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Title: A novel, highly discriminatory risk model predicting acute severe right ventricular failure in patients undergoing continuous-flow left ventricular assist device implant

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Abstract

Background: Various risk models with differing discriminatory power and predictive accuracy have been used to predict right ventricular failure (RVF) after left ventricular assist device (LVAD) placement. There remains an unmet need for a contemporary risk score for continuous flow (CF)-LVADs. We sought to independently validate and compare existing risk models in a large cohort of patients and develop a simple, yet highly predictive risk score for acute, severe RVF.

Methods: Data from the Mechanical Circulatory Support Research Network (MCSRN) registry, consisting of patients who underwent CF-LVAD implantation, were randomly divided into equal-sized derivation and validation samples. RVF scores were calculated for the entire sample, and the need for a right ventricular assist device (RVAD) was the primary endpoint. Candidate predictors from the derivation sample were subjected to backward stepwise logistic regression until the model with lowest Akaike information criterion value was identified. A risk score was developed based on the identified variables and their respective regression coefficients.

Results: Between May 2004 and September 2014, 734 patients underwent implantation of CF-LVADs [HeartMate II LVAD, 76% (n=560), HeartWare HVAD, 24% (n=174)]. A RVAD was required in 4.5% (n=33) of patients [Derivation cohort, n=15 (4.3%); Validation cohort, n=18 (5.2%); p=0.68)]. 19.5% of the patients (n=143) were female, median age at implant was 59 years (IQR, 49.4 - 65.3), and median INTERMACS profile was 3 (IQR, 2-3). RVAD was required in 4.5% (n=33) patients. Correlates of acute, severe RVF in the final model included heart rate, albumin, BUN, WBC, cardiac index, and TR severity. AUCs for most commonly used risk predictors ranged from 0.61 to 0.78. The AUC for the new model was 0.89 in the derivation and 0.92 in the validation cohort.

Conclusion: The proposed RVF risks model provides very high discriminatory power when compared to the prior risks scores and can be reliably applied to patients undergoing placement of a CF-LVADs.

Introduction

Development of right ventricular failure (RVF) after continuous-flow left ventricular assist device (CF-LVAD) implantation remains a leading cause of perioperative morbidity, end-organ

dysfunction and mortality. [1–3]. Consequently, several risk scores and indices have been reported as useful predictors for development of RVF following LVAD implantation[1,4–10]. Most have been developed based on the experience of single institutions and small numbers of patients (Table 1). With improved predictive capabilities, patients at high-risk for RVF can be pre-identified in the pre-operative period and a strategy of short-term support with a temporary right ventricular assist device (RVAD) has been shown to reduce perioperative morbidity, mortality and reduce hospital length of stay[11].

However, many risk scores were derived from populations treated with pulsatile LVADs that are no longer used in clinical practice and the outcome of RVF is variably defined. There is currently no RVF risk score that is uniformly accepted. As such, there is a need for developing and validating a contemporary risk score in a large multicenter patient cohort that focuses on current generation CF-LVADs.

Methods

A collaborative multi-institutional retrospective analysis of all primary CF-LVAD implanted as part of the Mechanical Circulatory Support Research Network (MCSRN) database was conducted. MCSRN is a prospectively collected retrospective database run by a dedicated long-term data manager using REDCap platform, who coordinated data entry at each member site. At the time of this project's performance MCRN consisted of data from Mayo Clinic, University of Michigan, and Vanderbilt University. Acute severe RV failure was defined as need for RVAD support within the index CF-LVAD hospital stay. RVAD support included all temporary and durable right-sided devices. Data used as input variables were acquired from patients' preoperative workup, including preoperative laboratory workup, echocardiograms, and cardiac catheterization.

The MCSRN dataset was divided randomly into two equal samples (n=367 each). The derivation cohort was used for MCSRN RVF risk model development, while a validation cohort for its validation. The MCSRN RVF Risk Score was developed using preimplant data from

derivation cohort. With the goal to maximally utilize the continuous data, dichotomization into categorical variables was avoided when developing the new risk model. Instead, logarithmic data transformation was utilized as needed for continuous data with skewed distribution and highly variable absolute ranges.

Candidate variables for the MCSRN RVF risks score included preoperative patient characteristics and demographics (age, gender, race, height, body mass index, body surface area, heart failure etiology, device indication), comorbidities (atrial fibrillation, hypertension, diabetes, dialysis-dependent renal failure), preoperative clinical status (intubated, intraaortic balloon pump, INTERMACS profile), preoperative laboratory (serum creatinine level, serum total bilirubin, aspartate aminotransferase, alanine aminotransferase, albumin, brain natriuretic peptide, hemoglobin, white blood cell count, platelet count, international normalized ratio), cardiopulmonary hemodynamics (preoperative heart rate, mean arterial pressure, central venous pressure, systolic pulmonary artery pressure, pulmonary capillary wedge pressure, cardiac index), echocardiographic (left ventricular ejection fraction, left ventricular end diastolic diameter, mitral regurgitation grade, tricuspid regurgitation grade, right ventricular dysfunction severity) variables (For regurgitation severity, 0=none, 0.5=trace, 1= mild, 1.5= mild to moderate, 2=moderate, 2.5=moderate to severe, 3=severe).

