Quantifying Healthcare Provider Perceptions of a Novel Deep Learning Algorithm to Predict Sepsis: Electronic Survey

Karthik Ramesh, Aaron Boussina, Supreeth Shashikumar, Atul Malhotra, Christopher Longhurst, Christopher Josef, Kimberly Quintero, Jake Del Rosso, Shamim Nemati, Gabriel Wardi

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Abstract

Background: Sepsis is a major cause of morbidity and mortality for which early intervention improves patient outcomes. However, many patients experience delays in appropriate diagnosis and treatment. Predictive modeling and artificial intelligence may aid in early recognition of sepsis but there remains a considerable disconnect between the development of predictive algorithms and their use in clinical care. Despite the importance of user experience for the adoption and efficacy of clinical predictive models, there are relatively few studies focused on provider acceptance and feedback on the deployment of such models.

Objective: Evaluate healthcare worker perception and acceptance of a deep learning model for the prediction of sepsis in the ED

Methods: COMPOSER, a previously described deep learning algorithm in use at two EDs of a large academic medical center, utilizes routinely collected vital-signs, laboratory results, demographics, medications, and comorbidities to predict sepsis prior to clear clinical presentation. When the COMPOSER risk score crosses a predefined detection threshold, a Best Practice Advisory (BPA) is triggered for nursing staff. For physicians and advanced practice providers (APP), COMPOSER alerts are displayed on the ED trackboard. An internally developed and validated survey in accordance with the CHERRIES checklist was distributed to a convenience sample of team members taking care of a patient for whom a COMPOSER alert crossed the pre-defined threshold. Recruitment occurred between May and September 2023 and was administered using a vendor survey tool.

Results: A total of 114 responses were received with 76 from MD/DOs, 34 from RNs, and 4 from NP/PAs. 53% of respondents were from providers with less than 5 years of experience. 77% of respondents had a positive or neutral perception of the alert's usefulness. Providers with 0-5 years of experience were more likely to have increased expectation that a patient had sepsis after the alert (p=.021), and were more likely to say that the alert was useful in care of a patient (p=.016), than those with 6+ years of experience. Finally, physicians with 0-5 years of experience were more likely to say that the alert changed their management of the patient (p=.048) than physicians with 6+ years of experience.

Conclusions: Less experienced providers and nurses were more likely to perceive benefit from the alert, and the alerts were overall received favorably. Future clinical AI model implementations might consider focused alert patterns and education to improve reception and reduce fatigue.

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Abstract

Background:
Sepsis is a major cause of morbidity and mortality for which early intervention improves patient outcomes. However, many patients experience delays in appropriate diagnosis and treatment. Predictive modeling and artificial intelligence may aid in early recognition of sepsis but there remains a considerable disconnect between the development of predictive algorithms and their use in clinical care. Despite the importance of user experience for the adoption and efficacy of clinical predictive models, there are relatively few studies focused on provider acceptance and feedback on the deployment of such models.

Objective:
Evaluate healthcare worker perception and acceptance of a deep learning model for the prediction of sepsis in the ED

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COMPOSER, a previously described deep learning algorithm in use at two EDs of a large academic medical center, utilizes routinely collected vital-signs, laboratory results, demographics, medications, and comorbidities to predict sepsis prior to clear clinical presentation. When the COMPOSER risk score crosses a predefined detection threshold, a Best Practice Advisory (BPA) is triggered for nursing staff. For physicians and advanced practice providers (APP), COMPOSER alerts are displayed on the ED trackboard. An internally developed and validated survey in accordance with the CHERRIES checklist was distributed to a convenience sample of team members taking care of a patient for whom a COMPOSER alert crossed the pre-defined threshold. Recruitment occurred between May and September 2023 and was administered using a vendor survey tool.

Results:
A total of 114 responses were received with 76 from MD/DOs, 34 from RNs, and 4 from NP/PAs. 53% of respondents were from providers with less than 5 years of experience. 77% of respondents had a positive or neutral perception of the alert's usefulness. Providers with 0-5 years of experience were more likely to have increased expectation that a patient had sepsis after the alert (p=.021), and were more likely to say that the alert was useful in care of a patient (p=.016), than those with 6+ years of experience. Finally, physicians with 0-5 years of experience were more likely to say that the alert changed their management of the patient (p=.048) than physicians with 6+ years of experience.

Conclusions:
Less experienced providers and nurses were more likely to perceive benefit from the alert, and the alerts were overall received favorably. Future clinical AI model implementations might consider focused alert patterns and education to improve reception and reduce fatigue.

