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Research and Applications

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Predicting pressure injury using nursing assessment phenotypes and machine learning methods

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ABSTRACT

Objective: Pressure injuries are common and serious complications for hospitalized patients. The pressure injury rate is an important patient safety metric and an indicator of the quality of nursing care. Timely and accurate prediction of pressure injury risk can significantly facilitate early prevention and treatment and avoid adverse outcomes. While many pressure injury risk assessment tools exist, most were developed before there was access to large clinical datasets and advanced statistical methods, limiting their accuracy. In this paper, we describe the development of machine learning-based predictive models, using phenotypes derived from nurse-entered direct patient assessment data.

Methods: We utilized rich electronic health record data, including full assessment records entered by nurses, from 5 different hospitals affiliated with a large integrated healthcare organization to develop machine learning-based prediction models for pressure injury. Five-fold cross-validation was conducted to evaluate model performance.

Results: Two pressure injury phenotypes were defined for model development: nonhospital acquired pressure injury (N = 4398) and hospital acquired pressure injury (N = 1767), representing 2 distinct clinical scenarios. A total of 28 clinical features were extracted and multiple machine learning predictive models were developed for both pressure injury phenotypes. The random forest model performed best and achieved an AUC of 0.92 and 0.94 in 2 test sets, respectively. The Glasgow coma scale, a nurse-entered level of consciousness measurement, was the most important feature for both groups.

Conclusions: This model accurately predicts pressure injury development and, if validated externally, may be helpful in widespread pressure injury prevention.

Key words: patient safety, quality of care, electronic health record, clinical phenotype, artificial intelligence

INTRODUCTION

Pressure injury is a localized injury to the skin and its underlying soft tissues. Pressure injury occurs as a result of pressure, shear, or both.[1] For patients in hospitals, pressure injury prevalence ranges from 3%–24%. Pressure injuries affect approximately 2.5 million individuals and are associated with 60 000 deaths annually in the

United States.[2–4] Pressure injuries contribute adversely to an individual's morbidity, mortality, and physical and psychosocial quality of life. They are also expensive. Pressure injuries increase hospital length of stay by 4–10 days and total healthcare costs by $10 708 per patient, accounting for approximately $26.8 billion per year.[5–7]

In 2001, the National Quality Forum defined pressure injury as a "never event" indicating that pressure injuries are a preventable medical error that should not occur in clinical settings.[8] Two decades later, pressure injuries remain a serious problem for hospitalized patients.[9] While pressure injuries are considered a "nursing sensitive outcome," a multidisciplinary healthcare team approach is needed to reduce their incidence and prevalence.[10–12] Meanwhile, nurses play a critical role in pressure injury care. They are often the first clinician to identify pressure injuries during physical assessment, provide pressure injury prevention activities (eg, patient position changes), and pressure injury care (eg, sore dressing, negative pressure therapy).

The Agency for Healthcare Research and Quality has published clinical practice guidelines for pressure injury care.[13] These guidelines state that early risk assessment is a key component of pressure injury care. Comprehensive skin assessment (including pressure injury risk assessment) is recommended when a patient is admitted or transferred to a clinical unit, undergoes a procedure where the patient will have limited mobility for an extended period of time, and as a component of the standard nursing shift assessment.[13] Nurses commonly use existing pressure injury assessment tools such as the Braden Scale[14] to assess a patient's risk of pressure injury. However, previous studies suggest that existing pressure injury risk assessment tools have limited accuracy.[15–18] The methods used to develop pressure injury risk assessments have suffered from heavy reliance on expert opinion, small sample sizes, and lack of adjustment for confounders.[15] These tools were developed without the support of advanced statistical methods and have not been shown to reduce pressure injuries.[15]

We conducted a study using machine learning models to overcome these limitations by building an enhanced early assessment tool for pressure injury risk using a large amount of clinical data including lab tests, medical diagnoses, and nursing flowsheet data which are routinely recorded by nurses in the electronic health record (EHR). Moreover, we separated the cohort into hospital acquired and nonhospital acquired pressure injury groups to provide a comprehensive understanding of pressure injury risk between these 2 different clinical scenarios.

MATERIALS AND METHODS

Database

We used the existing National Institute of Nursing Research funded Communicating Narrative Concerns Entered by RNs (CONCERN) database for EHR data exploration. The database contains inpatient clinical records of patients affiliated with 5 hospitals within Mass General Brigham (N = 188 512) from 05/2015 to 12/2018. Patients in the database were assigned a unique study identification number, and all information was deidentified at the point of analysis.