The MSCRN RVF Risks Score was compared to commonly used RVF predictor scores and indices, including the ones not reported in the literature for this purpose [central venous pressure to pulmonary capillary wedge pressure ratio (CVP/PCWP), model for end-stage liver disease (MELD)]. A nested cohort was used to allow comparative analyses of predictor models.

Statistical Analyses:

R statistical software, version 3.2.3 (R Foundation for Statistical Computing, Vienna, Austria) was used for data analysis and visualization. For continuous variables, median with interquartile range (IQR) was used given significant deviation from normality ($p < 0.05$, Shapiro-Wilk test). Categorical data were presented as percentages and analyzed using the chi-square test. Numeric values of the severity of valve regurgitation were treated as ranks on the ordinal scale.

Continuous variables were compared using Wilcoxon rank-sum test, while categorical variables were analyzed using chi-square test.

Candidate predictors for the MCSRN RVF risk model were entered into the model development process and subjected to backward stepwise logistic regression based on Akaike Information Criterion (AIC)[12]. First, highly correlated data in the same category (e.g., systolic, diastolic, and mean PA pressure values) were subjected to regression based on lowest AIC value to eliminate all but most promising variables prior to entering them into the model development process. Baseline variables were then entered into the backward stepwise logistic regression process. The baseline variables entered into the analysis are provided in Table 2. Each time, 8 to 12 variables were entered into the stepwise regression process to avoid overfitting the model. Lowest AIC level was used to identify the best fitting model. Calibration of the model was assessed using Hosmer-Lemeshow goodness of fit test. Odds of RVF development were assessed in a continuous manner using restricted cubic splines analysis.

Based on the variables in the final model and their respective regression coefficients developed from the derivation cohort, a novel risk score termed the MCSRN RVF Risk Score, was developed. The risk score was tested on the validation cohort to assess its validity and calibration.

Receiver operating characteristic (ROC) analysis was used to derive areas under the curve (AUC) for assessing the discriminatory power of the risk models (including the MCSRN RV Failure Risk Model), and to identify the optimal cutoff level between sensitivity and specificity of the novel risk score. DeLong's test[13] was used for statistical comparison of ROC curves.

For all analysis (except where mentioned), a $p < 0.05$ was considered statistically significant. Local IRB approval was granted for data analysis as part of the MCSRN.

Results

Between May 2004 and September 2014, 734 patients underwent implantation of CF-LVADs [HeartMate II LVAD, 76% (n=560), HeartWare HVAD, 24% (n=174)]. 19.5% of the patients (n=143) were female, median age at implant was 59 years (IQR, 49.4 - 65.3), and median INTERMACS profile was 3 (IQR, 2-3). RVAD was required in 4.5% (n=33) patients [Derivation sample, n=15 (4.3%); validation sample, n=18 (5.2%); p = 0.68]. Patient demographics and baseline clinical characteristics for each group as well as the entire sample are shown in table 2.

Derivation of the MCSRN RVF Risk Score

The candidate variables were entered into multivariable regression. The following variables were identified as correlates of RVF in the derivation cohort: Heart rate, WBC count, albumin level, BUN level, cardiac index, and the numeric value of the severity of tricuspid valve regurgitation (Table 3). Using regression coefficients in the final model as respective weights of these variables, following formula was created to provide the numeric risk score (please refer to the online supplement for the Excel-based risk score calculator):

4.2944 * *log*(HR) - 4.4917 * *log*(Albumin) + 1.2029 * *log*(BUN) + 1.0599 * *log*(WBC) - 1.0364 * *log*(CI) + 0.8213 * numeric TR severity

The numeric values of the MCSRN RVF risk model ranged from 14.5 to 26.9 and was normally distributed (p=0.2, Shapiro-Wilk test) with mean value of 20.2±1.8. The area under the curve was 0.86 (95% CI, 0.74 - 0.99) for the derivation cohort and 0.92 (95% CI 0.85 - 0.99) for the validation cohort indicating very good discriminatory power. The area under the curve for the entire sample was 0.89 (95% CI 0.82 - 0.96) (Figure 1). Continuous analysis showed exponential increase of odds ratio of requiring an RVAD with increasing risk score numbers (p<0.001) (Figure 2). Hosmer-Lemeshow test was consistent with good calibration (derivation sample, p = 0.45; validation sample, p = 0.57, entire sample, p = 0.17)

Based on the ROC analysis of the entire patient sample, the cutoff level of 21.9 yielded the optimal balance between the sensitivity (88.4%) and the specificity (78.3%). Resulting positive predictive value was 98.8%, and negative predictive value 25.7%. For clinical simplicity, patients can be stratified into a low, intermediate and high risk group using the thresholds 20 and 22, where the incidence of an RVAD was 78% above the cutoff of 22, it was 4% below the cutoff of 20.

