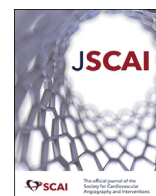




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Original Research

Using Machine Learning for Early Prediction of Cardiogenic Shock in Patients With Acute Heart Failure



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ABSTRACT

Background: Despite technological and treatment advancements over the past 2 decades, cardiogenic shock (CS) mortality has remained between 40% and 60%. Our objective was to develop an algorithm that can continuously monitor heart failure patients and partition them into cohorts of high and low risk for CS.

Methods: We retrospectively studied 24,461 patients hospitalized with acute decompensated heart failure, 265 of whom developed CS, in the Johns Hopkins Health System. Our cohort identification approach is based on logistic regression and makes use of vital signs, lab values, and medication administrations recorded during the normal course of care.

Results: Our algorithm identified patients at high risk of CS. Patients in the high-risk cohort had 10.2 times (95% confidence interval, 6.1-17.2) higher prevalence of CS than those in the low-risk cohort. Patients who experienced CS while in the high-risk cohort were first deemed high risk a median of 1.7 days (interquartile range, 0.8-4.6) before CS diagnosis was made by their clinical team. To evaluate *actionability*, we randomly selected 50 patients designated as high risk who did develop CS and 50 who did not. On review of true positive cases, from the time of model identification as high risk to the eventual diagnosis of CS, 12% of patients had possible inappropriate therapy, and for 50% of patients, more tailored therapy options existed. On review of the false positive cases, 44% of cases were considered at high risk of CS or end-stage cardiomyopathy by their clinical teams or went onto develop other types of shock.

Conclusions: This risk model was able to predict patients at higher risk of CS in a time frame that allowed a change in clinical care. The actionability evaluation demonstrates a possible opportunity to intervene as part of a CS algorithm for escalation of care.

Introduction

Mortality rates for cardiogenic shock (CS) patients have remained mostly unchanged at 40-60% over the last 2 decades,¹⁻⁸ despite the introduction of important innovations in cardiac care such as the cardiac intensive care unit (CICU) and mechanical circulatory support. The task of improving outcomes for CS is increasingly urgent, as the prevalence of CS and acute decompensated heart failure (ADHF) has been increasing for decades.^{9,10} While the factors that lead to poor CS outcomes are not well understood, there is some indication that they may be due to the difficulty of diagnosing and treating the condition early enough to reverse patients' downward clinical trajectories.^{11,12}

Early diagnosis of CS is complicated by the fact that it can present gradually and with nonspecific symptoms. Data in electronic health records (EHRs) of a patient may provide a valuable source of information as to whether a patient is at high risk for CS. However, for practical reasons, clinicians cannot fully synthesize and make use of the high volume of data collected on each patient over time. On the other hand, without the aid of clinical expertise, computational algorithms using EHRs are insufficient to the task of diagnosing CS on their own.

In this work, we present a computational method for identifying patients whose EHRs indicate that they should be treated as being at high risk for CS. Our method makes use of vital signs, lab values, and medication administrations throughout the patient's hospital stay to ascertain

Abbreviations: ADHF, acute decompensated heart failure; CICU, cardiac intensive care unit; CS, cardiogenic shock; EHR, electronic health records.

Keywords: Acute decompensated heart failure; cardiogenic shock; machine learning; risk prediction.

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risk status using a logistic regression model, which will be described in detail below.

Our method follows in the tradition of identifying risk categories for cardiac patients. Risk prediction models from the Acute Decompensated Heart Failure Registry,¹³ Get with the Guidelines-Heart Failure,¹⁴ and other similar retrospective data^{6,15,16} predict the risk of in-hospital and out-of-hospital mortality at the time of admission. Since these models do not track the dynamic variables of a hospitalized patient with ADHF but rather provide a single snapshot, they are challenging to use to change management or outcomes. Additionally, they are not automated but require clinicians to calculate a score, which increases work burden. Some of these issues are overcome by early warning systems (EWS)^{17,18} such as the modified EWS, targeted real-time EWS, which can provide continuous monitoring for adverse outcomes such as cardiac arrest, ICU admission, or mortality. Unfortunately, these systems have had variable performance and alert in close proximity to the outcome event which may not be sufficient to change the trajectory of a patient's clinical outcome.¹⁸

Unlike any previous approach, our method focuses specifically on identifying patients at high risk for CS by continuously monitoring their EHRs over the course of their stay. This method is one of a new generation of technologies that seek to take advantage of the tremendous stores of information in EHRs by combining the strengths of computers and clinicians. The computers have unlimited attention and can monitor vast quantities of data without tiring, while clinicians have the wisdom to act appropriately when important information is made available to them.

