**Explainable Artificial Intelligence for Predicting Hospital-Acquired Pressure Injuries in COVID-19–Positive Critical Care Patients**

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Hospital-acquired pressure injuries (HAPrIs) are areas of injury to the skin due to prolonged pressure or pressure in combination with shear. These injuries occur in 6% to 8% of critical-care patients and result in human suffering.¹⁻³ Most HAPrIs are preventable. Still, prevention may be better served with a more precise risk stratification approach and associated preventive interventions, given that every patient does not require the same level of care, nursing resources are limited and constrained by competing priorities (consider the COVID-19 pandemic), and cost-saving measures are further impacting care delivery. Risk stratification is essential in the ICU, but current risk assessment instruments, such as the widely used Braden Scale,⁴ an ML approach can incorporate multi-scale time dependencies, allowing for findings of new trends over time, thus producing a synergistic influence on HAPrI risk assessment and therefore prevention.¹²,¹³

The downside of ML algorithms is their “black box” nature—clinicians are unable to determine how the algorithm made the decision and are thus understandably unwilling to trust the algorithm for patient care decisions. Thus, the NPIAP’s call for ML algorithms to predict HAPrI includes the specification that models must be transparent and interpretable.³ Interpretability is defined as the ability of a human to understand the relationship between the features in an ML model and the model’s prediction.¹⁴ Explainable AI methods including the SHAP (SHapley Additive exPlanations) value are a way to increase transparency and interpretability.¹⁵ The SHAP value assigns each feature (variable) in the model an importance value for a particular prediction by averaging the marginal contribution of a feature across all possible permutations (sets of features).¹⁵ SHAP plots can be generated for global ML model interpretability (the collective SHAP values across a data set) and local interpretability (the SHAP values for one observation).

**Key Points**

- Hospital-acquired pressure injury risk assessment is vital for prevention, but current risk assessment instruments such as the Braden Scale lack specificity in critical-care patients.
- The current study shows good discrimination for predicting hospital-acquired pressure injuries in critical-care patients using machine learning algorithms combined into an ensemble SuperLearner.
- Explainable artificial intelligence was used to create transparent machine learning models at the global and single-patient levels.
- The most important variables in the top-performing model were hemoglobin, fragile skin, and serum albumin.

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### Table 1. Characteristics of the Sample

