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Heart failure mortality prediction using PRISM score and development of a classification and regression tree model to refer patients for palliative care consultation

Sindhu Avula [a,*], Michael LaFata [b], Mohammed Nabhan [b], Ambreen Allana [c], Bhavana Toprani [b], Caleb Scheidel [d], Anupam Suneja [b]

[a] Mercy St. Vincent Medical Center, Toledo, OH, United States
[b] St Joseph Mercy Ann Arbor Hospital, Ypsilanti, MI, United States
[c] UT Houston, TX, United States
[d] Methods Consultants of Ann Arbor, United States

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ABSTRACT

Introduction: We sought to assess one-year mortality in heart failure (HF) patients by using (Placement Resource Indicator for Systems Management) PRISM, a disease nonspecific risk stratification score, and use it along with modified Seattle Heart Failure Model (SHFM) to guide patient selection for palliative care consultation.

Methods: A retrospective study design was used to examine 1-year mortality in 689 HF patients admitted from 2012 to 2014. One-year mortality was calculated using Pmort30/PRISM and modified SHFM scores, and the predicted scores were validated using the area under the ROC curve. CART was used to develop an algorithm to classify patients based on their mortality risk.

Results: The discriminatory ability of PRISM categorical score (AUC = 0.701) was not significantly different than the discriminatory ability of modified SHFM (AUC = 0.686) (DeLong's test p = 0.56) but improved significantly with the combination of PRISM (categorical) score + modified SHFM (AUC = 0.740) (p = 0.002). The predictive capability of the CART tree model after cross-validation was 72.2% (AUC 0.631).

Conclusion: Our study suggests PRISM score performed as well as modified SHFM for one-year mortality prediction. Moreover, the addition of modified SHFM to PRISM score increases discriminatory ability in predicting 1-year mortality in heart failure patients compared to either of the two models alone. Together, when combined in a CART model, they can be used to identify the population subset with the highest mortality risk and hence guide goals of care discussion.

1. Introduction

Heart failure is a chronic progressive, debilitating condition with quality of life-limiting symptomatology impacting about 5.7 million U.S. adults [1]. Despite improved survival with medical therapy [2], 40% of patients with heart failure die within a year of the first hospitalization [3]. Advancements in the management of heart failure include newer medications and device therapies such as implantable Cardioverter's Defibrillators (ICDs), cardiac resynchronization therapies (CRTs), and ventricular assist devices (VADs). These newer management strategies, although being increasingly utilized, are not curative.

Palliative care focuses on providing the best possible quality of life for patients and their families. It provides support and assistance with decision making and ensures that the treatment provided matches the patient's goals of care. It assesses symptoms and provides appropriate treatments and ensures a secure living environment across a range of settings, whether home, hospital, or nursing home [4]. Potential benefit has been shown by introducing palliative care at the time of diagnosis of a serious or life limiting illness, while other beneficial medical therapies are simultaneously initiated [5,6]. Hospice, on the other hand, is a term used for care at the end of treatment regimens when life expectancy is less than 6 months.

Palliative care was originally introduced for the care of patients with advanced cancer. However, it has evolved to include other chronic progressive conditions such as heart failure [7]. The total cost incurred from heart failure is estimated to go up to $69.8 bil-

* Corresponding author at: Department of Cardiovascular Disease, Mercy St Vincent Medical Center, 2213 Cherry Street, Toledo, OH 43608, United States.
E-mail address: Sindhureddy.avula@outlook.com (S. Avula).

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lion by 2030 [3,8]. Up to 80% of this cost is related to hospitalization [8]. Although the involvement of palliative care has shown to reduce healthcare costs [8,9], access to palliative care and hospice was poor, and healthcare resource utilization more aggressive in patients with heart failure as compared to cancer patients despite their similar symptom burden [10,8,9,11].

Current evidence shows that patients' preferences vary widely concerning choosing treatment strategies for sudden death versus an anticipated death [12]. Considering this huge variability, it is important to provide a patient-centered approach to treatment that tailors to their lifestyle choices. A longitudinal study of 608 patients in the USA showed that only 41% had an advanced directive [12,13]. A randomized controlled study has shown that consultation with palliative care increased the chances of dying at home [14], as this allows patients an opportunity to spend more time with their families.