Methods

Data

Johns Hopkins Health System is composed of multiple hospitals and outpatient centers. Our study included patients admitted to Johns Hopkins Hospital between January 1, 2016 and March 31, 2018, Howard County General Hospital between February 1, 2014 and January 29, 2019, and Johns Hopkins Bayview Medical Center between January 1, 2016 and March 31, 2018. The study was approved by the Institutional Review Board of Johns Hopkins Medicine with waiver of consent. All data were obtained from Epic Systems Corp EHR. Patients under 18 years of age were excluded from the cohort.

Clinical cohort

Patients with ADHF were included for monitoring; however, they were excluded if they met criteria for ADHF after surgery or after development of CS or other shock. No other diagnosis was an exclusion including acute coronary syndrome. Patients who developed shock within 6 hours of admission were also excluded due to the assumption that the patient likely was in a peri-shock state at the time of admission. All patients who were discharged to hospice with end-stage cardiomyopathy were excluded if they never met the criteria for CS.

For both model development and validation, it was necessary to identify (label) patients who went into CS along with the time of onset. Patients were labeled as having CS if they had hypotension (systolic blood pressure ≤ 90 mm Hg or mean arterial pressure ≤ 65 mm Hg) that required inotropic therapy (dopamine, dobutamine, milrinone, or norepinephrine) or mechanical circulatory support and evidence of end-organ failure due to a cardiac cause.^{12,19,20} The diagnosis was retrospectively adjudicated by a study team cardiologist and required the clinical team to arrive at the diagnosis of CS based on EHR documentation. The time of CS onset was assumed to be the time of order of inotropic therapy or mechanical support, but practically, this ended up being the time of inotropic therapy as all patients who received mechanical support had gotten initial inotropic therapy to stabilize. During validation, each patient in the data set, set aside for this purpose, was

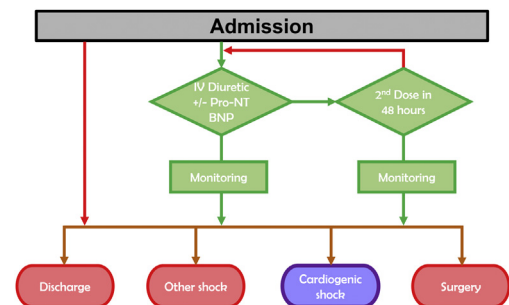


Figure 1. After patient admission, the model follows the patient to see if they received IV diuretics \pm pro-NT BNP testing within 24 hours. Once criteria are met, then the patient enters the monitoring as acute decompensated heart failure until the patient develops cardiogenic shock (outcome of interest), develops other type of shock, goes to surgery, or is discharged. If the patient does not develop one of these outcomes within 48 hours of the first dose of diuretic, then a second dose of IV diuretic is required to remain in the monitoring zone; if this second dose is not received, then monitoring is stopped and the model follows the patient to see if diuretic is started again later in the hospitalization. If a patient never receives diuretics or receives diuretics after one of the 4 outcomes, then they are never in the monitoring zone. IV, intravenous; Pro-NT BNP, pro-NT brain natriuretic peptide.

evaluated every 6 hours (sequentially) during hospitalization to see if their risk prediction hits the threshold for high risk.

