ESC HEART FAILURE
ESC Heart Failure (2023)
Published online in Wiley Online Library (wileyonlinelibrary.com) **DOI:** 10.1002/ehf2.13949

ORIGINAL ARTICLE

The value of multiparametric prediction scores in heart failure varies with the type of follow-up after discharge: a comparative analysis

Tiago Rodrigues*, João R. Agostinho, Rafael Santos, Nelson Cunha, Pedro Silvério António, Sara Couto Pereira, Joana Brito, Beatriz Valente Silva, Pedro Silva, Joana Rigueira, Fausto J. Pinto, Dulce Brito and for the RICA-HFteam Investigators

Cardiology Department, Santa Maria University Hospital, CHULN, Cardiovascular Centre (CCUL), Lisbon School of Medicine, Universidade de Lisboa, Avenida Professor Egas Moniz MB, Lisboa, 1649-028, Portugal

Abstract

Aims Multiple prediction score models have been validated to predict major adverse events in patients with heart failure. However, these scores do not include variables related to the type of follow-up. This study aimed to evaluate the impact of a protocol-based follow-up programme of patients with heart failure regarding scores accuracy for predicting hospitalizations and mortality occurring during the first year after hospital discharge.

Methods and results Data from two heart failure populations were collected: one composed of patients included in a protocol-based follow-up programme after an index hospitalization for acute heart failure and a second one—the control group—composed of patients not included in a multidisciplinary HF management programme after discharge. For each patient, the risk of hospitalization and/or mortality within a period of 12 months after discharge was calculated using four different scores: BCN Bio-HF Calculator, COACH Risk Engine, MAGGIC Risk Calculator, and Seattle Heart Failure Model. The accuracy of each score was established using the area under the receiver operating characteristic curve (AUC), calibration graphs, and discordance calculation. AUC comparison was established by the DeLong method. The protocol-based follow-up programme group included 56 patients, and the control group, 106 patients, with no significant differences between groups (median age: 67 years vs. 68.4 years; male sex: 58% vs. 55%; median ejection fraction: 28.2% vs. 30.5%; functional class II: 60.7% vs. 56.2%, I: 30.4% vs. 31.9%; P = not significant). Hospitalization and mortality rates were significantly lower in the protocol-based follow-up programme group (21.4% vs. 54.7%; $P < 0.001$ and 5.4% vs. 17.9%; $P < 0.001$, respectively). When applied to the control group, COACH Risk Engine and BCN Bio-HF Calculator had, respectively, good (AUC: 0.835) and reasonable (AUC: 0.712) accuracy to predict hospitalization. There was a significant reduction of COACH Risk Engine accuracy (AUC: 0.572; $P = 0.011$) and a non-significant accuracy reduction of BCN Bio-HF Calculator (AUC: 0.536; $P = 0.1$) when applied to the protocol-based follow-up programme group. All scores showed good accuracy to predict 1 year mortality (AUC: 0.863, 0.87, 0.818, and 0.82, respectively) when applied to the control group. However, when applied to the protocol-based follow-up programme group, a significant predictive accuracy reduction of COACH Risk Engine, BCN Bio-HF Calculator, and MAGGIC Risk Calculator (AUC: 0.366, 0.642, and 0.277, $P < 0.001$, 0.002, and <0.001, respectively) was observed. Seattle Heart Failure Model had non-significant reduction in its acuity (AUC: 0.597; $P = 0.24$).

Conclusions The accuracy of the aforementioned scores to predict major events in patients with heart failure is significantly reduced when they are applied to patients included in a multidisciplinary heart failure management programme.

Keywords Heart failure; Prediction scores; Multidisciplinary HF management programme

Received: 10 February 2022; Revised: 27 March 2022; Accepted: 4 April 2022
**Correspondence to: Tiago Rodrigues, Cardiology Department, Santa Maria University Hospital, CHULN, Cardiovascular Centre (CCUL), Lisbon School of Medicine, Universidade de Lisboa, Avenida Professor Egas Moniz MB, 1649-028 Lisboa, Portugal. Tel: +351911060669. Email: tiagoegrodrigues@gmail.com*
Tiago Rodrigues and João R. Agostinho contributed equally as first authors.

Introduction

Heart failure (HF) represents an important health problem across the globe, affecting 1–2% of the adult population in the western world.[1] It contributes to high rates of hospitalization and mortality (44% and 17%, respectively, at 1 year) and entails significant costs on the health system.[2]

Despite all the advances in diagnosis, treatment, and follow-up, the prognosis of HF remains poor and highly variable.[3] So, it is of utmost importance to predict the risk of major events (death and/or hospitalization) in HF, as this may be useful in the decision-making process, throughout the natural history of the condition.[4] Establishing a reliable method for risk prediction in HF is challenging, and to help in the field, several multivariable scores were created and validated over decades.[5–8]

There are several scores available to predict major events in HF patients, including (1) the Seattle HF Model[5]—a model derived in a cohort of 1125 patients, mainly with HF with reduced ejection fraction (HFrEF) and using hazard ratios from published literature; the model was prospectively validated in 5 additional cohorts from randomized control trials (RCTs) totalling 9942 HF patients and 17 307 person-years of follow-up. It provides an accurate estimate of 1, 2, and 3 year survival; (2) the COACH Risk Engine[6]—a model derived from a cohort of 1023 patients admitted for acute HF included in an RCT and validated in 620 patients hospitalized due to acute HF, that is able to predict all-cause mortality and HF hospitalization rates over 18 months; (3) the MAGGIC Risk Calculator,[7] derived from 39 372 patients with HF data, independently of the left ventricular ejection fraction (LVEF), collected from 30 cohort studies—6 RCTs and 24 observational registries—and that predicts 1 and 3 year all-cause mortality rates; and (4) the BCN Bio-HF Calculator[8] derived from a database that included 864 consecutive outpatients treated at a multidisciplinary HF unit and also used hazard ratios from published literature, allowing to predict 1, 2, 3, 4, and 5 year all-cause mortality and HF hospitalization rates.

