# Heart Failure Dashboard Design and Validation to Improve Care of Veterans

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# Abstract

**Background** Early electronic identification of patients at the highest risk for heart failure (HF) readmission presents a challenge. Data needed to identify HF patients are in a variety of areas in the electronic medical record (EMR) and in different formats. **Objective** The purpose of this paper is to describe the development and data validation of a HF dashboard that monitors the overall metrics of outcomes and treatments of the veteran patient population with HF and enhancing the use of guideline-directed pharmacologic therapies.

Methods We constructed a dashboard that included several data points: care assessment need score; ejection fraction (EF); medication concordance; laboratory tests; history of HF; and specified comorbidities based on International Classification of Disease (ICD), ninth and tenth codes. Data validation testing with user test scripts was utilized to ensure output accuracy of the dashboard. Nine providers and key senior management participated in data validation.

Results A total of 43 medical records were reviewed and 66 HF dashboard data discrepancies were identified during development. Discrepancies identified included: generation of multiple EF values on a few patients, missing or incorrect ICD codes, laboratory omission, incorrect medication issue dates, patients incorrectly noted as nonconcordant for medications, and incorrect dates of last cardiology appointments. Continuous integration and builds identified defects—an important process of the verification and validation of biomedical software. Data validation and technical limitations are some challenges that were encountered during dashboard development. Evaluations by testers and their focused feedback contributed to the lessons learned from the challenges.

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**Keywords** 

dashboard

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**Conclusion** Continuous refinement with input from multiple levels of stakeholders is crucial to development of clinically useful dashboards. Extraction of all relevant information from EMRs, including the use of natural language processing, is crucial to development of dashboards that will help improve care of individual patients and populations.

# **Background and Significance**

Heart failure (HF), a prevalent and costly condition, is one of the leading causes for hospitalization in the United States among adults<sup>1,2</sup> and is the most common Medicare inpatient discharge diagnosis.<sup>3</sup> Within the Veterans Affairs (VA) healthcare system, HF is the second most common diagnosis as well as one of the most costly diagnoses to treat annually.<sup>4–7</sup> The relatively higher prevalence of HF<sup>8,9</sup> among veterans may be secondary to their elevated risk of poor physical and mental health.<sup>10–13</sup> The Veterans Integrated Service Network (VISN 1) has eight medical centers located in six New England states that deliver care to approximately 4,200 veterans with HF. This subset of the population serviced by VISN 1 has serious cardiopulmonary disease, as well as the highest readmission rates.<sup>14</sup> Studies investigating reasons for these high readmission rates identified medication discrepancies and cognitive impairment as likely contributors.<sup>15,16</sup> One study noted that 30-day readmission rates were higher in HF patients who were not on a target dose of  $\beta$  blockers or vasodilators.<sup>9</sup>

However, early electronic identification of patients at the highest risk for admission presents a challenge.<sup>17</sup> The data needed to identify HF patients are located in a variety of areas in the electronic medical record (EMR) and in different formats (free text notes, images, and coded data). Dashboards for population health management are powerful tools that can be used to identify subsets of patients to improve their care and track their progress toward performance goals.<sup>18,19</sup> The use of dashboards within the VA has enabled the ability to implement system-wide processes for both population management and quality improvement.<sup>18,20,21</sup>

Dashboards that utilize both structured and unstructured data can produce patient-specific risk assessments and support guideline-directed medical therapy (GDMT) recommendations leading to greater evidence-based care.<sup>22–24</sup> Previous studies have demonstrated the efficacy of using multiple identifiers in algorithms or from notes using natural language processing (NLP) for identifying patient phenotype for early diagnosis of HF.<sup>25–28</sup> We therefore endeavored to develop and implement a dashboard that tracks clinical treatment. We hypothesized that the dashboard would help to identify all patients with HF that are at the highest risk for readmission across the medical center with the hopes of supporting better patient care and improving the cost-effectiveness of clinical practice, which is a major goal of the VA.<sup>29</sup>

## Objective

The purpose of this paper is to describe the development and data validation of a HF dashboard that monitors the overall

metrics of outcomes and treatments of the veteran patient population with HF while providing guidance to clinicians on mainstay of pharmacologic therapies.

