The Variable Journey in Learning to Interpret Pediatric Point-of-care Ultrasound Images: A Multicenter Prospective Cohort Study

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ABSTRACT

Objectives: To complement bedside learning of point-of-care ultrasound (POCUS), we developed an online learning assessment platform for the visual interpretation component of this skill. This study examined the amount and rate of skill acquisition in POCUS image interpretation in a cohort of pediatric emergency medicine (PEM) physician learners.

Methods: This was a multicenter prospective cohort study. PEM physicians learned POCUS using a computerbased image repository and learning assessment system that allowed participants to deliberately practice image interpretation of 400 images from four pediatric POCUS applications (soft tissue, lung, cardiac, and focused assessment sonography for trauma [FAST]). Participants completed at least one application (100 cases) over a 4week period.

Results: We enrolled 172 PEM physicians (114 attendings, 65 fellows). The increase in accuracy from the initial to final 25 cases was 11.6%, 9.8%, 7.4%, and 8.6% for soft tissue, lung, cardiac, and FAST, respectively. For all applications, the average learners (50th percentile) required 0 to 45, 25 to 97, 66 to 175, and 141 to 290 cases to reach 80, 85, 90, and 95% accuracy, respectively. The least efficient (95th percentile) learners required 60 to 288, 109 to 456, 160 to 666, and 243 to 1040 cases to reach these same accuracy benchmarks. Generally, the soft tissue application required participants to complete the least number of cases to reach a given proficiency level, while the cardiac application required the most.

Conclusions: Deliberate practice of pediatric POCUS image cases using an online learning and assessment platform may lead to skill improvement in POCUS image interpretation. Importantly, there was a highly variable rate of achievement across learners and applications. These data inform our understanding of POCUS image interpretation skill development and could complement bedside learning and performance assessments.

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The use of emergency point-of-care ultrasound (POCUS) in pediatric emergency medicine (PEM) can improve patient outcomes and expedite patient disposition.¹ As such, learning POCUS has become an increasing priority in PEM, with the learning experience typically including introductory courses and skill acquisition that relies on case-by-case clinical exposure.²⁻⁵ However, this approach may lead to challenges in achieving POCUS proficiency across a wide range of learners.⁶ Opportunities for bedside feedback may be limited by the number of POCUS-trained attendings available at a given site.² This deprives the learner of immediate feedback, one of the most powerful methods of skill acquisition.⁷ Further, since the baseline pathology rate in pediatrics is relatively low, relying on case-by-case exposure to achieve sufficient skill may take years with clinical practice alone.

Gaining POCUS expertise is multifaceted and complex since the technique includes image acquisition, image interpretation, and integration of interpretation into clinical decision making. To facilitate learning of complex tasks, instructional design models recommend intentionally alternating part-task with wholetask training.⁸ In this light, e-learning provides an opportunity to expose learners to an image interpretation learning experience (i.e., part-task) that could complement the resource intensive face-to-face teaching and learning at the bedside that addresses all facets of POCUS (i.e., whole-task).² However, to date, most POCUS simulation and online education focuses on image acquisition,^{3,5} specific conditions (e.g., cardiac tamponade),9 or adult applications.¹⁰⁻¹² As such, existing teaching tools are limited in being able to significantly improve learner exposure to the part-task of pediatric POCUS image interpretation. However, Web-based learning and assessment image banks that provide intentional sequencing and targeted analytic feedback on hundreds of cases have had demonstrated success for increasing electrocardiogram and musculoskeletal radiograph image interpretation skill.¹³⁻¹⁵ Using these types of learning platforms, the presentation of images is simulated to mirror how clinicians interpret them at the bedside. Specifically, cases are presented with a brief clinical stem, standard images and views, and juxtaposition of normal and abnormal cases.^{16,17} The cases are also presented in large numbers so that learners can learn similarities and differences between diagnoses, identify weaknesses, and build up a global representation of possible diagnoses.^{15,16,18} After each case the system provides visual

and text feedback, which allows for deliberate practice¹⁹ and an ongoing measure of performance as part of the instructional strategy.^{20,21} This type of learning assessment platform could be applied to the image interpretation component of POCUS and potentially improve our understanding of POCUS image interpretation skill development.