These scores have many variables—demographic, clinical, therapeutic, and laboratory data [including biomarkers such as N-terminal pro-brain natriuretic peptide (NT-proBNP)], but leave out of the equation the type of follow-up after hospital discharge.

The readmission rate is especially high in the first weeks/months after discharge, with 25% of the patients being readmitted in the first month and 66% in the following year.[2,9]

Therefore, it is particularly important to plan hospital discharge and follow-up, in order to avoid readmissions and to reduce mortality.[10,11]

Post-discharge multidisciplinary programmes (PFP) of follow-up based on regular consultations and timely decisions and interventions are associated with a decrease in readmission rates and in the risk of death.[12–15] Considering the available evidence, the inclusion of HF patients in multidisciplinary HF management programmes is strongly recommended (class of recommendation I; level of evidence A) by the European Society of Cardiology (ESC).[16]

However, currently, it is not known if different types of follow-up (structured programmes vs. conventional follow-up) influence the accuracy of the different scores; that is, it is not known if the type of follow-up has any impact in the capacity of these scores to predict the prognosis of HF patients. Considering the great heterogeneity in the type of follow-up of HF patients, this issue has major relevance.

The aim of this study was to evaluate the impact of the inclusion of patients with HF in a protocol-based follow-up programme in multiparametric scores accuracy for predicting hospitalizations and mortality occurring during the first year after hospital discharge.

Methods

Design and population

Retrospective study with prospective data registry of consecutive patients discharged after an index hospitalization due to acute/chronic decompensated HF, defined according to the ESC Guidelines[16] at a tertiary hospital cardiology ward. All patients had clinical, laboratorial, electrocardiographic, and echocardiographic data collected on admission, during hospitalization, at discharge, and early after discharge.

Two study groups were considered: a group composed of patients included in a protocol-based follow-up programme (PFP) after the index hospitalization for HF (between April 2016 and December 2017) and the control group composed of patients hospitalized for acute HF prior to the implementation of the HF management programme at the study centre (between October 2014 and April 2016). These patients were followed in General Cardiology, Internal Medicine, or Primary Care without any predefined schedule. All the decisions regarding follow-up setting, therapy up-titration, and visits frequency were defined by each patient physician.

The HF management programme was based on consultations with a cardiologist at 7–10 days and at 1, 3, 6, and 12 months after discharge, with pre-specified procedures, namely:

1- Clinical evaluation aimed to the identification of signs or symptoms of HF decompensation;
2- Laboratorial assessment, including monitoring of NT-proBNP (at 6 and 12 months), target organ dysfunction, and comorbidities;
3- Electrocardiogram at every consultation and transthoracic echocardiogram between the third and sixth months of follow-up;
4- Assessment of compliance and tolerance to therapy and individualized titration;

5- Patient education regarding self-care, lifestyle modifications, and management of HF decompensation; and
6- Quality of life evaluation, assessed using the validated Portuguese version of the Kansas City Cardiomyopathy Questionnaire (KCCQ),[17] at 6 and 12 months of follow-up.

Heart failure prognostic scores

The risk of hospitalization at 1 year was calculated using the COACH Risk Engine and BCN Bio-HF Calculator. The risk of death at 1 year was calculated using the MAGGIC Risk Calculator, Seattle HF Model, COACH Risk Engine, and BCN Bio-HF Calculator.

The COACH Risk Engine[6] consists of a model of seven predictors: age, female gender, diastolic blood pressure, pulse pressure, diabetes, previous HF hospitalization, and log (NT-proBNP). *Online calculator available at* https://github.com/Postmus/coach/wiki/COACH-Risk-Engine.

The BCN Bio-HF Calculator[8] consists of a model of 15 predictors (7 clinical and laboratorial variables, 5 treatment-related variables, and 3 variables related with biomarkers). *Online calculator available at* http://ww2.bcnbiohfcalculator.org/web/calculations.

The MAGGIC Risk Calculator[7] includes 13 highly significant independent predictors of mortality in the following order of predictive strength: age, lower LVEF, New York Heart Association (NYHA) class, serum creatinine, diabetes, not prescribed beta-blocker, lower systolic blood pressure, lower body mass, time since diagnosis, active smoking, chronic obstructive pulmonary disease, male gender, and not prescribed angiotensin-converting enzyme inhibitor or angiotensin receptor blockers. *Online calculator available at* http://www.heartfailurerisk.org.

The Seattle HF Model[5] consists of a model of more than 30 components (clinical, medications, laboratory data, devices, and interventions in the follow-up). *Online calculator available at* https://depts.washington.edu/shfm/app.php?width=1280&height=800.

Statistical analysis

Statistical analysis was performed using IBM® SPSS® Statistics 23 (Chicago, IL, USA).

Differences between groups regarding demographic, clinical, and therapeutic data were established using the Mann–Whitney, Student's t, χ^2, one-way ANOVA, and Fisher's exact tests. P values of <0.05 were considered to indicate statistical significance.

The accuracy of each individual score in both study groups was established using the area under the receiver operating characteristic (ROC) curve (AUC), calibration, and discordance calculation.