#### Methods

The process improvement project took place at VA Boston Medical Center, a 150-bed tertiary care hospital that provides care to veterans from four of the six New England states within VISN 1. The initial project team of a business analyst, database programmer, and a cardiologist with expertise in HF met to discuss the dashboard's development and determined that an Agile software development approach<sup>30</sup> would be most feasible. The team collaborated with the Director of Primary Care, Chief Medical Officer, and Primary Care Patient Aligned Care Teams (PACTs) who would be the primary users of the dashboard. PACTs consist of providers, nurse care managers, clinical associates, pharmacists, and ancillary staff that manage Veteran patients' overall health care.<sup>31</sup> Key Performance Indicators (KPIs) and data points used to develop the dashboard were determined by the cardiologist and refined with input from the PACTs, Director of Primary Care, and Chief Medical Officer. The KPIs evaluate effectiveness of HF management across VISN 1: admissions per 100 patients by fiscal year; admissions for HF per 100 patients by fiscal year; bed day of care per 100 patients by fiscal year; and ER visit per 100 patients by fiscal year. These KPIs were based on the quality metrics for HF care that now exist based on process of care and outcomes.<sup>1,32</sup>

#### **Data points**

Data points were obtained from three different databases and included: care assessment need (CAN) score, 33,34 EF, medication history, specific laboratory testing (creatinine, B-type natriuretic peptide, hemoglobin, and sodium), specific comorbidities (chronic kidney disease, chronic obstructive pulmonary disease, diabetes, and coronary artery disease), primary care, and cardiology appointments. The CAN score is calculated by the Veterans Health Administration Support Service Center. It reflects the estimated probability of three outcomes for an individual veteran patient: (1) hospitalization, (2) death, and (3) hospitalization or death. The percentile of these probabilities ranges from 0 (lowest risk of hospitalization or death) to 99 (highest risk hospitalization or death), and it gives a perspective on how the patient compares with other veterans in terms of their likelihood of a given event over a 90-day period.<sup>33</sup> NLP and information extraction techniques were used to extract EF data from free text notes. Based on the literature, four distinct EF cohorts were formed: HF with preserved EF (HFpEF) >50%, HF

Medication class	Prescription and target dose
β blockers	<ul> <li>Metoprolol succinate target dose 200 mg daily</li> <li>Carvedilol target dose 25 mg twice a day</li> <li>Bisoprolol target dose 10 mg daily</li> </ul>
Vasodilators	<ul> <li>Lisinopril, or fosinopril, or enalapril target dose 20 mg daily</li> <li>Captopril target dose 50 mg three times a day</li> <li>Valsartan target dose 160 mg twice a day</li> <li>Candesartan target dose 32 mg daily</li> <li>Losartan 150 mg daily</li> <li>Hydralazine 300 mg daily and isosorbide 160 mg daily (both prescriptions)</li> </ul>
Aldosterone blockers	<ul><li>Spironolactone 25 mg daily</li><li>Epleronone 25 mg daily</li></ul>
Diuretics (no specific dosage or frequency)	<ul> <li>Furosemide</li> <li>Bumetanide</li> <li>Torsemide</li> <li>Metolazone</li> <li>Chlorthalidone</li> </ul>

Table 1	Prescriptions	and res	pective	target	dose

with reduced EF(HFrEF) < 40%, HF with recovered EF(HFrecEF), patients who had an EF at one time of <40%, and is now >50%, and HF with intermediate or mid-range EF (HFmrEF) 41 to 49%.<sup>1</sup> Querying of structured data was done by the database programmer who first confirmed a HF diagnosis using International Classification of Disease (ICD) 9 code of 428.x or an ICD 10 code of 150.x. An algorithm was used to determine patients' prescription concordance which is the agreement between the provider's treatment plan and current GDMT.<sup>1,35</sup> The algorithm searched the records to see if any of the target medications (**Table 1**) were ordered in the past 5 years. In addition to prescription concordance, medication concordance was evaluated. Medication concordance provides information on whether patients are on target doses of GDMT. The algorithm determined patients' medication concordance for each class of medication listed in **-Table 1** and noted if there was full concordance, partial concordance, partially concordant but not at target dose or nonconcordant. Fully concordant are those on target doses of medications noted in **-Table 1**. Partially

concordant are those on at least one class of medication at target dose while partially concordant but not at target dose(s) are those on all classes of medications, but none are at target dose. Nonconcordant refers to those not taking any recommended medications.

# **Data Validation**

Members of the PACTs conducted data validation testing at three different points during the dashboard development. They were given a test guide and scripts which were used to validate information from excel spreadsheets containing graphs, dashboard table, and patient detail reporting for a specific site and clinician. Validation testers were directed to indicate "P" for pass if the test case presented the expected result in each field or "F" for fail if that expectation was not met.