Study hospitals include both academic medical centers and community hospitals. In addition, patients were included if they were hospitalized 24 hours or longer on a nonspecialty acute and/or intensive care unit. Patients who had palliative or hospice care or were admitted to oncology, obstetric/labor and delivery, observational, or virtual units were excluded.

Cohort development and feature selection

We used nursing flowsheet pressure injury documentation routinely recorded by nurses to identify patients with a pressure injury during hospitalization. The nursing flowsheet is a record of clinical observations, including the head-to-toe assessment and vital signs that serves as an historical and real-time display of a patient's hospital encounter. The "pressure injury" section of the flowsheet is dedicated to skin assessment and is completed daily by nurses. When a pressure injury is first found during an admission, nurses fill out flowsheet entries for the date and time that the pressure injury is assessed, and information on pressure injury stage, location, and whether it was present on admission is documented. We separated the pressure injury cohort into 2 groups: hospital acquired, and nonhospital acquired pressure injury. The 2 study cohorts are comprised of patients with 1 or more pressure injury records during hospitalization including information about whether the pressure injury was present or absent on admission. If the flowsheet entry for pressure injury present on admission was entered as "yes," the patient was assigned to nonhospital acquired pressure injury group, and if the answer was recorded as "no," the patient was assigned to hospital acquired pressure injury group. When a patient had multiple pressure injury records, we used the earliest recorded pressure injury. Prediction models were trained and compared between the 2 groups. We removed patients that did not have a pressure injury record in the flowsheet and patients with more than 25% missing values. The nonhospital acquired pressure injury group included 4398 patients and the hospital acquired pressure injury group included 1767 patients. In addition, patients without a pressure injury record and any risk of pressure injury (based on Braden Scale scores in the range of 19–23) were defined as the control group. Overall, 10 000 control patients matched to the case group patients' age and gender distributions were randomly selected. After that, the same data preprocessing steps with case patients were performed among control subjects resulting in a cohort of 9148 patients (Figure 1). All relevant features were extracted from the CONCERN database for model development, including patient demographic factors, lab tests, pain scores, chronic disease diagnoses, and nursing flowsheet assessment, such as Glasgow coma scale (GCS).

Data preprocessing and feature engineering

To predict the risk of pressure injury, we conducted a literature review and generated a list of relevant features based on previous studies.[3,16,19,20] These features were then reviewed by clinical experts and validated in the CONCERN database. A subset of 28 potential predictive variables were selected, including the 9 most common lab results, 4 nursing features, and 5 chronic disease diagnoses (Table 1). Four nursing features include the Glasgow coma scale, gait/transferring, level of consciousness, and activity. The Glasgow coma scale and level of consciousness are used to assess a patient's neurological status. Gait/transferring, subquestions of the Morse Fall Scale, and activity are used to access the patient's mobility status with common notations including on bed rest, and impaired gait, etc. Each of the 2 groups of features have similar foci but different degree of detail in measurement resolution.

For feature input, we used lab records and pain scores which were within 30 days before the pressure injury was recorded. Variables that changed over time (eg, lab results, functional status) were sorted chronologically for each patient and the most recent measurements before the pressure injury records were used as model inputs.

