. Due to DeepCADCR, I was able to reduce the number of requests for CR readings by radiologists.	43.5
Q8. DeepCADCR improved the effectiveness of care overall.	82.6
Safety	69.5
Q9. I was able to recommend appropriate outpatient follow-up for abnormal findings incidentally discovered by CADCR.	69.6
Q10. DeepCADCR readings may lead to additional tests for patients that they would not have undergone without CADCR.	60.9
Q11. DeepCADCR may delay patient care.	43.5
Q12. DeepCADCR can cause unnecessary confusion.	26.1
Q13. DeepCADCR was able to reduce the number of missed cases requiring emergency treatment.	69.6
Q14. Implementation of DeepCADCR in the ER could increase patient safety overall.	87.0
Satisfaction	85.9
Q15. The benefit of the DeepCADCR system is worth the cost.	82.6
Q16. I am willing to continue using the DeepCADCR reading system.	87.0
Q17. I would recommend DeepCADCR use to my colleagues and other EPs.	87.0
Q18. Overall, I am satisfied with the performance of the DeepCADCR reading system.	87.0
Reliability	76.1
Q19. I have a good understanding of the DeepCADCR reading algorithm.	34.8
Q20. DeepCADCR readings were easy to interpret.	95.7
Q21. I trust the DeepCADCR readings.	82.6
Q22. DeepCADCR readings were mostly consistent with my readings.	91.3
Average	86.0

DeepCADCR, deep learning-based computer-aided detection system for chest radiographs.
Scores over 4 were regarded as acceptance of DeepCADCR.
Q6, Q11, Q12 were negative items. The 100-value was used for average acceptability.
CR, chest radiography; EPs, emergency physicians; ER, emergency room.

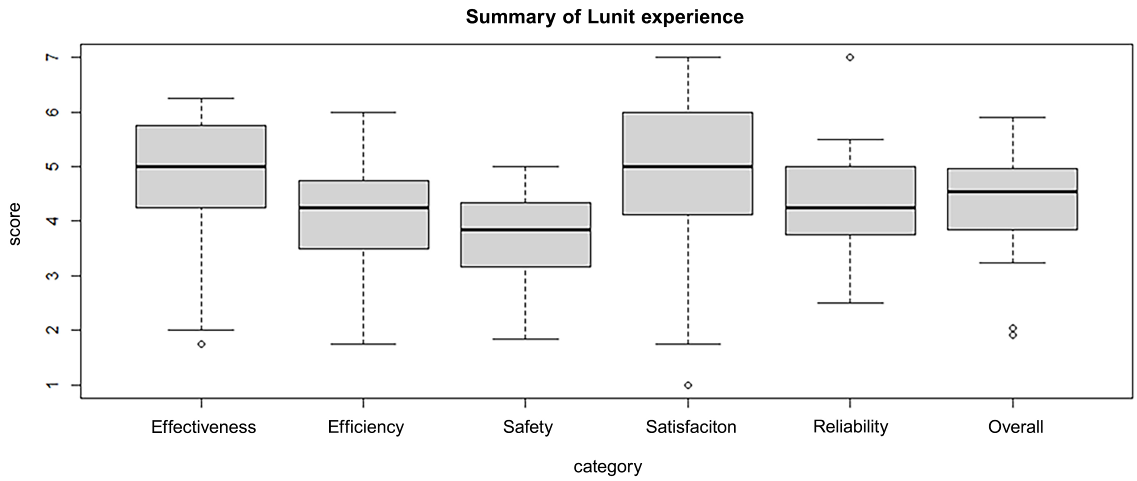

FIGURE 4. Summary of user experience responses.

3.3.1 Effectiveness and efficiency

Effectiveness of DeepCADCR was 80.4%, and efficiency was 72.8%. In terms of effectiveness, the statement "DeepCADCR made me more confident in my reading" (Q3) received the highest acceptance. In the efficiency subscale, participants were least likely to agree with DeepCADCR to not request a CR reading by a radiologist (Q7, 43.5%).

3.3.2 Safety, satisfaction and reliability

Safety of DeepCADCR was 69.5%, satisfaction was 85.9%, and reliability was 76.1%. Acceptance of safety was lowest among all subscales, indicating that participants were not convinced that DeepCADCR would improve patient safety. Nevertheless, participants were largely satisfied with DeepCADCR and intended to use (Q16, 87.0%) and recommend it to their colleagues and other EPs (Q17, 87.0%). Most participants were satisfied with DeepCADCR presentation of results (Q22, 95.7%) but did not understand the model algorithm (Q19, 34.8%).