## Results

We developed the dashboard and completed validation testing in March of 2019. The landing page of the HF dashboard has four graphs see  $\succ$  Fig. 1. All graphs display outcomes for each medical center within VISN 1. The landing page also has four tables that show the patient base for each of the four defined cohorts by EF level **Fig. 2**. Note that medication concordance is not displayed for patients in the HFpEF and HF with intermediate EF cohort as no current guidelines exists for patients with these EFs. The medication concordance algorithm will re-run on a nightly basis to capture changes in patient's medications as patients have the potential to transition to another cohort if they experience a major cardiovascular event. A drill down report of individual patients is available to clinicians by clicking on their respective home Veteran Affairs Medical Center from one of the four cohort-based tables noted in ► Fig. 2. ► Fig. 3 is an example of a drill down report that is populated with fictitious data. The report displays in a left to right with color coded columns to enhance the ease of reading and includes a hyperlink to GDMT for providers to review if necessary.

Eleven clinicians in total, seven physicians, two nurse practitioners, and two nurses validated dashboard data by comparing it with patient EMRs. A total of 43 medical records were reviewed and 66 HF dashboard data discrepancies or issues



Fig. 1 Graphs on dashboard home screen.

	Patient Base: Heart Failure with Preserved (Normal) Ejection Fraction => 50%					Patient Base: Heart Failure with Reduced Ejection Fraction =<40%											
Home VAMC	Total Active Pt	%Having PCP	%Having Cardio	%Fully Concordant	%Partially Concordant	%Partially Concordant But Not At Target Doses	%Non Concordant	Average Age	Home VAMC	Total Active Pt	%Having PCP	%Having Cardio	%Fully Concordant	%Partially Concordant	%Partially Concordant But Not At Target Doses	%Non Concordan	Average t Age
VISN1	1587	85.7%	34.7%					78.4	VISN1	832	77.8%	30.3%	0.7%	19.1%	35.2%	45.0%	77.6
VAMC#1	299	87.6%	35.8%					76.4	VAMC#1	129	80.6%	27.9%	0.8%	11.6%	41.9%	45.7%	75.2
VAMC#2	145	87.6%	42.8%					78.6	VAMC#2	53	84.9%	39.6%	1.9%	20.8%	41.5%	35.8%	77.2
VAMC#3	93	84.9%	30.1%					80.4	VAMC#3	52	82.7%	23.1%	0.0%	28.8%	30.8%	40.4%	78.4
VAMC#4	322	75.2%	37.6%					79.2	VAMC#4	124	66.9%	35.5%	0.8%	17.7%	31.5%	50.0%	77.8
VAMC#5	228	93.0%	31.6%					76.0	VAMC#5	65	84.6%	30.8%	3.1%	18.5%	43.1%	35.4%	76.3
VAMC#6	128	90.6%	19.5%					79.5	VAMC#6	97	94.8%	28.9%	1.0%	21.6%	40.2%	37.1%	76.2
VAMC#7	100	89.0%	42.0%					78.5	VAMC#7	138	76.8%	38.4%	0.0%	28.3%	30.4%	41.3%	79.2
VAMC#8	272	85.7%	34.6%					80.0	VAMC#8	174	68.4%	21.8%	0.0%	13.8%	30.5%	55.7%	79.3
	Patient Ba	se: Heart Fai	lure with In	termediate Eje	ction Fraction	1 41% – 49%				Patient Base	e: Recovered	Ejection Fr	action – EF a	t one time EF «	:40%, now >50%		
Home VAMC	Total Active Pt	Having PCP	%Having Cardio	%Fully Concordant	%Partially Concordant	%Partially Concordant But Not At Target Doses	%Non Concordant	Average t Age	Home VAMC	Total Active Pt	%Having PCP	%Having Cardio	%Fully Concordant	Concordant	%Partially Concordant But Not At Target Doses	%Non Concordant	Average t Age
VISN1	778	86.1%	49.5%					76.4	VISN1	1080	88.3%	62.8%	1.0%	27.5%	39.6%	31.9%	75.4
VAMC#1	131	81.7%	48.1%					75.3	VAMC#1	122	95.9%	73.8%	0.8%	23.8%	42.6%	32.8%	73.7
VAMC#2	71	87.3%	50.7%					76.2	VAMC#2	94	83.0%	47.9%	1.1%	28.7%	42.6%	27.7%	75.3
VAMC#3	23	78.3%	43.5%					80.5	VAMC#3	37	83.8%	48.6%	0.0%	18.9%	45.9%	35.1%	76.4
VAMC#4	130	81.5%	54.6%					77.5	VAMC#4	182	80.8%	65.4%	2.7%	27.5%	40.1%	29.7%	75.6
VAMC#5	87	95.4%	37.9%					74.6	VAMC#5	93	96.8%	51.6%	0.0%	24.7%	41.9%	33.3%	74.0
VAMC#6	71	95.8%	23.9%					75.8	VAMC#6	42	97.6%	28.6%	0.0%	28.6%	28.6%	42.9%	75.3
VAMC#7	93	83.9%	73.1%					76.1	VAMC#7	228	86.4%	73.7%	1.3%	32.9%	36.4%	29.4%	76.3
VAMC#8	172	86.0%	50.6%					77.3	VAMC#8	282	89.7%	63.1%	0.4%	26.2%	39.7%	33.7%	75.8