We developed a POCUS image interpretation learning and assessment system that included four common pediatric POCUS applications (100 cases/application): soft tissue, lung, cardiac, and focused assessment sonography for trauma (FAST).³ We sought to determine PEM physician performance metrics and the number of cases and time within which most participants could achieve specific performance benchmarks.

METHODS

Education Intervention

We used previously established methods to develop the education intervention.^{15-17,22} Deidentified images in the four POCUS applications acquired using the departmental ultrasound machine (Zonare Medical Systems) were exported from the local POCUS archive (Q-Path, Telexy Healthcare) in JPEG (still images) or MPEG-4 (cine-clips) formats. From this pool, two PEM POCUS fellowship-trained physicians selected a consecutive sample of 100 cases per application (400 total) that demonstrated acceptable image quality and a spectrum of pathology and normal anatomy. Any images with embedded technical clues that pointed to a diagnosis were excluded. Further, each application contained 50 cases with and 50 cases without pathology.¹⁷ For lung and cardiac applications, both video and still images were used because recognition of movement is key to interpretation. For soft tissue and FAST (except cardiac view) still images alone were used since these were more likely to adequately capture the subtleties distinguishing abnormal and normal cases and were more cognitively efficient for learners.23

As the skill of assigning clinical significance and a specific diagnosis to POCUS findings (e.g., pneumonia) is best assessed at the bedside, the main goal of this education intervention was to develop the skill of distinguishing normal from any abnormal POCUS findings on video/still images, alongside forcing the learner to visually locate any abnormality for cases allocated as "abnormal." The key initial educational outcome of accurately distinguishing normal from abnormal cases (vs. confirming a specific diagnosis) is also in keeping with the user goals pediatric POCUS at the bedside since identifying an abnormal POCUS image should then prompt the physician to consider additional tests or consultations as needed to confirm or refine the diagnosis.²⁴ Nevertheless, learning the possible specific diagnoses from POCUS imaging findings is also important. As a result, this information is presented with every case for the participant to consider in the text feedback. This approach satisfies the essential learning goals for pediatric POCUS, while providing additional information to participants to also learn specific diagnostic interpretations for each case.

All images were reviewed jointly by two POCUS experts and classified as POCUS images as normal versus abnormal, where abnormal images had changes that could be considered pathological (Table 1). A third POCUS expert then independently provided normal/abnormal classifications, and discrepancies between the classifications were resolved by consensus ($\kappa = 0.86$, 95% confidence interval [CI] 0.81 to 0.91). Two POCUS experts then subsequently marked up the abnormal images using graphics to highlight pathology, creating clickable areas over the pathology with 2 to 3 mm of allowance just outside the abnormal area. These images were then embedded into a template generated using a Flash-integrated development environment.

Table 1

Pathology Presented by the Learning and Assessment System for Each POCUS Application

Pathology $(n = 50)^{\dagger}$	n (%)					
Soft tissue						
Cellulitis and abscess	29 (58)					
Cellulitis	19 (38)					
Foreign body	2 (4)					
Lung						
Pneumonia, with and without pleural effusion	25 (50)					
Inflammation/bronchiolitis	20 (40)					
Pneumothorax	3 (6)					
Pulmonary edema	2 (4)					
Cardiac						
Pericardial effusion	32 (64)					
Poor function	18 (36)					
FAST						
Multiple areas of free fluid	25 (50)					
Pelvic free fluid	8 (16)					
Right or left upper quadrant free fluid	12 (24)					
Pericardial effusion	5 (10)					

FAST = focused assessment sonography in trauma.

[†]50 cases with pathology per application; 50 cases without pathology to make up 100 total.