Introduction

Sepsis remains a major public health concern accounting for over 1.7 million adult cases and 270,000 deaths annually in the United States alone [1-3]. Early intervention, particularly prompt administration of antibiotics, improves patient outcomes [4-6]. However, many patients experience delays in appropriate diagnosis and treatment [7,8]. Predictive modeling and artificial intelligence (AI) may aid in early recognition of sepsis [9-13]. However, there remains a considerable disconnect between the development of predictive algorithms and their use in clinical care [14]. The clinical adoption of predictive models, particularly in sepsis, has faced resistance due to concerns about the accuracy and relevance of the alerts, alongside a general skepticism towards algorithmic decision-making [15, 16]. Poorly designed interfaces and inferior implementation strategies may lead to disregard of the system-generated advice [17-19]. Despite the importance of user experience for the adoption and efficacy of clinical predictive models, there are relatively few studies focused on provider acceptance and feedback on the deployment of such models. Henry et al. found that emergency department (ED) providers and providers who had previously seen an alert were more likely to perform a follow-up evaluation, but did not evaluate perceived provider or nurse diagnostic utility [20]. Ginestra et al. directly evaluated provider perception of a sepsis predictive model and found significant differences in acceptance between nurses and physicians for a machine learning-based algorithm for inpatient sepsis [21]. In this *Short Paper*, we aim to evaluate healthcare worker perception and acceptance of a deep learning model for the prediction of sepsis in the ED where rapid triage can be facilitated by advanced risk models. We test the hypothesis that nurses and less experienced providers perceive greater utility in the sepsis model than more experienced physician.

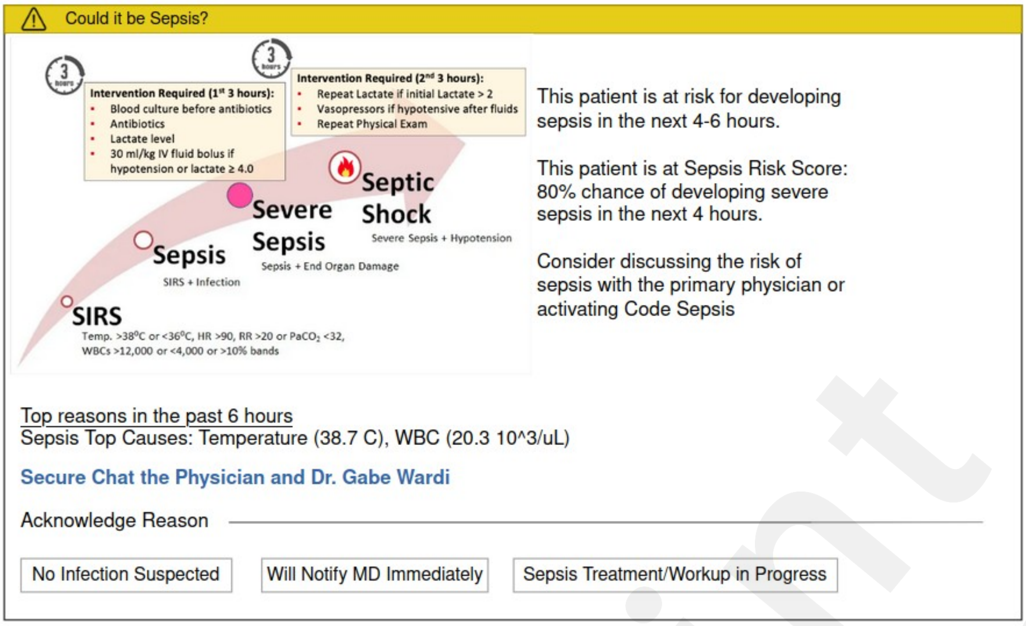
Methods

Implementation of the Sepsis Model

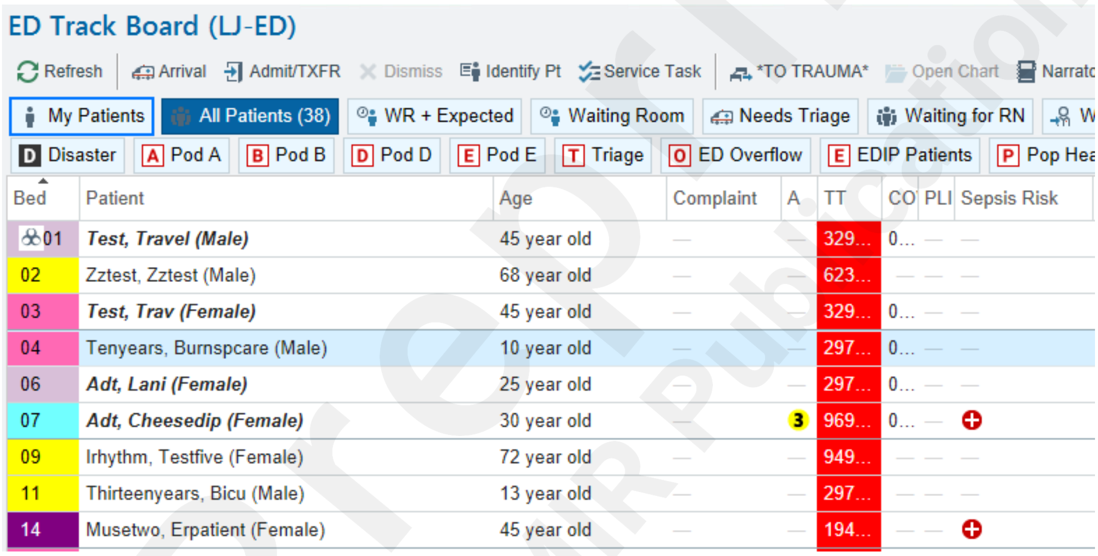
COMPOSER, a deep learning algorithm for the early prediction of sepsis, utilizes routinely collected vital-signs, laboratory results, demographics, medications, and comorbidities to predict sepsis prior to clear clinical presentation [10]. COMPOSER is used at two EDs at UC San Diego Health, a large academic medical center [22]. Details regarding the clinical implementation and improvement in patient-centered outcomes and quality metrics are described elsewhere [23]. Briefly, we followed the EPIS (Exploration, Planning, Implementation, Sustainment) framework and worked extensively with our nursing staff during the planning and implementation phase. When the COMPOSER risk score crosses a predefined detection threshold, a flowsheet entry is written back to the EHR containing the model score and the corresponding top factors for the generated prediction. The alert is suppressed for various predefined conditions or scenarios (e.g., a sepsis bundle has already been initiated or comfort measures only have been initiated). When a nurse opens the chart of a patient with a COMPOSER flowsheet entry, a Best Practice Advisory (BPA) is triggered (Figure 1A). For physicians and advanced practice providers (APP), COMPOSER flowsheet entries are displayed on the ED trackboard (Figure 1B). To increase transparency, we specifically included top features in the BPA and provided a risk score.