Comparison of RVF risk scores

AUCs for most commonly used RVF risk predictors as calculated by us ranged from poor (AUC 0.60-0.69) to satisfactory (AUC 0.70-0.79): pulmonary artery pulsatility index (PAPI) (AUC 0.78), central venous pressure-RV dysfunction-preoperative intubation-severe tricuspid regurgitation-tachycardia (CRITT) (AUC 0.74), right ventricle to left ventricle (RV/LV) ratio (AUC 0.71), RV stroke work index (RVSWI) (AUC 0.71), tricuspid annular plane systolic excursion (TAPSE) (AUC 0.70), MELD (AUC 0.69), CVP/PCWP ratio (AUC 0.68), Severe TR (AUC 0.67), HMII RVF score (AUC 0.64), and Michigan score (AUC 0.61). On AUC comparison, the MCSRN RVF Risk Score performed better than other scores tested (Table 4, Figure 3).

Discussion

Out of the commonly used risk models for RVF in CF-LVAD patients, none of them have been developed with a contemporary patient population. We were not able to identify an existing model with strong performance (AUC 0.80-0.89) to predict acute severe RVF requiring RVAD after CF-LVAD implantation. In contrast, the AUC for our risk model reached 0.89 for the entire sample and there was no drop in AUC from derivation (AUC 0.86) to validation (AUC 0.92) cohorts, indicating a strong performance. We chose to use a RVAD as primary outcome due to

varying definitions of RVF at our institutions, many of which are dependent on institutional practice variation in management of inotropes or nitric oxide after CF-LVAD as opposed to an RVAD which is only employed in the sickest cohort of patients with acute severe RVF.

Variables identified to predict RV failure after LVAD placement vary widely[1,9,10,14,15] and reflect the complexity in the multifactorial mechanism of the RV failure onset. While no single best predictor variable has been identified, some form of RV hemodynamics[9,10,16] or tricuspid valve function[6,8] surrogates are most commonly used alone[6,8–10,16] or as part of a predictive risk score[1,4]. Additional variables reflective of renal[1,7] and liver[7,17] function have commonly been factored in the prediction process, however are not used alone. Heart rate and cardiac index represent hemodynamic variables that are not specific for the RV function and, to a degree, it is surprising to find them in the final model since they can be altered significantly with different interventions. However, other predictive risk models have used these variables as well[4,18]. WBC count has also been identified among the variables associated with RV failure in CF LVAD patients[1,4] and may be reflective of a systemic component of the disease, or a sicker patient. An important part of our risk model development process that (to the best of our knowledge) has not been employed in deriving other risk models is not dichotomizing continuous data. This, while imposing additional steps (like logarithmic data transformation) on the process, is more likely to retain the predictive strength both in individual variables and the combined model.

While dichotomization of continuous variables should be avoided, cutoff values for the continuous scale can be helpful to aid the physician in the decision process, hence, the need for identifying an optimal cutoff that minimizes the compromise between the sensitivity and the specificity. The cutoff level of approximately 22 resulted in good sensitivity (88.4%) and fair specificity (78.3%). While negative predictive value was poor (25.7%), positive predictive value at this cutoff was excellent (98.8%). Although, the negative predictive value was low, the positive predictive value of the model makes it a very useful tool to identify high-risk patients in the pre-operative period who would benefit from a temporary or permanent right ventricular assist device to mitigate perioperative morbidity and mortality. As well, it may be helpful to

identify "less ideal" candidates for LVAD, especially those who are being considered DT LVAD. The numeric value of the model can be of additional use since the further it deviates from the cutoff, the more likely the positive or negative outcome becomes, further aiding the clinician in the decision-making.

In medicine, despite many prognostic models that are published each year, relatively few are validated and even fewer find their way into clinical practice[19]. This is true for RVF risk models as well. Deriving and validating a model on the same dataset leads to overly optimistic estimates of the model's accuracy, even if the dataset is divided into two separate parts for model derivation and validation[19]. This is because "quirks" individual to a dataset will also occur in both the derivation and validation samples that are derived from the same dataset and may lead to optimistic estimates of prognostic power[20]. Therefore, existing risk scores performed worse using an independent sample set when compared to the dataset used for its development. This effect, however, is even more prominent with smaller, single-institution samples that will allow higher variation. Our risk model still needs validation in an external dataset.

Study limitations

Even though the analysis was performed using a multiinstitutional registry, both patient samples (derivation and validation) stem from the same data and therefore display similar comorbidities and intervention patterns. In addition, there may be similar unidentified confounders in both samples that was not picked up by the analysis and may pose a risk of systemic bias. Because of these reasons, this "split-sample validation" can be overly optimistic and our results should be interpreted with caution.