Real-time flagging of likely ADHF patients

An accurate diagnosis of ADHF may not be made immediately or be recorded in physician notes at the time of treatment, which most commonly involves initiation of diuretics. We therefore created a set of criteria to use as a proxy for an ADHF diagnosis, to enable timely, automatic identification and monitoring of patients with likely ADHF (Figure 1; Supplemental Methods).²¹ We note that this definition is different to some of the previously proposed definitions used in some studies of EHRs,²¹⁻²⁴ but a similar definition has also been tested showing a high sensitivity.²¹ This is for 3 reasons. First, some existing definitions rely on information not routinely captured in the EHR, and it is important that we are able to automatically identify ADHF patients. Second, for our application, the cost of missing ADHF patients far exceeds the cost of including patients who do not have ADHF, as missed ADHF patients would not be monitored for CS. Third, any model would need to be able to identify ADHF immediately for prospective monitoring, and therefore, patient notes are limited in timely identifying ADHF. Patients were monitored until they developed CS, developed other type of shock (referred to as “other shock”), went to the operating room, or were discharged. Monitoring for these outcomes began with the first dose of intravenous diuretics.

Variables

Clinical inpatient data from admission to discharge were extracted from the EHR into our PostgreSQL (PostgreSQL Global Development Group) database. Data extracted included demographics, vital signs, laboratory results, medications, past medical history, admitting service, hospital unit, discharge disposition, and discharge diagnosis International Classification of Diseases, Tenth Revision codes (see Supplemental Methods).

Our approach to missing data is discussed in the Supplemental Methods. Missing data are part of real-life EHR data, and accommodating missing data using imputations methods is important for clinical usefulness of any risk prediction model. Therefore, no patients were excluded from the analysis due to missing data. In addition, the validation of the model was performed prospectively using k -nearest neighbors

imputation for missing data and reflects how the model would function in a real-life deployment.

Model development and statistical analysis

At the beginning of our study, we randomly partitioned the data into training and testing sets, with 75% of the data being used for training and 25% used for evaluation after the completion of model development.

Our model sought to identify high- and low-risk cohorts. During model development, we chose a single time point at random for each patient who never developed any form of shock. Among patients who developed shock, we used 2 sample points—one within 24 hours of the onset of shock and the other beforehand. We treat cohort membership as a binary classification problem, that is, the 24 hours before being diagnosed as CS patients are high risk and patients who do not develop CS within 24 hours as low risk. Using these 2 samples violates the independence assumption under which the model is learned but was necessary due to the limited CS cases. However, we determined that it was important to have examples of patients who would go on to develop shock both within and outside the risk classification window.

We considered using, and evaluated, several machine learning classification algorithms: decision tree, random forest, support vector machine, linear discriminant analysis, *k*-nearest neighbor, and logistic regression (Supplemental Table S1). The performances of all the algorithms were similar with logistic regression performing most consistently when evaluated using odds ratios, sensitivity, specificity, positive and negative predictive values, accuracy, and area under the receiver operating curve (AUC/C-statistic).

For each model we evaluated, hyperparameter tuning was performed by means of a 5-fold cross-validation.²⁵ Variable selection was performed by means of cross-validation and L1 regularization, a technique that encodes a preference for disregarding unimportant features. Ultimately, our choice of binary classification model was made based on cross-validation as well. The performance of the model was evaluated using a second validation data set, which was separate from the development data set and was not seen during model development.

Method evaluation

We evaluated our method in 2 ways. First, we evaluated the statistical properties of our model on the model development data set and on the separate validation data set as described above including sensitivity, specificity, positive predictive value, and odds ratio. This evaluation provides a quantitative assessment of the different properties of the 2 cohorts.

Next, we examined whether and how the knowledge that a patient belongs to the high-risk cohort is *actionable*, ie, whether and how treatment and diagnosis might change in the face of this knowledge. In some cases, clinicians may have already been aware the patient was high risk, in which case little would change. But in other cases, this designation may have induced a consult with a cardiologist or a beneficial change in the treatment regime.

To evaluate actionability, we randomly selected 50 patients designated as high risk who did develop CS and 50 who did not. These patients were selected from the testing portion of each fold during cross-validation techniques²⁰ (see Supplemental Methods), such that none were in the model development data for the model used for their classification. We did not make changes to the model based on these evaluations.

Each true positive case was reviewed from the time the model first designated the case as high risk to the time of CS diagnosis by the clinical team based on EHR documentation. These patients were categorized into one of 3 groups (details in Supplemental Methods):

- (a) Patients who may have received treatment that was potentially harmful or contributed to deterioration (group A), including
 - Uptitration of negative inotropes such as beta-blockers or non-dihydropyridine calcium channel blockers for sinus tachycardia,

intravenous fluid bolus, and target net positive fluid balance by the clinical team.