Figure 1: User-interface designs for notification of nurses (A) and providers (B) once the risk prediction threshold of COMPOSER was surpassed.

A


Could it be Sepsis?
Intervention Required (1st 3 hours):
Blood culture before antibiotics
Antibiotics
Lactate level
30 ml/kg IV fluid bolus if hypotension or lactate ≥ 4.0
Intervention Required (2nd 3 hours):
Repeat Lactate if initial Lactate > 2
Vasopressors if hypotensive after fluids
Repeat Physical Exam
Septic Shock
Severe Sepsis + Hypotension
Severe Sepsis
Sepsis + End Organ Damage
Sepsis
SIRS + Infection
SIRS
Temp. >38°C or <36°C, HR >90, RR >20 or PaCO2 <32, WBCs >12,000 or <4,000 or >10% bands
This patient is at risk for developing sepsis in the next 4-6 hours.
This patient is at Sepsis Risk Score: 80% chance of developing severe sepsis in the next 4 hours.
Consider discussing the risk of sepsis with the primary physician or activating Code Sepsis
Top reasons in the past 6 hours
Sepsis Top Causes: Temperature (38.7 C), WBC (20.3 10^3/uL)
Secure Chat the Physician and Dr. Gabe Wardi
Acknowledge Reason
No Infection Suspected
Will Notify MD Immediately
Sepsis Treatment/Workup in Progress

B


ED Track Board (LJ-ED)
Refresh
Arrival
Admit/TXFR
Dismiss
Identify Pt
Service Task
TO TRAUMA
Open Chart
Narrato
My Patients
All Patients (38)
WR + Expected
Waiting Room
Needs Triage
Waiting for RN
Disaster
Pod A
Pod B
Pod D
Pod E
Triage
ED Overflow
EDIP Patients
Pop Hea
Bed Patient Age Complaint A TT CO PLI Sepsis Risk
01 Test, Travel (Male) 45 year old 329... 0...
02 Zztest, Zztest (Male) 68 year old 623...
03 Test, Trav (Female) 45 year old 329... 0...
04 Tenyears, Burnspcare (Male) 10 year old 297... 0...
06 Adt, Lani (Female) 25 year old 297... 0...
07 Adt, Cheesedip (Female) 30 year old 3 969... 0...
09 Irhythm, Testfive (Female) 72 year old 949...
11 Thirteenyears, Bicu (Male) 13 year old 297...
14 Musetwo, Erpatient (Female) 45 year old 194...

Development of the Survey Tool

To assess perceptions of COMPOSER by providers and nurses, we developed and internally validated a survey based on Ginestra et al. in accordance with the CHERRIES checklist [24]. This was an closed survey sent to a convenience sample of team members taking care of a patient for whom a COMPOSER alert crossed the pre-defined threshold. The UC San Diego Institutional review board approval was obtained with waiver of informed consent (#805726) and additional approval was obtained from the Aligning and Coordinating QUality Improvement, Research, and Evaluation (ACQUIRE) Committee (Project #609). Participants were informed of the primary investigator and the purpose of the study during recruitment in the electronic health record (Epic Systems, Verona, WI) via secure chat message during pre-selected times from several study authors (J.D.R., G.W., K.S.R.). No identifiable personal data were collected. The survey was developed and tested by key stakeholders across provider types prior to distribution to respondents (Supplemental Table 1). This was a closed survey where participants were contacted via secure message, and was not otherwise advertised. Completion was voluntary, and not otherwise compensated. Recruitment occurred between May and September 2023 and was administered using a vendor survey tool (Qualtrics). All items except optional commentary feedback were mandatory. Participants were able to edit their responses until submitting, but not afterwards.