Mortality prediction tools may assist in efficiently triaging patients for palliative care consultation to establish goals of care. PRISM (Placement Resource Indicator for Systems Management) score was initially developed to stratify all hospitalized adult patients to predict 30-day mortality risk and identify those who are at increased risk for poor outcomes [15]. It was developed using data from 2008 to 2009 and validated on data from 2010 from its sister hospital, to predict death within 30 days, Area under the curve (AUC) (0.88), 30-day readmission (0.68–0.69) and death within 180 days (0.87–0.89), with excellent discrimination [16]. It utilizes over 20 pieces of information to develop a continuous risk score. Subsequently, the risk score is stratified into strata ranging from 1 to 5, with 1 being the highest risk stratum and 5 the least. In our institution, PRISM score is used to implement well-coordinated bundles of intervention across the care continuum, such as guiding placement into appropriate nursing units, determining urgency of initiating treatment, and coordinating transitions of care such as palliative care for those patients with highest risk PRISM score and thus mortality risk [17,18].

The SHFM (Seattle Heart Failure Model) is a well-known risk prediction tool that incorporates multiple patient parameters in an equation that provides a risk score for each patient [19]. We used modified SHFM as we substituted default values for certain parameters (e.g., uric acid level). The goal of this retrospective observational study was to evaluate PRISM's performance to predict 1-year mortality in patients with heart failure and develop a CART (Classification and Regression Tree) model that combines PRISM and modified SHFM.

2. Methods

A retrospective study design was used to examine 1-year mortality for 689 patients admitted with heart failure to a community hospital between January 2012 and December 2014. The study population was derived from the Ann Arbor Metropolitan Area in Michigan, which lies in the Midwestern part of North America. It included patients between the age groups of 18–99 who were admitted to the Internal Medicine service at Saint Joseph Mercy Hospital. Patients with an observation stay in the hospital were excluded. The institution's Quality Institute extracted data electronically using Trinity Health Information delivery stream, billing data from Revenue Solution Warehouse, and one-year mortality data was obtained using data from the Social Security Death Index (SSDI), hospital administrative data, and Michigan Death Index. SHFM predicted mortality was calculated manually from variables extracted from PowerChart for each patient, using the link from the University of Washington (https://depts.washington.edu/shfm/).

PRISM Score includes about 20 routinely available patient parameters such as current or past history of cognitive defects or other neurological deficits, atrial fibrillation, cancer, presence of respiratory failure, heart failure, sepsis or injury during the current admission, medical versus surgical admission and other variables such as age, gender, blood urea nitrogen, white blood count, platelet count, lactate, hemoglobin, albumin, arterial pH, arterial PaO2, troponin and a history of hospitalization within the past year, and discharge to an extended care facility within past year. PRISM does not need all the parameters to be collected for calculating the score, but rather uses whichever variable is available from routine clinical care. The calculator for PRISM score is available in the supplemental material of its original article [15].

The SHFM includes 10 continuous variables (age, left ventricular ejection fraction [LVEF], New York Heart Association [NYHA] class, systolic blood pressure, diuretic dose adjusted for weight, lymphocyte count, hemoglobin, serum sodium, total cholesterol, and uric acid) and 10 categorical variables (gender, ischemic cardiomyopathy, QRS > 0.15 sec, use of beta-blocker [BB], angiotensin-converting enzyme inhibitor [ACEI], angiotensin receptor blockers [ARBs], potassium-sparing diuretic, statins and allopurinol, and ICD, or CRT status in an equation that provides a continuous risk score for each patient. SHFM itself was created using data previously collected from 6 cohorts of patients: one study's data set (PRAISE I) was used to develop the model, and the other 5 were used to validate the model. For missing variables from the data in the validation set, the median values for the covariates in the data set were used. Similarly, for missing values in our study, the median default values in the SHFM calculator were used. As most patients admitted to the hospital are NYHA class III or IV, unclear documentation led to using NYHA class IV as the default value. Because of these substitutions, we have labelled the SHFM score in this study as the modified SHFM score and have incorporated this modified score into the CART model.