A website was developed using HTML, PHP, and a mySQL database.¹⁵ In brief, once a participant was provided unique access, they were taken to the online system and presented with 100 cases per application. For each case, they considered a brief clinical description stem and an unmarked POCUS image (still \pm video). Cases were presented in random order unique to each participant. After review of the case, the user declared the case as definitely normal, probably normal, probably abnormal, or definitely abnormal. The definitely/probably assignments permitted the user to express the certainty of their response. If their answer was in the "abnormal" category, the user was then required to designate one area of abnormality using an interactive system. When ready, the participant submitted their response, after which they received immediate visual and written feedback on the correctness of their response, diagnosis of the case, and normal anatomy (demonstration at https://imagesim.c om/demo/ or Figure 1). Prior to launch, the system was pilot tested on five participants (one POCUS nonexpert, four POCUS experts) for technical and content issues and revised in consequence.

Study Design and Setting

The education tool was developed in collaboration with two tertiary care pediatric centers and an industry partner. This research was undertaken using a multicenter prospective cohort design. We recruited a convenience sample of PEM physicians in the United States and Canada from September to November 2018.

Selection of Participants

An e-mail was sent to PEM division heads, PEM fellowship program directors, and P2 Network (an international collaborative of pediatric POCUS physicians, https://p2network.com/) site leads asking them to forward the e-mail to their respective fellows and attending physicians. Interested participants contacted the study coordinator. We also recruited five "expert" PEM POCUS physicians (separate from study team) who had each completed a PEM POCUS fellowship and performed at least 1,500 bedside scans.²⁵ This study was approved by the institutional review boards at the study institutions.

Measurements

Secure entry was ensured via unique participant login credentials and access to the system was available 24 hours per day, 7 days per week. We collected information on type of learner (fellow vs. attending), geographic



Figure 1. Visual feedback includes labeling of normal anatomy as well as any abnormalities (if present), and the red circle is the token placed by the user within the mask designating the abnormal region. Text feedback details if the case is normal or abnormal and the specific abnormalities where present. LA = left atrium; LV = left ventricle; RA = right atrium; RV = right ventricle.

location, and self-reported POCUS scans completed (none, <50, 51–100, 101–500, 501–1,000). Participants were asked to complete an introductory tutorial and at least one of the four 100-case POCUS applications. The system automatically time stamped the time a case was started to the time a case response was submitted. Participants were given a time limit of 4 weeks to minimize decay of learning that may confound results.²⁶ At 2 weeks, participants who had not completed at least one application were sent an e-mail reminder.

Outcomes

By surveying 150 members of the P2 network, we determined that the performance benchmarks of 80, 85, 90, and 95% accuracy could be considered educationally meaningful for a variety of contexts. Thus, we provided data that demonstrated learning curves of the participants and the median number of cases that participants need to complete to achieve the latter performance benchmarks (primary outcome). Since we anticipated that there would be a variation between participants to achieve these performance benchmarks, we provided this data separately for the average (50th percentile) and least efficient learner (95th percentile) of nonexpert participants.

We also examined the change in accuracy per application between the first and last 25 cases.²⁶ Further, we measured the effect size of learning gains, changes in sensitivity and specificity per application, and differences in learning gains between fellows versus attendings and made comparisons between applications. We examined if there was any association between demographic variables and the odds of achieving expert-level performance. Expert-level data were also used to examine relations-to-other variables validity (construct),²⁷ where we would expect that expert performance would be significantly higher than those that are relative nonexperts. Finally, to examine feasibility, we calculated average amount of time spent by participants per case and per 100-case module.

Data Analyses

Sample Size. From our previous work, the educationally important difference between initial and final scores was approximately 10% and the proportion of discordant pairs is about 12%.²⁶ We also assumed that $\alpha = 0.05$ and $\beta = 0.80$. Using a McNemar test power analysis (PASS 11), we calculated a minimal sample size of 95 of PEM POCUS nonexpert participants per application.

Scoring. Participants were scored only on the broad category selections of "normal" or "abnormal" and not the subassignments of "probably or definitely" normal/abnormal. Specifically, normal items were scored dichotomously, while abnormal items were scored correct if the participant classified the case as abnormal and indicated one correct region of abnormality.