Statistical Methods

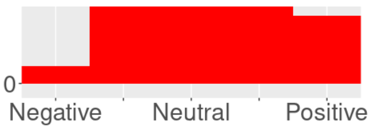
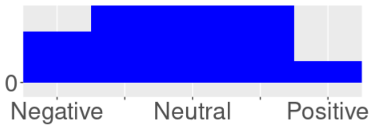
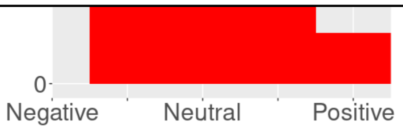
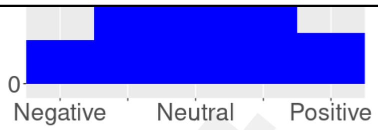
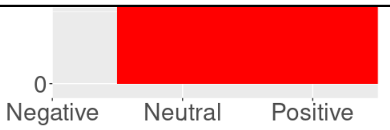
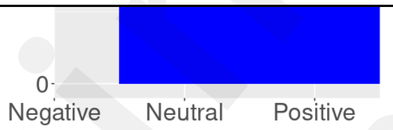
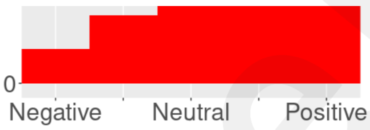
Data were analyzed with R version 4.1.2 (R Foundation for Statistical Computing). Descriptive statistics are provided as indicated. Survey responses were analyzed using Mann-Whitney-U testing to evaluate if pre-alert sepsis suspicion, post-alert sepsis suspicion, post-alert change in management, and overall perceived utility varied by provider type and experience. Experience level was categorized a priori as either ≤ 5 years or > 5 years. A p value < 0.05 was considered significant in all analyses. We did not have any missing data.

Results

The survey was distributed to nearly 250 providers who were exposed to the COMPOSER intervention. A total of 114 responses were received with 76 from MD/DOs, 34 from RNs, and 4 from NP/PAs with an overall response rate of roughly 50%, although the exact rate may vary slightly due to the possibility of the same provider receiving the survey more than once (Supplemental Table 2). 53% of respondents were from providers with less than 5 years of experience. Of the 76 physician responses, 49 were from trainees. 38% of respondents had a positive perception of the alert's usefulness, while 39% had a neutral perception , and only 23% found it not useful. Nurses were more likely to think a patient had sepsis prior to an alert than providers (p=.007). Moreover, providers with 0-5 years of experience were more likely to have increased expectation that a patient had sepsis after the alert (p=.021), and were more likely to say that the alert was useful in care of a patient (p=.016), than those with 6+ years of experience. Finally, physicians with 0-5 years of experience were more likely to say that the alert changed their management of the patient (p=.048) than physicians with 6+ years of experience (Figure S1 in Multimedia Appendix 1). Overall, 14% of physicians with 0-5 years of experience noted they changed their management, whereas none with 6+ years did so. Response distribution to key questions by provider type and experience are displayed in Figures 2 and 3 respectively.

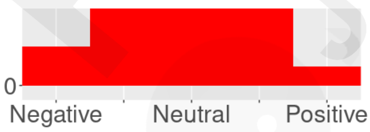
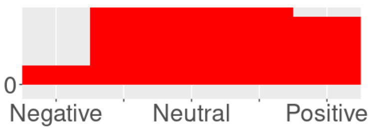
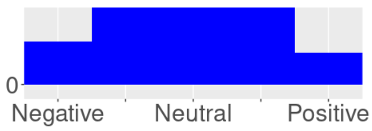
Figure 2. Key Survey Results by Provider Type.

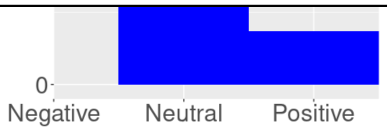
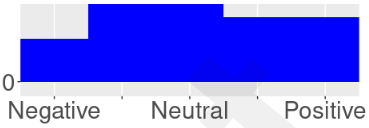
	Nurses	**Physicians & APPs**	*P* value[a]

Before the alert, do you think the patient had sepsis?			**.007**
After the alert, did you think the patient had sepsis?			**.011**
Did the alert affect your expectation that the patient would develop sepsis?			.947
How much do you agree with this statement: "This alert was useful in the care of this patient"			.449

[a]*P* values are based on Mann-Whitney-U tests between groups on each row. $P < 0.05$ indicates significance.

Figure 3. Key Survey Results from Providers by Experience Level

	0 - 5 Years	**6+ Years**	*P* value[a]
Before the alert, do you think the patient had sepsis?			.882
After the alert, did you think the patient had sepsis?			.461

Did the alert affect your expectation that the patient would develop sepsis?			**.021**
How much do you agree with this statement: “This alert was useful in the care of this patient”			**.016**

[a]*P* values are based on Mann-Whitney-U tests between groups on each row. *P < 0.05* indicates significance.