Variables collected electronically were age, race, gender, insurance status, BUN, creatinine, co-morbidities, PRISM, and 1-year mortality. Variables collected manually were ejection fraction, systolic blood pressure (SBP) on day of discharge, medications (ACE inhibitors, BB, ARB, aldosterone antagonists, statin, diuretics, and allopurinol), diuretic dose on discharge, lymphocyte percentage, weight on day of discharge, use of devices (biventricular pacer, ICD, or LVAD) and sodium level closest to discharge. Double data abstraction was used for the first 10 charts. The study was approved by the institutional IRB.

2.1. Primary analysis

PRISM scores were used to predict the risk of 1-year mortality for patients with heart failure. PRISM is available as a continuous score labelled Pmort30, which is categorized into an ordinal variable with values ranging from 1 to 5. Both Pmort30 and the ordinal PRISM scores were evaluated as predictors of mortality in different models. SHFM and Pmort30/PRISM score was used to predict risk of 1-year mortality for patients with heart failure. Predicted scores from SHFM, PRISM and, combined SHFM and Pmort30/PRISM scores were validated using AUC.

2.2. Secondary analysis

After the 1-year mortality logistic regression model was analyzed using PRISM, CART models were used to create a decision tool to classify patients based on their mortality risk upon application of PRISM and modified SHFM score. The CART model only uses two variables: the first split of the classification tree was the PRISM (categorical) score, and the second split of the tree was the modified SHFM score. Predictive accuracy of the model was assessed after cross-validation, which was performed by fitting the model to two thirds ($^2/_3$) of the data selected at random and assessing

how well it fit the remaining one third (⅓) of the data. The model was created on the training set, and the accuracy was calculated on the testing set. The fit of the logistic regression models was compared through NRI (Net reclassification Index), IDI (Integrated Discrimination Index) and LRT (Likelihood Ratio Test), which are all measures of discriminative ability of a model. All three measures were reported in this study for the robustness of results.

3. Results

3.1. Primary analysis

The demographic and clinical variables of the heart failure patients in the study sample are summarized in Table 1. Notable aspects of the study population were predominantly white population (85%) with an equal distribution of male and female subjects. Among comorbidities, 28.3% had chronic obstructive pulmonary disease (COPD), 13.9% had cancer, and 32.9% had anemia. The mean age of the population was 74.1 and the average body mass index (BMI) was 31.3 kg per meter square (kg/m^2).

Table 2 summarizes PRISM and modified SHFM scores of the study sample. The first part of the table shows the number and percentage of patients from the study sample in each PRISM category. The second part of the table shows the mean and standard deviation of both PRISM (probability) score and continuous SHFM score. It is noteworthy here that the majority of the sample population was PRISM 2 (31.6%) or 3 (40.6%), and the smallest subset were those of PRISM 5 (0.3%). PRISM 1 was the third biggest category at 16.1%.

Table 3 shows the predicted and actual number, with the percentage in parenthesis, of patients in each PRISM group with respect to one-year mortality. It shows that while mortality prediction for PRISM 1 patients was similar to the actual mortality, one-year mortality prediction for PRISM 2 and 3 categories were under predicted compared to actual one-year mortality. Table 4 shows the mean modified SHFM 1 year mortality percentage prediction for each PRISM group. The predicted one-year mortality for PRISM 1 and 2 patients was 26% and 23% respectively, with progressively lesser mortality percentage as PRISM scores increased.

