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Incorporating patient-centered factors into heart failure readmission risk prediction: A mixed-methods study

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Abstract

Background—Capturing and incorporating patient-centered factors into 30-day readmission risk prediction after hospitalized heart failure (HF) could improve the modest performance of current models.

Methods—Using a mixed-methods approach, we developed a patient-centered survey and evaluated the additional predictive utility of the survey compared to a traditional readmission risk model (the Krumholz et al. model). Area under the receiver operating characteristic curve (AUC) and the Hosmer-Lemeshow goodness-of-fit statistic quantified the performance of both models. We measured the amount of model improvement with the addition of patient-centered factors to the Krumholz et al. model with the integrated discrimination improvement (IDI). In an exploratory analysis, we used hierarchical clustering algorithms to identify groups with similar survey responses and tested for differences between clusters using standard descriptive statistics.

Results—From 3/24/2014 to 3/12/2015, 183 patients hospitalized with HF were enrolled from an urban, academic health system and followed for 30 days after discharge. The Krumholz et al. plus patient-centered factors model had similar-to-slightly lower performance (AUC [95%CI]:0.62 [0.52, 0.71]; goodness-of-fit p=0.10) than the Krumholz et al. model (AUC [95%CI]:0.66 [0.57, 0.76]; goodness-of-fit p=0.19). The IDI (95%CI) was 0.003 (-0.014,0.020). We identified three patient clusters based on patient-centered survey responses. The clusters differed with respect to gender, self-rated health, employment status, and prior hospitalization frequency (all p<0.05).

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Conclusions—The addition of patient-centered factors did not improve 30-day readmission model performance. Rather than designing interventions based on predicted readmission risk, tailoring interventions to all patients, based on their characteristics, could inform the design of targeted, readmission reduction strategies.

Keywords

heart failure; readmissions; patient-centered care; transitional care

Introduction

Heart failure is a morbid and costly condition with frequent hospitalizations and high readmission rates.¹ Federal programs have stimulated interest among stakeholders in risk-prediction models for 30-day readmission for patients hospitalized with heart failure.² Payers employ risk-adjustment models for value-based payment models and penalties, while health system administrators, interdisciplinary care teams, and researchers have developed models in an attempt to identify patients who might benefit from targeted interventions to reduce risk of readmission or improve overall health or, ideally, both.

Risk-prediction models for 30-day readmission after hospitalized heart failure that use a combination of demographic and clinical variables have modest performance.^{3,4} For example, the Krumholz et al.⁵ model used by the Centers for Medicare and Medicaid Services (CMS) as part of the 30-day heart readmission measure has a c-statistic of approximately 0.60. Studies that have incorporated additional socioeconomic (SES) and functional variables have had mixed success.³ Amarasingham et al. found modest improvement in performance when adding variables reflecting SES and social instability, while Eapen et al. found no difference in performance with the addition of county-level SES variables.^{6,7}

Expert-driven approaches for predicting and addressing readmissions can be contrasted with an understanding of readmission from the patient and family perspective.⁸⁻¹¹ The absence of these patient-centered factors—those identified by patients as challenges to home heart failure management and reasons for hospitalization—could in part explain the overall moderate model performance.

To understand challenges to home heart failure management, we designed a three-phase, mixed-methods approach to identify patient-centered factors related to hospital readmission for patients with heart failure and to develop a quantitative survey capturing the importance of those factors among patients with heart failure. We hypothesized that incorporating patient-centered factors would improve 30-day readmission risk prediction for heart failure beyond a traditional model. Based on the primary results of the study, we also hypothesized that identifying groups of patients with similar responses to the quantitative survey would elucidate common reasons for readmission and inform targeted interventions. Therefore, in an exploratory analysis, we applied clustering algorithms to identify and characterize groups of participants.

Methods

Study Overview

In this paper, we present the results from Phase 3 of a three-phase, mixed-methods study. In the first of three phases in this mixed-methods study, we performed freelistings to understand and contrast how key stakeholders view challenges to managing heart failure at home. These results have been previously published.¹²

In Phase 2, using the results from Phase 1, we developed a semi-structured interview guide and conducted qualitative interviews with 31 patients who had recently been hospitalized for heart failure. Of these, 16 patients had been readmitted within 30-days of discharge and 15 patients were not readmitted within 30 days after their initial heart failure hospitalization. The purpose of this phase of the study was to elicit from the patient's perspective factors that they identify as challenges to home heart failure management. The factors that were identified formed domains for a survey that was administered to a new cohort of heart failure patients in Phase 3. The results from this qualitative study, together with data from additional focus groups, are being reported separately.