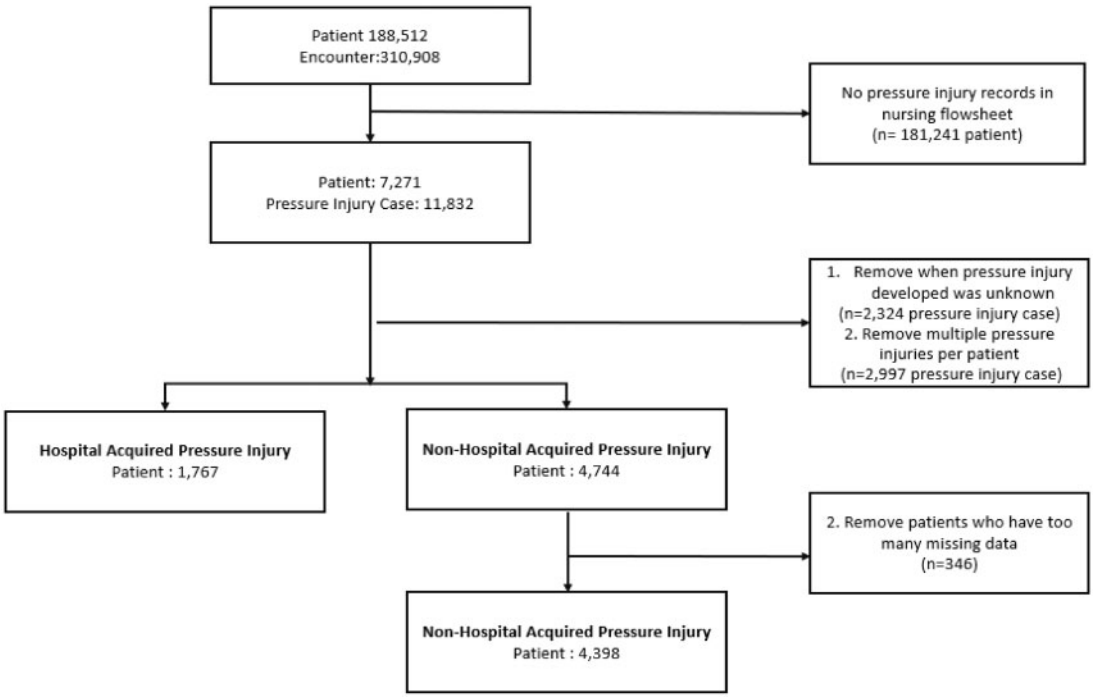

Figure 1. Process of data cleaning and study cohort development.

Table 1. Summary of potential predictive variables

Definition	Electronic Health Record Measures
Pressure injury	Records from nurse flowsheet
Demographics	Race, gender, age
Nursing features	Glasgow coma scale, level of consciousness, gait/transferring, activity
Clinical features	Pain score, diabetes, peripheral vascular disease, spinal cord injury, stroke, anemia
Lab tests	Albumin, blood urea nitrogen, chloride, potassium, sodium, creatinine, hemoglobin, white blood cell count, platelet blood count

Model development and evaluation

Four pressure injury prediction models were developed using these EHR-derived features, including logistic regression (LR), support vector machines (SVM), random forest (RF), and neural network (NN). We selected these 4 algorithms given their increasing popularity in clinical settings for prediction of binary outcomes and their varied ability in modeling complex relationships between the outcome and clinical features.

LR is the most frequently used method to predict the occurrence of an event in clinical studies. Its advantage relative to other models is that it provides meaningful and easy-to-interpret coefficients for assessing feature importance in a prediction task. However, LR also has clear limitations given its parametric assumptions and difficulty in capturing nonlinear relationships. To overcome these limitations, we also included more complex models. Our SVM model uses the radial basis function kernel to learn a nonlinear boundary for classifying patients into 2 groups. RF is a tree-based ensemble learning method. It operates by constructing a multitude of decision trees at training phase and outputting the class of each patient following the majority vote from all the decision trees. The NN model is a multilayer perception with 1 hidden layer between the input and output layer. The hidden layer uses a rectified linear unit activation function, and the output layer uses a sigmoid activation function to predict the probability of pressure injury for each patient. The downside of SVM, RF, and NN is that they are more computationally intensive to train than LR due to higher model complexity. Deep neural network is more likely to overfit especially when the sample size is small. To overcome the overfitting issue, we tuned models through cross-validation to select the best set of parameters and evaluated their performance on an independent test set.

Our goal was to predict the incidence of pressure injury in the test data given the training set. We randomly split the data into 80% training and 20% test set. To ensure that our results would be generalizable, we repeated this random splitting process 30 times and reported the average model performance on the test set over the 30 splits. For a given split, we further divided the 80% training data into 5 equal-sized folds. We trained the model on 4 folds and evaluated its performance on the fifth fold (validation set). We repeated this process 5 times while each time a different fold served as the validation set. Model performance was averaged across the 5 folds to determine the best hyperparameters.

To evaluate model performance, we used the area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, and F1 score. Our pressure injury cohorts are nearly balanced, so the above-mentioned statistical measures are good evaluation metrics. All metrics were calculated using the test set. The mean and standard deviation of each evaluation metric across the 30 test sets are reported.