Number of Cases to a Performance Bench-

mark. We modeled the learning curves of each individual participant with a random coefficients hierarchical logistic regression model.²⁸ Using these learning curves, we predicted the median number of cases required for a participant to attain a performance benchmark by solving the individual regression equation for the number of cases required to achieve the log odds (logit) that would correspond to the selected performance benchmark. From these data, we also plotted the proportion of participants that would reach 95% accuracy for a given number of cases to determine if these histograms were normally distributed by testing for both skewness and kurtosis of the distributions.²⁹

Learning Outcomes. Using the initial (pre) and final (post) 25 cases, we calculated change in accuracy, sensitivity, specificity, and Cohen's d-effect sizes for each application, with respective 95% CI. We analyzed for the association of achieving POCUS expert accuracy performance (dependent variable) and a priori selected independent variables using a logistic regression model. The independent variables included years in practice (\leq 5 years vs. >5 years), academic setting (university affiliated children's hospital vs. other), POCUS training during fellowship (yes vs. no), number of any type of scan completed prior to participation (\geq 100 vs. <100), and accuracy score on initial 20 cases (\geq 80% vs. <80%).

Comparisons Between Applications. Independent and dependent normally distributed parametric data were compared with a Student's t-test and paired Student's t-test, respectively. Analysis of variance (ANOVA) testing was used to compare three or more means from independent proportions, and the Bonferonni test was used to perform post hoc analyses.

Time Commitment. We determined the median time it took to complete each 100-case application with respective interquartile range. We compared the time commitment between applications using the Kruskal-Wallis test.

Significance was set at p < 0.01 to account for multiple testing. All analyses except the regression analyses were carried out using SPSS (Version 23, IBM 2015). The regression models were performed using Stata (Version 14, StataCorp LLC).

RESULTS

Study Participants

We enrolled 177 PEM physicians. Of these, 172 were PEM POCUS learner physicians (fellows [n = 65] and attendings [n = 107]) and five were PEM POCUS experts (Figure 2). Participants represented 28 (56%) of the 50 US states and five (50%) of the 10 Canadian provinces. There were significantly more fellows than attendings that received POCUS training as part



Figure 2. POCUS PEM physician participation. *Sum total of all specific application participants was greater than 128 since most participants completed more than one application. FAST = focused assessment sonography for trauma; PEM = pediatric emergency medicine; POCUS = point-of-care ultrasound.

of their fellowship experience (82.0% vs. 30.8%; difference = 51.2% [95% CI = 36.2–61.7]; Table 2).

At least one application was completed by 128 (74.4%) participants (Figure 2), 88 (68.8%) of whom completed all four applications, while 11 (8.6%) completed three, seven (5.5%) completed two, and 22 (17.2%) completed one application.

Number of Cases to Performance Benchmarks

A qualitative review of the modeled learning curves demonstrates significant variation between participants in rates of achieving higher performance (Figure 3). For the average (50th percentile) learners, the predicted median number of cases needed across our four applications was 0 to 45 for 80% accuracy, 25 to 97 for 85% accuracy, 66 to 175 for 90% accuracy, and 141 to 290 for 95% accuracy (Figure 4A). The least efficient (95th percentile) of learners would have to complete 60 to 288 cases to achieve 80% accuracy, 109 to 456 cases for 85% accuracy, 160 to 666 cases for 90% accuracy, and 243 to 1,040 cases for 95% accuracy. Participants required the highest number of cases for the cardiac application and the lowest number for the soft tissue application to reach a specified benchmark (Figure 4B).

The distribution of the number of participants that would achieve the expert benchmark for a given number of cases was skewed for all applications (p < 0.0001). The lung and cardiac distributions also demonstrated kurtosis (p < 0.0001; Figure 5).

Performance Outcomes

The pre/post change in accuracy for each application is detailed in Table 3. The Cohen's d-effect sizes for each application were moderate to large and ranged