In Phase 3, based on analyses of the Phase 2 qualitative patient interviews, we designed a survey to understand the types of issues that patients with heart failure experience and the extent to which those issues were a problem in the month before they were hospitalized. Thirty questions were developed by the research team, including a patient with heart failure, covering seven domains: following instructions, management strategies, financial effects, daily activities, physical effects, emotional effects, and social support and relationships (Figure 1). For each of thirty questions, the survey provides the following prompt: "In the month before you came to this hospital, how much of a problem did you have with:" The individual has the option of responding "not a problem," "a minor problem," "a moderate problem," and "a major problem," corresponding to a numeric scale of 0 to 3.

We prospectively enrolled hospitalized heart failure patients to test if survey responses improved prediction models for 30-day readmission over the clinical model used as the basis of the CMS readmission measure (referred to as the Krumholz et al.⁵ model). As an exploratory analysis, we sought to identify groups of patients facing similar issues identified by the survey when they left the hospital.

The Institutional Review Board of the University of Pennsylvania approved this study. All participants provided informed consent.

Study Sample

We recruited patients from two study sites within an urban health system: a large academic medical center and an affiliated, community teaching hospital. We identified patients through a combination of a daily electronic health record query for patients with heart failure, chart review by research assistants, and direct contact with floor nurses.

We enrolled patients who were admitted to a cardiology or general medicine service primarily for management of acute decompensated heart failure from 3/24/2014 to

3/12/2015. Exclusion criteria were: 1) Scheduled for or history of left ventricular assist device (LVAD) or heart transplant; 2) Discharged on home inotropes; 3) Discharged to skilled nursing facility or long-term care facility; 4) Unable to provide informed consent (cognitive impairment, visual disability, does not speak or read English); 5) Participated in a prior phase of the study.

Ascertainment of baseline demographic, clinical, and patient-centered variables

A trained research coordinator administered the survey and obtained demographic and clinical variables via a combination of patient interview and chart review. Each participant completed the 30-item questionnaire on a paper form prior to hospital discharge.

Ascertainment of outcomes

The primary outcome of interest was all-cause hospitalization within 30 days of discharge. Hospitalizations were identified through chart reviews at the two participating hospitals and participant reports. All participants were called up to three times to assess for hospitalization within 30 days of discharge. Participants who were not reached by phone and did not have any encounters within the health system within 30 days of discharge were considered lost to follow-up.

Sample Size

Assuming a readmission rate of 25%,¹³ we determined that a sample size of 200 would achieve 80% power to detect an increase in area under the receiver operating characteristic curve (AUC) of at least 0.10 (a meaningful improvement in discrimination) with the addition of patient-centered factors to the Krumholz et al. model with a AUC of 0.60 (PASS, NCSS LLC, Kaysville, Utah).¹⁴ This calculation was based on a one-sided test (chosen because the addition of variables associated with readmission were not expected to reduce discrimination) with a type-1 error rate of 5%. Because the patient-centered model would include all of the variables in the Krumholz et al. model, the correlation between the Krumholz et al. model and the patient-centered model was assumed to be at least 0.65.

Statistical methods

Participant characteristics, reported at the index discharge, were summarized using standard descriptive statistics and stratified by 30-day readmission. We used a mosaic plot (a graphical representation of a contingency table) to visualize the distribution of survey responses and 30-day readmission for each survey question. For each survey question, Fisher's exact test was used to evaluate independence between the response and 30-day readmission.

For the primary analysis, a multiple correspondence analysis (a generalization of principal component analysis when the variables are qualitative rather than quantitative) summarized the survey responses.¹⁵ The multiple correspondence analysis was performed on a symmetric matrix of all two-way cross-tabulations between the survey responses. We retained coordinates from the first two dimensions (hereafter, "components") as an aggregate summary of the survey responses. We used a logistic regression model for 30-day readmission to develop a multivariable score based on the combination of these two

components and the linear predictor from the Krumholz et al. model. The linear predictor for the Krumholz et al. model was obtained by applying the model's published regression coefficients to the observed data from our study participants; we did not refit the Krumholz et al. model. To avoid overly optimistic prediction from developing and evaluating a model from the same set of data, leave-one-out cross-validation estimated the value of the score for each participant as a combination of the covariate values (the two survey components and the Krumholz et al. model linear predictor) and regression coefficients estimated from the data for all other participants.¹⁶ The AUC and the Hosmer-Lemeshow statistic quantified discrimination and calibration, respectively, for each model; the difference in AUCs between alternative models was compared using the DeLong test.¹⁷ We also used the integrated discrimination improvement (IDI)¹⁸ to compare the difference in discrimination slopes between models. A confidence interval for the IDI was calculated from 1,000 bootstrap samples.