Discussion

Our findings represent the first study of providers’ perception of alerts generated by a deep learning sepsis model. As there are few deep learning models deployed in routine clinical practice, our findings are significant for a variety of reasons. To begin with, we found that nurses and less experienced providers (≤5 years of experience) derive greater perceived benefit from the alert. Providers with less experience indicated that they were more likely to believe the model was accurate in prediction of sepsis [25]. Additionally, less experienced physicians indicated they were more likely to make changes to their management based on the alert when compared to more experienced physicians. We believe that a 14% rate of indicated change in management is significant and is a potential major contributor to the decrease in mortality we have described previously [23]. Finally, we found that nearly 80% of respondents had a positive or neutral view of the alert system.

With increasing data that predictive models may be cost effective and improve patient centered outcomes, our data may inform effective implementation strategies [11, 23, 26]. First, recognition that perceived benefit may vary significantly amongst provider groups may impact implementation and education strategies. For example, our data suggest additional education targeted to more experienced providers and nurses may be indicated. Second, there are increasing data that shared mental models of risk between physicians and non-physicians may be an elegant strategy to improve care and minimize risk in complex medical scenarios through objective assessment [27]. Our findings demonstrate that nurses had greater perceived benefit of our model in the diagnosis of sepsis, and although speculative, this finding may further increase nurse utilization of the model for patient care. As our recent data demonstrate an improvement in patient-centered outcomes and quality metrics with this model [23], further empowering non-providers to use this model to voice concerns about possible sepsis based on an objective assessment of risk may further improve patient-centered outcomes.

We posit that there are important intersections with generational attitudes towards technology, as well as in the fundamental way that different types of healthcare workers interact with alerts. Provider and nurse experience is highly correlated with age and the general acceptance of a machine learning alert may align with age groups with greater native exposure to such technologies. More experienced physicians may have additional clinical experience to anticipate better which patients may develop sepsis, whereas such slight presentations may be more likely to be missed by those with less experience. Additionally, we used proactive and passive methods of alert notification (Figure 1). This approach may impact perceived utility since our nurses received a BPA alert, a much more visible alerting method compared to a provider-facing trackboard display which is a more passive approach to drawing attention to at-risk patients. However, while less experienced physicians and nurses overall perceived greater benefit, care should be taken when considering exclusive deployments to these groups given the possible risk of automation bias [28]. Overall, we believe that a combinatorial effect of generational exposure to machine learning and the more obvious alert to nursing staff may account for the differences observed in this study. Furthermore, future implementations may leverage this knowledge with careful design of clearly displayed and explainable decision support prompts and education to all staff regarding the alert and its purpose.

We acknowledge several limitations. First, we had a limited sample size with moderate response rate. Additionally, there may be response bias. We were not able to track changes in management based on alerts alongside survey responses to evaluate how treatment may have been altered by the alert regardless of provider perception. Finally, different notification processes which were used for nurses and providers may impact perceptions of our alert system.

Conclusions

Less experienced providers and nurses were more likely to perceive benefit from the alert, and the alerts were overall received favorably. Future clinical AI model implementations might consider focused alert patterns and education to improve reception and reduce fatigue.

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Conflicts of Interest
S.N, A.B., S.S., and A.M. are co-founders of a UCSD start-up, Healcisio Inc., which is focused on commercialization of advanced analytical decision support tools and formed in compliance with UCSD conflict of interest policies. The remaining authors declare no competing interests.