Our model has six variables. A generally recommended number of predictor variables in a model is one variable per 10 to 20 events. Since we only had 15 outcome events, we were not able to follow this recommendation. Otherwise, the low number of RVAD events would not leave us with any model at all. On the other hand, the more candidate variables there are in the model, the

more opportunity there is for some of those variables to end up in the model purely by chance. This is possible for our model as well, however we used AIC to mitigate the problem (since AIC rewards for significance while punishing for higher number of predictor variables).

We chose RVAD implant as the endpoint for the risk model as it was a hard endpoint, not influenced by local or institutional practices. One obvious downside is that RVAD is a rare event. With just RVAD as an endpoint, the model may not fully encompass risk stratification of a much larger group of patients who with RV failure without need for RVAD and, as such, may lack in generalizability. On the other hand, the strength of the model is that it produces a numeric score where higher values should intuitively mean higher risk for RV failure, even without an RVAD.

In summary, the present model should be considered as an exploratory tool rather than a validated risk score due to low rate of events in both groups. To control for these potential confounders and demonstrate such a generalizability, a rigorous external validation process by other authors is required.

Conclusions

To conclude, the proposed RVF MCSRN risk score provides the highest-to-date discriminatory power with an AUC of 0.89 which favors comparably to already published models. The risk score is applicable to a contemporary patients implanted with a CF-LVADs. After appropriate validation, the risk score may be used to identify patients at very high-risk for severe RVF after LVAD who would benefit from either a temporary or permanent RVAD.

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Table 1: Studies reporting predictors of RVF after LVAD implantation. CRITT, central venous pressure-RV dysfunction-preoperative intubation-severe tricuspid regurgitation-tachycardia; PAPI, pulmonary artery pulsatility index; TAPSE, tricuspid annular plane systolic excursion; RVSWI, RV stroke work index.

Author	Year	Location	Index/score reported	Number of patients	LVAD types	Number of institutions	Primary outcome	Reported AUC
Atluri[4]	2013	Philadelphia	CRITT	218	Pulsatile and CF-LVAD	Single	Need for RVAD	0.8
Morine[16]	2013	Boston	PAPI	104	CF-LVAD	Single	Need for RVAD or > 14 of inotropic dependence	NA
Kormos[1]	2010	Pittsburgh	HMII RV Failure SCore	484	CF-LVAD	Multi	Need for RVAD, at least 14 days of continuous inotropic support after implantation, or late inotropic support starting after the 14th day	0.68
Potapov[6]	2008	Berlin	Severe TR (III-IV)	54	Pulsatile and CF-LVAD	Single	Two of the following criteria within the first 48 hours after surgery: MAP <55 mm Hg, CVP >16 mm Hg, MVO2 <55%, CI <2 liters/min/m2, inotropic support >20 units.	NA

Matthews[7]	2008	Ann Arbor	Michigan score	197	Pulsatile and CF-LVAD	Single	Need for inotrope support for 14 days, inhaled nitric oxide for 48 h, RVAD, or discharge on an inotrope	0.73
Puwanant[8]	2008	Gainesville	TAPSE	34	Pulsatile and CF-LVAD	Single	Need for inotropic support or pulmonary vasodilators for ≥14 days postoperatively	0.81
Ochiai[9]	2002	Cleveland	RVSWI	245	Pulsatile	Single	Need for RVAD	NA
Fukamachi[10]	1999	Cleveland	RVSWI	100	Pulsatile	Single	Need for RVAD	NA

Table 2: Baseline patient characteristics. BMI, body mass index; BSA, body surface area; HTN, hypertension; IABP, intraaortic balloon pump; BUN, blood urea nitrogen; eGFR, estimated glomerular filtration rate; AST, aspartate aminotransferase; ALT, alanine aminotransferase; BNP, brain natriuretic peptide; WBC, white blood cell count; INR, international normalized ratio; PCWP, pulmonary capillary wedge pressure; RVSWI, right ventricular stroke work index; LVEF, left ventricular ejection fraction; RVEDD, right ventricular end diastolic dimension; LVEDD, left ventricular end diastolic dimension; LVESD, left ventricular end systolic dimension; MR, mitral regurgitation; TR, tricuspid regurgitation.