|                               | All Patients With COVID (N = 407) | Patients With HAPrI (n = 74 [18%]) | No HAPrI (n = 333 [82%]) | P       | Missing Data |
|-------------------------------|----------------------------------|-------------------------------------|--------------------------|---------|--------------|
| **Demographic and discharge information** |                                  |                                     |                          |         |              |
| Age, mean (SD), y             | 59 (15)                          | 63 (16)                             | 58 (14)                  | <.001   | 0%           |
| Sex, male, n (%)              | 256 (63)                         | 47 (64)                             | 209 (63)                 | 1.0     | 0%           |
| Race, n (%)                   | Native American or Alaska native: 22 (5%) | Native American or Alaska native: 5 (7%) | Native American or Alaska native: 17 (5%) | <.001   | 0%           |
|                               | Asian: 11 (3%)                    | Asian: 1 (1%)                        | Asian: 10 (3%)           |         |              |
|                               | Black: 10 (2%)                    | Black: 0 (0%)                        | Black: 10 (3%)           |         |              |
|                               | Native Hawaiian or Other Pacific Islander: 19 (5%) | Native Hawaiian or Other Pacific Islander: 4 (5%) | Native Hawaiian or Other Pacific Islander: 15 (5%) |         |              |
|                               | White: 229 (56%)                  | White: 58 (78%)                      | White: 171 (51%)         |         |              |
|                               | Other, Unknown, or choose not to disclose: 116 (29%) | Other, Unknown, or choose not to disclose: 6 (8%) | Other, Unknown, or choose not to disclose: 110 (33%) |         |              |
| Ethnicity, Hispanic, n (%)    | 98 (24)                          | 4 (5)                               | 94 (28)                  | <.001   | 0%           |
| Hospital length of stay, mean (SD) | 16 (16)                           | 16 (14)                             | 16 (16)                  | .89     | 0%           |
| Died during hospitalization, n (%) | 101 (25)                          | 21 (28)                             | 80 (24)                  | .74     | 0%           |
| Time in the emergency department, mean (SD), hours | 2.7 (2.6)                          | 2.2 (2.9)                           | 2.9 (2.5)                | .10     | 0%           |
| **Braden Scale scores**       |                                  |                                     |                          |         |              |
| Minimum Braden Scale total score, mean (SD) | 11.3 (3.8)                          | 11.0 (4.2)                           | 11.4 (3.7)               | .25     | 0%           |
| **Treatments**                |                                  |                                     |                          |         |              |
| Ventilator days, mean (SD)    | 5 (10)                           | 5 (12)                              | 5 (10)                   | .26     | 0%           |
| Reintubation, n (%)           | 46 (11)                          | 9 (12)                              | 37 (11)                  | .96     | 0%           |
| Dialysis, n (%)               | 89 (22)                          | 21 (28)                             | 68 (20)                  | .18     | 0%           |
| Vasopressor infusion, n (%)   | 49 (12)                          | 17 (23)                             | 32 (10)                  | .003    | 0%           |
| **Laboratory values**         |                                  |                                     |                          |         |              |
| Maximum lactate, mean (SD), mg/dL | 3.81 (3.87)                       | 4.37 (3.93)                         | 3.69 (3.85)              | <.001   | 9%           |
| Maximum serum creatinine, mean (SD), mg/dL | 2.16 (2.22)                       | 2.66 (2.97)                         | 2.05 (2.01)              | <.001   | 0.01%         |
| Maximum serum glucose, mean (SD), mg/dL | 266 (128)                        | 258 (125)                           | 269 (129)                | .53     | 0.01%         |
| Minimum hemoglobin, mean (SD), g/dL | 10.46 (3.00)                      | 8.85 (2.85)                         | 10.80 (2.93)             | <.001   | 0.01%         |
| Minimum albumin, mean (SD), mg/dL | 2.68 (0.52)                       | 2.24 (0.52)                         | 2.74 (0.51)              | <.001   | 9%           |
| Mean PaO2, mean (SD), mm Hg   | 104 (62)                         | 101 (62)                            | 117 (63)                 | .06     | 6%           |
| Maximum PaCO2, mean (SD), mm Hg | 53 (21)                           | 59 (21)                             | 52 (21)                  | .19     | 6%           |
| Minimum pH, mean (SD)         | 7.44 (0.07)                       | 7.44 (0.10)                         | 7.44 (0.07)              | .44     | 6%           |

(continues)
The purpose of this study was to evaluate HAPrI injury risk in COVID-19–positive ICU patients. The specific aims include the following: (1) develop an ML model to predict HAPrI risk and (2) apply the SHAP explainable AI method for global and local model interpretability.

**METHODS**

**Design**

This retrospective cohort study was conducted using EHR data extracted from one hospital system's enterprise data warehouse. Extracted data were limited to the duration of the patients' ICU stay and verified for accuracy by an informaticist and ICU nurse with Epic EHR system expertise (Epic Systems Corp, Madison, WI, USA). The study was approved by the facility's institutional review board.

**Sample**

Adult patients who tested positive for COVID-19 and admitted to one of two medical ICUs at a single level-1 trauma center and academic medical center between April 2020 and April 2021 were eligible for inclusion in the study. Patients with a pre-existing (community-acquired) pressure injury were included because of the increased likelihood of developing an additional pressure injury after hospitalization.

**Measures**

The HAPrI outcome variable was defined according to the NPIAP staging definitions (stages 2–4, unstageable, or deep tissue injury). Stage 1 HAPrIs were not included because stage 1 injuries are reversible and considered less severe. Hospital-acquired pressure injuries were deemed to be hospital-acquired if occurring at least 48 hours after the ICU admission. All HAPrIs were verified by a certified wound nurse and evaluated to determine whether the injury was medical device–related. Medical device–related pressure injuries were excluded from this analysis because those injuries have different risk factors.