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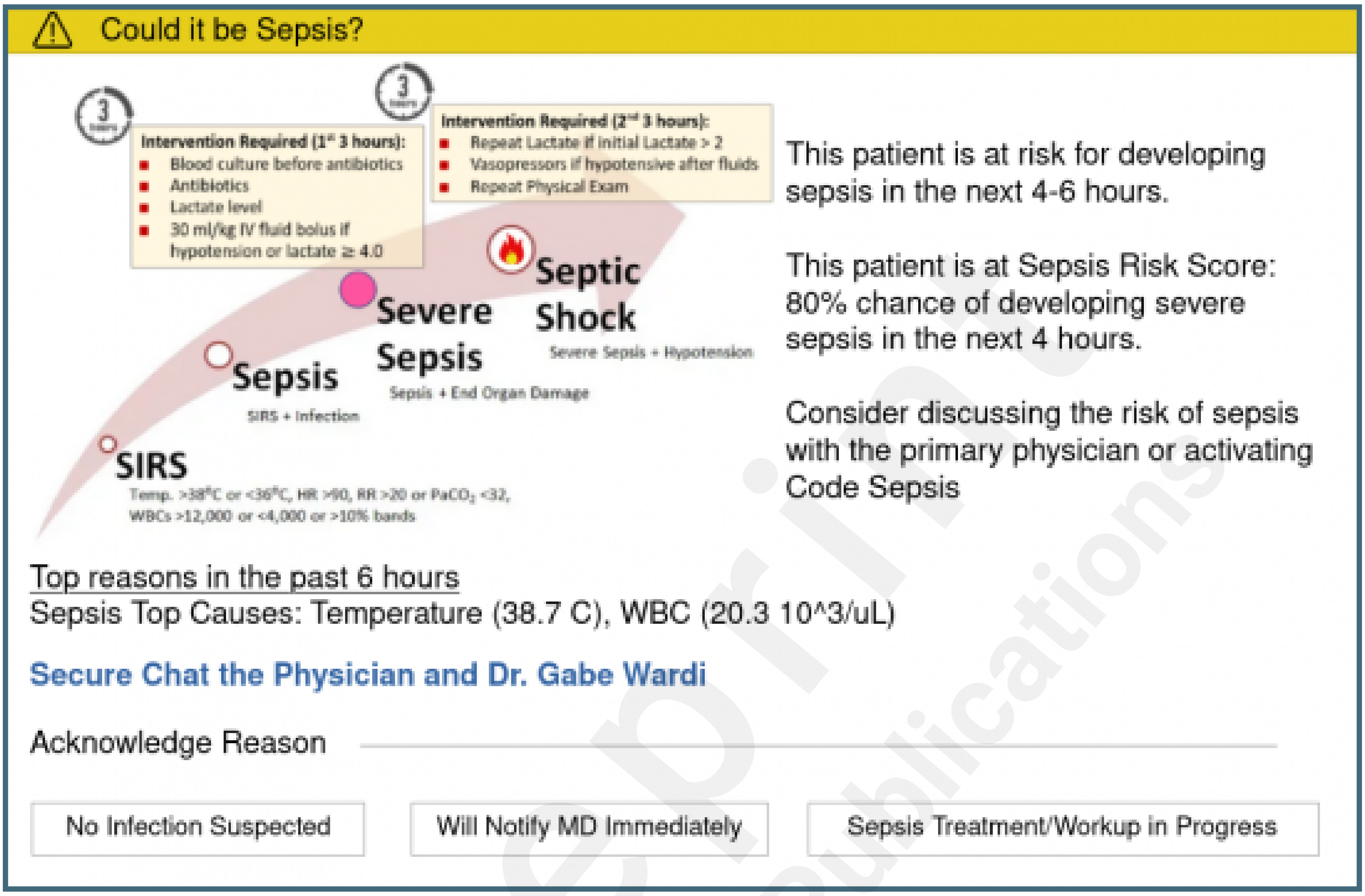
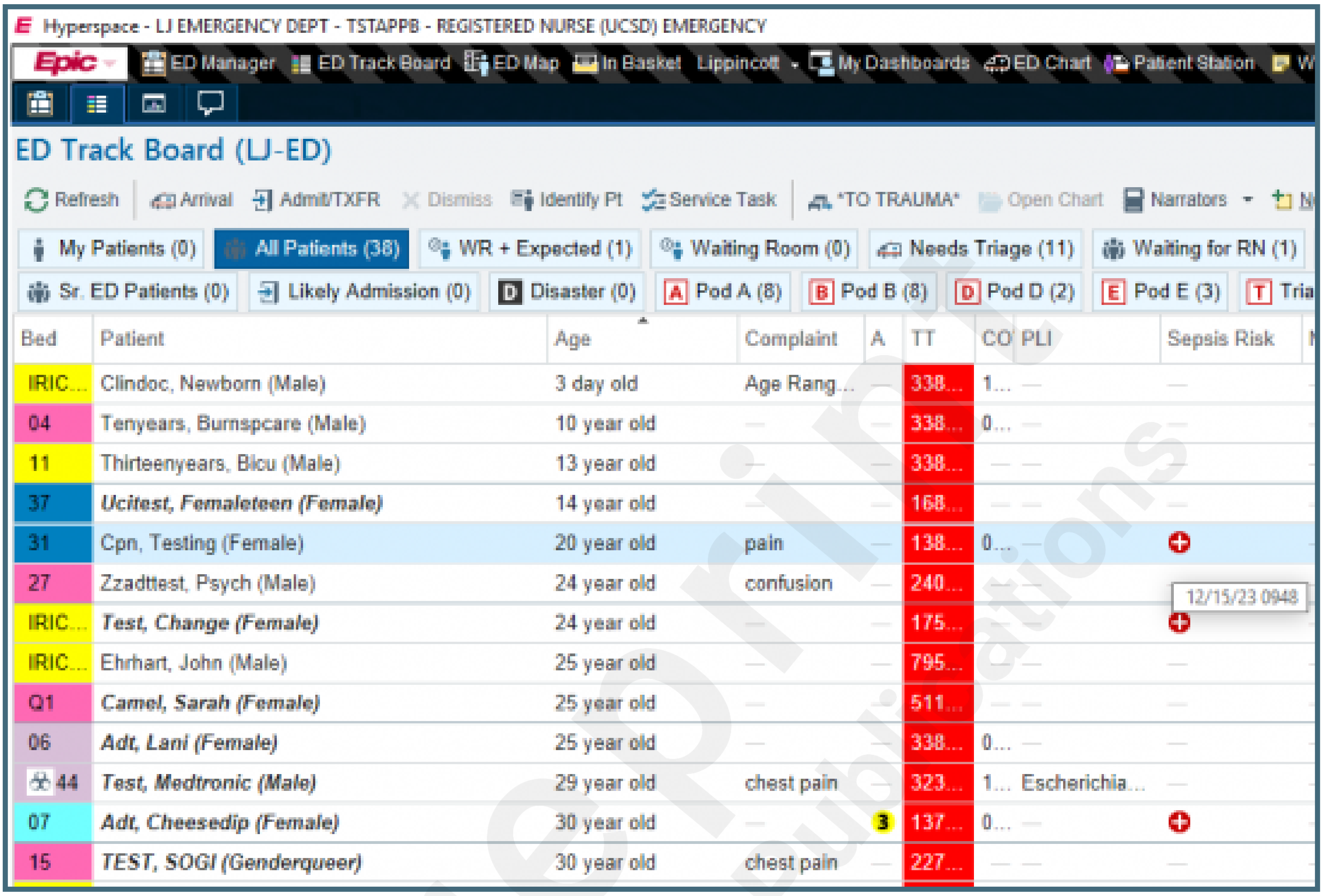
Supplementary Files