Variable	**Derivation (n=367)**	**Validation (n=367)**	**Total (n=734)**	**p-value**
Patient demographics and comorbidities				
Age, median [IQR]	58.5 [48.1, 65.0]	60.0 [50.2, 65.8]	59.1 [49.4, 65.3]	0.05
Female (%)	80 (21.8)	63 (17.2)	143 (19.5)	0.14
BMI, median [IQR]	28.5 [24.6, 33.0]	28.0 [24.0, 32.0]	28.3 [24.3, 32.6]	0.22
BSA, median [IQR]	2.0 [1.9, 2.2]	2.0 [1.9, 2.2]	2.0 [1.9, 2.2]	0.46
Ischemic etiology (%)	174 (47.5)	186 (51.4)	360 (49.5)	0.34
Bridge to transplant (%)	211 (57.5)	225 (61.5)	436 (59.5)	
Atrial fibrillation (%)	141 (38.4)	128 (35.0)	269 (36.7)	0.37
HTN (%)	178 (48.5)	186 (50.8)	364 (49.7)	0.58
Diabetes (%)	106 (29.4)	146 (40.1)	252 (34.8)	0.00
Dialysis (%)	8 (2.2)	5 (1.4)	13 (1.8)	0.58
Preoperative variables				
Intubated preoperatively (%)	8 (3.8)	10 (4.9)	18 (4.4)	0.75

Preoperative Inotropic support (%)	269 (73.7)	285 (78.1)	554 (75.9)	0.19
Preoperative Vasopressors (%)	80 (38.1)	73 (36.0)	153 (37.0)	0.73
Preoperative IABP (%)	165 (45.6)	163 (44.9)	328 (45.2)	0.91
Temporary cardiac support bridge (%)	27 (11.2)	23 (8.8)	50 (10.0)	0.46
INTERMACS profile, median [IQR]	3.0 [2.0, 3.5]	3.0 [2.0, 3.0]	3.0 [2.0, 3.0]	0.76
Device type				
HeartMate II LVAD (%)	282 (76.8)	278 (75.7)	560 (76.3)	
HeartWare HVAD (%)	85 (23.2)	89 (24.3)	174 (23.7)	0.79
Reoperative sternotomy (%)	115 (31.3)	123 (33.7)	238 (32.5)	0.55
Preoperative laboratory variables				
BUN, median [IQR]	25.0 [19.0, 36.0]	27.0 [19.0, 39.0]	26.0 [19.0, 37.0]	0.16
Creatinine, median [IQR]	1.3 [1.0, 1.6]	1.3 [1.1, 1.6]	1.3 [1.1, 1.6]	0.30
eGFR, median [IQR]	54.0 [41.0, 60.0]	53.0 [41.6, 60.0]	54.0 [41.0, 60.0]	0.73
AST, median [IQR]	31.0 [24.0, 49.0]	31.0 [25.0, 46.0]	31.0 [24.0, 47.0]	0.75
ALT, median [IQR]	29.0 [19.0, 50.0]	30.0 [20.0, 47.5]	30.0 [20.0, 49.0]	1.00
Total bilirubin, median [IQR]	1.0 [0.7, 1.6]	1.0 [0.7, 1.5]	1.0 [0.7, 1.5]	0.32
Albumin, median [IQR]	3.7 [3.4, 4.1]	3.8 [3.3, 4.0]	3.7 [3.4, 4.0]	0.64
BNP, median [IQR]	764.0 [373.8, 1310.8]	652.0 [289.5, 1196.2]	698.0 [325.5, 1284.5]	0.08
WBC, median [IQR]	7.9 [6.1, 9.9]	7.8 [6.3, 9.6]	7.9 [6.2, 9.8]	0.85
INR, median [IQR]	1.2 [1.1, 1.4]	1.2 [1.1, 1.4]	1.2 [1.1, 1.4]	0.54
Preoperative hemodynamics				

Heart rate, median [IQR]	80.0 [70.0, 95.0]	80.0 [71.0, 93.5]	80.0 [70.0, 94.2]	0.55
Systolic PA presure, median [IQR]	47.0 [39.0, 58.0]	46.0 [38.0, 58.0]	47.0 [38.0, 58.0]	0.71
Diastolic PA pressure, median [IQR]	23.0 [16.0, 29.0]	23.0 [18.0, 28.0]	23.0 [18.0, 28.0]	0.86
Median PA pressure, median [IQR]	33.0 [27.0, 41.0]	33.0 [28.0, 39.0]	33.0 [27.0, 40.0]	0.69
PCWP, median [IQR]	22.0 [15.2, 26.0]	22.0 [16.0, 26.0]	22.0 [16.0, 26.0]	0.60
Cardiac output, median [IQR]	4.4 [3.5, 5.2]	4.1 [3.4, 5.0]	4.3 [3.4, 5.2]	0.02
Cardiac index, median [IQR]	2.1 [1.8, 2.5]	2.1 [1.7, 2.5]	2.1 [1.7, 2.5]	0.06
RVSWI, median [IQR]	508.0 [367.8, 715.5]	492.0 [326.0, 660.0]	504.0 [341.7, 690.0]	0.12
Echicardiographic parameters				
LVEF, median [IQR]	15.0 [10.0, 20.0]	15.0 [11.0, 20.0]	15.0 [10.0, 20.0]	0.95
RVEDD, median [IQR]	3.2 [2.9, 3.9]	3.4 [3.0, 3.7]	3.4 [3.0, 3.7]	0.61
LVEDD, median [IQR]	66.0 [46.5, 75.5]	66.0 [8.9, 75.0]	66.0 [39.0, 75.0]	0.35
LVESD, median [IQR]	59.0 [8.9, 69.0]	58.0 [7.8, 67.0]	59.0 [8.1, 68.0]	0.32
Median degree of MR [IQR]	2.0 [1.0, 4.0]	2.0 [2.0, 4.0]	2.0 [1.0, 4.0]	0.24
Median degree of TR [IQR]	2.0 [1.0, 3.0]	2.0 [1.0, 3.0]	2.0 [1.0, 3.0]	0.29
Median degree of RV dysfunction [IQR]	2.0 [2.0, 3.0]	2.0 [2.0, 3.0]	2.0 [2.0, 3.0]	0.80