Calibration was defined as agreement between observed and predicted endpoints, and discordance calculation defined as the difference between expected and observed outcomes as follows: discordance = [(%predicted outcomes − %observed outcomes)/(%observed outcomes)] × 100.

The AUC comparison between the scores was performed using the DeLong method—contrast matrix approach.[18]

Ethical considerations

The study was approved by the local ethics committee and by the national Data Protection Authority. Patient confidentiality was ensured through anonymization of the collected data. All study procedures were carried out in accordance with the ethical principles expressed in the 2013 revision of the Declaration of Helsinki.[19]

Results

Population characteristics

A total of 56 patients were enrolled in the PFP group and 106 in the control group. Patients' demographic and clinical characteristics at baseline are described in *Table 1*.

The median age in the PFP group was 67 (58–75) years and 32 patients (57.1%) were male. Most patients were in NYHA II (61%) at discharge, the median LVEF was 28.2% (20.5–36.5), and 48 (86%) patients had HFrEF. There were no differences between the two groups regarding age, NYHA, LVEF, or HF aetiology (the most frequent aetiology was idiopathic dilated cardiomyopathy followed by ischaemic heart disease). Overall, 70% of the patients had a history of hypertension, making it the most common comorbidity in both groups. Median plasma NT-proBNP at discharge did not differ significantly between groups (1950 pg/mL vs. 1683 pg/mL, P = not significant).

In the subgroup of patients with HFrEF, HF medical therapy prescription and cardiac devices usage rates at discharge were similar between the two groups. At the end of follow-up, medical therapy was more efficiently up-titrated in the PFP group as almost all patients were treated with beta-blocker (98% vs. 79% in the control group; P = 0.002), angiotensin-converting enzyme inhibitors/angiotensin receptor antagonists/sacubitril–valsartan (ARNI) (96% vs. 89%; P = 0.181; ARNI: 21% vs. 0%; $P < 0.001$), or mineralocorticoid receptor antagonists (83% vs. 60%; P = 0.001). Also, cardiac devices, mainly implantable cardioverter defibrillators, were more frequently used in patients included in the PFP group at the end of follow-up. Medical therapy prescription and cardiac device usage rates are detailed in *Table 2*.

Table 1 Population characteristics at discharge

Population characteristics	HF management programme ($N = 56$)	Control group ($N = 106$)	P
Age—median (IQR), years	67 (58–75)	68.4 (60–76.5)	NS
Male gender—*N* (%)	32 (57.1)	58 (54.7)	NS
LVEF—median (IQR), %	28.2 (20.5–36.5)	30.5 (22–43)	NS
HFrEF—*N* (%)	48 (85.7)	85 (80.1)	NS
HFmrEF—*N* (%)	7 (12.5)	15 (14.2)	NS
HFpEF—*N* (%)	1 (1.8)	6 (5.7)	NS
Time from symptoms onset—median (IQR), months	20 (1–103)	24 (3–68.5)	NS
Acute *de novo* heart failure—*N* (%)	9 (16.1)	16 (15.1)	NS
Chronic decompensated heart failure—*N* (%)	47 (83.9)	90 (84.9)	NS
Number of previous hospitalizations—mean (SD)	0.6 (0.9)	0.5 (0.7)	NS
Length of hospital stay—median (IQR), days	7 (4–11)	7 (3–13)	NS
NYHA functional class			
I—*N* (%)	17 (30.4)	34 (32)	NS
II—*N* (%)	34 (60.7)	60 (56.6)	NS
III—*N* (%)	5 (8.9)	12 (11.3)	NS
IV—*N* (%)	0 (0)	0 (0)	NS
Aetiology			
Ischaemic heart disease—*N* (%)	16 (28.6)	33 (31.1)	NS
Dilated cardiomyopathy—*N* (%)	30 (53.6)	52 (49.1)	NS
Valvular heart disease—*N* (%)	6 (10.7)	14 (13.2)	NS
NT-proBNP—median (IQR), pg/mL	1950 (852–4228)	1683 (414–5143)	NS
Uric acid—median (IQR), pg/mL	7 (5.7–8.5)	7.9 (6.4–10.2)	NS
Haemoglobin—median (IQR), g/dL	13.8 (12.7–15)	12.8 (11.5–14.5)	NS
Lymphocytes—median (IQR), $\times 10^9$/L	1.9 (1.5–2.5)	1.6 (1.3–2.3)	NS
Na+—median (IQR), mmol/L	138 (135–140)	138 (136–141)	NS
eGFR—median (IQR), mL/min/1.73 m^2	63.9 (48.1–81.3)	52.1 (38.3–69)	NS
Creatinine—median (IQR), pg/dL	1.1 (0.89–1.4)	1.26 (0.97–1.63)	NS
Comorbidities			
Diabetes mellitus—*N* (%)	19 (33.9)	51 (48.1)	0.038
COPD—*N* (%)	12 (21.4)	21 (19.1)	NS
Atrial fibrillation—*N* (%)	31 (55.4)	59 (55.6)	NS
Systolic BP—median (IQR), mmHg	107 (100–117)	108 (97–120)	NS
Diastolic BP—median (IQR), mmHg	60 (52–71)	57.5 (54–65)	NS
BMI—median (IQR), kg/m^2	26.8 (24.4–29.8)	27.4 (24.2–31)	NS
Weight—median (IQR), kg	79 (70–85)	75 (65–84)	NS

BMI, body mass index; BP, blood pressure; COPD, chronic obstructive pulmonary disease; eGFR, estimated glomerular filtration rate; HF, heart failure; HFmrEF, heart failure with mildly reduced ejection fraction; HFpEF, heart failure with preserved ejection fraction; HFrEF, heart failure with reduced ejection fraction; IQR, interquartile range; LVEF, left ventricular ejection fraction; *N*, number; NS, not significant; NT-proBNP, N-terminal pro-brain natriuretic peptide; NYHA, New York Heart Association.

