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Enhanced Clinical Phenotyping by Mechanistic Bioprofiling in Heart Failure with

Preserved Ejection Fraction: Insights from the MEDIA-DHF study (The Metabolic

Road to Diastolic Heart Failure)

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Abstract

Background

Heart failure with preserved ejection fraction (HFpEF) is a heterogeneous syndrome for which clear evidence of effective therapies is lacking. Understanding which factors determine this heterogeneity may be helped by better phenotyping. An unsupervised statistical approach applied to a large set of biomarkers may identify distinct HFpEF phenotypes. *Methods*

Relevant proteomic biomarkers were analyzed in 392 HFpEF patients included in Metabolic Road to Diastolic HF(MEDIA-DHF). We performed an unsupervised cluster analysis to define distinct phenotypes. Cluster characteristics were explored with logistic regression. The association between clusters and 1-year cardiovascular (CV) death and/or CV hospitalization was studied using Cox regression.

Results

Based on 415 biomarkers we identified 2 distinct clusters. Clinical variables associated with cluster 2 were diabetes, impaired renal function, loop diuretics and/or betablockers.

Additionally, 17 biomarkers were higher expressed in cluster 2 *vs.* 1. Patients in cluster 2 *vs.* those in 1 experienced higher rates of CV death/CV hospitalization (adj.HR 1.93,95%CI 1.12- 3.32,p=0.017). Complex-network analyses linked these biomarkers to immune system activation, signal transduction cascades, cell interactions, and metabolism. *Conclusion*

Unsupervised machine-learning algorithms applied to a wide range of biomarkers identified 2 HFpEF clusters with different CV phenotypes and outcomes. The identified pathways may provide a basis for future research.

Keywords:

HFPEF, machine learning, biomarkers, cluster analysis, phenotype, complex-network analysis

Introduction

Heart failure with preserved ejection fraction (HFpEF) is a clinical syndrome with multiple causes, and little evidence for effective therapies (Ponikowski et al., 2016). The increasing prevalence of HFpEF and its poor prognosis both make it important to understand the factors contributing to the heterogeneity of the syndrome and its underlying mechanisms (Tsao et al., 2018).

Several studies have sought to identify distinct HFpEF phenotypes based on clinical, echocardiographic and hemodynamic characteristics (Kao et al., 2015; Sanchez-Martinez et al., 2018; Shah et al., 2015; Tabassian et al., 2018). Additionally, biomarkers have also been studied in an attempt to identify HFpEF subgroups with different characteristics and prognosis(Hage et al., 2017; Sanders-van Wijk et al., 2015; Santhanakrishnan et al., 2012; Tromp et al., 2017; Tromp et al., 2018). In these studies, only a limited number of biomarkers were assessed (up to a maximum of 92 biomarkers). Whether a wider biomarker panel may provide further information on the pathophysiology of HFpEF is yet to be determined.

In this study, we performed unsupervised machine-learning algorithms using 415 proteomic biomarkers to identify HFpEF potential mechanistic phenotypes in a prospective observational cohort of HFpEF patients (The Metabolic Road to Diastolic Heart Failure study (MEDIA-DHF); NCT02446327).

Methods

Study population

Between 2012 and 2014, 626 patients were enrolled in MEDIA-DHF ((NCT02446327) which was a multicenter, multinational, observational study in 10 centers (listed in *Supplemental table 1*). After standardized echocardiography (*Supplemental data*) and/or local natriuretic peptide measurements, eligible patients were included when they had a diagnosis of left ventricular diastolic dysfunction following 2007 ESC consensus recommendations (Paulus et al., 2007). Patients included in MEDIA-DHF presented as: 1) acute decompensated HF patients, or 2) patients recently discharged after admission for an acute HF episode (<60 days), or 3) ambulatory chronic disease patients. At inclusion in the study, data on demographics, clinical parameters, laboratory values (including biomarker measurements), electrocardiography and echocardiography were obtained. Follow-up took place at 3, 6 and 12 months after inclusion in the study.

For this substudy, only patients with available biomarkers were included (N=392; see also the flowchart in *Supplemental figure 1*). There were no biomarker measurements in acute decompensated HF patients. The study protocol complied with the Declaration of Helsinki and was approved by the respective Ethics Committees of the participating institutions. All patients provided written informed consent. (ClinicalTrials.gov Identifier: NCT02446327)

Biomarker measurements

Plasma samples taken at inclusion in the study were analyzed for protein biomarkers (including natriuretic peptides) using 5 different Olink Proseek Multiplex panels: cardiovascular disease (CVD) II, CVD III, Inflammation, Cardiometabolic and Organ damage (Olink Proteomics, Uppsala, Sweden). The characteristics of the biomarkers within the different Olink panels are described in *Supplemental table 2* (and [www.olink.com\)](http://www.olink.com/)*.* For this

assay, a proximity extension assay (PEA) technology is used where 92 oligonucleotidelabelled antibody probe pairs per panel may bind to their respective targets in 1 μ L plasma sample (Lundberg, Eriksson, Tran, Assarsson, & Fredriksson, 2011). When bound, they give rise to new DNA amplicons with each ID barcoding their respective antigens. Quantification of the amplicons is subsequently performed using a Fluidigm BioMark HD real-time PCR platform. The PCR platform provides log2-normalized protein expression (NPX) data and an increase of 1 NPX means a doubling in concentration of the specific biomarker. Forty-five proteins that were below the lower limit of detection (LOD) in more than 50% of the patients, were excluded from further analyses (N=45 biomarkers excluded). For the proteins below the LOD in less than 50% of patients, the LOD value was imputed. A total of 415 protein biomarkers were studied.