Table 3: Model derived from the derivation cohort after logarithmic data transformation and backward stepwise logistic regression

Variable	OR	Lower 95% CI	Upper 95% CI	P value
log(HR)	67.3	5.2	867.1	<0.01
log(Albumin)	0.01	0.0	0.4	0.01
log(BUN)	3.0	1.1	8.2	0.03
log(WBC)	4.2	1.0	17.9	0.05
log(CI)	0.1	0.0	0.4	<0.01
Numeric value of TR severity	2.4	1.5	3.8	<0.01

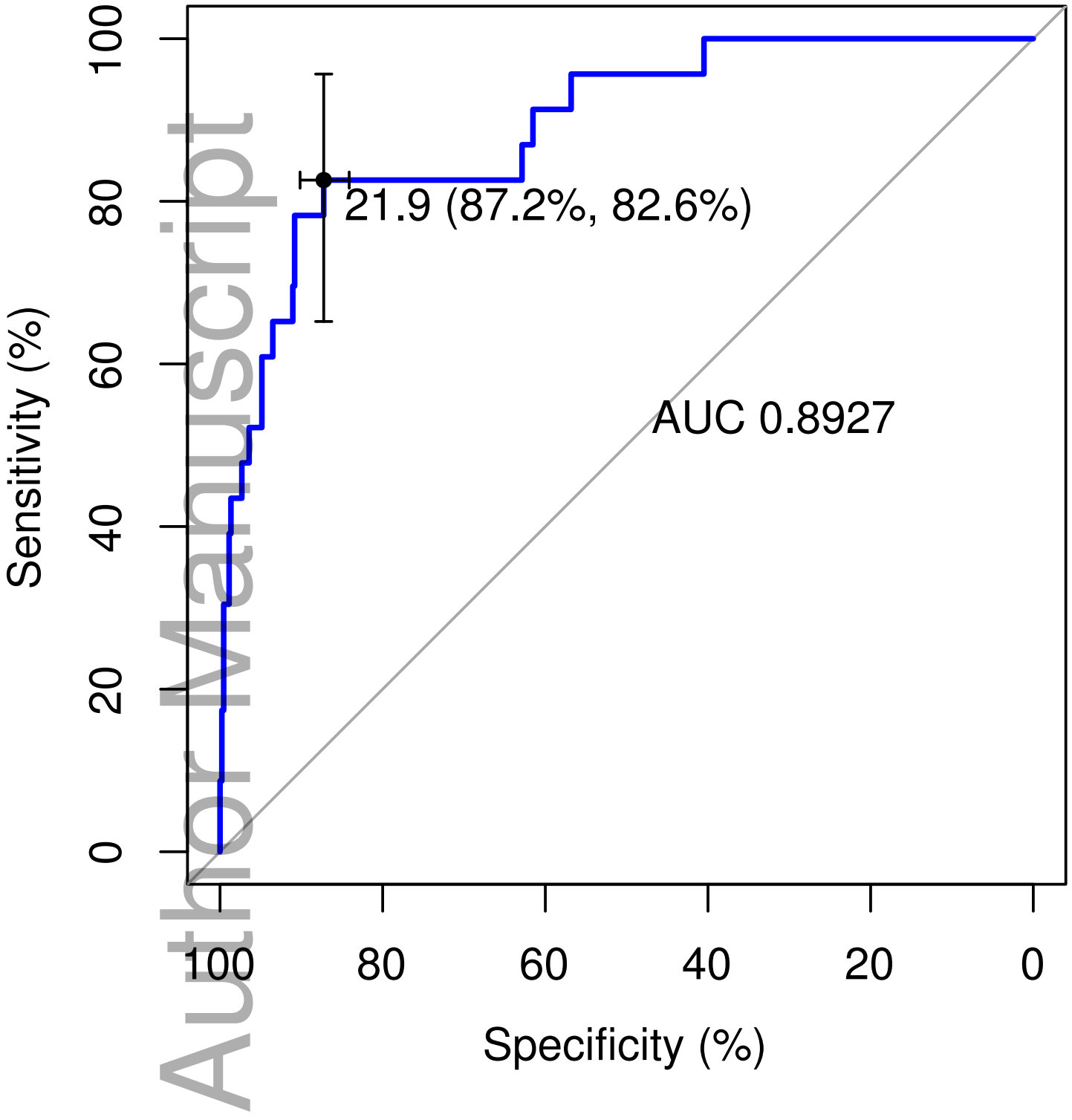
Table 4: Receiver operating characteristic analysis of commonly used RVF predictors applied to the full MCSRN dataset (n=734) with need for RVAD as a hard endpoint. PAPI, pulmonary artery pulsatility index; CRITT, central venous pressure-RV dysfunction-preoperative intubation-severe tricuspid regurgitation-tachycardia; RVSWI, RV stroke work index; TAPSE, tricuspid annular plane systolic excursion; MELD, model for end-stage liver disease.