In an exploratory analysis, we performed a hierarchical clustering analysis of the results from the multiple correspondence analysis.¹⁵ The hierarchical clustering analysis sought to identify clusters of participants with similar survey responses. The number of clusters was selected by partitioning a classification tree based on the relative loss of inertia. Among the identified groups, we compared participant characteristics, survey responses, and readmission rates using standard descriptive statistics. A mosaic plot presented the distribution of survey responses by cluster membership for each survey question. To examine the extent to which each domain was a problem, mean scores for each domain were categorized: <1.0, low problem; 1.0-1.5, moderate problem; >1.5, high problem.

All analyses were completed using R 3.3.2 (R Foundation for Statistical Computing, Vienna, Austria), including the vcd¹⁹ and FactoMineR²⁰ extension packages.

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Results

Sample

We screened a total of 1,091 consecutively admitted participants. Of these, 375 (34.4%) were eligible for the study. The majority of potential participants were excluded because the primary reason for admission was determined to not be for heart failure (n=421) or the participants were undergoing advanced heart failure therapies (LVAD, transplant evaluation, or home inotropes; n= 144). We approached 250 participants, of which 202 were enrolled and consented. Eleven participants were lost-to-follow-up and censored from the final analytical dataset. Eight additional participants were censored. One consented participant informed the research coordinator during interview that he/she did not have a history of heart failure and did not participate. Another participant received incorrect instructions during the administration of the patient-centered factors survey. An additional three

participants were removed from the risk prediction and clustering analyses because the patient-centered factors survey was not fully completed. Three were removed after they died prior to hospital discharge or in hospice as part of the hospitalization. The final analytical dataset included 183 participants.

Table 1 summarizes the socio-demographics, clinical characteristics, and predicted readmission risk using the Krumholz et al. model for the entire sample and stratified by 30-day readmission status. The median age was 61 years, over 50% of the sample was African American, and 84% of participants stated that they had a primary caregiver. There was no significant difference in the predicted risk for 30-day readmission using the Krumholz et al. model for those who were readmitted vs those who were not.

Responses to the patient-centered factors survey and risk prediction models

Figure 2 depicts the extent to which each item in the survey was noted as a problem for participants in the month before coming to the hospital and compares the proportion of those readmitted versus not readmitted across survey responses. There was no evidence that the readmission rate differed according to survey response (all $p>0.05$).

The multiple correspondence analysis identified two principal components that appeared to separate question responses into groups (Figure 3A). The first component explained 30.0% of the variability in responses between participants, and was primarily a contrast between “major problem” and “not a problem.” The second component explained an additional 11.7% of the variability, and was primarily a contrast between minor or moderate problems and no or major problems.

The Krumholz et al. model in our sample had a performance similar as previously reported in other populations (AUC [95%CI]: 0.66 [0.57, 0.76]; Hosmer-Lemeshow goodness-of-fit $p=0.19$). The combination of the first two components of the survey responses (Figure 3A) and the linear predictor from the Krumholz et al. model had similar-to-slightly lower performance (AUC [95%CI]: 0.62 [0.52, 0.71]; Hosmer-Lemeshow goodness-of-fit $p=0.10$). There was no improvement in AUC ($p>0.99$). The IDI (95% CI) was 0.003 (-0.014, 0.020).

Exploratory analysis to identify groups of participants with different challenges

The hierarchical clustering analysis of the results from the multiple correspondence analysis, which sought to identify groups of individuals with similar survey responses, resulted in the identification of three groups (Figure 3B). Each cluster differed in their responses to the patient-centered factors survey by domain (Table 2 and Figure 4). All groups reported physical symptoms to be either a moderate or major (“high”) problem. Participants in cluster 1 tended to not view any of the questions in the remaining six domains as moderate or major problems, while participants in cluster 3 on average identified questions in all domains as moderate or major problems. Participants in cluster 2 on average reported financial effects, daily activities, physical effects, and emotional effects as moderate to major problems while following instructions, management strategies, and social support and relationships were seen as low problems.