Cluster analysis

Pearson correlations were assessed between 415 biomarkers. When two biomarkers were highly correlated (>0.8), the biomarker with the largest mean absolute correlation was excluded. Hence, 66 biomarkers were excluded from further analyses. The optimal number of clusters was determined using the *NbClust* package in R (distance=euclidean, min.nc=2, max.nc=15, method=kmeans, index=alllong). Next, k-means cluster analysis (nstart=1000) was performed with data of 349 biomarkers to partition the patients into separate clusters. There were no missing values for these biomarkers. Cluster stability was verified using *Clusterboot* (B=100, clustermethod=kmeansCBI). Jaccard similarities values were highly stable (cluster 1=0.91; cluster 2=0.93). The cluster analysis resulted in two different patient clusters (clusters 1 and 2).

Network analyses

The FHF-GKB (Fight Heart Failure - Graph Knowledge Box) resource, representing most available public knowledge about human protein-disease, protein-protein and protein-pathway relationships is a customized upgraded version of the EdgeBox provided by the EdgeLeap company (available from: [https://www.edgeleap.com/edgebox/\)](https://www.edgeleap.com/edgebox/). FHF-GKB data is extracted from public data sources resulting in 20,386 protein nodes imported from Uniprot("UniProt: the universal protein knowledgebase," 2017), including all biomarkers involved in this study, 28,176 disease nodes from Disease Ontology(Kibbe et al., 2015) and DisGenet(Pinero et al., 2017) and 2,222 pathway nodes from Reactome (v65)(Fabregat et al., 2018). Protein - protein relationships were retrieved from STRING (v10.5) (Szklarczyk et al., 2015), Reactome or WikiPathways(Slenter et al., 2018), Mentha(Calderone, Castagnoli, & Cesareni, 2013), or BioGrid(Chatr-Aryamontri et al., 2017) and protein – pathway relationships from Reactome.

Cardiovascular outcome

The pre-specified endpoint of MEDIA-DHF was a composite of CV death and/or CV hospitalizations (NCT02446327). Clinical outcomes were ascertained by telephone interview and recorded in the electronic case report form (including date and place). For hospitalizations, the letter of discharge was provided, while the death certificate was provided in instances of mortality. The primary outcome of this specific substudy was cardiovascular hospitalizations or cardiovascular death at 12 months. Endpoints were adjudicated by a committee blinded to the biomarker data.

Statistical analyses

Baseline clinical, demographic and echocardiographic characteristics across clusters were compared using chi-square, t-test or Mann-Whitney tests, as appropriate.

To identify clinical variables associated with cluster membership defined by the protein biomarkers, a logistic regression analysis was performed. All variables considered are listed in *Supplemental table 3.* Missing predictor values with <20% of missing values were imputed using linear regression analysis (see *Table 1* for the percentage of missing data for each variable). We imputed missing data 10 times, performed the analysis over all the 10 imputations and averaged results using Rubin's rules (Rubin, 2004). Log-linearity of continuous variables was assessed visually by inspecting the shape of the distribution of the beta-estimates vs. the median by quintiles with regard to the outcome of interest (cluster 2). If deemed appropriate based on log-linearity, continuous variables were categorized. Variables with significant p-values $(<0.05$) in univariate analyses were considered in the multivariate model. Age and sex were "forced" in the model. The discrimination of the final multivariate model was assessed by calculating the area under the curve (AUC). Similar beta-estimates of variables in the multivariate model derived from the multiple imputation datasets were obtained when the pooled mean eGFR and E/E' were imputed in the original datasets (in N=23 and N=26 patients respectively; data not shown). Further analyses were therefore performed in the original dataset.

Thereafter, we studied which specific biomarkers were significantly associated with cluster 2 membership on top of the clinical multivariate model accounting for multiple comparisons using a Bonferroni adjusted p-value of <0.00014. To identify independent biomarkers, we subsequently excluded those correlated to each other (>0.3) . Also here, from two correlated biomarkers, the biomarker with the largest mean absolute correlation was excluded.

The FHF-GKB complex network was queried in order to explore pathways and proteins that could connect together biomarker (BM) nodes of interest. Queries were expressed according to query patterns defining a path structure between two nodes such as BM-BM and BM-pathway-BM, where the BM nodes are taken from a list of interest. The resulting graphs were merged in a figure illustrating all possible paths not longer than two edges, connecting BMs through pathways.