Mortality and hospitalization rates

Patients included in the PFP had a significant reduction in hospitalization rate comparing with the control group (21.4% vs. 54.7%, $P < 0.001$). Mortality was also significantly lower in the PFP group (5.4% vs. 17.9%, $P < 0.001$). Mortality and hospitalization rates at 1, 6, and 12 months of follow-up are depicted in *Table 3*.

Multiparametric scores' accuracy

The COACH Risk Engine and BCN Bio-HF Calculator tend to underestimate the occurrence of HF hospitalizations in the control group (24.5% and 11.5%, respectively, vs. an observed rate of 54.7%; discordance: −55% and −79%, respectively). In the PFP group, the two scores had divergent results, with COACH Risk Engine overestimating the rate of HF hospitalization (25.5% vs. 21.4%; discordance: 19%) and the BCN Bio-HF Calculator underestimating the rate of HF hospitalization (7.5% vs. 21.4%; discordance: −65%) (*Table 4*).

When applied to the control group, COACH Risk Engine and BCN Bio-HF Calculator had, respectively, good (AUC: 0.835) and reasonable (AUC: 0.712) accuracy to predict hospitalizations. There was a significant reduction of COACH Risk Engine accuracy (AUC: 0.572; $P = 0.011$) and a non-significant accuracy reduction of BCN Bio-HF Calculator (AUC: 0.536; $P = 0.1$) when applied to the PFP group (*Table 5* and *Figure 1*).

Regarding mortality rates, in the control group, BCN Bio-HF Calculator, MAGGIC Score, and Seattle HF Model underestimated the mortality rate when compared with the observed rate (13.1%, 11.65%, and 14.5%, respectively, vs. an observed rate of 17.9%) and COACH Risk Engine slightly overestimated the mortality rate (20% vs. 17.9%). In the PFP group, all the scores overestimated the mortality rate

Table 2 Pharmacological therapy and cardiac devices at discharge and at 12 months of follow-up in the group of heart failure with reduced ejection fraction

Patients with reduced LVEF	HF management programme (N = 48)	Control group (N = 85)	P
Discharge			
Pharmacological therapy—*n* (%)			
Beta-blocker	43 (90)	71 (84)	0.181
ACEI/ARB/ARNI	44 (92)	76 (89)	0.378
ARNI	0 (0)	0 (0)	1.0
MRA	38 (63)	49 (58)	0.276
Diuretics	42 (88)	79 (93)	0.285
Device therapy—*n* (%)			
CRT	11 (23)	23 (27)	0.261
ICD	16 (33)	23 (27)	0.167
12 months of follow-up			
Pharmacological therapy—*n* (%)			
Beta-blocker	47 (98)	72 (85)	**0.002**
ACEI/ARB/ARNI	46 (96)	76 (89)	0.188
ARNI	10 (21)	0 (0)	**<0.001**
MRA	40 (83)	51 (60)	**0.001**
Diuretics	42 (88)	78 (92)	0.332
Device therapy—*n* (%)			
CRT	19 (39)	27 (32)	0.074
ICD	27 (57)	28 (33)	**0.001**

ACEI, angiotensin-converting enzyme inhibitors; ARB, angiotensin receptor antagonists; ARNI, sacubitril–valsartan; CRT, cardiac resynchronization therapy; HF, heart failure; ICD, implantable cardioverter defibrillators; LVEF, left ventricular ejection fraction; MRA, mineralocorticoid receptor antagonists.
Values in bold are statically significant.

Table 3 Mortality and hospitalization rates at 1, 6, and 12 months of follow-up

Follow-up	HF management programme (N = 56)	Control group (N = 106)	P
Mortality rate			
1 month	0 (0.0)	9 (8.5)	0.001
6 months	2 (3.6)	15 (14.2)	<0.001
12 months	3 (5.4)	19 (17.9)	<0.001
Hospitalization rate			
1 month	5 (8.9)	24 (22.6)	0.001
6 months	9 (16.1)	37 (34.9)	<0.001
12 months	12 (21.4)	58 (54.7)	<0.001

HF, heart failure.

(COACH Risk Engine: 21.5%, BCN Bio-HF Calculator: 8.35%, MAGGIC Score: 20%, Seattle HF Model: 13.7% vs. an observed rate of 5.4%) (*Table 6*).

All scores showed good accuracy to predict 1 year mortality (COACH Risk Engine AUC: 0.863; BCN Bio-HF Calculator AUC: 0.87; MAGGIC Score AUC: 0.818; Seattle HF Model AUC: 0.82) when applied to the control group. However, when applied to the PFP group, a significant predictive accuracy reduction of COACH Risk Engine, BCN Bio-HF Calculator, and MAGGIC Score (AUC: 0.366, 0.642, and 0.277; P: <0.001, 0.002, and <0.001, respectively) was observed. Seattle HF Model had a non-statistically significant reduction in its accuracy (AUC: 0.597, P = 0.24) (*Figure 2* and *Table 7*). Only BCN Bio-HF Calculator maintained predictive capacity although only slightly satisfactory, for mortality in the PFP group.