Predictor	AUC	98% CI	P value compared with MCSRN RVF Risk Score
MCSRN RVF	0.89	0.82 - 0.96	---
PAPI	0.78	0.66 - 0.89	<0.01
CRITT	0.74	0.60 - 0.89	0.02
RVSWI	0.71	0.59 - 0.83	<0.01
TAPSE	0.70	0.48 - 0.92	<0.01
MELD score	0.69	0.60 - 0.79	0.05
CVP/PCWP ratio	0.68	0.58 - 0.79	<0.01
Severe TR	0.67	0.59 - 0.76	<0.01
HMII RVF score	0.64	0.48 - 0.79	0.05
Michigan score	0.61	0.48 - 0.74	<0.01

Figure 1: Receiver operating characteristic analysis of the novel RV risk model

Figure 2: Restricted cubic splines analysis showing continuous relationship between the risk model values and the odds ratios of requiring an RVAD. Odds ratio of needing an RVAD approaches 0 with lower values of the risk model.

Figure 3: Receiver operating characteristic curves illustrating the performance of commonly used RVF predictors. AUC: area under the curve.



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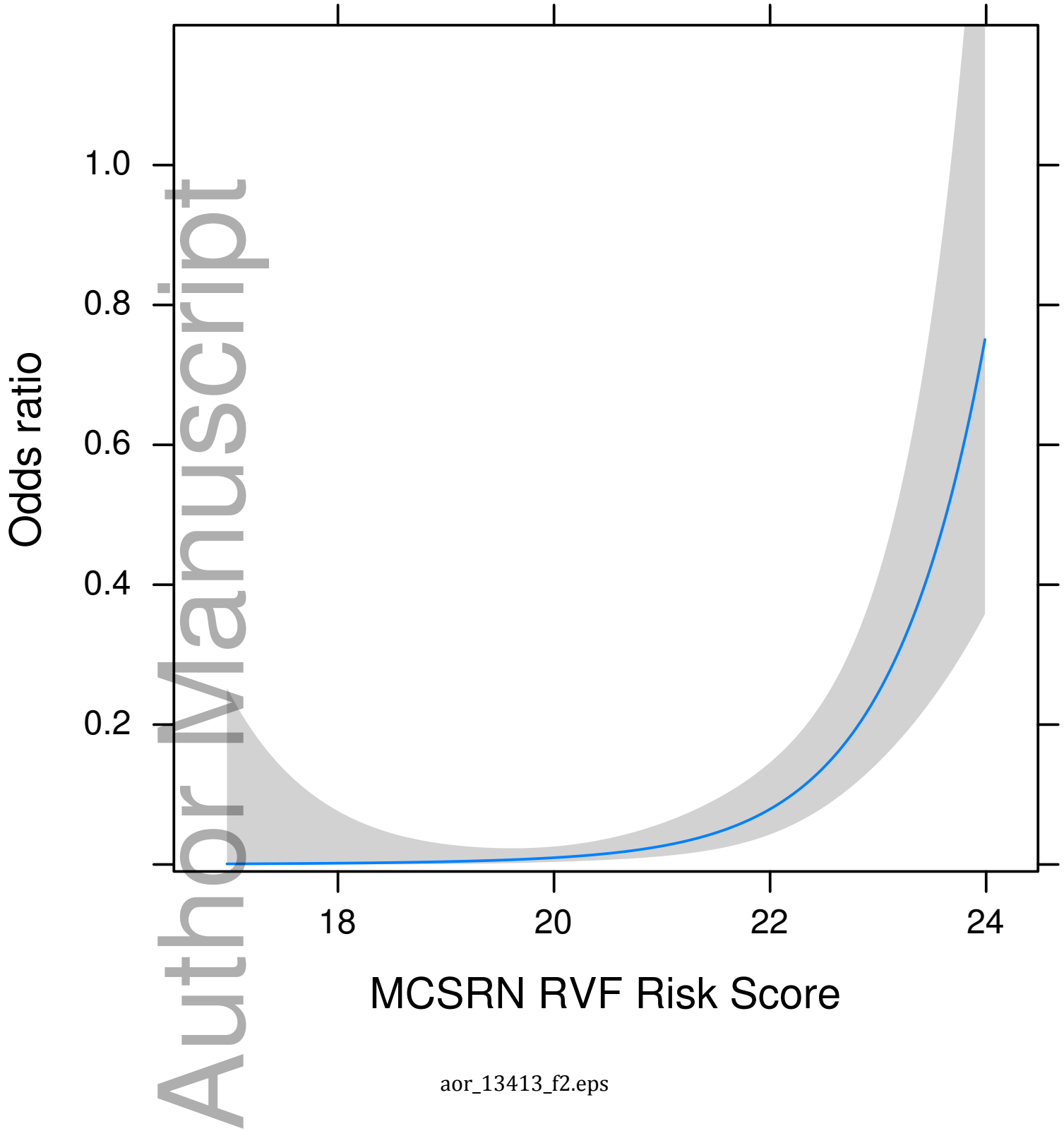