The association between cluster membership and the composite endpoint of CV death and/or CV hospitalizations (primary endpoint of MEDIA-DHF) within 1 year after inclusion in the study was studied using Kaplan–Meier estimates and Cox proportional hazards models. To derive clinical variables for adjustment, we constructed a clinical risk model (considering all aforementioned clinical variables) and used the variables that were significantly associated with the primary outcome in multivariate Cox regression as adjustment variables. Natriuretic peptides were included in the cluster analysis and therefore not included in the prognostic model. All significant clinical variables $(p<0.05)$ in univariate analysis were considered for the multivariate risk model. Age (per 10 years increase) and sex were "forced" in the model.

Statistical analyses were performed using SPSS 24 (IBM inc., Armonk, New York) and R (The R Foundation for Statistical Computing, Vienna, Austria).

Results

Cluster characteristics

The optimal number of clusters within this biomarker substudy of MEDIA-DHF was 2 (*Supplemental figure 2)*. The distribution of demographic, clinical and echocardiographic variables according to the specific clusters is summarized in *Table 1*. Compared to cluster 1, patients in cluster 2 were older, more often had a recent episode of decompensated HF (<60 days), a previous HF hospitalization, atrial fibrillation, diabetes mellitus, peripheral arterial disease, NYHA class III/IV, complaints of fatigue on exertion, anemia, lower diastolic blood pressure, lower cholesterol measures (total cholesterol, LDL and HDL), worse renal function, higher E/e', lower TAPSE and higher E/A. In addition, they were more often prescribed betablockers, loop or thiazide diuretics, oral anticoagulants, and insulin.

Clinical determinants of cluster 2 membership

Crude and adjusted odds ratios for the association between clinical variables and cluster 2 membership are listed in *Table 2*. There were four variables independently associated with cluster 2 membership: prescription of loop diuretics or betablockers, diabetes mellitus, and lower eGFR (="clinical model").

Association between biomarkers and cluster 2 membership

For all individual biomarkers, associations with cluster 2 membership were assessed on top of the clinical model. A total of 17 biomarkers were identified (*Table 3*). These were: angiopoietin-1 receptor (TIE2), ectonucleoside triphosphate diphosphohydrolase 2 (ENTPD2), eotaxin (CCL11), tumor necrosis factor ligand superfamily member 13B (TNFSF13B), platelet-derived growth factor C (PDGFC), L-selectin (SELL), proprotein convertase subtilisin/kexin type 9 (PCSK9), tumor necrosis factor (Ligand) superfamily, member 12 (TWEAK), nitric oxide synthase (NOS3), granulysin (GNLY), E-selectin (SELE), serpin A9 (SERPINA9), azurocidin (AZU1), proto-oncogene tyrosine-protein kinase Src (SRC), adhesion G-protein coupled receptor G1 (ADGRG1), fibroblast growth factor 21 (FGF21) and growth hormone (GH). Addition of these 17 biomarkers to the clinical model significantly improved the multivariate model for the prediction of cluster 2 membership (AUC from 0.81 to 0.96). Distribution of the biomarkers according to the respective clusters is listed in *Supplemental table 4.*

Network analyses

Of the 17 cluster-associated protein biomarkers, 15 were linked with each other by known direct interactions or pathway-interactions linked to the immune system, signal transduction/cell interactions and metabolism (*Figure 1*).

Clinical risk model for cardiovascular outcome

Crude and adjusted hazard ratios for clinical variables associated with CV death and/or CV hospitalization are listed in *Supplemental table 5.* These variables were a history of CAD, pulmonary rales, age and sex.

Cluster outcomes

The composite endpoint of CV death and/or CV hospitalization occurred more often in cluster 2 compared to cluster 1 (resp. 20% (33/163) versus 12% (27/229), Log rank test: p=0.024; *Figure 2*). After adjustment for the clinical risk model, patients within cluster 2 had a significantly higher rate of CV death and/or CV hospitalizations than those in cluster 1 (adjusted hazard ratio 1.93, 95% CI 1.12-3.32, p=0.017). Adjusting on additional clinical variables in the model (such as previous HF hospitalization, diabetes mellitus, renal function, systolic blood pressure and different HF medication) did not change the significant association between cluster assignment and outcome (*Supplemental table 6*).

Discussion

The performance of unsupervised machine learning using data on >400 biomarkers in a large cohort of 392 HFpEF, otherwise well-characterized patients, led to the identification of 2 distinct HFpEF clusters. In addition to differences in clinical features and cardiovascular prognosis between clusters, we found 17 biomarkers to be significantly associated with cluster membership. This may indicate differences in pathophysiological mechanisms.

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Differences between clusters: clinical features

Clinical variables that were significantly associated with cluster 2 membership were the prescription of loop diuretics or betablockers, diabetes mellitus, and lower eGFR. These have previously been associated with poor prognosis in HFpEF patients (Damman et al., 2014; Tribouilloy et al., 2008) and may indicate the presence of a cardiorenal syndrome as recently proposed (Zannad & Rossignol, 2018).