LR, RF, and SVM were implemented using the sci-kit learn library in python. The NN is implemented using the keras library in python. The hyperparameters we tuned for each model are given below:

- LR: All other parameters are same as the default except the regularization parameter C, which is tuned from 0.1 to 10

- RF: All other parameters are same as the default except n_estimators and max_depth. We tuned n_estimators from 100 to 1000 and max_depth from 50 to 100
- SVM: All other parameters are same as the default except the regularization parameter C. We tuned C from 0.1 to 10
- NN: We tuned batch_size from 5 to 50, and epochs from 50 to 200

The data preprocessing was conducted using R (version 3.3.3). The algorithm training and validation were conducted using Python (version 3.7.3).

This study was approved by the Institutional Review Boards (IRBs) at Mass General Brigham (IRB Protocol# 2015P002472).

RESULTS

Cohort development and feature selection

The average age for both case group and control groups was 69∼75 years and white was the most common race for both groups (83.1% for case group and 82.8% for control group, consistent with demographics of the study location) (Table 2, Supplementary Figure 1).

Table 2. Demographics of the case and control groups

Groups	Features Summary		Mean (SD)
Nonhospital acquired pressure injury (N = 4398)	Age		74.4(15.1)
	Female		46.3%
	Race	White	83.5%
		Black	7.7%
		Hispanic	1.1%
		Asian	1.8%
Hospital acquired pressure injury (N = 1767)	Age		69.1(15.5)
	Female		40.4%
	Race	White	82.7%
		Black	7.2%
		Hispanic	1.4%
		Asian	2.2%
Control (N = 9148)	Age		70.3(7.3)
	Female		49.0%
	Race	White	82.8%
		Black	6.4%
		Hispanic	1.8%
		Asian	2.7%

Abbreviation: SD, standard deviation.

Model performance

Four predictive models were implemented to predict pressure injury for both pressure injury phenotypes. Five-fold cross-validation was conducted to evaluate model performances. For both groups, LR achieved AUC greater than 80% (84% for the nonhospital acquired pressure injury and 89% for the hospital acquired pressure injury). All 3 machine learning models showed more robust performance than LR. Neural network and SVM models had worse performance than RF but were slightly better than LR (Table 3).

Among them, RF achieved the best predictive performance. An AUC = 0.92 for nonhospital acquired pressure injury group and AUC = 0.94 for hospital acquired pressure injury group (Figure 2).

Top significant features associated with pressure injury

We identified potential significant features associated with risk of developing a pressure injury by evaluating LR coefficients (Supplementary Figure 2). Among the top features, the GCS and albumin were found to have the most impact on the risk of nonhospital acquired pressure injury group. For the hospital acquired pressure injury group, the GCS and hemoglobin were found to be the top 2 features (Table 4).

DISCUSSION

Pressure injuries among hospitalized patients are common, painful, and expensive complications. Pressure injuries cause significant disability, increase costs, and they represent a marker of poor nursing care. Using nursing flowsheet data to identify pressure injury phenotypes and feature inputs from multiple sections of an EHR system, we developed a predictive model using machine learning approaches for pressure injury events.

The limitations of the Braden Scale and other pressure injury risk assessment tools have been widely reported.[15,21] Existing tools have limited accuracy because of the phenotyping methods. These tools used codified data (rather than clinical observations), the Braden Scale, and manual chart review to distinguish pressure injury patients.[15–17] In clinical practice, pressure injuries are often identified and assessed primarily by nurses. The nursing record provides an important foundation for pressure injury diagnosis. In light of this, we derived a pressure injury phenotype from longitudinal nursing documentation records. Previous studies using ICD codes or the Braden Scale have achieved an average range AUC of 70%–80% with indirect phenotyping.[3,17,22] Our study achieved 0.94 AUC for RF model based on 5-fold cross-validation. These results suggest that phenotyping methods based on more direct assessment from

Table 3. Prediction model performance of hospital acquired and nonhospital acquired pressure injury group