3.2. PRISM ordinal scale

AUCs for the PRISM (categorical) score, modified SHFM score, and combined PRISM (categorical) and modified SHFM score are shown in Fig. 1. The discriminatory ability of PRISM (categorical) model (AUC = 0.701) was not significantly different (DeLong's test p = 0.56) than the discriminatory ability of modified SHFM (AUC = 0.686). The discriminatory ability of modified SHFM (AUC = 0.686) was significantly lower (DeLong's test p = 0.002) than the discriminatory ability of the combined modified SHFM + PRISM (categorical) score (AUC = 0.740). Results from the NRI (0.649, p < 0.001), IDI (0.0745, p < 0.001), and LRT (Chi-square = 54.7, p < 0.001), all provide evidence to conclude that the addition of the PRISM (categorical) score increases the accuracy of the SHFM score. The discriminatory ability of the combined PRISM (categorical) and SHFM score model (AUC = 0.740) is significantly different (DeLong's test p < 0.001) than that of the PRISM (categorical) model alone (AUC = 0.701). Results from the NRI (NRI = 0.4751, p < 0.001), IDI (IDI = 0.0370, p < 0.001), and LRT (Chi-square = 25.7, p < 0.001) all provide evidence to conclude that the addition of the SHFM score increases the accuracy of the PRISM (categorical) score in predicting 1-year mortality in CHF patients.

Table 1
Demographic and clinical characteristics of study sample.

Categorical Variable	*N (%)*
Gender (Male)	330 (47.9%)
Race (White)	589 (85.5%)
COPD (Yes)	195 (28.3%)
Cancer (Yes)	96 (13.9%)
Anemia (Yes)	227 (32.9%)
Continuous Variable	*Mean (Std. Dev.)*
Age	74.10 years (13.7)
BMI	31.3 kg/m^2 (12.7)
BUN	36.9 (21.9) mg/dL*
Creatinine	1.83 (1.32) mg/dL
Hospital length of stay (LOS)	4.92 (3.49) days
Nadir SBP on index admission	122.30 (21.40) mmHg[1]
SBP on first admission	148.70 (31.80) mmHg

Note: *mg/dl = milligrams per deciliter, [1] mmHg = Millimeters of mercury.

Table 2
PRISM and SHFM scores of study sample.

Variable	
Categorical	*N (%)*
PRISM Score (Categorical) = 1	111 (16.1%)
PRISM Score (Categorical) = 2	218 (31.6%)
PRISM Score (Categorical) = 3	280 (40.6%)
PRISM Score (Categorical) = 4	78 (11.3%)
PRISM Score (Categorical) = 5	2 (0.3%)
Continuous	*Mean (Std. Dev.)*
PRISM Score (Probability)	0.11 (0.12)
Modified SHFM Score	0.21 (0.13)

Table 3
Predicted and Actual 1-Year Mortality by PRISM group, by numbers (N) and percentage (%).

Variable	**Predicted 1-Year Mortality**	**Actual 1-Year Mortality**	**p-value**
	N (%)	*N (%)*	
PRISM Score (Categorical) = 1	71 (64.5%)	58 (52.7%)	0.076
PRISM Score (Categorical) = 2	19 (8.7%)	83 (38.1%)	<0.001
PRISM Score (Categorical) = 3	5 (1.8%)	48 (17.1%)	<0.001
PRISM Score (Categorical) = 4	0 (0.0%)	6 (7.8%)	0.013
PRISM Score (Categorical) = 5	0 (0.0%)	0 (0.0%)	–
All PRISM Groups	95 (13.8%)	195 (28.4%)	<0.001

Table 4
Mean modified SHFM percentage score for patients in each PRISM group.

PRISM Score	SHFM Percentage (Mean (SD))
1	26 (14)
2	23 (12)
3	20 (13)
4	14 (8)
5	11 (6)

3.3. PRISM (Probability Scale)

Similar results are found when repeating this analysis with the probability version of the PRISM score. AUC for the PRISM (probability) score, modified SHFM score, and the combined PRISM (probability) and modified SHFM score are shown in Fig. 2. The discriminatory ability of the PRISM (probability) group (AUC = 0.736) was not significantly different (DeLong's test p = 0.052) than the discriminatory ability of the modified SHFM (AUC = 0.686). The discriminatory ability of the modified SHFM (AUC = 0.686) was significantly lower (DeLong's test p = 0.002) than the discriminatory ability of the combined modified SHFM + PRISM (probability) scores (AUC = 0.749). Results from