Potential predictor variables were selected based on a review of the relevant literature and Coleman and colleagues' conceptual framework for pressure injury etiology. The conceptual framework classified variables based on a proposed causal pathway with immobility, skin status, and poor perfusion as direct causal factors. Predictor variables were only recorded before an HAPrI occurred so that data in the ML models were limited to events preceding the HAPrI. Predictor variables and their operationalizations are described in Table 1.

**Analysis**

All data analyses were performed using open-source R software version 4.1.2 (R Core Team, Vienna, Austria). Missing data were quantified and assessed for patterns of missingness using graphical clustering displays. For prediction engineering, data were split into 80:20 training and testing data sets. Random forest (single value) imputation was...
applied independently to training and testing sets to avoid information leakage. Imputation was performed on variables not informatively missing; variables with potential informative missingness were given an indicator for whether the value was observed. Several competing predictive models (deep neural nets, extreme gradient boosting [xgboost], deep random forests, and logistic regression) were developed on the training data set using the H2O package in R and assembled into an ensemble (composite) SuperLearner. Model performance was evaluated based on continuous performance on the receiver operating characteristic curve in the testing data set. Finally, the most important variables (features) were extracted from the best-performing model based on the mean decrease in accuracy.

Global and local (individual patient) SHAP plots were developed for the best-performing model in the ensemble algorithm (Deep Neural Network). The local SHAP plot was developed for a synthetic patient because of privacy concerns.

RESULTS
Sample
The final sample consisted of 407 patients. Seven patients were excluded from the analysis because of excessive missing data. The sample was predominantly male (n = 256 [63%]), and the mean age was 59 (SD, 15) years. Characteristics of the sample are presented in Table 1.

Hospital-Acquired Pressure Injury Outcome
Hospital-acquired pressure injuries (defined as stage 2 or worse) occurred in 18% of the sample (n = 74).

Predictor Variables
Relationships between the potential predictor variables and HAPrI formation are outlined in Table 1.

Predictive Models
The predictive models’ discrimination based on area under the receiver operating characteristic curve is shown in Figure 1. The best-performing model was the ensemble SuperLearner with an area under the receiver operating characteristic curve of 0.807.

Explainable AI
The global SHAP plot for ensemble SuperLearner is presented in Figure 2. The most important variables in the ensemble SuperLearner were, in descending order, hemoglobin, the presence of fragile skin (defined as thin epidermis with loss of subcutaneous tissue), and albumin. Note that red dots indicate negative correlations, and blue dots indicate positive correlations. For example, in Figure 2, low levels of hemoglobin were associated with risk for HAPrI, whereas higher levels were protective, and a positive value (1 = yes) for fragile skin conferred risk, whereas a negative value was associated with reduced risk. The local SHAP plot for a synthetic patient is presented in Figure 3. The model predicted that the synthetic patient would develop an HAPrI. The most important risk factor in the synthetic patient SHAP plot was the length of stay, followed by the presence of renal disease.

DISCUSSION
The purpose of this study was to evaluate HAPrI risk in ICU patients with COVID-19, to develop ML model to predict
HAPrI risk, and apply explainable AI for model transparency and human interpretability. The best-performing ML model, an ensemble SuperLearner, showed good discrimination (area under the receiver operating characteristic curve = 0.807), and the global and local SHAP plots allow nurses to understand how the model is using the variables. This study adds to the body of literature showing ML approaches are useful for assessing HAPrI risk in critical-care patients, and it is the first study to apply explainable AI for HAPrI risk prediction. The next step is model validation and development of associated clinical decision support.