Discussion

The present study shows that the multiparametric scores COACH Risk Engine, BCN Bio-HF Calculator, MAGGIC Score, and Seattle HF Model, despite a tendency to globally underestimate the risk for their intended outcomes, have good accuracy to predict mortality and a reasonable to good accuracy to predict HF hospitalizations in HF patients not followed in multidisciplinary HF programmes. However, when applied to patients included in a protocol-based HF programme, the scores tend to overestimate the risk of these outcomes. More importantly, they lose accuracy when applied to this population and no score is able to satisfactorily predict HF hospitalizations and only one score—BCN Bio-HF Calculator—has some capacity to predict mortality although marginally satisfactory (AUC: 0.642).

Ever since the publication of the first ESC Guidelines for the diagnosis and treatment of chronic HF in 2001, inclusion of patients in multidisciplinary HF follow-up programmes has been recommended.[20] The focus on models of care and follow-up protocols has grown in parallel to the evidence supporting their implementation.[12–15,21] This supposedly led to the development of an increasing number of multidisciplinary HF clinics.

Despite the heterogenicity between the different models of care followed in each HF clinic,[22] some characteristics are essential in order to reduce hospitalizations and mortality. Globally, these follow-up programmes provide multidisciplinary care throughout the whole HF spectrum, from de onset through adverse events as hospitalizations or ambulatory treated decompensations, stable phases, and terminal/advanced stages.[16] As the majority of patients are referred to these follow-up programmes after a hospitalization,[23] special focus is usually given to the transition phase, starting in the pre-discharge phase (when discharge is planned, patient education is started, medical therapy is initiated/up-titrated, comorbidities are initially accessed, and a medium-term and long-term plan is drawn) and continuing after discharge (when therapy up-titration is proceeded, adverse events are managed, signs of decompensation are pursued and promptly treated, comorbidities assessment is continued, patient education is reinforced, and doubts and difficulties are addressed).[15]

The implementation of these programmes is crucial to ensure that correct diagnostic work-up, use of guideline recommended therapy, and patient education are adequately applied. The achievement of these objectives is certainly related to the magnitude of reduction in major events rate that these programmes entail.

Accordingly, the results of this study were largely impacted by the reduction in HF admissions (21.4% vs. 54.7%, $P < 0.001$) and mortality (5.4% vs. 17.9%, $P < 0.001$) in the PFP group. This is supported by the fact that globally the scores tended to significantly overestimate

Table 4 Observed and COACH Risk Engine and BCN Bio-HF Calculator predicted heart failure hospitalization rates

HF hospitalizations	HF management programme (N = 56)	Discordance	Control group (N = 106)	Discordance	P
Observed rate—*N* (%)	12 (21.4)	NA	58 (54.7)	NA	<0.001
COACH Risk Engine estimated rate—median (IQR), %	25.5 (15–33)	19%	24.5 (18.75–32)	−55%	NS
BCN Bio-HF Calculator estimated rate—median (IQR), %	7.45 (4.5–14.4)	−65%	11.5 (6.88–18.73)	−79%	NS

HF, heart failure; IQR, interquartile range; *N*, number; NA, not applicable; NS, not significant.

Table 5 COACH Risk Engine and BCN Bio-HF Calculator accuracy to predict heart failure hospitalizations

HF hospitalizations	HF management programme (N = 56)	Control group (N = 106)	P
COACH Risk Engine AUC (95% CI)	0.572 (0.461–0.712)	0.835 (0.687–0.921)	0.011
BCN Bio-HF Calculator AUC (95% CI)	0.536 (0.421–0.661)	0.712 (0.634–0.869)	0.1

AUC, area under the receiver operating characteristic curve; CI, confidence interval; HF, heart failure.

Figure 1 COACH Risk Engine and BCN Bio-HF Calculator predicting heart failure hospitalizations receiver operating characteristic curves.

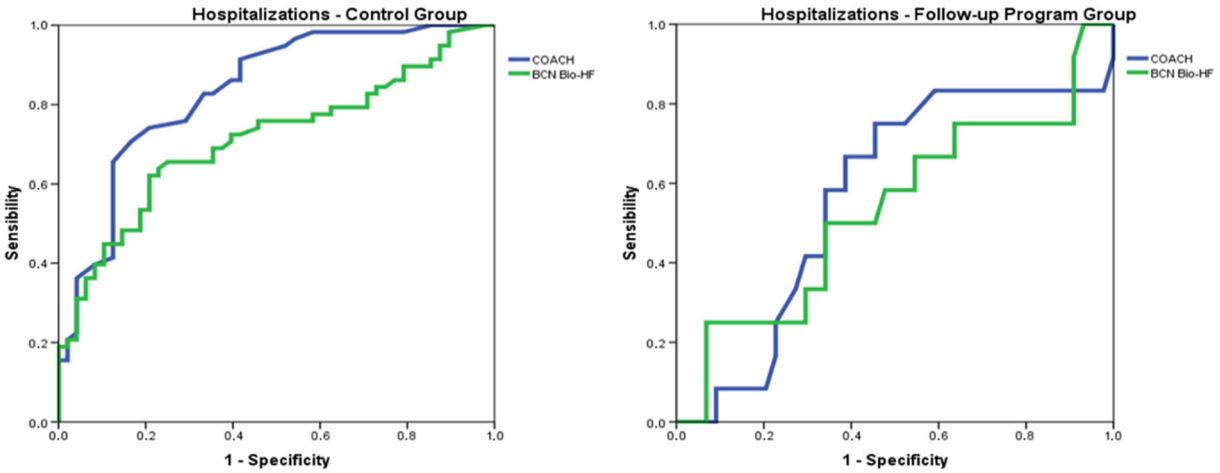

Table 6 Observed and COACH Risk Engine, BCN Bio-HF Calculator, MAGGIC Score, and Seattle HF Model predicted mortality rates