3.3.3 Subgroup analysis

We analyzed the results of user experience in terms of EP experience. Average scores were higher in the resident group than in the specialist group for all subscales; however, the difference in reliability was not significant (**Supplementary Fig. 3**). The mean (SD) for all questions was 4.7 (SD 1.3) in the resident group and 3.9 (SD 1.6) in the specialist group. The largest difference was in perceived effectiveness of DeepCADCR (5.3 (SD 1.0) in the resident group *vs.* 3.7 (SD 1.6) in the specialist group, $p < 0.001$), and the smallest difference was in perceived reliability (4.5 (SD 1.4) in the resident group *vs.* 4.2 (SD 1.5) in the specialist group, $p = 0.308$).

We calculated Cronbach's alpha for the five-subscale questionnaire. The effectiveness subscale of four questions had an α value of 0.94, the efficiency subscale of 4 questions had an α value of 0.78, the safety subscale of 6 questions had an α value of 0 .74, the satisfaction subscale of 4 questions had an α value of 0.96, and the reliability subscale of 4 questions had an α value of 0.84.

3.4 System usability scale of DeepCADCR

The mean (SD) SUS score was 64.5 (7.7). Table 3 provides details of each statement. Of all statements, "the system was easy to use" received the best evaluation from participants, with the highest mean score and lowest SD. Other statements such as "ease of learning the system" (mean 4.0, SD 0.6), "confident in the system" (mean 3.4, SD 0.8), and "intend to use the system" (mean 3.4, SD 0.8) obtained relatively high scores.

3.5 Survey results by specific abnormal findings

Participants showed the highest agreement with the DeepCADCR interpretation for pleural effusion (mean 5.5, SD 0.5) and pneumothorax (mean 5.5, SD 0.8). Areas of lower agreement were atelectasis (mean 4.3, SD 1.0) and fibrosis (mean 4.4, SD 1.1). DeepCADCR had the greatest impact when participants were diagnosed or required further treatment for pneumothorax (mean 4.7, SD 1.8) and pneumoperitoneum (mean 4.5, SD 1.8) (**Supplementary Table 1**).

3.6 Future DeepCADCR application

Seven questions about the one-year use of DeepCADCR were answered by participants. The results are described in Table 4. Although patient safety received the lowest score based on user evaluation, participants felt that continuous use of DeepCADCR would help improve patient safety (mean 4.9, SD 1.2). Other questions such as "help in chest radiograph interpretation" (mean 4.6, SD 1.3), "satisfaction with performance" (mean 4.6, SD 1.4), and "trust the CADCR interpretation" (mean 4.6, SD 1.4) obtained relatively high scores.

4. Discussion

This is the first study to evaluate user experience with DeepCADCR in the workflow of an ED. The study showed high acceptance of CADCR among EPs; its acceptance level varied from 69.5% (patient safety category) to 85.9% (satisfaction category) (Table 2). Residents were more positive toward DeepCADCR than were board-certified ED specialists.

TABLE 3. System usability scale results.

Standard questions	Mean (SD)
I think that I would like to use this system frequently	3.4 (0.8)
I found the system unnecessarily complex	1.0 (0.5)
I thought the system was easy to use	4.1 (0.5)
I think that I would need the support of a technical person to be able to use this system	2.0 (0.7)
I found that the various functions in this system were well integrated	3.3 (0.9)
I thought there were too many inconsistencies in this system	1.9 (0.7)
I imagine that most people would learn to use this system very quickly	4.0 (0.6)
I found the system very cumbersome to use	1.8 (0.7)
I felt very confident using the system	3.4 (0.8)
I needed to learn a lot of things before I could start using the system	1.8 (0.6)

Range 1–5; 1, strongly disagree and 5, strongly agree. SD, standard deviation.

TABLE 4. Perceptions of DeepCADCR use in the future.

Survey Questions	Scores, mean (SD)
After using DeepCADCR for a year, my ability to read chest radiographs will have improved	4.3 (1.5)
After using DeepCADCR for a year, I will use it to help read chest radiographs	4.6 (1.3)
After using DeepCADCR for a year, the efficiency of treatment will have improved	4.5 (1.3)
After using DeepCADCR for a year, patient safety will have improved	4.9 (1.2)
After using DeepCADCR for a year, I will be satisfied with the performance of the AI reading system	4.6 (1.4)
After using DeepCADCR for a year, I will trust the AI readings	4.6 (1.4)
After using DeepCADCR for a year, I will use the AI reading system frequently	4.5 (1.5)

Range 1–7; 1, strongly disagree and 7, strongly agree. DeepCADCR, deep learning-based computer-aided detection system for chest radiographs; AI, artificial intelligence; SD, standard deviation.