Table 2 Participant Demographics

Demographic Variable	PEM Fellow N=65	PEM Attending N=107	p-value
Participant from the Unites States, no. (%)	52 (80.0)	67 (62.6)	0.02
Years since completing postgraduate training, no. (%)			
< 6 years	NA [†]	44 (41.1)	NA [†]
6-10 years		20 (18.7)	
11-15 years		13 (12.1)	
16-20 years		10 (9.3)	
> 20 years		20 (18.7)	
Female sex, no. (%)	44 (72.1)	72 (63.2)	0.23
Employment Setting, no. (%)			
University affiliated general/community hospital	3 (4.6)	6 (5.6)	0.53 [§]
University affiliated children's hospital	61 (93.8)	99 (92.5)	
Non-university affiliated general/community hospital	2 (3.1)	1 (0.9)	
Non-university affiliated children's hospital	0	1 (0.9)	
Type of Point-of-Care Ultrasound Training, no. (%) [‡]			
None	2 (3.1)	13 (12.1)	<0.0001 [§]
Integrated into emergency medicine residency training	3 (4.6)	9 (8.4)	
Integrated into pediatric residency training	3 (4.6)	1 (0.9)	
Integrated into PEM fellowship training	53 (82.0)	33 (30.8)	
Workshops/ Courses	7 (10.8)	75 (70.70)	
Institutional faculty training	NA	61 (57.0)	
Self-directed learning	8 (12.3)	27 (25.2)	
Number of educational/clinical point-of-care ultrasound exam	inations completed, no. (%)		
None	2 (3.1)	5 (4.4)	0.12
<u><</u> 50	30 (45.2)	43 (40.4)	
51-100	17 (26.2)	20 (18.4)	
101-500	15 (23.1)	28 (26.3)	
501-1000	1 (0.2)	15 (14.0)	



Figure 3. Predicted learning curves for soft tissue, lung, cardiac, and FAST. FAST = focused assessment sonography for trauma.



Figure 4. (**A**) The *x*-axis represents the benchmark level of proficiency as chosen by the educator. The *y*-axis represents the predicted number of cases required to achieve that benchmark based on the logistic regression model described in the text. The two panels represent two different educational contexts. (**A**) The median learner is represented—50% of learners required fewer cases to achieve the benchmark; 50% required more. (**B**) A higher ambition is presented: the number of cases required of the marginal learner so that 95% of the learners will have achieved the given benchmark (i.e., 95% of learners would need to do fewer; 5% would need to do even more). FAST = focused assessment sonography for trauma.



Figure 5. The predicted number of cases needed to achieve 95% accuracy, based on the modeled learning curve for each individual. The overlaid curves are smoothed kernel density plots, which demonstrate that all four distributions are significantly skewed (i.e., not normally distributed). FAST = focused assessment sonography for trauma.

from 0.6 to 1.0.30 There were no differences in fellow versus attending final accuracy, sensitivity, or specificity scores for soft tissue, lung, or cardiac applications. For FAST, however, attendings had higher final accuracy, (+6.0% difference; 95% CI = 1.8, to 10.2) and sensitivity (+7.5% difference; 95% CI = 0.6 to 14.4). There was no association of PEM POCUS physician learners achieving expert performance with any of the baseline variables: >100 POCUS scans experience versus <100 (odds ratio [OR] = 1.2, 95% CI = 0.5 to 2.6), initial accuracy >80% versus <80% (OR = 2.1, 95% CI = 0.8 to 5.6), <5 versus >5 years in practice (OR = 1.4, 95% CI = 0.5 to 3.5), children's hospital versus other setting (OR = 1.6, 95% CI = 0.3 to 8.8), POCUS training in fellowship versus none (OR = 2.1, 95% CI = 0.9 to 4.5). Per application, PEM POCUS expert mean (95% CI) accuracy scores were soft tissue 96.0% (92.3% to 99.7%), lung 96.0% (93.9% to 98.1%), cardiac 90.0% (81.8% to 98.2%), and FAST 93.0% (88.0% to 98.0%). Expert final scores were significantly higher than those of nonexpert participant scores, with an accuracy difference of 7.3% (4.4% to 10.4%).

Comparisons Between Applications

The final accuracy sensitivity and specificity (Table 3) differed between applications (ANOVA p < 0.001), with post hoc Bonferroni analyses showing that the cardiac application had lower final accuracy (p < 0.01), sensitivity (p < 0.01), and specificity (p < 0.01) relative to each of the other applications. For the soft tissue application, there were greater learning gains for normal cases (specificity = +18.9%) versus abnormal cases (sensitivity = +4.9%), with a difference of 14.0% (95% CI = 9.8% to 18.2%). There were no differences in learning gains for abnormal versus normal cases in the other applications.