Mortality	HF management programme (N = 56)	Discordance	Control group (N = 106)	Discordance	P
Observed rate—*N* (%)	3 (5.4)	NA	19 (17.9)	NA	<0.001
COACH Risk Engine estimated rate—median (IQR), %	21.5 (8–41.25)	298%	20 (13.75–31)	12%	NS
BCN Bio-HF Calculator estimated rate—median (IQR), %	8.35 (4.5–18.15)	55%	13.1 (6.2–23.48)	−26%	NS
MAGGIC Score estimated rate—median (IQR), %	20 (7–20.05)	106%	11.65 (8.4–16)	−35%	0.043
Seattle HF Model estimated rate—median (IQR), %	13.7 (7.4–20.35)	153%	14.5 (9.05–20.73)	−19%	NS

HF, heart failure; IQR, interquartile range; *N*, number; NA, not applicable; NS, not significant.

the risk of events in the PFP group. Also, all the scores presented good accuracy to predict mortality and reasonable to good accuracy to predict hospitalizations in the control group. Actually, in this group, the scores had a slightly better performance than what has been reported in literature as they usually show moderate accuracy to predict mortality and only satisfactory accuracy to predict hospitalizations.[24,25] Concurrently, the prediction estimates tended to slightly underestimate the risk of events in this group, which may be explained by the fact that data from RCTs were used to derive and validate these scores and, as mortality rates are lower in RCT than in observational studies,[26] some underestimation of risk is expected when applying these tools to a real world population.

Figure 2 COACH Risk Engine, BCN Bio-HF Calculator, MAGGIC Score, and Seattle HF Model predicting mortality receiver operating characteristic curves.

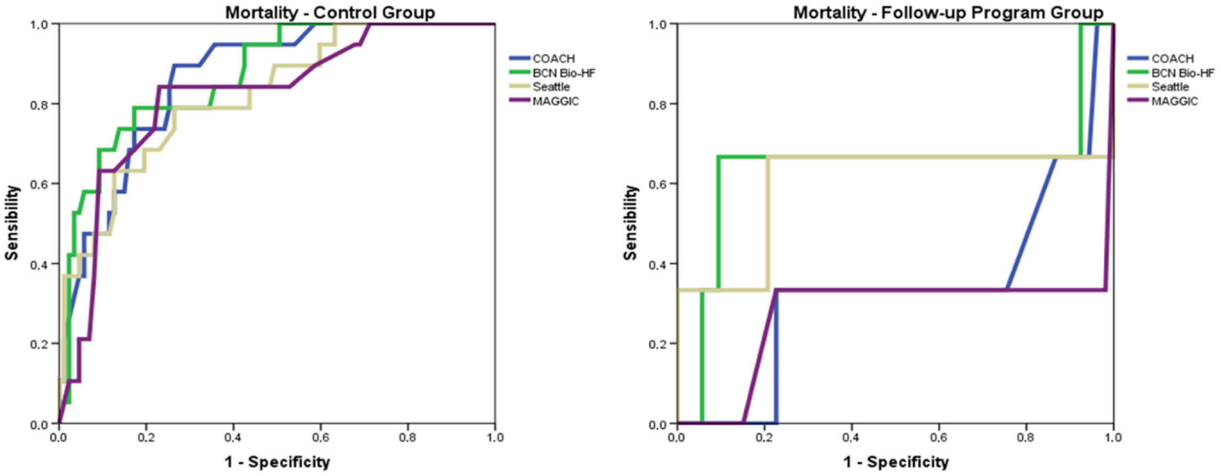

Table 7 COACH Risk Engine, BCN Bio-HF Calculator, MAGGIC Score, and Seattle HF Model accuracy to predict heart failure hospitalizations

Mortality	HF management programme (N = 56)	Control group (N = 106)	P
COACH Risk Engine AUC (95% CI)	0.366 (0.178–0.543)	0.836 (0.648–0.871)	<0.001
BCN Bio-HF Calculator AUC (95% CI)	0.642 (0.421–0.766)	0.870 (0.699–0.941)	<0.001
MAGGIC Score AUC (95% CI)	0.277 (0.109–0.413)	0.818 (0.691–0.909)	<0.001
Seattle HF Model AUC (95% CI)	0.597 (0.369–0.712)	0.820 (0.698–0.911)	0.24

AUC, area under the receiver operating characteristic curve; CI, confidence interval; HF, heart failure.

Considering this, one may postulate that these scores were developed using populations followed in a similar way to what was practised in the control group, as no other significant differences were found between groups besides the type of follow-up. Accordingly, the results of this study suggest that these tools may be inadequate to predict outcomes in patients included in multidisciplinary HF follow-up programmes, which in accordance to the recommendations may be becoming more frequent worldwide.[16]

On the other hand, since the derivation of these scores, HF care has changed, not only regarding the type of follow-up practised but also regarding medical therapy. In fact, effective medical therapy up-titration and timely cardiac devices implantation may have played an important role in mortality and hospitalization rates reduction in the PFP group and consequently may also have accounted for scores underperformance in this population. It is also worth noting that, despite the fact that this study was conducted while ARNI was being introduced in Portugal, there were significantly more patients treated with ARNI in the PFP group (21% vs. 0%; $P < 0.001$). Besides concluding that ARNI prescription contributed to the event rate reduction in this group, one should hypothesize that ARNI prescription also contributed for the scores underperformance, as its impact in event rates reduction is not taken into account in most scores as they were developed previously to the publication of PARADIGM-HF.[27] This may also become true for sodium glucose cotransporter 2 inhibitors.