Machine learning transparency and interpretability are essential for model implementation because clinicians will not—and should not—be willing to trust a model if they do not understand how the model reached its decision. The global SHAP value is a human-interpretable way to visualize the relationships between the features in the ML model and its predictions. Yet, it is also necessary to consider that every patient is an individual with a unique constellation of risk factors, only some of which are represented in EHR data. For example, the clinician may be aware of individual contextual factors that may affect overall health and HAPrI risk (e.g., unstable housing) that are invisible to the ML model. Moreover, ML models are generated on a data set that may or may not be representative of a given patient (consider racial minorities or unique disease states); therefore, it is necessary for the clinician to understand how the model decided for the individual patient in order to decide whether the model is trustworthy for that patient. The individual SHAP plot is one way to allow clinicians to see how a model decided and then choose whether to act on the risk prediction generated by the model.

Study findings show that COVID-19–positive critical-care patients have high risk for HAPrI compared with similar, non–COVID-19–positive ICU populations. The HAPrI incidence in the study sample (18%) was significantly higher than the incidence typically reported in non-COVID-19 ICU patients in the United States (6%-8%). The high HAPrI

**FIGURE 2.** Global SHapley Additive exPlanations (SHAP) plot for the ensemble SuperLearner.
incidence is particularly striking, given that the current study was limited to stage 2+ non–medical device–related injuries.

The most important variables in the top-performing model were hemoglobin, fragile skin, and serum albumin. Two of those—hemoglobin and serum albumin—are further evidence for the role of altered perfusion in HAPrI etiology. Low levels of hemoglobin and serum albumin are previously identified HAPrI risk factors thought to affect tissue perfusion and therefore HAPrI risk through oxygen-carrying capacity (hemoglobin) and colloid osmotic pressure (serum albumin). Furthermore, hemoglobin may be considered a modifiable factor, given that low levels can be corrected with blood transfusion; future research is needed to evaluate the effects of so-called permissive anemia and blood transfusion on risk for HAPrI formation.

LIMITATIONS
This study is limited by its relatively small sample size (N = 407) and its single-site, retrospective design. The study was limited to HAPrI that occurred in the ICU, and therefore any HAPrIs that developed immediately after the ICU stay (and thus were formed in the ICU) were not captured.

CONCLUSIONS
Machine learning is a feasible approach for evaluating HAPrI risk in critical-care patients with COVID-19. Explainable AI methods such as SHAP plots are a way to ensure human interpretability and foster trust.

References
1. Alderden J, Rondinelli J, Pepper G, Cummins M, Whitney J. Risk factors for pressure injuries among critical care patients: a systematic review. International Journal of Nursing Studies. 2017;71:97–114. doi:10.1016/j.ijnurstu.2017.03.012.
2. Padula WV, Delamerte BA. The national cost of hospital-acquired pressure injuries in the United States. International Wound Journal. 2019;16(3):634–640. doi:10.1111/iwj.13071.
3. Haesler E, ed. 2019 European Pressure Ulcer Advisory Panel, National Pressure Injury Advisory Panel, and Pan Pacific Pressure Injury Alliance. Prevention and Treatment of Pressure Ulcers/Injuries: Clinical Practice Guideline. The International Guideline. EPUAP/NPIAP/PPPPIA; 2019.
4. Bergstrom N, Braden BJ, Laguzza A, Holman V. The Braden Scale for predicting pressure sore risk. Nursing Research. 1987;36(4):205–210.
5. Adilbeyi S, Korkmaz F. Pressure injury risk assessment in intensive care units: a comparison of the reliability and predictive validity of the Braden and Jackson/Cubbin scales. *Journal of Clinical Nursing.* 2019;28(23–24): 4595–4605. doi:10.1111/jocn.15054.

6. Huang C, Ma Y, Wang C, et al. Predictive validity of the Braden Scale for pressure injury risk assessment in adults: a systematic review and meta-analysis. *Nursing Open.* 2021;8(5): 2194–2207. doi:10.1002/nop2.792.

7. Delawder JM, Leontle SL, Maduro RS, Morgan MK, Zimbo KS. Predictive validity of the Cubbin-Jackson and Braden skin risk tools in critical care patients: a multisite project. *American Journal of Critical Care.* 2021;30(2): 140–144. doi:10.4037/ajcc2021669.