Differences between clusters: biomarkers and mechanistic significance

In this study, plasma levels of 17 biomarkers were significantly more elevated in cluster 2 compared to cluster 1. Network analysis revealed that these biomarkers may be grouped in 3 different mechanistic pathways: the immune system, signal transduction/cell interactions and metabolism. An overview of the biomarkers and their mechanistic significance is given in *Table 4*.

Other studies with smaller samples and fewer biomarkers found several biomarkers associated with outcome in HFpEF. In a sub study of Karolinska Rennes (KaRen), growth/differentiation factor-15 (GDF-15) was the strongest predictor for poor outcome (Hage et al., 2017), while Tromp *et al.* investigated 33 biomarkers in a cohort of HF patients and demonstrated that the remodeling marker osteopontin and the angiogenesis marker neuropilin predicted outcome (Tromp et al., 2017). Another study compared profiles of 92 biomarkers between HFrEF, HFmrEF and HFpEF patients and found that central proteins in HFpEF were integrin subunit beta-2 and catenin beta-1 (Tromp et al., 2018). A substudy of the Trial of Intensified versus standard Medical therapy in Elderly patients with Congestive Heart Failure (TIME-CHF) compared 15 biomarker from different pathways between HFrEF and HFpEF patients and found that markers of inflammation (hsCRP and cystatin C), fibrosis (ST2) and anemia (hemoglobin) were more prominent in HFpEF than in HFrEF(Sanders-van Wijk et al., 2015). Interestingly, our results are novel since no overlap was present between the biomarkers that we found in our study and the biomarkers in other HFpEF studies(Hage et al., 2017; Santhanakrishnan et al., 2012; Tromp et al., 2017; Tromp et al., 2018). However, a common pathway of the biomarkers that were associated with poor prognosis in HFpEF patients in previous studies (Hage et al., 2017; Tromp et al., 2017) and our study seems to be the immune system. Our findings need to be confirmed by other studies investigating similar biomarkers.

Difference between clusters: cardiovascular outcome

In line with previous reports (Chioncel et al., 2017; Hwang, Melenovsky, & Borlaug, 2014; Vedin et al., 2017), we found that CAD and pulmonary rales were associated with poor outcome. Age and sex were kept in the models by their known prognostic value (Chioncel et al., 2017). After adjustment for these clinical variables, patients in cluster 2 had a worse cardiovascular outcome compared to the patients in cluster 1.

Clinical implications

This study may have clinical and research implications. More insight into the mechanisms related to poor outcome in HFpEF is obtained by the finding that the majority of the biomarkers associated with cluster 2 (the cluster with a higher risk for poor CV outcome) seem to be involved in processes related to the immune system, signal transduction cascades, cell interactions and metabolism. Our findings encourage additional studies investigating the underlying mechanisms and their clinical relevance. The biomarkers (and pathways) identified in this study may help select high-risk HFpEF patients which could be helpful for the inclusion or exclusion of patients in future trials. Moreover, our findings may be the basis

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of investigating therapies specifically targeting these pathways and the potential use of corresponding markers potentially identifying patients with distinct mechanistic bioprofiles most likely to respond to the selected mechanistically targeted therapies. Such strategies could remediate the poor track record of past HFpEF large outcome trials (Rossignol et al., 2019).

Strengths and limitations

A strength of our study is that MEDIA-DHF was a large prospective European cohort in which data on >400 biomarkers from different disease domains were collected allowing for an unbiased approach to identify underlying pathophysiological pathways in HFpEF.

The most important limitation of this study is that we could not perform external validation of our prediction model due to the absence of other HFpEF cohorts with similar biomarkers, echocardiographic and follow up data. It is clear that other studies need to confirm our findings. Furthermore, at the time of enrollment, HFpEF was diagnosed following 2007 ESC diagnostic recommendations. Since the 2007 criteria, other criteria have been proposed and it has recently been shown that large variations in prevalence of diastolic dysfunction may be expected according to which criterion is used (Huttin et al., 2017). However, when applying the H_2 FPEF score by Reddy and colleagues(Reddy, Carter, Obokata, Redfield, & Borlaug, 2018) to the MEDIA-DHF cohort, only 2% of patients had a low probability of HFpEF whereas 58% and 40% of patients had an intermediate or high probability respectively. Third, the biomarker assay does not provide standard concentration units, making comparisons with clinically applied cut-offs difficult. Fourth, although the biomarker assay in this study covers a wide variety of disease domains, the possibility exists that other, now unmeasured, biomarkers may (also) play a role in the pathophysiology of HFpEF. Fifth, although it is biologically plausible that increased activation of processes related to, for example, the immune system may be associated with a poorer outcome in

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HFpEF, it should be noted that reference values (from a healthy population) for most of the candidate biomarkers in this study are lacking. Sixth, although HFpEF is known to be a heterogeneous disease, the *NbClust* package identified only 2 clusters based on the available biomarker data. Including more (clinical) data may identify a larger number of clusters. Seventh, due to the observational nature of our study with only few CV events we did not study whether differences in treatment effects (for ACEi/ARBs, BBs, etc.) can be expected for the different clusters. Also, the low number of adverse events and small sample size preclude to obtain robust estimates. Last, our cohort consists of chronic and recently discharged HFpEF patients and results can therefore not be extrapolated to different (sicker) **HFpEF** populations.