In previous works, DeepCADCR was only evaluated in simulation settings or in general wards or outpatient departments. This is the first study to evaluate DeepCADCR implementation in clinical practice in the ED. Simulation-based studies have previously been used to evaluate the performance of EPs with or without DeepCADCR [6, 19]. Because CR interpretation is influenced by various factors such as severity of disease, ED crowding, and EP workload, it is unclear whether the results of simulation studies are generalizable to real-world clinical practice. Moreover, when implementing machine learning-based CDSS, user acceptance needs to be high in addition to acceptance of the system [22].

We also provided evidence that CAD systems can positively impact non-radiologists in a clinical setting. The effect of DeepCADCR on clinical decision-making is unclear. Most studies have targeted radiologists in related fields rather than non-radiologists; however, radiologists do not interact with patients directly or make decisions regarding care. We believe that DeepCADCR can improve patient treatment and prognosis [23, 24]. We implemented DeepCADCR into clinicians' workflows and found that EPs made most use of the system when they had to make a diagnosis or develop a treatment plan. Residents were more satisfied and influenced by DeepCADCR than were board-certified ED specialists.

Generally, a resident's ability to interpret radiology images is lowest when they are in Post graduate year (PGY1) and improves as they become more advanced residents and board-certified specialists [25]. Novice residents typically lack knowledge to interpretate radiology images and time to assess images, which are possible reasons why higher satisfaction was reported in the resident group. DeepCADCR can assist residents not only in terms of interpretation accuracy, but also aid in visualization to result in higher satisfaction and usability.

Only 34.8% of participants said they had a good understanding of the DeepCADCR algorithm. Before implementing this system in our ED, we described the function and instructions to our participants. However, we did not cover all knowledge and mechanisms of the deep learning algorithms because the participants had various backgrounds in medical artificial intelligence (AI). According to one study, education has a positive influence on physician acceptance of AI [26]. However, less than half of the participants in our study had prior experience with medical AI. We suggest that aggressive medical AI education can improve physicians' acceptance, especially with regard to safety and reliability.

User acceptance could vary by work environment [27]. Because DeepCADCR does not differentiate interval changes between abnormal CRs, it is less useful for chronic diseases. The proportions of normal and abnormal interpretations by DeepCADCR would likely impact EP acceptance; a multicenter prospective study should be performed to assess this.

EPs provided high scores for DeepCADCR for abnormal findings requiring emergent management such as pneumothorax, pneumoperitoneum, and pleural effusion. One study reported similar results to our study; when a CAD system was used to detect pneumothorax in CR after lung biopsy, physicians gave a high rating to the interpretation performance. Additional significant factors should be discovered and investigated to implement and maximize the usability of DeepCADCR.

First, we conducted this study in a single-center ED. Multicenter prospective studies are recommended to evaluate the generalizability of our findings. Second, we used only one type of DeepCADCR; the results could differ with another type of DeepCADCR with a different user interface and display. Third, we only conducted the survey once, so we were not able to analyze outcomes over time. Changes in learning, acceptance, and user experience over time should be evaluated in future studies. Fourth, we evaluated the user experience and the impact of DeepCADCR through a survey. However, in real-world clinical settings, many confounding factors can affect the interpretation of chest radiographs and therapeutic procedures. Finally, we did not directly investigate the effectiveness of DeepCADCR in the ED setting.

5. Conclusions

DeepCADCR implemented in the ED workflow was well accepted by EPs. They were highly satisfied with the system, with residents being more positive toward DeepCADCR than board-certified ED specialists.

AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

AUTHOR CONTRIBUTIONS

WCC—designed the research study and supervised the overall study process. DHY, SJH and SUL—performed the survey. SYH and GTL—provided help and advice on the research. SJH, HY, JYY and TGS—curated and analyzed the data. DHY—wrote the manuscript. JEP, HSC and TRK—reviewed and edited the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The methods were performed in accordance with relevant guidelines and regulations and approved by the Samsung Medical Center institutional review board (IRB no. 2022-06-116-001). All participants provided written informed consent prior to inclusion in the study.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. Won Chul Cha is serving as one of the Editorial Board members of this journal. We declare that Won Chul Cha had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to MAM.

SUPPLEMENTARY MATERIAL

Supplementary material associated with this article can be found, in the online version, at `https://oss.signavitae.com/mre-signavitae/article/1722143294146658304/attachment/Supplementary%20material.docx`.

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