Time Commitment

The initial (first 25 case) mean time per case was 31.7 seconds, which decreased to 21.2 seconds on the final 25 cases (difference = -10.5 seconds, 95% CI = -8.6 to -12.4). The median time (interquartile range) in

	Accuracy (95% CI)			Sensitivity (95% CI)			Specificity (95% CI)			Cohen's effect size,
Application	Pre	Post	Difference	Pre	Post	Difference	Pre	Post	Difference	
Soft Tissue N=119	74.8	86.4	11.6 (9.6,13.6)	86.4	89.5	4.9 (2.4, 7.5)	64.8	83.7	18.9 (15.6, 22.2)	1.0 (0.9, 1.2)
Lung N=99	79.8	89.6	9.8 (7.2, 12.5)	79.4	87.2	7.8 (3.9, 11.7)	80.6	91.8	11.2 (7.6, 14.8)	0.8 (0.6, 1.0)
Cardiac N=102	74.2	81.6	7.4 (4.9, 10.0)	70.8	80.6	9.8 (5.5, 14.0)	76.3	82.5	6.3 (2.6, 9.9)	0.6 (0.4, 0.8)
FAST N=99	79.3	88.0	8.6 (6.2, 11.1)	78.3	88.0	9.7 (6.0, 13.4)	80.2	87.5	7.3 (4.0, 10.6)	0.7 (0.5, 0.9)

Performance Metrics for Point-of-care Ultrasound Pediatric Emergency Medicine Physicians

Pre - performance on the initial 25 cases

Post - performance on the final 25 cases

N – Number of participants

Table 3

minutes it took to complete each 100-case application was as follows: soft tissue (still image) 29.5 (20.9 to 40.7), lung (video + still image) 52.3 (39.7 to 72.7), cardiac (video + still image) 52.0 (39.7 to 72.7), and FAST (video + four still images) 63.6 (49.1 to 76.6) minutes (p < 0.0001).

Missing Data

There were no differences in the demographics of the 44 of 172 (25.6%) who dropped out versus the 128 who completed at least one 100-case application. Further, there were no differences in initial accuracy of those participants who completed the 100-case application versus those who did not (mean initial accuracy difference = 0.14%, 95% CI = -4.2 to 3.9).

DISCUSSION

We demonstrated that the case numbers required to reach the performance benchmarks ranged considerably for both the average and least efficient learners. Further, we noted that the deliberate practice of POCUS image interpretation led to skill improvement within a 100-case online learning experience, and most participants needed only about 2 to 3 hours to achieve the highest performance benchmark accuracy of 95% for all applications except cardiac, which required 3 to 10 hours. These data could inform education strategies and potentially add to the skill development of POCUS image interpretation.

Most organizations are faced with decisions about ideal credentialing POCUS standards to allow their physicians to safely practice at the bedside. This complex discussion often includes consensus building, stakeholder engagement, and the use of standardized competency-setting methods.^{31,32} Our results can inform these organizational discussions on the variable journey learners take to a given performance benchmark, while the broader POCUS community

considers which performance benchmarks are most appropriate. Our data also demonstrate that the numbers of cases required to achieve a performance benchmark were not normally distributed, with skewed distribution tails, indicating that a minority of learners required considerably more cases to attain each benchmark. This has policy implications for education guidelines based on an "average" learner. Specifically, our data suggest that a shift away from the current standard of recommending specific numbers of cases for POCUS proficiency (e.g., 25-50 cases^{2,33}) in favor of learners achieving a performance-based competency benchmark.¹¹ This approach is also in keeping with evolving performance-based competency frameworks in residency training, which promote greater accountability and documentation of actual capability.³⁴