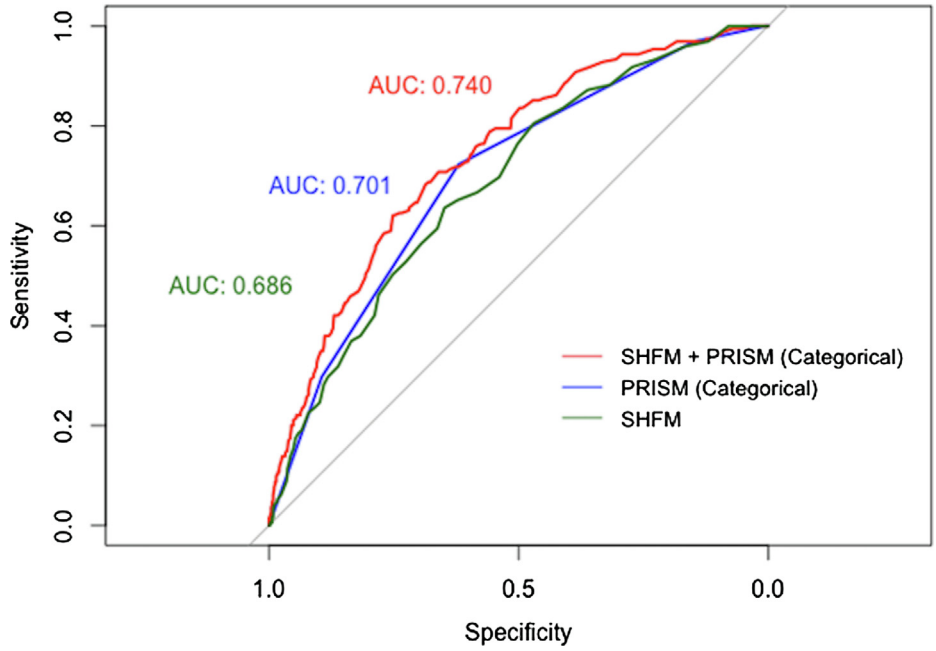

Fig. 1. AUC curves for PRISM (categorical) model, SHFM score model, and combined PRISM (categorical) and SHFM score model.

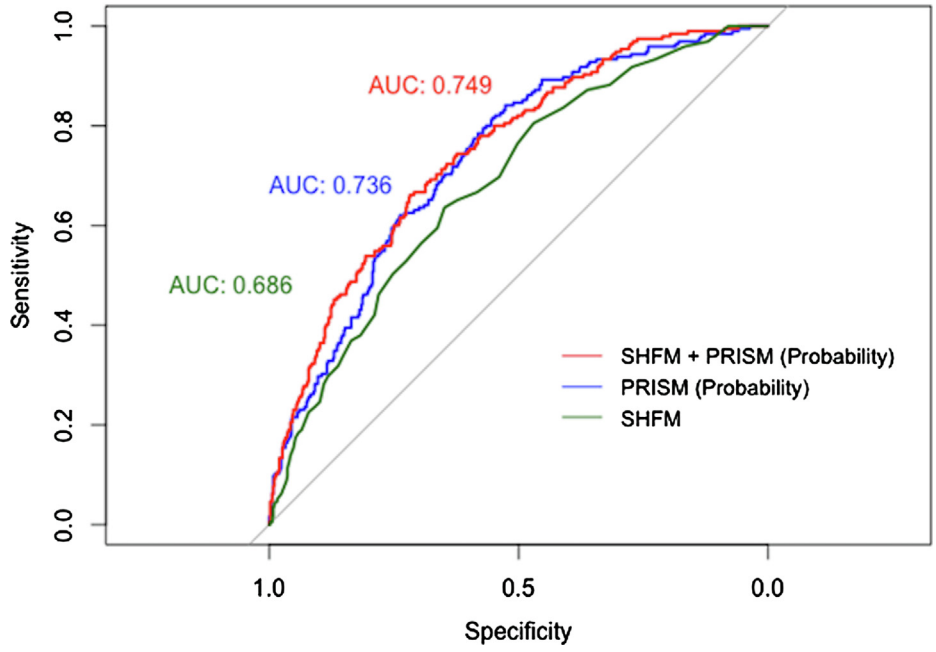

Fig. 2. ROC curves for PRISM (probability) model, modified SHFM score model and combined PRISM (probability) and modified SHFM score model.

the NRI (0.505, $p < 0.001$), IDI (0.079, $p < 0.001$), and LRT (Chi-square = 53.9, $p < 0.001$), all showed that the addition of PRISM (probability) score increased accuracy of the modified SHFM score.