Fig. 2 Tables on dashboard home screen.

Patient Name	Patient A	Overall Concordance with Rx. Guideline	Partially Concordant but not at target doses	EF Data Update Date	2018-08-24	Last Hgb Value	13.2
Last 4	9661	Concordance for beta- blockers	Partially Concordant but not at target dose	Last EF Note Date	2017-05-18	Last Sodium Test Date Within 2Y	2018-11-02
Age	60	Concordance for vasodilators	Non-Concordant	Last BNP Test Date Within 2Y	2018-09-18	Last Sodium Value	140
Date of Birth	1958-10-26	Concordance for aldosterone blockers	Non-Concordant	Last BNP Value	306.1	Have CKD	Yes
CAN 90 Day	98	Cardio Appt in Next 2Y	NA	Last Creat Test Date Within 2Y	2019-01-10	Have COPD	No
PCP	Provider A	Cardio Appt Within Last 1Y	2018-09-18	Last Creat Value	1.97	Have CAD	Yes
Next PCP Appt	2019-02-15	Last EF Value	20	Last Hgb Test Date Within 2Y	2018-11-02	Have Diabetes	Yes
Treatment Plan		Class	Drug	Daily Dosage	Initial Rx Date	Last Rx Date	Last Refill Date
		Beta-blockers	Metoprolol Succinate	25.00	2018-11-16	2018-11-16	2018-11-16
		Diuretics	Furosemide		2018-10-11	2018-10-11	2018-12-07

Fig. 3 Example of a drill down reduced EF cohort report (fictional patient data). EF, ejection fraction.

were identified – Table 2. In addition to the discrepancies, users also provided suggestions on how to increase usability of the dashboard. Suggestions included the flow of information within the dashboard, the use of color to differentiate columns in the drill-down reports page as well as changes in wording, for example, compliance was replaced by concordance and we modified cohort definitions to make them clearer.

## Discussion

For this process improvement project, an Agile software development approach was used to carefully explore and integrate the perspectives of key stakeholders into the dashboard. Dashboards developed with input from end-users, leadership, and subject matter experts have a greater chance of being adopted and have higher user acceptance.<sup>21,36,37</sup> The project team used structured and unstructured VA data to develop the dashboard. The dashboard presents data via a clear mechanistic interface and allows users to see comparisons between hospitals. The HF dashboard is suitable for the use case because it will allow for collaborative population care among members of primary care PACTs. It can also be used by pharmacy to review prescriptions concordance and collaborate with primary care/cardiology for appropriate follow-up.

During dashboard development, we encountered several challenges, duplicate data, missing data, inaccuracy in the last EF note date (the date when the note was added to EMR, not necessarily the actual day the echocardiogram was performed), and multiple EFs noted on the same patient in a single date. This occurred because the dashboard reports the date of the note containing an EF value and not the date when the echocardiogram was performed. It should be noted that although EF data are initially important to first categorize patients into a cohort, once patients are placed in a cohort the exact dates of the EF data update and last EF note date are unlikely to affect the HF cohort designation. Multiple EFs in a single note were encountered by the NLP algorithm which led to several EFs being generated for a few patients. The issue was discovered and adjustments were made to the algorithm used to cleanse the data to ensure that the algorithm would handle similar future cases appropriately by choosing a truly representative EF value. Furthermore, re-running of the algorithm will occur approximately every 6 months to capture EF changes over that time period. This will ensure that the newest EF is represented in the dashboard. Another issue involved deceased patients populating in the dashboard. Data are uploaded nightly to the VA's corporate data warehouse and therefore if a patient's status is listed as alive that person will