Conclusion

Unsupervised learning algorithms applied to >400 biomarkers in a large cohort of 392 HFpEF patients led to the identification of 2 distinct HFpEF cluster phenotypes. In addition to differences in clinical features between clusters, we found 17 uncorrelated biomarkers with higher expression in cluster 2 compared to cluster 1. These biomarkers are involved in pathways linked to the immune system, signal transduction cascades, cell interactions and metabolism, that may contribute to different HFpEF phenotypes.

Clinical significance

- More insight is obtained in the mechanisms related to poor outcome in HFpEF patients since it was demonstrated that biomarkers associated with the high-risk cluster were related to the immune system, signal transduction cascades, cell interactions and metabolism
- Biomarkers (and pathways) identified in this study may help select high-risk HFpEF patients which could be helpful for the inclusion/exclusion of patients in future trials.
- Our findings may be the basis of investigating therapies specifically targeting these pathways and the potential use of corresponding markers potentially identifying patients with distinct mechanistic bioprofiles most likely to respond to the selected mechanistically targeted therapies.

Disclosures

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Legend: HF, heart failure; BMI, body mass index; DM, diabetes mellitus; CAD, coronary artery disease; PAD, peripheral artery disease; COPD, chronic obstructive pulmonary disease; OSAS, obstructive sleep apnea syndrome; TIA, transient ischemic attack; DBP, diastolic blood pressure; SBP, systolic blood pressure; NYHA, New York Heart Association; eGFR, estimated glomerular filtration rate, BNP, brain natriuretic peptide; NT-proBNP, N-terminal pro-brain natriuretic peptide; ASA, acetylsalicylic acid; ACEi, ACE-inhibitor; ARB, angiotensin receptor blocker, BB, betablocker; MRA, mineralocorticoid receptor antagonist; LVEF, left ventricular ejection fraction; E/e', the ratio of mitral inflow velocity and early mitral annulus velocity, PASP, pulmonary artery systolic pressure; TAPSE, Tricuspidal Annular Plane Systolic Excursion; E/A, ratio of the early (E) to late (A) ventricular filling velocities; IQR, interquartile range.

Anemia is defined following the definition of the World Health Organization (<12 g/dL in females and <13 g/dL in males)

Table 2 Crude and adjusted odds ratios for the association between clinical variables and cluster membership

Legend: eGFR, estimated glomerular filtration rate; OR, odds ratio; CI, confidence interval; AUC, area under the curve. Age & sex were "forced" in the model.

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	Bivariate logistic regression analyses		
	<i>OR</i> (95% CI)	p-value	
TIE ₂	19.83 (6.53-60.23)	< 0.001	
ENTPD2	13.21 (4.12-42.36)	< 0.001	
CCL11	$6.44(3.15-13.17)$	< 0.001	
TNFSF13B	5.39 (2.79-10.41)	< 0.001	
PDGFC	5.09 (2.27-11.39)	< 0.001	
SELL	4.47 (2.42-9.28)	< 0.001	
PCSK9	$4.04(2.14-7.62)$	< 0.001	
TWEAK	$4.00(2.02 - 7.94)$	< 0.001	
NOS3	$3.46(2.14-5.62)$	< 0.001	
GNLY	$3.45(1.89-6.29)$	< 0.001	
SELE	$2.43(1.65-3.58)$	< 0.001	
SERPINA9	$2.17(1.49-3.16)$	< 0.001	
AZU1	$1.87(1.42 - 2.45)$	< 0.001	
SRC	$1.63(1.29-2.05)$	< 0.001	
ADGRG1	$1.55(1.26-1.91)$	< 0.001	
FGF-21	$1.49(1.23-1.79)$	< 0.001	
GH	$1.34(1.16-1.56)$	< 0.001	

Table 3 Multiple testing-corrected and uncorrelated (Pearson correlation <0.3) biomarkers associated with cluster 2 membership on top of the clinical model

Legend: TIE2, angiopoietin-1 receptor; ENTPD2, ectonucleoside triphosphate diphosphohydrolase 2; CCL11, eotaxin; TNFSF13B, tumor necrosis factor ligand superfamily member 13B; PDGFC, platelet-derived growth factor C; SELL, Lselectin; PCSK9, proprotein convertase subtilisin/kexin type 9; TWEAK, tumor necrosis factor (Ligand) superfamily, member 12; NOS3, nitric oxide synthase; GNLY, granulysin; SELE, E-selectine; SERPINA9, serpin A9; AZU1, azurocidin; SRC, Proto-oncogene tyrosine-protein kinase Src; ADGRG1, adhesion G-protein coupled receptor G1; FGF_21_1, fibroblast growth factor 21; GH, growth hormone.