One exception is the BCN Bio-HF Calculator, which is regularly updated to include the prognostic benefit of newer HF medications and devices.[8] This in association with the fact that BCN Bio-HF Calculator is derived from a cohort of patients followed in a multidisciplinary HF clinic[8] may explain why BCN Bio-HF Calculator was the only score to maintain some capacity, although only slightly satisfactory, to predict mortality in the PFP group. On the other hand, being derived from a cohort of patients with a very low rate of HF hospitalizations may also explain why BCN Bio-HF Calculator largely underestimated the risk of hospitalization in both groups.[8]

As both study groups were similar in the vast majority of variables, the four scores tended to estimate a similar risk of events in both groups. The exception was MAGGIC Score that paradoxically predicted a significantly higher risk of hospitalization in the PFP group when compared with the control group (20% vs. 11.25%; $P = 0.043$). The authors hypothesized that this may be related to the non-significantly lower LVEF

and higher rate of patients with HFrEF in the PFP group as LVEF is the sole variable with greatest impact in risk estimation in the MAGGIC Score prediction model.[7]

The new HF Guidelines do not include any reference to the utilization of multiparametric scores to estimate risk,[15] what may be related to their lack of accuracy to predict outcomes in HF patients.[24] By suggesting that their accuracy is even lower when the gold standard of HF care—multidisciplinary HF programmes—is applied, the present study results corroborate the new HF Guidelines view. However, these tools may still be helpful in the identification of patients who need specific interventions, namely, patients with advanced HF. As the incidence of multidisciplinary HF management programmes may be growing, prognostic predictive scores may either be derived from populations followed in these programmes or include variables regarding the model of care adopted. To guarantee clinical meaningfulness, variables that help clearly stratify patients with advanced HF must also be included.

Limitations

The main limitation of this study is the fact that it is a single-centre study with a small population. External validity of the results presented must be sought. On the other hand, the small size of both groups, mainly the PFP group, may have resulted in a lower rate of events and consequently may have contributed to the scores' lack of accuracy in this group. As so, these results must also be validated in multidisciplinary HF programmes with larger populations and in different models of care. Lastly, since the end of follow-up of this study, new drugs with significant prognostic impact have been included in the HFrEF foundational therapy, so it would the enlightening to replicate this study under the current standard of HF care.

Conclusions

The accuracy of multiparametric scores to predict hospitalizations and mortality occurring during the first year after hospital discharge in HF patients is significantly reduced when they are applied to patients included in a protocol-based follow-up programme.

Acknowledgements

This work was supported by national funds, Fundação para a Ciência e a Tecnologia, reference number UIDB/00306/2020.

Conflict of interest

The authors have no disclosures.

Funding

Nothing to declare.

References

1. Groenewegen A, Rutten FH, Mosterd A, Hoes AW. Epidemiology of heart failure. *Eur Heart J*. 2020; **22**: 342–256.
2. Maggioni AP, Dahlström U, Filippatos G, Chioncel O, Leiro MC, Drozdz J, Fruhwald F, Gullestad L, Logeart D, Fabbri G, Urso R, Metra M, Parissis J, Persson H, Ponikowski P, Rauchhaus M, Voors AA, Nielsen OW, Zannad F, Tavazzi L, on behalf of the Heart Failure Association of the European Society of Cardiology (HFA). EURObservational Research Programme: regional differences and 1-year follow-up results of the Heart Failure Pilot Survey (ESC-HF Pilot). *Eur J Heart Fail*. 2013; **15**: 808–817.
3. Thom T, Haase N, Rosamond W, Howard VY, Rumfeield J, Manolio T. Heart disease and stroke statistics—2006 update: a report from the American Heart Association Statistics Committee and Stroke Statistics Subcommittee. *Circulation*. 2006; **113**: e85–e151.
4. Allen LA, Stevenson LW, Grady KL, Goldstein NE, Matlock DD, Arnold RM, Cook NR, Felker GM, Francis GS, Hauptman PJ, Havranek EP, Krumholz HM, Mancini D, Riegel B, Spertus JA. Decision making in advanced heart failure: a scientific statement from the American Heart Association. *Circulation*. 2012; **125**: 1928–1952.
5. Levy WC, Mozaffarian D, Linker DT, Sutradhar SC, Anker SD, Cropp AB, Anand I, Maggioni A, Burton P, Sullivan MD, Pitt B, Poole-Wilson PA, Mann DL, Packer M. The Seattle Heart Failure Model: prediction of survival in heart failure. *Circulation*. 2006; **113**: 1424–1433.
6. Postmus D, Van Veldhuisen DJ, Jaarsma T, Luttik ML, Lassus J, Mebazaa A, Nieminen MS, Harjola VP, Lewsey J, Buskens E, Hillege HL. The COACH risk engine: a multistate model for predicting survival and hospitalization in patients with heart failure. *Eur J Heart Fail*. 2012; **14**: 168–175.
7. Pocock SJ, Ariti CA, McMurray JJV, Maggioni A, Køber L, Squire IB, Swedberg K, Dobson J, Poppe KK, Whalley GA, Doughty RN. Predicting survival in heart failure: a risk score based on 39 372 patients from 30 studies. *Eur Heart J*. 2013; **34**: 1404–1413.
8. Lupón J, De Antonio M, Vila J, Peñafiel J, Galán A, Zamora E, Urrutia A, Bayes-Genis A. Development of a novel heart failure risk tool: the Barcelona bio-heart failure risk calculator (BCN bio-HF calculator). *PLoS ONE*. 2014; **9**.
9. Cowie MR, Anker SD, Cleland JGF, Felker GM, Filippatos G, Jaarsma T, Jourdain P, Knight E, Massie B, Ponikowski P, López-Sendón J. Improving care for patients with acute heart failure: before, during and after hospitalization. *ESC Heart Failure*. 2014; **1**: 110–145.
10. Fonseca C, Brito D, Cernadas R, Ferreira J, Franco F, Rodrigues T, Morais J, Silva Cardoso J. Cardiologia. *Rev Port Cardiol*. 2017; **36**: 1–8.