	1	1	1
	Time I charts reviewed $(n = 18)$ Number of providers $(n = 5)$	Time II charts reviewed $(n = 11)$ Number of providers $(n = 4)$	Time III charts reviewed $(n = 14)$ Number of providers $(n = 2)$
Issue/discrepancy	Number of frequencies of issu	e/discrepancy over time	
Missing Hgb value	6	3	
Inaccuracy of last EF note date	7	3	10
CKD, CAD, and DM diagnosis not captured	14	5	
BNP value missing		1	
Patients concordant for medications in chart, but it did not show up on dashboard	7	1	
Cardiology was not noted as the specialty care	1		
Furosemide issue date was incorrect	3		
Metoprolol issue date was incorrect	1		
Spironolactone issue date was incorrect	1		
Cardio Appt within last 1 year was incorrect			2
Deceased patient included in the dashboard population			1

#### Table 2 Results of testing over time

Abbreviations: BNP, brain natriuretic peptide; CAD, coronary artery disease; CKD, chronic kidney disease; DM, diabetes mellitus; EF, ejection fraction; Hgb, hemoglobin.

populate in the dashboard but will automatically be removed from the dashboard, once the system refreshes at the next upload. With the validation of the data elements, we see great potential for the dashboard to enhance HF care at VA Boston. Overall, evidence indicates that implementing healthcare dashboards can improve clinician adherence to quality guidelines and more consistently provide GDMT<sup>38</sup> and may play an important role in decreasing readmission rates.<sup>39</sup> Furthermore, if used consistently the HF dashboard could encourage discussions between providers and patients regarding appropriate HF treatment goals. However, it is recognized that introducing dashboards can impact workflow.<sup>40</sup> Therefore. the goal is to continue to seek feedback from users on how to improve the dashboard's usefulness, information quality and efficiency<sup>40</sup> to ensure that the dashboard leverages data that informs clinicians on how best to manage HF patients.

# Limitations

One major drawback is that the current structure of the EMR does not support either embedding or placing a direct link to the dashboard into the EMR. However, primary care clinicians agreed to add the dashboard to their hub which can be accessed via a link from the EMR. The data hub is a location

where common data tools, reports, and dashboards are stored for use by primary care staff to perform their duties. Another limitation is that the dashboard does not capture prescriptions written and filled by providers outside of the VA. To capture this information, both cardiology and primary care providers collect this information from patients and place it in the EMR.

# Conclusion

This paper presents a HF dashboard providing real-time information to support better patient care and thereby improve population metrics. Healthcare dashboards that utilize both structured and unstructured data, such as the HF Dashboard, can provide cohort-based groupings as well as individual patient-based risk assessments to help primary care providers identify and appropriately treat HF patients according to GDMT. Overall, there are several challenges and opportunities that come with using the HF dashboard. The collaboration between primary care and cardiology to accomplish the shared goal of increasing access to quality HF healthcare is central to the success of this project. Future work with this dashboard will involve follow-up user testing to evaluate the tool's usefulness, usability, and effectiveness by a group of primary care providers and their PACTs. In addition, process of care and outcomes will be reassessed at the 1-year mark to determine the quality of HF care within VISN 1.

# **Clinical Relevance Statement**

This case report has clinical relevance for clinicians, programmers, and quality improvement staff because it adds to the evidence that developing dashboards with input from end-users enhances the willingness to adopt new software.

# **Multiple Choice Questions**

- 1. Which of the following are best practices of data validation testing?
  - a. Compare the output result with the expected.
  - b. Test on full complete data instead of sample data.
  - c. No need to have a detailed plan as things will change along the way.
  - d. Handle bad data incorrectly.

**Correct Answer:** The correct answer is a, compare the output result with the expected. One challenge in our improvement process project was dealing with the inaccurate outputs over the development process and determining the root cause. Because validation testers alerted us to the incorrect output, we were able to remedy the issues.

- 2. When developing dashboards to support a process improvement project, besides an SQL database programmer who should be a partner in the design?
  - a. A postdoctoral medical informatics fellow who is completing the last month of their fellowship.
  - b. The chief informatics officer.
  - c. The end user.
  - d. Another database programmer.

**Correct Answer:** The correct answer is option c, the end user. This is crucial because they are the people who will use the software daily. Our project used an Agile approach to ensure that the stakeholders who were the end users not only gave input to the dashboard during development but also validated the data used in the dashboard.

## **Authors' Contributions**

All authors meet the requirements for authorship and manuscript submission.

#### Protection of Human and Animal Subjects

This project was approved and given nonresearch designation by the VISN 1 Research and Development committee.

#### **Conflict of Interest**

None declared.

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