3.4. Secondary analysis

To help identify patients who would be appropriate for consultation by palliative care, a first CART classification tree was developed with PRISM (categorical) as the main decision trunk and modified SHFM score as the next branch. This tree is visualized in Fig. 3. For cross-validation, the model was fit on two-thirds of the sample and was tested on the remaining one-third of the original sample. After cross-validation, the out-of-sample predictive accuracy of the CART model was 72.2%, and the out-of-sample AUC was 0.631. Results from the CART model show that at the top node, all heart failure patients have a 72% probability of 1-year survival (28% one-year mortality). A heart failure patient with PRISM (categorical) score of 3, 4, or 5 had an 84% probability of 1-year survival (16% mortality). On the other hand, a heart failure patient with a PRISM (categorical) score of 1 or 2 had 57% probability of 1-year survival (43% mortality rate), which dropped further to a survival of 43% (57% mortality) with the addition of modified SHFM score<23.

The clinical characteristics of patients in the left-most arm of the CART tree are shown in Table 5. These were patients with a PRISM score of 1 or 2 and had>23% predicted 1-year mortality rate

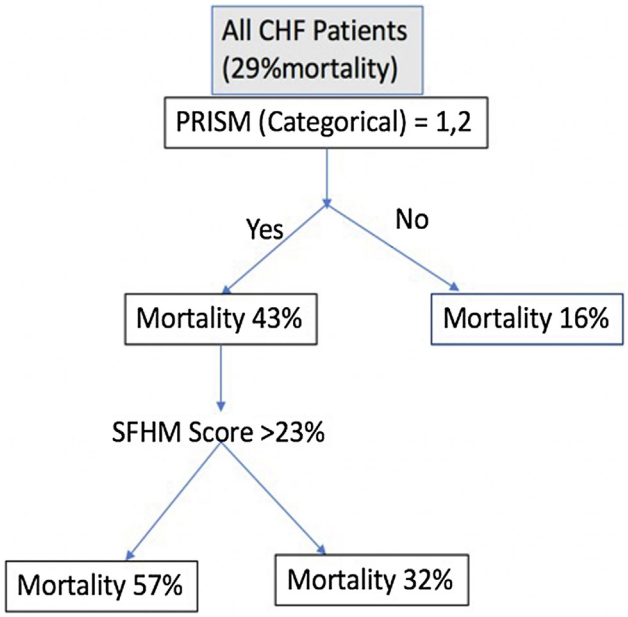

Fig. 3. Classification tree with PRISM (categorical) score as the main trunk, and modified SHFM score as the second branch.

by SHFM. The mean age was 81.32 years, most of the patients were white (92.68%), and 42.68% of them were male. About a third of them had COPD, and about 23.17% and 49.39% had cancer and anemia, respectively. The mean hospital length of stay for this subset of the population was about five days.

Upon the addition of PRISM to SHFM, three patients were correctly classified as alive at one year (Table 6). These included one male and two female patients, and the mean age of the patients was 76.33 years. One of the patients had cancer, and none of them had COPD or anemia. However, thirty-nine patients were correctly reclassified as dead at one year, when PRISM score was added to SHFM as compared to utilizing modified SHFM alone for mortality prediction. The clinical characteristics of these patients have been summarized in Table 7. Interestingly, among these patients, 48.72% had COPD, 35.9% had cancer, and 48.2% had anemia.

4. Discussion

Our retrospective pragmatic study was an attempt at developing a tool for triaging heart failure patients who would benefit from palliative care consult. At our hospital where the study was conducted, all inpatients have a PRISM score calculated in the Emergency Department itself. All patients with a PRISM score of 1, regardless of the underlying reason for admission, had their goals of care discussed with a palliative care team professional. With this practice, all patients with a PRISM score of 1, which predicts the subgroup of patients at high risk for mortality and 30-day readmission, are given an opportunity for their wishes to be heard regarding the intensity and location for ongoing care. A patient may fall into the PRISM 1 category because of any significant comorbidity they might have, which need not necessarily be heart failure. In this study, we sought to see how this disease nonspecific stratification score performed particularly in heart failure patients by comparing it with modified SHFM, which is a modification of a standard risk stratification tool used in heart failure patients.