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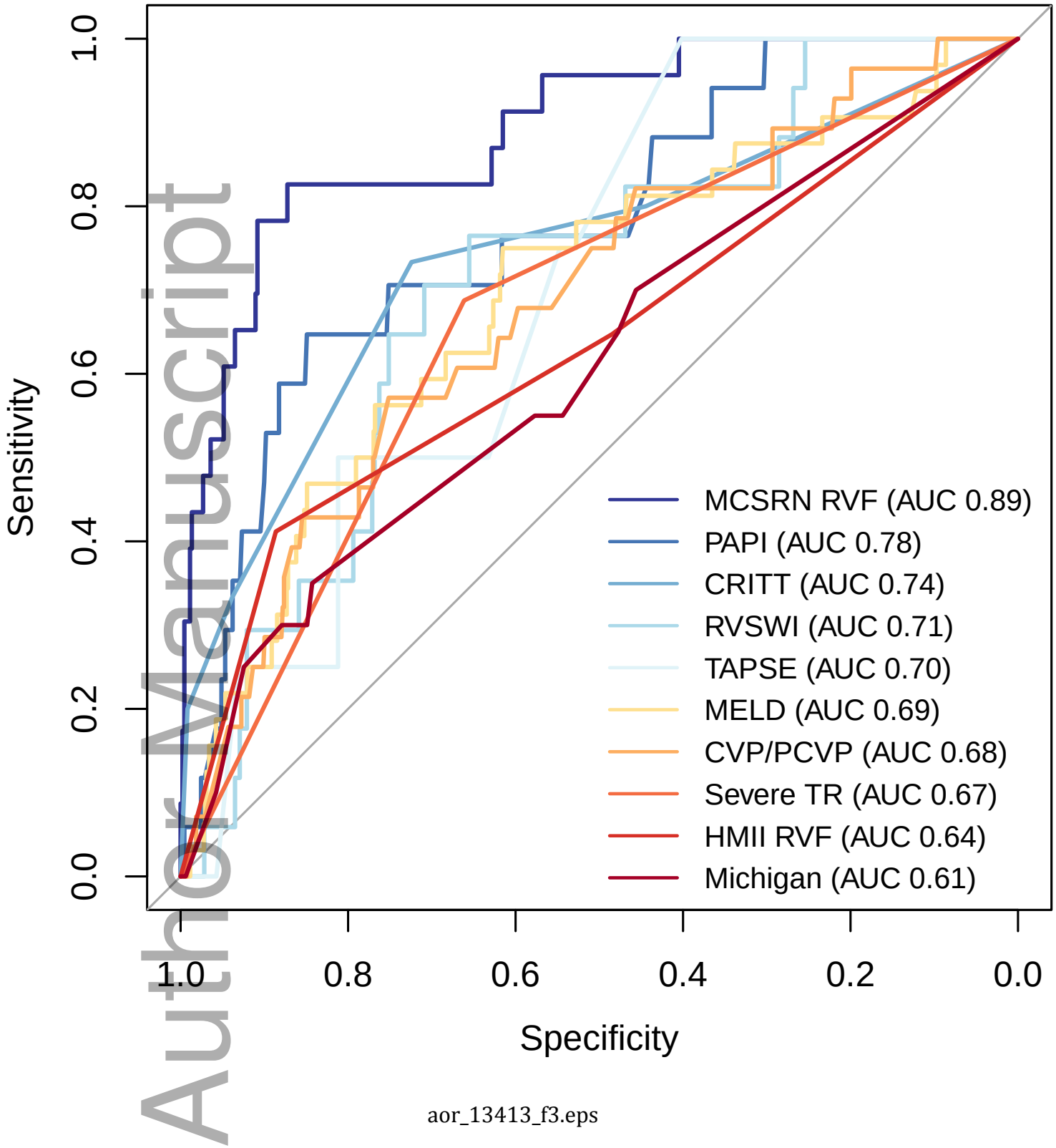

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