- (b) Patients for whom more tailored noninvasive or invasive therapies may be available (group B)
 - Cessation of negative inotropic agents, continuation of diuresis despite creatinine rise, uptitration of diuretic doses if poor diuretic response, or invasive therapy which included pulmonary artery catheter insertion to evaluate cardiac performance and filling pressures, and/or transfer to a higher level of care for closer monitoring and possible earlier initiation of inotropic therapy.
- (c) Patients who are already known by the team to be critically ill and high risk of CS, where a high-risk identification does not provide any new information (group C).

Results

There were 24,461 cases identified as ADHF, of which 265 were validated cases of CS. The in-hospital mortalities of the ADHF and CS cases were 4% and 34%, respectively. Table 1 shows patient baseline characteristics.

The quantitative performance of the model is shown in Figure 2, Supplemental Fig. S1, and Table 2. Based on cross-validation performance, we chose to classify an individual as high risk when the output of the logistic model was >0.1 , balancing the sensitivity, specificity, positive predictive value, and negative predictive value. At this threshold, 58% of CS patients were in the high-risk cohort (ie, there was a 58% sensitivity) and 88% of ADHF patients who did not experience CS were in the low-risk cohort (ie, an 88% specificity). These numbers correspond to 10.2 times (95% confidence interval, 6.1-17.2) higher prevalence of CS in the high-risk cohort than in the low-risk cohort.

Age, systolic blood pressure, heart rate, temperature, blood urea nitrogen, sodium, oxygen saturation, venous pH, hemoglobin, white blood cell count, hydralazine use, trend of respiratory rate, and trend of systolic blood pressure were associated with risk of developing CS (Table 3, Supplemental Table S2).

During validation, CS patients who were categorized as high risk were identified at a median time of 1.7 days (interquartile range, 0.8-4.6 days, Figure 3) prior to CS diagnosis. On review of true positive cases, 12% of patients had possible inappropriate therapy (group A), 50% of patients had more tailored therapy options (group B), and 38% of patients were in group C. See supplement for an example group A case (Supplemental

Table 1. Baseline characteristics of patients classified as acute decompensated heart failure and cardiogenic shock

Characteristic	Acute decompensated heart failure <i>n</i> = 24,196	Cardiogenic shock <i>n</i> = 265
Age, y	67.6 ± 15.6	64.3 ± 15.5
Male sex	12,327 (51%)	118 (45%)
Body mass index, kg/m ²	30.6 ± 9.3	29.6 ± 7.9
Mortality	1054 (4.3%)	89 (33.5%)
Study site		
Johns Hopkins Hospital	9242 (38.1%)	141 (53.2%)
Bayview Medical Center	5200 (21.5%)	82 (30.9%)
Howard County General Hospital	9754 (40.3%)	42 (15.8%)
Comorbidities		
Hypertension	15,111 (62.5%)	132 (49.8%)
Diabetes mellitus	8000 (33.1%)	92 (34.7%)
Coronary artery disease	4920 (20.3%)	68 (25.7%)
Atrial fibrillation	4744 (19.6%)	87 (32.8%)
Chronic renal disease	2777 (11.4%)	41 (15.4%)
Cardiomyopathy	7557 (31.2%)	134 (50.6%)
Chronic obstructive pulmonary disease	4523 (18.7%)	45 (17.0%)

Variables presented as mean ± standard deviation or *n* (%).

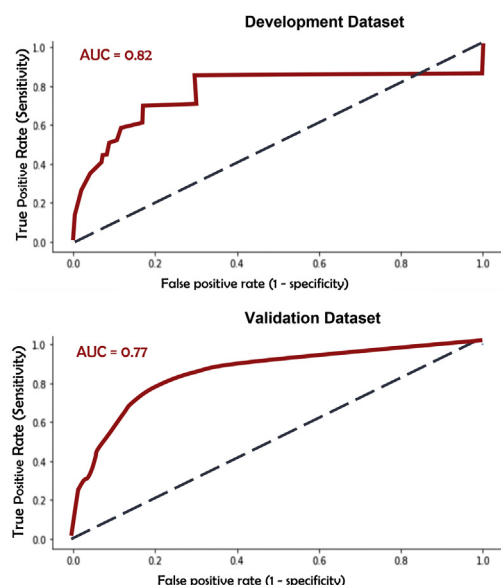


Figure 2. Receiver operating characteristic curves for the prediction model during model development cross-validation and with validation data set. AUC, area under the curve.