In cluster 1, participants tended to be older and were more likely to be male, retired, and have a self-rated health of good or excellent (online-only Data Supplement Table 1). This group also had the fewest prior hospitalizations. Participants in cluster 2 were younger, more likely to be female, more likely to be disabled, and have self-rated health of fair. Participants in cluster 3 were more likely to be unemployed, have poor self-rated health, and have the most prior hospitalizations.

The clusters did not have significantly different predicted 30-day readmission rates by the Krumholz et al. model or actual readmission rates (20%, 26%, and 24% in clusters 1, 2, and 3, respectively, $p>0.05$ for all pairwise comparisons).

Discussion

In an observational study informed by rigorous qualitative research, we found that the addition of patient-identified factors to a heart failure, 30-day readmission risk model did not improve model performance, which remained at best moderately predictive. In an exploratory analysis, we identified three clusters of patients with different demographic and clinical characteristics and differing views on problems related to heart failure management. These results suggest that patients face different types of difficulties in managing their heart failure, but that no specific set of patient-centered factors is associated with a higher rate of 30-day readmission.

Although numerous studies have examined barriers to HF care from patient, caregiver and clinician experience,²¹ none, to our knowledge, has developed a survey based on two phases of qualitative research and then prospectively tested the predictive capabilities of that survey. This novel, mixed-methods approach could be applied to other patient-centered outcomes research studies addressing complicated issues with varying perspectives among patients, caregivers, and clinicians.

In a secondary analysis of a telemonitoring clinical trial (Tele-HF Study), Krumholz et al.²² found that the addition of patient-reported socioeconomic, health status, adherence, and psychosocial variables did not improve 30-day readmission risk model performance. However, many of the patient interview questions were not specifically derived from interviews with hospitalized heart failure patients or addressed problems faced by patients in the month prior to admission. We identified patient-centered factors around the time of hospitalization through two stages of qualitative research and then tested whether those factors added predictive value to a clinical risk model. The null findings likely reflect the complex interaction of patient, clinician, and health system factors that contribute to readmission and are challenging to capture in a model. However, while this rigorous approach did not improve prediction of readmission, it provides additional, new insights.

Our findings illustrate that important heterogeneity exists in patient perspectives of challenges to heart failure management. We identified three groups with different perspectives on the extent to which following instructions, management strategies, financial effects, daily activities, physical effects, emotional effects, and social support and relationships were problems for them in the month prior to hospitalization. These groups

also differ in socio-demographics, clinical characteristics, and self-reported health. Prior studies, using clustering algorithms, have shown clinical heterogeneity within patients with heart failure,^{23,24} but those studies employ demographic and clinical variables as covariates in their algorithms. In contrast, in this study, we used patient-centered factors derived from formal qualitative research. Our study raises the hypothesis that tailoring interventions to all patients with heart failure, rather than trying to intervene only in those predicted to be at high risk, could be a better strategy to reduce readmissions. Several studies, with some success, have tested tailored interventions for heart failure self-management strategies.²⁵ The clusters identified in this study could be helpful in informing the design of future, targeted interventions to reduce readmissions, improve overall health, and increase quality of life. For example, patients such as those in cluster 1, who do not view any of the domains as problematic, might have limited insights into the causes of symptom distress and therefore benefit from interventions tailored to improved understanding of the importance of medication adherence or to understanding that they are at risk for readmission.

The strengths of this study include the formal mixed-methods approach, prospective testing of predictive capacity of the patient-centered factors survey, and the racial/ethnic diversity of the sample. There are limitations to this study. First, these findings are from a single health system. Second, the study was not designed to develop a specific “instrument,” but rather determine if patient-centered factors predict future readmission. As such, we did not perform extensive psychometric testing of the items in the patient-centered factors survey. Third, some of the factors that were problems for participants after hospital discharge may be different from those prior to the index hospitalization. Fourth, further work is needed to validate our findings of the three clusters of patients hospitalized with heart failure and understand whether these data are informative to designing targeted interventions. Lastly, the study was not powered to detect differences in readmission rates between the clusters.