\ddotsc <i>rival in puttu</i> Individual biomarker Mechanistic significance		Previous relevant reports	
		Basic reports	Clinical reports
<i>Immune</i> system			
TWEAK	Belongs to the TNF receptor superfamily and regulates several cell functions such as proliferation, apoptosis, inflammation, angiogenesis, and collagen synthesis in cardiac fibroblasts(Blanco-Colio, 2014)'(Chen, Wang, Ren, Wang, & Sui, 2012; Ptaszynska- Kopczynska et al., 2016)		Increased in HFREF(Ptaszynska- Kopczynska et al., 2016). No study in HFPEF
TNFSF13B	Member of the TNF superfamily. Regulates B- and T-cell function(Ferraccioli & Gremese, 2017)	A key driver of coronary heart disease and aggravates atherosclerosis(Tsiantoulas et al., 2018)	High levels associated with poor prognosis in MI(Zouggari et al., 2013)
GNLY	Antimicrobial protein present in the granules of cytotoxic T lymphocytes and natural killer cells(Kumar, Okada, Clayberger, & Krensky, 2001) and involved in apoptosis(Pardo et al., 2001)		Increased in infection, auto- immune disease and after NSTEMI (Ikezoe et al., 2006; Kotsch et al., 2004; Nagasawa, Ogawa, Imashuku, & Mizutani, 2007; Persic et al., 2012)
AZU1	Stored in neutrophil granules. Acts as an inflammatory mediator inducing endothelial leakage(Gautam et al., 2001; Linder, Soehnlein, & Akesson, 2010)		Early indicator of organ dysfunction after infection (Linder et al., 2012) and cardiac arrest(Dankiewicz, Linder, Annborn, Rundgren, & Friberg, 2013). Serial measurements predicted poor outcome in chronic HF(Brankovic et al., 2018)
CCL11	Eosinophil chemoattractant	Plays a role in the pathogenesis of several allergic conditions (e.g. asthma)(Williams, 2015)	Increased in eosinophilic myocarditis(Diny et al., 2016), abdominal aortic aneurysms (Jones, Phillips, Williams, van Rij, & Kabir, 2016) and CAD (Economou et al., 2001).

Table 4 Overview of the mechanistic significance of biomarkers that were more highly expressed in patients in cluster 2 than in cluster 1

TNF, tumor necrosis factor; MI, myocardial infarction; HFREF, heart failure with reduced ejection fraction; HFPEF, heart failure with preserved ejection fraction; CAD, coronary artery disease; CMP, cardiomyopathy; SNPs single nucleotide polymorphisms, MI myocardial infarction, NSTEMI non-ST segment elevation myocardial infarction; BNP, brain natriuretic peptide; LDL, low-density lipoprotein; TIE2, angiopoietin-1 receptor; ENTPD2, ectonucleoside triphosphate diphosphohydrolase 2; CCL11, eotaxin; TNFSF13B, tumor necrosis factor ligand superfamily member 13B; PDGFC, platelet-derived growth factor C; SELL, L-selectin; PCSK9, proprotein convertase subtilisin/kexin type 9; TWEAK, tumor necrosis factor (Ligand) superfamily, member 12; NOS3, nitric oxide synthase; GNLY, granulysin; SELE, E-selectine; SERPINA9, serpin A9; AZU1, azurocidin; SRC, Proto-oncogene tyrosine-protein kinase Src; ADGRG1, adhesion G-protein coupled receptor G1; FGF-21, fibroblast growth factor 21; GH, growth hormone.

Figure 1 Network analyses for the visualization of pathways and proteininteractions between uncorrelated biomarkers with higher expressing in cluster 2 vs. cluster 1

SERPINA9

Figure legend. The FHF-GKB (Fight Heart Failure - Graph Knowledge Box) complex network was used to extract available knowledge about human protein-protein and protein-pathway relationships from public resources in order to explore pathways that could connect together biomarker nodes of interest. Queries were expressed according to query patterns defining a path structure between two nodes such as BM-BM and BM-pathway-BM and BMpathway, where the BM nodes are taken from a list of interest. The resulting graphs were merged in a figure illustrating all possible paths not longer than two edges, connecting biomarkers through pathways and proteins. This graph depicts interactions between biomarkers: biomarker – biomarker, biomarker – pathway - biomarker and biomarker - pathway. Pink: biomarkers; Green: pathways. Two out of 17 biomarkers were not linked.

CV death / CV readmissions

Supplemental data Echocardiography

At baseline, echocardiography was performed in all patients and images were stored in a digital cine-loop format for off-line analysis following recommendations of the American Society of Echocardiography and the European Association of Cardiovascular Imaging relative to the cardiac chamber and right heart measurements¹

From standard 2D views, left ventricular (LV) structure and function were evaluated (including apical four-chamber, apical two-chamber and parasternal long- and short-axis views). Ventricular dimensions, wall thickness, mass and geometry were determined from 2D parasternal short- and long-axis views. LV volumes, stroke volume and ejection fraction were calculated using the biplane method (modified Simpson's rule). All cardiac chamber volumes and mass measurements were indexed to body surface area.