Fig. S2). On review of 50 false positive cases, 27% of cases were considered at high risk of CS or end-stage cardiomyopathy by their clinical teams and 17% went on to develop other types of shock.

The patient location at the time of high-risk categorization and CS diagnosis is shown in Supplemental Fig. S3.

Discussion

In the present study, an algorithm to identify patients who may be at a higher risk of developing future CS was developed. The model can continuously monitor complex patient trajectories in the background. Patients identified as high risk are substantially more likely to develop CS than those in the low-risk cohort. Moreover, high-risk patients were identified with lead time that future studies could use to evaluate if it would alter the course of their treatment and therefore outcomes.

Our method follows in the tradition of identifying risk categories for cardiac patients. Risk prediction models from the ADHF Registry,¹³ Get with the Guidelines-Heart Failure,¹⁴ and other similar retrospective data^{6,15,16} predict the risk of in-hospital and out-of-hospital mortality at the time of admission. Since these models do not track the dynamic variables of a hospitalized patient with ADHF but rather provide a single snapshot, they are challenging to use to change management or outcomes. Additionally, they are not automated but require clinicians to

Table 3. Selection of variables that are statistically significant in the cardiogenic shock prediction model (see Supplemental Table for all variables)

Variable	Coefficient	P-value
Age	−0.015 (−0.028 to −0.002)	.028
Systolic blood pressure	−0.050 (−0.060 to −0.041)	<.001
Heart rate	0.020 (0.011-0.028)	<.001
Temperature	−0.0789 (−0.152 to −0.005)	.035
Blood urea nitrogen	0.032 (0.023-0.040)	<.001
Sodium	−0.059 (−0.090 to −0.028)	<.001
Oxygen saturation (SpO ₂)	0.078 (0.021-0.135)	<.001
Venous pH	3.653 (1.040-6.266)	.006
Hemoglobin	0.108 (0.027-0.188)	.009
White blood cell count	−0.051 (−0.096 to −0.006)	.025
Hydralazine	0.826 (0.367-1.285)	<.001
Respiratory rate trend	0.341 (0.104-0.577)	.005
Systolic blood pressure trend	0.031 (0.000-0.062)	.049

calculate a score, which increases work burden. Some of these issues are overcome by EWS,^{17,18} which can provide continuous monitoring for adverse outcomes such as cardiac arrest, ICU admission, or mortality. Unfortunately, these systems have had variable performance and alert in close proximity to the outcome event which may not be sufficient to change the trajectory of a patient's clinical outcome.¹⁸

We also demonstrate that several variables are each individually associated with increased risk of developing CS in our model. These predictive variables cannot be directly compared with previous risk prediction models as those used single time point measurements at admission and evaluated inpatient or posthospitalization mortality.^{6,13-16} In our study, individuals who develop CS are more likely to have a lower temperature which may be related to the peripheral vasoconstriction seen in a low output state. Just as importantly, we also demonstrate that most trends (such as heart rate) are not as pertinent for risk prediction.

How does our work translate?

Unlike previous approaches, our method focuses specifically on identifying patients at high risk for CS by continuously monitoring their EHRs over the course of their stay. This method is one of a new generation of technologies that seek to take advantage of the tremendous stores of information in EHRs by combining the strengths of computers and clinicians. Computers have unlimited attention and can monitor vast quantities of data without tiring, while clinicians have the wisdom to act appropriately when important information is made available to them. We find that a patient characterized as high risk has a greater than 10 times the odds of developing CS. However, this model at a threshold of 0.1 had a positive predictive value of 5%, which at first glance would be concerning low. However, it is not unusual for certain risk prediction tools to have low positive predictive value,²⁶ for example, the CHA₂DS₂-VAsc score for atrial fibrillation has been used with a risk score of 2 as

Table 2. Risk prediction model sensitivity, specificity, negative and positive predictive values, and diagnostic odds ratio at different thresholds