8. Lima-Serrano M, Gonzalez-Mendez M, Martin-Castano C, Alonso-Anaujo I, Lima-Rodriguez JS. Predictive validity and reliability of the Braden Scale for risk assessment of pressure ulcers in an intensive care unit. *Medicina Intensiva.* 2018;42(2): 82–91.

9. Wei M, Wu L, Chen Y, Fu Q, Chen W, Yang D. Predictive validity of the Braden Scale for pressure ulcer risk in critical care: a meta-analysis. *Nursing in Critical Care.* 2020;25(3): 165–170. doi:10.1111/nicc.12500.

10. Team V, Team L, Jones A, Teede H, Weller CD. Pressure injury prevention in clinical practice: an update. *Journal of Wound, Ostomy & Continence Nursing.* 2020;47(1): 46–48. doi:10.1111/jocn.15054.

11. Johnson C, Giordano NA, Patel L, et al. Pressure injury outcomes of a prone-positioning protocol in patients with COVID and ARDS. *American Journal of Critical Care.* 2021;33: e1–e8. doi:10.4037/ajcc2022242.

12. Raj R, Luostarinen T, Pursiainen E, et al. Machine learning-based dynamic mortality prediction after traumatic brain injury. *Scientific Reports.* 2019;9(1): 17672. doi:10.1038/s41598-019-53889-6.

13. Saria S, Butte A, Sheikh A. Better medicine through machine learning: what’s real, and what’s artificial? *PLoS Medicine.* 2018;15(12): e1002721. doi:10.1371/journal.pmed.1002721.

14. Reyes M, Meier R, Pereira S, et al. On the interpretability of artificial intelligence in radiology: challenges and opportunities. *Radiology: Artificial Intelligence.* 2020;2(3): e190043. doi:10.1148/ryai.202020043.

15. Lundberg SM, Lee SL. A unified approach to interpreting model predictions. In: Proceedings of the International Conference on Neural Information Processing Systems (NIPS). 2017: 4768–4777. https://proceedings.neurips.cc/paper/2017/file/8a20ae82197863276cc43df2b8677676/Paper.pdf.

16. Alderden J, Cadavero A, Zhao YL, Yap TL, et al. Dysphagia, immobility, and diet occlusions, deep-tissue pressure injuries, and competing theories: a case report. *Advances in Skin & Wound Care.* 2021;34(8): 412–416. doi:10.1097/01.ISW.0000752770.00049.b5.

17. Mervis JS, Phillips TJ. Pressure ulcers: pathophysiology, epidemiology, risk factors, and presentation. *Journal of the American Academy of Dermatology.* 2019;81(4): 881–890. doi:10.1016/j.jaad.2018.12.069.

18. Alderden J, Zhao YL, Zhang Y, et al. Outcomes associated with stage 1 pressure injuries: a retrospective cohort study. *American Journal of Critical Care.* 2018;27(9): 471–476. doi:10.4037/ajcc2018293.

19. Jackson D, Sarki AM, Betteridge R, Brooke J. Medical device-related pressure ulcers: a systematic review and meta-analysis. *International Journal of Nursing Studies.* 2019;59(2): 109–120. doi:10.1016/j.ijnurstu.2019.02.006.

20. Barakat Johnson M, Barnett C, Wand T, White K. Medical device-related pressure injuries: an exploratory descriptive study in an acute tertiary hospital in Australia. *Journal of Tissue Viability.* 2017;26(4): 246–253. doi:10.1016/j.jtv.2017.09.006.

21. Coleman S, Nixon J, Keen J, et al. A new pressure ulcer conceptual framework. *Journal of Advanced Nursing.* 2014;70(10): 2222–2234.

22. Cox J. Pressure injury risk factors in adult critical care patients: a review of the literature. *Ostomy & Wound Management.* 2017;63(11): 30–43.