	Model	AUC (SD)	Accuracy (SD)	Specificity (SD)	Sensitivity (SD)	F1 Score (SD)
Nonhospital acquired pressure injury	Logistic regression	0.84(0.03)	0.78(0.01)	0.79(0.02)	0.77(0.02)	0.73(0.02)
	Support vector machine	0.87(0.03)	0.80(0.02)	0.80(0.03)	0.80(0.02)	0.75(0.01)
	Random forest	0.92(0.03)	0.85(0.03)	0.85(0.02)	0.84(0.02)	0.81(0.01)
	Neural network	0.91(0.02)	0.84(0.03)	0.86(0.03)	0.82(0.03)	0.80(0.01)
Hospital acquired pressure injury	Logistic regression	0.89(0.02)	0.87(0.02)	0.80(0.01)	0.83(0.01)	0.80(0.03)
	Support vector machine	0.90(0.02)	0.88(0.01)	0.83(0.02)	0.80(0.02)	0.82(0.03)
	Random forest	0.94(0.02)	0.91(0.01)	0.88(0.02)	0.87(0.03)	0.86(0.02)
	Neural network	0.93(0.02)	0.89(0.02)	0.88(0.02)	0.84(0.03)	0.82(0.03)

Abbreviations: AUC, area under the curve; SD, standard deviation.

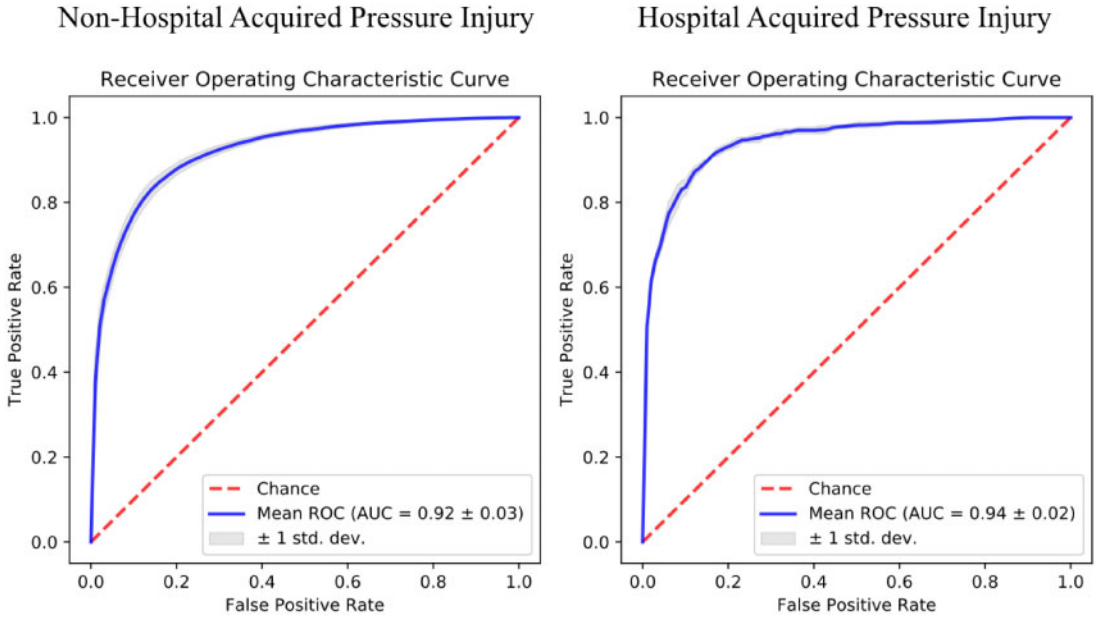

Figure 2. The model performance from Random Forest (ROC curve).

Table 4. Top features from logistic regression between hospital acquired and nonhospital acquired pressure injury group

Variables	Nonhospital Acquired Pressure Injury Standardized Coefficient	Hospital Acquired Pressure Injury Standardized Coefficient
Glasgow coma scale	−3.18	−2.46
Albumin	−1.21	−0.43
Hemoglobin	−1.01	−1.45
Gait/transferring	1.00	0.89
Activity	0.92	0.74
Blood urea nitrogen	0.52	0.69
Consciousness	0.29	0.36
Chloride	−0.35	−0.30
Creatinine	−0.28	−0.27
Spinal cord injury	0.31	0.18

documentation of nursing practice may improve model performance.