Model development data set						
Threshold	Sensitivity	Specificity	NPV	PPV	Accuracy	
0.03	0.78	0.79	0.99	0.04	0.79	
0.05	0.70	0.87	0.99	0.05	0.87	
0.06	0.65	0.89	0.99	0.06	0.89	
0.19	0.39	0.97	0.99	0.13	0.97	
Validation data set						
Threshold	Sensitivity	Specificity	NPV	PPV	Accuracy	Diagnostic OR (95% CI)
0.02	0.88	0.55	0.99	0.02	0.55	9.1 (4.1-20.1)
0.06	0.75	0.80	0.99	0.04	0.80	11.9 (6.7-21.7)
0.10	0.58	0.88	0.99	0.05	0.88	10.2 (6.1-17.2)
0.20	0.34	0.95	0.99	0.07	0.94	9.7 (5.6-16.8)
0.30	0.27	0.98	0.99	0.11	0.97	14.6 (8.1-26.6)

CI, confidence interval; NPV, negative predictive value; OR, odds ratio; PPV, positive predictive value.

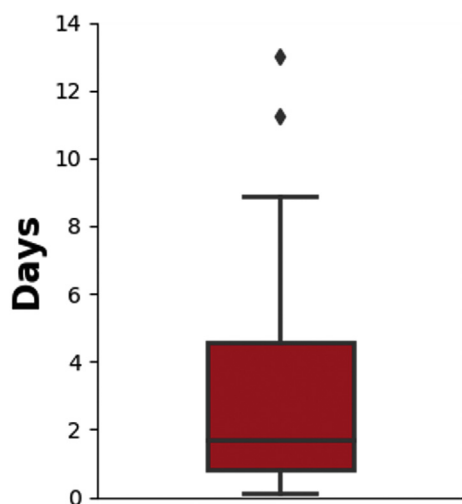


Figure 3. The boxplot shows the distribution of the difference between the time the model identified the patient at high risk of cardiogenic shock and the time that the diagnosis of cardiogenic shock was made by the primary clinical team.

significant, which equates to an estimated annual stroke risk of 2.2% per year.²⁷ Similarly, any risk prediction model for CS is not designed to be used in isolation but in addition to clinical evaluation.

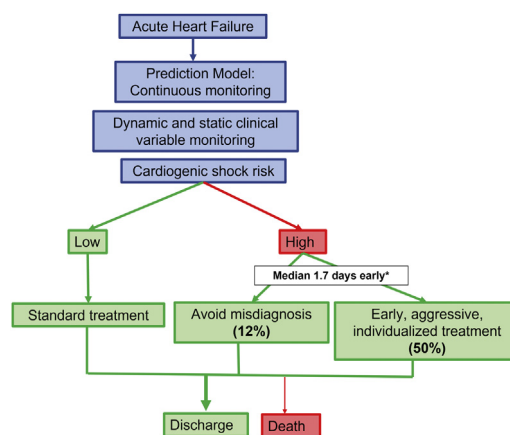
We see the future of medicine involving a dashboard for clinicians where algorithms monitor patients for risk stratification for poor outcomes during continuous surveillance. This dashboard would act to aid the clinician during their daily decision-making for patients.

To that extent, we ensured that our model could provide a timely, automated method of entrance for likely ADHF by using intravenous diuretics as a surrogate to diagnose ADHF. Although this is a very sensitive approach, the specificity for ADHF is reduced and therefore reduces the positive predictive value for CS, eg, if diuretics are administered incorrectly or for other diagnoses such as renal or hepatic disease. However, we believe that in addition to a clinician evaluation, particularly when the trajectory of a patient is unclear, risk stratification by an algorithm could aid a clinician to vary their level of concern for CS. For example, does a rise in creatinine suggest over-diuresis or low-output state? In such cases, the patient's risk classification may help the clinical team to decide next steps.

We do believe that our model requires continual improvement and further development. For example, future work by ourselves and other groups could include other variables such as echocardiogram data or other imaging tools, etc. to help improve the model. These approaches will require collaboration between computer science and clinical teams to help us reach the goal of precision medicine leveraging big data and greater computing skills available in the 21st century.