Left atrial (LA) volume was assessed by the biplane area-length method from apical 2 and 4-chamber views at end-systole and was indexed to body surface area (LA volume index, LAVi). LA area (cm²) was estimated from the apical views. If LA volume was not available, LA area was used to evaluate remodeling. Patients with either LAVi >40 ml/m² or LA area>20cm² were considered to have dilated LA.

Pulsed-wave Doppler obtained at the tip of mitral leaflets was used to assess the peak velocities of early (E) and late (A) wave of transmitral flow and E-wave deceleration time (DT). The average of septal and lateral annular velocities (e') was measured using tissue Doppler imaging (TDI). The peak E-wave velocity and the average of septal and lateral e' were used to calculate the E/e′ratio. LV outflow tract (LVOT) time velocity integral, isovolumic relaxation time (IVRT) and color M-mode of early diastolic mitral inflow into the left ventricle (Flow propagation velocity, Vp) were acquired from apical four- and five-

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¹ Lang RM *et al.* Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. Eur Heart J Cardiovasc Imaging 2015; 16(3):233-70.

chamber views. Pulmonary venous flow (PVF) was sampled using pulsed-wave Doppler at 1 cm into the orifice of the right upper pulmonary vein.

TAPSE (in mm) measurement was performed to estimate right ventricular (RV) function and pulmonary arterial systolic pressure (PASP) was calculated using the peak velocity of tricuspid regurgitation (TR) and the maximum IVC diameter (IVC baseline) and respiratory variation (Ratio IVC inspiration / IVC baseline) measured 3 cm before merger with the right atrium.

Overall, echocardiographic data were complete in >75% of patients, except for A (and E/A ratio) (which were available in 70% and 61% of the population, respectively).

Supplemental table 1 Participating centers MEDIA-DHF

Nancy Clinical Investigation Centre, University of Lorraine, France (and EDDH European Drug Development Hub, Nancy, France as project manager)