The top 10 clinically significant features we identified can be grouped into 3 categories: neurological assessment (GCS, consciousness), physical mobility (gait/transfer, activity, spinal cord injury), and blood chemistry panel (albumin, hemoglobin, blood urea nitrogen, chloride, and creatine), which represent how a patient's neurological status and their physiological condition contribute to pressure injury risk. Physiological data such as albumin, creatine, and blood urea nitrogen are not captured in existing pressure injury assessment tools, but previous reports indicate that they are associated with risk of developing pressure injuries.[16,23–25]

The GCS was found to have the highest contribution to the risk of pressure injury. Additionally, gait/transfer, activity, and spinal cord injury were high among the top 10 factors in both groups. Not surprisingly, these suggest that immobilization is an important pressure injury risk factor. In addition, we showed that low levels of hemoglobin, a measure of a patient's hemodynamic status, such as bleeding or anemia, can a be significant risk factor for predicting pressure injuries. Age was not significant in our study but was found to be significant in other studies.[16,23,26] This may be due to the similar age distribution across the case and control groups in our study cohort, making the binary classification of age insignificant in our model.

In our study, we developed 2 classes of models for pressure injury prediction in which 2 different clinical scenarios were reflected. In the hospital acquired pressure injury case, we developed a time sequential prediction model compared to nonhospital acquired pressure injury case which is more focused on evaluating the association between input features and model outcome. In the latter case, the features and model outcomes and pressure injury assessment are all collected in a very small time window following admission. Even though the 2 different models are based on different clinical scenarios, we still observed similar model performance and similar significant features. We did observe some differences among the significant feature sets in the LR models. Albumin was the second most significant feature in nonhospital acquired pressure injury group, and falls the sixth most significant feature, in the hospital acquired pressure injury group. These results suggest that nonhospital acquired pressure injury group may include patients with chronically poor nutritional status compared to the hospital acquired pressure injury group which includes relatively acute patients and may have better baseline nutritional status. In addition, the 2 different

case groups showed different model performance, indicating that we should carefully differentiate pressure injury patients and use a tailored approach for patients based on whether they developed a pressure injury before or after the hospital admission. In addition, for future study, it would be important to investigate how risk factors impact outcomes of newly hospital acquired pressure injuries for patients with a history of pressure injury versus those who have no previous history of pressure injury. It is also likely that additional data will become available that will enable even better performance in the future. In particular, sensors which assess for the presence of moisture and detect whether or not the patient is moving or has been turned may be valuable in predicting pressure injury risk.[27,28]

A limitation of this study is that patient comorbidity, acuity, and pressure injury stage were not considered in our models and may be associated with the risk factors and its interpretation. In addition, only structured data were used for the study, and other data types including narrative nursing notes may provide additional predictive power. We did use nursing assessment features, which served as significant predictors like risk factors identified in previous studies, to boost our predictive accuracy. Our study used a dataset extracted from 5 hospitals within an integrated health care delivery system to enable the collection of a relatively large sample size for the development of a data-driven, generalizable pressure injury prediction model, but performance in other systems might differ. Finally, using a DNN model is often used for patient classification. Our NN model is relatively simple compared with more complex DNN model systems, which could be the reason why the NN model performed less well than others in our study. Future work includes using our pressure injury prediction model to develop a prediction tool for clinical decision support and independently validating the model in other systems.

CONCLUSION

Our study used a patient dataset extracted from multiple hospitals within an integrated healthcare delivery system to enable the collection of a relatively large cohort for the development of a data-driven, generalizable pressure injury prediction model. Our AUC was over 90% and may be used as a prediction tool in clinical practice and as a baseline model in future pressure injury studies. Our models derived from both hospital and nonhospital acquired pressure injury events could provide valuable information to clinicians and nurses to facilitate early prevention of these distinct types of pressure injury. The strong relationship between nurse-assessment features and occurrence of pressure injury revealed in our results could also help nurses to identify high-risk hospitalized patients and inform tailored preventative interventions.

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AUTHOR CONTRIBUTIONS

PD conceived the study and PD, WS, and MK initiated study design. WS and LZ conducted data analysis and MK, WJ, JS, and PD interpreted the results. DB and PD were involved in study supervision and provided critical revision of the manuscript. All authors participated in manuscript development and are accountable for the integrity of this work.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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DATA AVAILABILITY STATEMENT

The clinical data set generated and/or analyzed during the current study are not publicly available due to patient privacy and IRB regulation. The summary statistics will be shared on reasonable request to the corresponding author.

CONFLICT OF INTEREST STATEMENT

DWB reports grants and personal fees from EarlySense, personal fees from CDI Negev, equity from ValeraHealth, equity from Clew, equity from MDClone, personal fees and equity from AESOP, and grants from IBM Watson Health, outside the submitted work.

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