Separating out the POCUS image interpretation task and then integrating knowledge gained into whole task activities can reduce cognitive load during face-to-face bedside POCUS teaching.⁸ This may result in more efficient and effective learning and greater learning satisfaction as demonstrated in similar forms of blended learning.³⁵ Alternatively, one could argue that POCUS image interpretation may be inherently easier to learn at the bedside, where one can pursue visual hints, make comparisons to unaffected areas, or better integrate the clinical context. However, these bedside advantages are challenged by the learner also needing to simultaneously acquire the images and conditions that lead to suboptimal image acquisition may limit the learning of image interpretation. Further, given the relatively low frequency of pathology in pediatrics, bedside learning may not efficiently offset the fact that many cases may be needed for most learners to achieve practice-ready standards, whereby a 50% or higher abnormal rate has previously been shown to be optimal for achieving an acceptable user sensitivity.¹⁷ Given the pace of case exposure, bedside education may also not be very effective at identifying specific areas of individual participant weaknesses or applications that are more difficult to learn. For example, our results provided evidence that cardiac and normal soft tissue cases were more difficult than other POCUS applications. Future research should explore the interaction between learning the image interpretation skill via online deliberate practice and the real-time application of POCUS at the bedside.^{36,37}

The education intervention demonstrated a large effect size for the soft tissue and lung applications and a moderate effect size for the cardiac and FAST applications.³⁰ One possible explanation for these disparities is that cardiac and FAST applications were more difficult to interpret, due to increased complexity of anatomy (cardiac, FAST), differences in number of views (FAST), or low a priori skill due to low rates of pathology of these applications at the bedside. Strategies that may enhance diagnostic performance outcomes using the education intervention in this study include scaffolding (e.g., embedding electronic hints or coaching),^{38,39}more deliberate review of incorrect cases (including referring to supplemental resources), and/or repeating cases as many times as needed to reach a desired performance outcome.

None of the participant baseline variables that we tested predicted for achieving expert-level performance. While it is not possible to be certain of the reasons for this from our data, we can consider some possible explanations. With respect to the variable of number of scans (100 vs. >100), the number alone may not be sufficient to predict for achieving expert level if a participant did not routinely receive feedback on images acquired at the bedside, which may limit a participant's ability to learn from each scan performed.⁷ POCUS training during PEM fellowship versus no training during fellowship may not have alone impacted participant ability to achieve expert scores since many of our study attendinglevel participants also engaged in institutional and other POCUS workshops/courses. Further, since almost all our participants worked at children's hospitals, we were likely underpowered to examine the impact of practice setting. Finally, since scores are weighted for the 25 most recent cases and case interpretation difficulty varied over the 100-case experience, initial accuracy scores may not have predicted for subsequent and final scores.

LIMITATIONS

Image interpretations were based on the expert opinion of three POCUS experts and the interobserver agreement between these opinions was high; however, expert opinions may be subject to error.⁴⁰ Participants were able to select the applications and about onequarter of our enrolled participants did not complete the minimum study intervention; therefore, our results may be biased by increased engagement for the selected applications and/or toward more POCUS-motivated PEM physicians. Since this is a part-task education intervention removed from the bedside and utilizes a higher proportion of pathological cases than is typically experienced at the bedside, it is uncertain how knowledge gained via this tool will translate to patient-level skill and outcomes. Some participants required considerably more than the 100 cases prescribed within the study design. Like other models of educational outcome distributions, we have the most information about persons at the mean and the extreme predictions run the risk of spectrum bias.

Over the 4-week study period, other factors may have contributed to the study's reported learning outcomes. However, our data demonstrates that most participants completed the cases in one sitting so it is unlikely additional POCUS exposure influenced our study results significantly. The changes in participant performance were reported using a pre-post designs, which may be subject to confounders that impact the validity of the results. Finally, this study included PEM physician participants and thus may not be generalizable to other categories of physician learners.

CONCLUSIONS

Deliberate practice of pediatric point-of-care ultrasound image cases using an online learning and assessment platform may lead to skill improvement in point-ofcare ultrasound image interpretation. Further, this method allows an efficient review of a larger number of cases than would be typically available with bedside practice alone. Our results also demonstrated that the rate of learning the image interpretation task of pointof-care ultrasound can be highly variable across learners. These data could inform education strategies and potentially add to our understanding of how the skill of point-of-care ultrasound image interpretation is acquired among pediatric emergency medicine physicians.

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