Our study is interesting in that PRISM score performed as well as 'modified SHFM,' though we used a default value of NYHA class IV while calculating one-year mortality using the 'original SFHM' calculator. This modification might have been over predicted mortality for some of the patients who might have been class III.

The CART model developed utilizing both the PRISM score and modified SHFM can help stratify patients into mortality risk groups. By initially applying PRISM score to patients with heart failure, those with PRISM 1 and 2 scores are identified. These patients would belong to the set of the population with a 43% mortality rate. On applying the modified SFMH score to this subset, patients with SHFM score < 23 would fall in 32% mortality group and those with SHFM score > 23 who would fall into 57% mortality

Table 5
Clinical Characteristics of Patients in the leftmost arm of the CART Tree with highest mortality (N = 164).

Variable	Statistics
Categorical Variables	N (%)
Gender (Male)	70 (42.68%)
Race (White)	152 (92.68%)
COPD (Yes)	54 (32.93%)
Cancer (Yes)	38 (23.17%)
Anemia (Yes)	81 (49.39%)
Continuous Variables	Mean (SD)
Age	81.32 (9.17)
BMI	28.41 (8.63)
BUN	46.09 (27.2)
SBP on first admission	142.03 (29.22)
Hospital LOS	5.46 (3.62)
Creatinine	2.18 (1.66)
Nadir SBP on first admission	112.95 (21.84)

Table 6
Clinical Characteristics of patients that were correctly reclassified as 'Alive' at 1 Year (N = 3) when PRISM score was added to SHFM score.

Categorical Variables	N (%)
Number of Patients	3 (100%)
Gender (Male)	1 (33.3%)
Race (White)	3 (100%)
COPD	0 (0.0%)
Cancer (Yes)	1 (33.3%)
Anemia (Yes)	0 (0.0%)
Continuous Variables	Mean (SD)
Age in years	76.33 (10.69)
BMI in kg/m^2	28.77 (9.9)
BUN in mg/dl	31.33 (16.29)
SBP on first admission mm/Hg	135 (15.56)
Hospital LOS in days	7.33 (2.89)
Creatinine in mg/dl	1.22 (0.12)
Nadir SBP on first admission in mm/Hg	96 (6.56)

Table 7
Clinical Characteristics of patients that were correctly reclassified as 'Dead' at 1 Year (N = 39) when PRISM score was added to SHFM score, as compared to SHFM score alone.

Variable	Statistics
Categorical Variables	N (%)
Number of Patients	39 (100%)
Gender (Male)	19 (48.7%)
Race (White)	36 (92.3%)
COPD	19 (48.7%)
Cancer (Yes)	14 (35.9%)
Anemia (Yes)	19 (48.7%)
Continuous Variables	Mean (SD)
Age	85.38 (9.62)
BMI	26.79 (8.82) kg/m^2
BUN	56.56 (35.29) mg/dL
SBP on first admission	133.92 (21.5) mmHg
Hospital LOS	5.36 (4.11) days
Creatinine	2.68 (2.3) mg/dL
Nadir SBP on first admission	114.1 (26.38) mmHg

group. The CART model pertains to population mortality and cannot be used on an individual patient basis. By identifying the population set a patient belongs to, it can guide further management decisions such as palliative care consult when a patient belongs to a higher mortality subgroup despite having a similar functional class. This could help the involvement of palliative care for patients based on their overall higher mortality rate and help with the efficient utilization of resources. The decision to obtain Palliative Care Input should be left to the individual treating physician.