23. R Core Team. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing; 2021. https://www.R-project.org/.

24. H2O.ai Open Source Machine Learning Platform. https://www.h2o.ai/products/h2o/.

25. Cooper JN, Minneci PC, Deans KJ. Postoperative neonatal mortality prediction using superlearning. *The Journal of Surgical Research.* 2018;221: 311–319. doi:10.1016/j.jsr.2017.09.002.

26. Alderden J, Pepper GA, Wilson A, et al. Predicting pressure injury in critical care patients: a machine-learning model. *American Journal of Critical Care.* 2018;27(6): 461–468. doi:10.4037/ajcc2018525.

27. Song W, Kang MJ, Zhang L, et al. Predicting pressure injury using nursing assessment phenotypes and machine learning methods. *Journal of the American Medical Informatics Association.* 2021;28(4): 759–765. doi:10.1093/jamia/ocaa336.

28. Alderden J, Drake KP, Wilson A, Dimas J, Cummmins MR, Yap TL. Hospital acquired pressure injury prediction in surgical critical care patients. *BMC Medical Informatics and Decision Making.* 2021;21(1): 12. doi:10.1186/s12911-020-01371-z.

29. Cramer EM, Seneviratne MG, Sharifi H, Dzturk A, Hernandez-Boussard T. Predicting the incidence of pressure ulcers in the intensive care unit using machine learning. *eGEMs (Washington, DC).* 2019;7(1): 49. doi:10.5334/egems.307.

30. Hatherley JJ. Limits of trust in medical AI. *Journal of Medical Ethics.* 2020;46(7): 478–481. doi:10.1136/medethics-2019-105935.

31. Röösli E, Rice B, Hernandez-Boussard T. Bias at warp speed: how AI may contribute to the disparities gap in the time of COVID-19. *Journal of the American Medical Informatics Association.* 2021;28(1): 190–192. doi:10.1093/jamia/ocaa210.

32. Straw J. The automation of bias in medical artificial intelligence (AI): decoding the past to create a better future. *Artificial Intelligence in Medicine.* 2020;110: 101965. doi:10.1016/j.artmed.2020.101965.

33. Alderden J, Cowan LJ, Dimas JB, et al. Risk factors for hospital-acquired pressure injury in surgical critical care patients. *American Journal of Critical Care.* 2020;29(6): e128–e134. doi:10.4037/ajcc2020810.

34. Cox J, Schallion M, Jung C. Identifying risk factors for pressure injury in adult critical care patients. *American Journal of Critical Care.* 2020;29(3): 204–213. doi:10.4037/ajcc2020243.

35. Yap TL, Alderden J, Lewis M, Taylor K, Fife CE. Angiosome vascular occlusions, deep-tissue pressure injuries, and competing theories: a case report. *Advances in Skin & Wound Care.* 2021;34(3): 157–164. doi:10.1097/01.ASW.0000732804.13066.30.

36. Schott M, Golin A, de Jesus SR, et al. Dysphagia, immobility, and diet acceptance: main factors associated with increased risk of pressure injury in patients hospitalized after stroke. *Advances in Skin & Wound Care.* 2020;33(11): 527–532. doi:10.1097/01.ASW.0000694140.54146.75.

37. Liu Y, Xu X, Ma Y, et al. The prevalence, incidence, and associated factors of pressure injuries among in-hospital inpatients: a multicentre, cross-sectional, exploratory descriptive study in China. *International Wound Journal.* 2019;16(2): 459–466. doi:10.1111/iwj.13054.

38. Alderden J, Cummmins M, Zaratiekiewicz S, Lucy’ Zhao Y, Drake K, Yap TL. Hospital-acquired pressure injury development among surgical critical care patients admitted with community-acquired pressure injury: a retrospective cohort study. *Journal of Wound Ostomy & Continence Nursing.* 2020;47(5): 470–476. doi:10.1177/0090693320960069.

39. Kougias P, Sharath S, Mi Z, Bliews K, Mills JL. Effect of postoperative permissive anemia and cardiovascular risk status on outcomes after major general and vascular surgery operative interventions. *Annals of Surgery.* 2019;270(4): 602–611. doi:10.1097/SLA.0000000000003525.