Figures

User-interface designs for notification of nurses (1A) and providers (1B) once the risk prediction threshold of COMPOSER was surpassed.

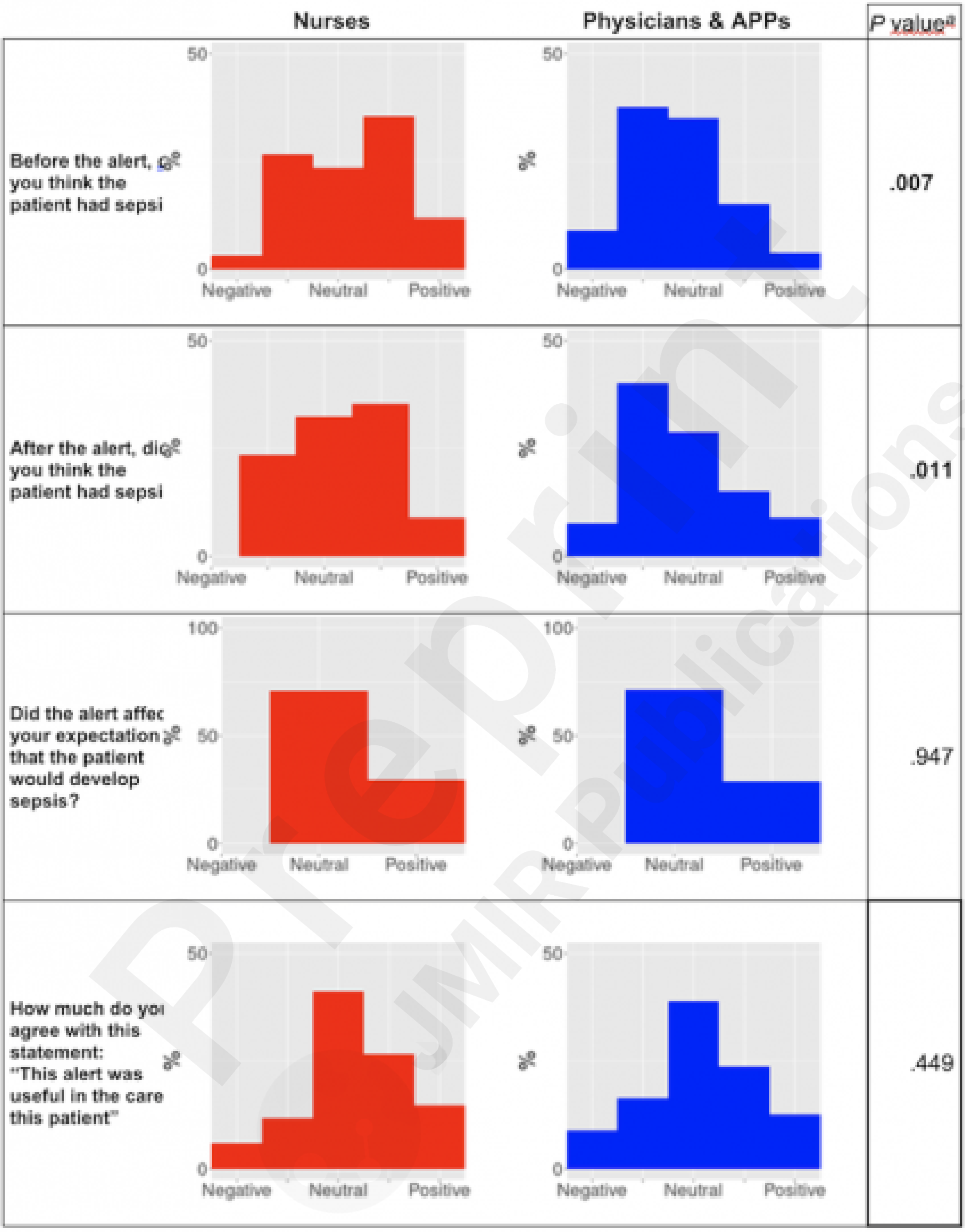


User-interface designs for notification of nurses (1A) and providers (1B) once the risk prediction threshold of COMPOSER was surpassed.