The 2013 ACC (American College of cardiology)/AHA guidelines recommend incorporating palliative care in the care of patients with heart disease, which entails providing patients with access to continuous, comprehensive, coordinated, high-quality palliative care while simultaneously providing specialist care [2]. It has been included as a class Ib recommendation to improve the quality of life in patients with advanced symptomatic disease [2]. However, a lot of factors have contributed to the underutilization of palliative care in this patient population, ranging from uncertainty in the disease trajectory, poor communication, lack of knowledge, and complex treatment decisions such as ICD implantation and deactivation, LVADs and heart transplant. A survey including cardiologists and primary care providers showed that many did not know the difference between palliative care and hospice, neither were they aware of the eligibility criteria for these services [20]. Patients with heart failure may choose either continuing care at the same level, escalation of care to VADs and transplant, or a treatment plan that enhances the quality of life by reducing readmissions and spending more time with family in their home setting.

A major barrier in involving palliative care in the management of patients with heart failure is its unpredictable trajectory with periods of stability interspersed by exacerbations, which can lead to sudden decompensation and at times, irreversible pump failure. To help with prognosis, a few mortality prediction tools have been developed over the last three decades to aid physicians in prognostication of heart failure patients to guide pharmacologic interventions and device implantations. The first of its kind was Heart Failure Survival Score (HFSS) [21], and years later, SHFM was developed, which included device therapy in its parameters.

HFSS and SHFM are the only two scores that have been evaluated to guide heart transplant listing [22]. A study has shown that the HFSS model and SHFM underestimate the risk, while the newer scores such as MAGGIC (Meta-analysis Global Group in Chronic Heart Failure) and MECKI (Metabolic Exercise Cardiac Kidney Index) overestimate the risk [23]. However, the MECKI score was shown to have a better discriminatory capability even for guiding heart transplant listing [23]. However, scores such as MECKI and HFSS require VO2 testing, unlike SHFM. Interestingly the addition of VO2 to SHFM has shown to improve its discriminatory capability [24].

Both PRISM score and SHFM do not require VO2 testing, unlike the HFSS and MECKI scores. They have some overlapping parameters; the major differences between the two scores include lack of medications and cardiac devices among PRISM score parameters and non-inclusion of neurological status or recent hospitalization in SHFM. Although the AUC for PRISM was higher than that for modified SHFM, the lack of significant P-value refutes a clear superiority of one score over the other. While inadequate power could have potentially contributed to this finding, the addition of PRISM to modified SHFM had improved the predictability of modified SFMH. It is possible that the increased predictive capability could be due to the addition of other comorbidities such as COPD, cancer, and neurological status, which are absent in SHFM. LACE score is a tool widely used to predict readmissions in heart failure patients. A recent study has shown that the addition of abnormal mini cog to a high LACE was a better prediction tool for 30 day readmissions [25], which potentially underscores the role of cognitive deficits in heart failure prognosis. However, it is hard to make a definite statement regarding the relevance of cognitive status without matching for other confounding factors.

The limitations of this study were that it is a retrospective observational study and a single-center experience. The study might not be generalizable to all races, as most of our population was Caucasian (85.5%). We had to use a NYHA score of IV during our calculations as it was difficult to ascertain retrospectively whether patients were class III or class IV. Besides, we used default values in the SHFM calculator as a substitute for any missing lab values, and we do not know by what percentage the missing values in our study differed from the study population on which original SHFM was developed. There was a significant overlap in conditions included in the PRISM score and SHFM, but a direct comparison of each of the non-overlapping factors is required to identify factors that play a key role in providing a prognostic advantage. While SHFM is typically applied to heart failure clinic and ambulatory patients, which potentially could have lowered SHFM's predictive capability in the hospitalized patients, we used values at the time of discharge to evaluate patients ready to be discharged to an ambulatory setting. PRISM has been previously validated for predicting 30 day and 6-month mortality, but not for one-year mortality.

5. In conclusion

Our study shows that PRISM, a disease nonspecific mortality prediction score, performs as well as the more heart failure specific modified SHFM. We also developed a risk stratification tool to identify patients who are at higher mortality risk and hence benefit from palliative care consultation. By applying such a stratification tool during hospital admission for heart failure, we can efficiently use palliative care resources for the highest risk patients. This could help develop a plan that respects the patient's wishes, whether it is to continue the current course of treatment, escalate care to treatments such as VADs or heart transplant in those who chose to seek more aggressive management or pave the way for advance planning to limit hospitalizations. Quality of life could be potentially increased by seeking care at home for those who seek to limit interventions in their care.

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