Risk prediction tools are common in the scientific literature, but few are regularly used and implemented into daily practice.²⁸ Early risk prediction tools are even more relevant as providers spend increasing amounts of time on administrative and documentation activities with frequent interruptions to patient care and experience increasing volumes of patient data.^{29,30} As our study shows, the overall inpatient mortality for ADHF is low (4% in our study) unless the patient deteriorates into CS, which increased the mortality by more than 8-fold, demonstrating the need to improve care for these patients.

Although mortality after CS has remained stagnant,¹⁻⁶ recent evidence in CS after acute myocardial infarction demonstrates that early, coordinated, aggressive treatment improves inpatient mortality.¹¹ We believe that similar early, tailored treatment in patients identified to have a high risk of developing CS may improve outcomes. Using the expert consensus from The Society of Cardiovascular Angiography and Interventions, our algorithm attempts to identify patients in stage B or early stage C of CS instead of later stages where outcomes are worse.¹²



Central Illustration. Future of Heart Failure? Real-time risk prediction model to identify patients at a high risk of cardiogenic shock. Currently, 12% patients are misdiagnosed and treated inappropriately; 50% of patients have the opportunity for early, aggressive treatment. *Our model could identify these patients a median of 1.7 days earlier than the primary clinical team diagnosing cardiogenic shock. This may potentially reduce mortality associated with cardiogenic shock.

This also explains the variables that we demonstrate to be significant (Table 3) for the prediction algorithm in comparison to variables that are commonly used to aid in the diagnosis of CS by clinical teams (eg, lactate, creatinine, liver function tests).³¹ We demonstrate a model with an AUC of 0.77, where positive cases are identified at a median of 1.7 days before the diagnosis of CS was made by the clinical team. This early identification of high-risk patients could provide clinicians time to initiate individualized, tailored treatment strategies to proactively prevent further decompensation instead of reactively responding after CS.

Further, we demonstrate that from the time of high-risk categorization by our model to clinical diagnosis of CS, approximately 1 of 8 patients received therapy that may have worsened their clinical status likely due to lack of recognition of worsening ADHF. In addition, in half of patients, there was time and opportunity to undertake early tailored treatment, which may include simple approaches, such as discontinuation of negative inotropes or appropriate diuretic adjustments, to more invasive options, such as pulmonary artery catheter insertion for hemodynamic guided therapy, early initiation of inotropes, and initiating mechanical circulatory support. Although these treatment options exist, it is unclear if identification of cases ~1.7 days earlier would change a patient's clinical trajectory such as reducing hospital morbidity, mortality, and length of stay, as demonstrated in the sepsis literature.³² Therefore, we propose a new paradigm where clinical acumen is combined with our prediction model to risk stratify patients for individualized, patient-specific treatment (Central Illustration).

Our study has several strengths including the several years of data from 3 hospitals, the use of novel machine learning tools for risk prediction, inclusion of trend data, inclusion of large number of clinical variables, an algorithm that can run automated in the background, and evaluation of actionability of a risk prediction model. Limitations include the moderate number of CS cases that limits the number of variables and learning that is possible. Additionally, we use data from 1 health care system; further studies using data from other systems will be required to improve model generalizability and robustness. As discussed above, several variables are not included such as echocardiogram data as these were not accurately available. Finally, EHR data do have several weaknesses including missing data, nonsystematic way of data collection for each patient, and erroneous recording by providers. However, this reflects real-world practice, and any model that is to be clinically useful needs to account for these weaknesses.³³

In this study, we present a risk prediction tool that can use continuous EHR data monitoring in patients with ADHF to help identification of patients at a high risk of CS. Early identification of at-risk patients is essential to allow for enough time to change the disease trajectory. Future intervention studies are needed using this model to observe how early identification and potential effects on treatment strategies may alter patient outcomes.

Declaration of competing interest

Dr Suchi Saria reports a relationship with Bayesian Health that includes the founder and board member and with PatientPing that includes board membership. The other authors report no financial interests.

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Ethics statement

The research reported has adhered to current ethical guidelines.

Supplementary material

To access the supplementary material accompanying this article, visit the online version of the *Journal of the Society for Cardiovascular Angiography & Interventions* at <https://doi.org/10.1016/j.jscai.2022.100308>.

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