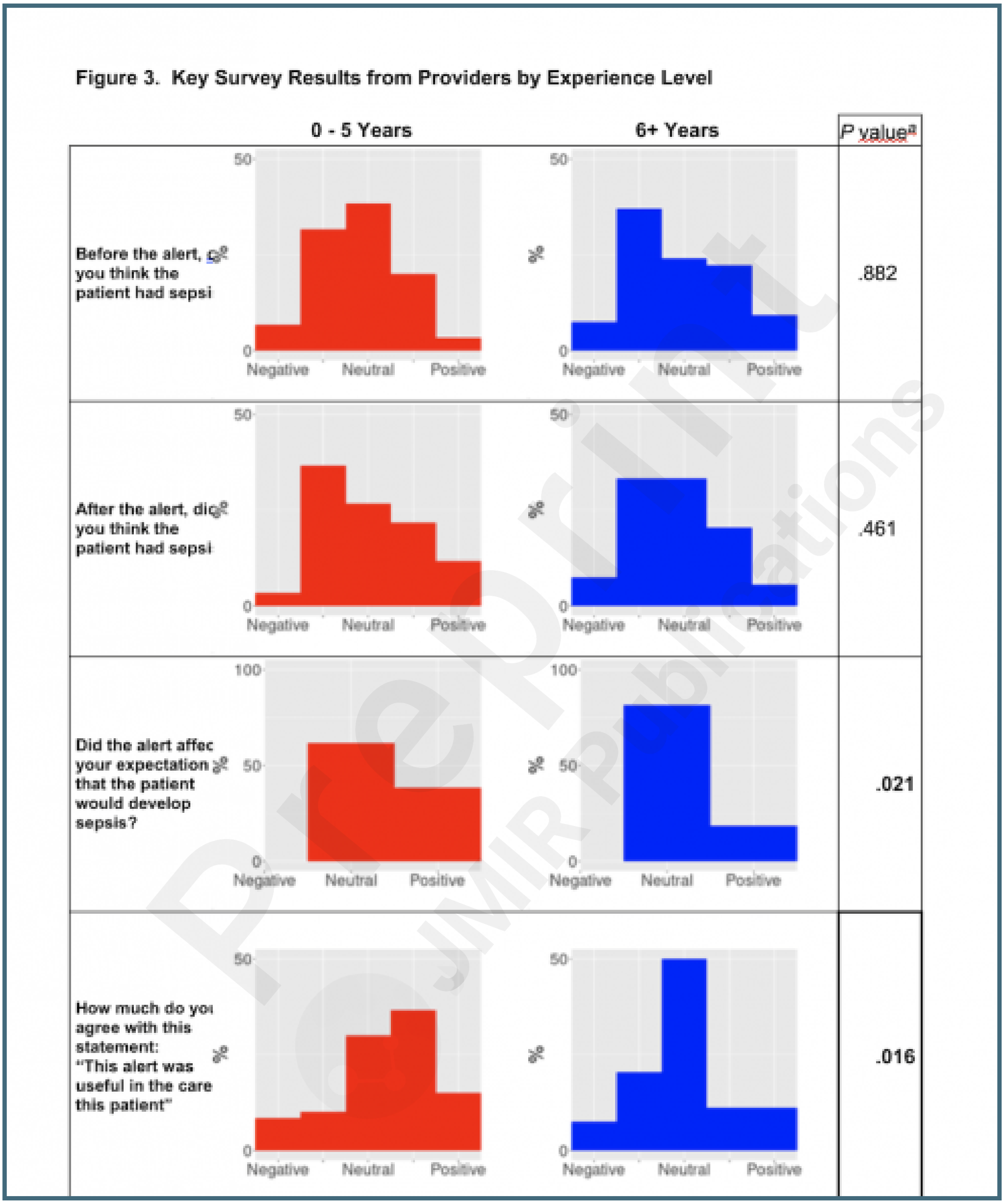
Key Survey Results by Provider Type.

Figure 2. Key Survey Results by Provider Type.



[a]P values are based on Mann-Whitney-U tests between groups on each row. $P < 0.05$ indicates significance.

Key Survey Results from Providers by Experience Level.



Multimedia Appendixes

Supplemental figures.
URL: http://asset.jmir.pub/assets/99ff069a010efede7610c7149a9fa020.docx

CHERRIES Checklist.
URL: http://asset.jmir.pub/assets/bdb27d79515179cd13d1f4005631f84f.docx