Lariboisière Hospital, Paris, France

Free University Medical Centre, Amsterdam, The Netherlands

CHARITE, universitätsmedizin Berlin, Berlin Germany

University of Porto, Porto, Portugal

University of Maastricht, Maastricht, The Netherlands

Hartcentrum ZNA, Antwerp, Belgium

Cardiff University, Cardiff, United Kingdom

Foundation for Applied Medical Research, Pamplona, Spain

University of Eastern PIEMONTE Medical School, Novara, Italy

University of Brescia, Brescia, Italy

University of Perugia, Perugia, Italy

University College Dublin, National University of Ireland, Dublin, Ireland

University Debrecen, Debrecen, Hungary

Oslo University Hospital, Norway

Supplemental table 2 Overview of biomarkers measured at baseline in MEDIA-DHF

Organ damage panel		
5'-AMP-activated protein kinase subunit beta-1 (PRKAB1) Q9Y478	Kidney Injury Molecule (KIM1) Q96D42	
Adhesion G-protein coupled receptor G1 (ADGRG1) Q9Y653	Leukotriene A-4 hydrolase (LTA4H) P09960	
Aldehyde dehydrogenase, dimeric NADP-preferring (ALDH3A1) P30838	Linker for activation of T-cells family member 2 (LAT2) Q9GZY6	
Anterior gradient protein 2 homolog (AGR2) O95994	Lutropin subunit beta (LHB) P01229	
Apoptosis-inducing factor 1, mitochondrial (AIFM1) O95831	Macrophage erythroblast attacher (MAEA) Q7L5Y9	
B-cell scaffold protein with ankyrin repeats (BANK1) Q8NDB2	Macrophage-capping protein (CAPG) P40121	
BH3-interacting domain death agonist (BID) P55957	Melanoma-associated antigen D1 (MAGED1) Q9Y5V3	
BMP and activin membrane-bound inhibitor homolog (BAMBI) Q13145	Methionine aminopeptidase 1 (METAP1) P53582	
Calcitonin (CALCA) P01258	Mevalonate kinase (MVK) Q03426	
Calreticulin (CALR) P27797	Mitogen-activated protein kinase kinase kinase kinase 5 (MAP4K5) Q9Y4K4	
Carbonic anhydrase 12 (CA12) O43570	Mothers against decapentaplegic homolog 1 (SMAD1) Q15797	
Carbonic anhydrase 14 (CA14) Q9ULX7	NAD-dependent protein deacylase sirtuin-5, mitochondrial (SIRT5) Q9NXA8	
Casein kinase I isoform delta (CSNK1D) P48730	NEDD8 ultimate buster 1 (NUB1) Q9Y5A7	
Claspin (CLSPN) Q9HAW4	Neutrophil cytosol factor 2 (NCF2) P19878	
CMP-N-acetylneuraminate-beta-galactosamide-alpha-2,3-	Nibrin (NBN) O60934	
sialyltransferase 1 (ST3GAL1)	Nitric oxide synthase, endothelial (NOS3) P29474	
Q11201	Nucleobindin-2 (NUCB2) P80303	
Cocaine esterase (CES2) O00748	Parvalbumin alpha (PVALB) P20472	
Contactin-2 (CNTN2) Q02246	Paxillin (PXN) P49023	
Corticoliberin (CRH) P06850	Peptidyl-prolyl cis-trans isomerase FKBP1B (FKBP1B) P68106	
C-type lectin domain family 1 member A (CLEC1A) Q8NC01	Perilipin-1 (PLIN1) O60240	
C-type natriuretic peptide (NPPC) P23582	Placenta growth factor (PGF) P49763	
Desmoglein-4 (DSG4) Q86SJ6	Platelet-derived growth factor C (PDGFC) Q9NRA1	
Dipeptidyl aminopeptidase-like protein 6 (DPP6) P42658	Pleiotrophin (PTN) P21246	
DNA topoisomerase 2-beta (TOP2B) Q02880	Phosphatidylinositol 3,4,5-trisphosphate 5-phosphatase 2 (INPPL1) O15357	
Ectonucleoside triphosphate diphosphohydrolase 2 (ENTPD2) Q9Y5L3	Plexin domain-containing protein 1 (PLXDC1) Q8IUK5	
Ectonucleoside triphosphate diphosphohydrolase 6 (ENTPD6) O75354	Polypeptide N-acetylgalactosaminyltransferase 10 (GALNT10) Q86SR1	
EGF-like repeat and discoidin I-like domain-containing protein 3 (EDIL3) O43854	Probetacellulin (BTC) P35070	
Enteropeptidase (TMPRSS15) P98073	Programmed cell death protein 1 (PDCD1) Q15116	
Epidermal growth factor-like protein 7 (EGFL7) Q9UHF1	Prolow-density lipoprotein receptor-related protein 1 (LRP1) Q07954	
Erbin (ERBIN) Q96RT1	Proteasome subunit alpha type-1 (PSMA1) P25786	
Erythropoietin (EPO) P01588	Protein amnionless (AMN) Q9BXJ7	
Fatty acid-binding protein 9 (FABP9) Q0Z7S8	Protein fosB (FOSB) P53539	
Forkhead box protein O1 (FOXO1) Q12778	Protein max (MAX) P61244	
Fructose-2,6-bisphosphatase TIGAR (TIGAR) Q9NQ88	Protein phosphatase 1B (PPM1B) O75688	
Hematopoietic prostaglandin D synthase (HPGDS) O60760	[Pyruvate dehydrogenase [acetyl-transferring]]-phosphatase 1,	
Inactive tyrosine-protein kinase 7 (PTK7) Q13308	mitochondrial (PDP1) Q9P0J1	
Integrin beta-1-binding protein 1 (ITGB1BP1) O14713	Ras association domain-containing protein 2 (RASSF2) P50749	
Interferon-inducible double-stranded RNA-dependent protein	Ras GTPase-activating protein 1 (RASA1) P20936	
kinase activator A (PRKRA) O75569	Receptor-type tyrosine-protein phosphatase eta (PTPRJ) Q12913	
Renin receptor (ATP6AP2) O75787	EGF-containing fibulin-like extracellular matrix protein 1 (EFEMP1)	

Supplemental table 3 Clinical variables in MEDIA-DHF

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Supplemental table 4 Average measure of biomarkers according to respective clusters

Legend: TIE2, angiopoietin-1 receptor; ENTPD2, ectonucleoside triphosphate diphosphohydrolase 2; CCL11, eotaxin; TNFSF13B, tumor necrosis factor ligand superfamily member 13B; PDGFC, platelet-derived growth factor C; SELL, Lselectin; PCSK9, proprotein convertase subtilisin/kexin type 9; TWEAK, tumor necrosis factor (Ligand) superfamily, member 12; NOS3, nitric oxide synthase; GNLY, granulysin; SELE, E-selectine; SERPINA9, serpin A9; AZU1, azurocidin; SRC, Proto-oncogene tyrosine-protein kinase Src; ADGRG1, adhesion G-protein coupled receptor G1; FGF_21_1, fibroblast growth factor 21; GH, growth hormone.

Biomarker results depict log2-normalized protein expression (NPX) data and an increase of 1 NPX confers therefore a doubling in concentration of the specific biomarker. For every biomarker the mean and standard deviation are listed.

Supplemental table 5 Crude and adjusted hazards ratios for the baseline prediction of cardiovascular death and/or cardiovascular hospitalization at 1 year in MEDIA-DHF

The table depicts pooled estimates derived after multiple imputation in 10 datasets. Anemia is defined following the WHO criteria for anemia (Hb < 12 g/dl in women; Hb < 13 in males).

Legend: HR, hazard ratio; CI, confidence interval; CAD, coronary artery disease; HF, heart failure; eGFR, estimated glomerular filtration rate; E/E', the ratio of early mitral inflow E to e'

The optimal number of clusters determined by the *NbClust* package in R was 2. This package uses a total of 30 indices for determining the most optimal number of clusters from the results obtained by varying combinations of number of clusters, distance measures and clustering methods