11. Van WC, Bennett C, Ma AJ, Austin PC, Forster AJ. Proportion of hospital readmissions deemed avoidable: a systematic review. *Can Med Assoc or its Licens*. 2011; **183**: 391–402.
12. McAlister FA, Stewart S, Ferrua S, McMurray JJJV. Multidisciplinary strategies for the management of heart failure patients at high risk for admission: a systematic review of randomized trials. *J Am Coll Cardiol*. 2004; **44**: 810–819.
13. Phillips CO, Wright SM, Kern DE, Singa RM, Shepperd S, Rubin HR. Postdischarge support for older patients. *JAMA*. 2004; **291**: 1358–1367.
14. Feltner C, Jones CD, Cene CW, Zheng ZJ, Sueta CA, Coker-Schwimmer M, Arvanitis KN, Lohr JC, Middleton DEJ. Transitional care interventions to prevent readmissions for persons. *Ann Intern Med*. 2014; **160**: 774–784.
15. Agostinho JR, Gonçalves I, Aguiar-Ricardo I, Nunes-Ferreira A, Santos R, Guimarães T, Alves P, Cunha N, Rodrigues T, André Ń. Protocol-based follow-up program for heart failure patients: impact on prognosis and quality of life. *Rev Port Cardiol*. 2020; **38**: 755–764.
16. McDonagh T, Metra M, Adamo M, Gardner RS, Baumbach A, Böhm M, Burri H, Butler J, Čelutkienė J, Chioncel O, Cleland JG. 2021 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure. *Eur Heart J*. 2021; **42**: 3599–3726.
17. Nave-Leal E, Pais-Ribeiro J, Oliveira MM, Da Silva N, Soares R, Fragata J, Ferreira R. Psychometric properties of the Portuguese version of the Kansas City cardiomyopathy questionnaire in dilated cardiomyopathy with congestive heart failure. *Rev Port Cardiol*. 2010; **29**: 353–372 http://www.ncbi.nlm.nih.gov/pubmed/20635562
18. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics*. 1988; **44**: 837.
19. Review C, Communication S, Principles G. World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects. *J Am Coll Dent*. 2014; **81**: 14–18.
20. Remme WJ, Swedberg K. Guidelines for the diagnosis and treatment of chronic heart failure. *Eur Heart J*. 2001; **22**: 1527–1560.
21. Van Spall HGC, Rahman T, Mytton O, Ramasundarahettige C, Ibrahim Q, Kabali C, Coppens M, Brian Haynes R, Connolly S. Comparative effectiveness of transitional care services in patients discharged from the hospital with heart failure: a systematic review and network meta-analysis. *Eur J Heart Fail*. 2017; **19**: 1427–1443.
22. Jonkman NH, Westland H, Groenwold RH, Ågren S, Anguita M, Blue L, Bruggink-André de la Porte PWF, DeWalt DA, Hebert PL, Heisler M, Jaarsma T, Kempen GIJM, Leventhal ME, Lok DJA, Mårtensson J, Muñiz J, Otsu H, Peters-Klimm F, Rich MW, Riegel B, Strömberg A, Tsuyuki RT, Trappenburg JCA, Schuurmans MJ, Hoes AW. What are effective program characteristics of self-management interventions in patients with heart failure? An individual patient data meta-analysis. *J Card Fail*. 2016; **22**: 861–871.
23. Virani A, Zieroth S, Bray S, Ducharme A, Harkness K, Koshman SL, McDonald M, OMeara E, Swiggum E, Chan M, Ezekowitz JA, Giannetti N, Grzeslo A, Heckman GA, Howlett JG, Lepage S, Mielniczuk L, Moe GW, Toma M, Abrams H, al-Hesaye A, Cohen-Solal A, D'Astous M, De S, Delgado D, Desplantie O, Estrella-Holder E, Green L, Haddad H, Hernandez AF, Kouz S, LeBlanc MH, Lee D, Masoudi FA, Matteau, McKelvie R, Parent MC, Rajda M, Ross HJ, Sussex B. The status of specialized ambulatory heart failure care in Canada: a joint Canadian Heart Failure Society and Canadian Cardiovascular Society Heart Failure Guidelines Survey. *CJC Open*. 2020; **2**: 151–160.
24. Rahimi K, Bennett D, Conrad N, Williams TM, Basu J, Dwight J, Woodward M, Patel A, McMurray J, MacMahon S. Risk prediction in patients with heart failure. *JACC Heart Fail*. 2014; **2**: 440–446.
25. Ouwerkerk W, Voors AA, Zwinderman AH. Factors influencing the predictive power of models for predicting mortality and/or heart-failure hospitalization in patients with heart failure. *JACC Heart Fail*. 2014; **2**: 429–436.
26. Heiat A, Gross CP, Krumholz HM. Representation of the elderly, women, and minorities in heart failure clinical trials. *Arch Intern Med*. 2002; **162**: 1682–1688.
27. McMurray J, Packer M, Desai A. Angiotensin–neprilysin inhibition versus enalapril in heart failure. *N Engl J Med*. 2014; **371**: 993–1004.