In summary, we found that the addition of patient-centered factors to the Krumholz et al. model did not improve 30-day risk prediction for readmission after heart failure hospitalization and that, overall, risk prediction for readmission remains challenging. The three clusters of patients with distinct characteristics and perspectives that we identified all face a similar risk of readmission, but perhaps for different reasons. Rather than focusing interventions only for patients predicted (often inaccurately) to be at high risk of readmission, it might be better to target all patients on hospital discharge and use their patient-specific difficulties in managing heart failure to tailor interventions to reduce readmissions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Domain	Items
<i>Following instructions</i>	1. Knowing how and/or when to take my medications 2. Taking my medications as directed 3. Knowing how to manage my diet 4. Being able to follow instructions (about diet, salt, weight or exercise)
<i>Management strategies</i>	5. Checking my weight regularly 6. Getting to the doctor when I need to 7. Feeling sicker and not knowing what to do 8. Other illnesses beside heart problems 9. Drug or alcohol use
<i>Financial effects</i>	10. Being able to pay for my medications 11. Being able to pay other bills after paying for health care
<i>Daily activities</i>	12. Walking or going up stairs 13. Getting around my house or neighborhood 14. Being able to take care of myself at home (bathing, dressing, etc) 15. Household chores such as cooking or cleaning
<i>Physical effects</i>	16. Fatigue or weakness 17. Shortness of breath 18. Side-effects of medication
<i>Emotional effects</i>	19. Feeling sad or depressed 20. Feeling afraid 21. Feeling nervous 22. Loss of interest or pleasure in things 23. Making changes in my "old" way of life because of my illness
<i>Social support and relationships</i>	24. Needing someone who can help me manage my medical problems at home 25. Needing someone who can help me with daily chores 26. Trust in my doctor 27. Communication with my doctor 28. Living alone 29. Feeling like I am a burden to others 30. Being responsible for taking care of others

Figure 1.

Patient-centered factors survey. The survey comprised of 30 items across seven domains.

The participants were asked: "In the month before you came to this hospital, how much of a problem did you have with:" For each item, participants had the option of responding as "not a problem," "a minor problem," "a moderate problem," and "a major problem," corresponding to a numeric scale of 0 to 3.

Figure 2. Distribution of survey responses and 30-day readmission for each question on the 30-item survey. For each question, the width of the boxes represents the proportion of participants with that response (0, not a problem; 1, a minor problem; 2, a moderate problem; 3, a major problem). For each response, the dark shading represents the proportion of participants readmitted within 30 days. All $p > 0.05$.

Figure 3. Results from the multiple correspondence analysis (A), which summarized responses on the 30-item survey into coordinates in two dimensions. Numbers indicate question number on the survey. Results from the hierarchical clustering analysis (B), which identified three clusters of participants based on the similarity of their survey responses.

Figure 4. Distribution of survey responses for each question on the 30-item survey, stratified by cluster membership. The red shading represents the proportion of participants who responded not a problem, a minor problem, a moderate problem, or a major problem.

Table 1

Summary statistics for study participants at discharge, total and stratified by subsequent readmission to the hospital within 30 days. Summaries presented as n (%) or median (25th, 75th percentile).

	All participants (n=183)	Readmitted (n=41)	Not readmitted (n=142)
<i>Demographic characteristics</i>			
Age, years *	61 (53, 71)	59 (55, 69)	61 (52, 72)
Male sex *	120 (66)	26 (63)	94 (66)
Race			
White	78 (43)	18 (44)	60 (42)
Black	97 (53)	21 (51)	76 (54)
Other	8 (4)	2 (5)	6 (4)
Hispanic ethnicity	4 (2)	1 (2)	3 (2)
Marital status			
Married or partnered	81 (44)	18 (44)	63 (44)
Separated or divorced	25 (14)	4 (9)	21 (15)
Widowed	27 (15)	3 (7)	24 (17)
Single	48 (26)	16 (39)	32 (23)
Did not respond	2 (1)	0	2 (1)
Has a primary caregiver	154 (84)	32 (78)	122 (86)
Education past high school	87 (48)	23 (56)	64 (45)
Employment status			
Employed	37 (20)	6 (15)	31 (22)
Unemployed	14 (8)	3 (7)	11 (8)
Disabled	59 (32)	16 (39)	43 (30)
Retired	67 (37)	16 (7)	51 (36)
Did not respond	6 (3)	0	6 (4)
Insurance status			
Commercial	44 (24)	10 (24)	34 (24)
Public	135 (74)	30 (73)	105 (74)
Uninsured	4 (2)	1 (2)	3 (2)
Self-reported health status			
Excellent or very good	13 (7)	3 (7)	10 (7)
Good	26 (14)	1 (2)	25 (18)
Fair	72 (39)	19 (46)	53 (37)
Poor	66 (36)	14 (34)	52 (37)
Did not respond	6 (3)	4 (10)	2 (1)
<i>Medical history</i>			
Diabetes *	99 (54)	24 (59)	75 (53)
Heart failure *	177 (97)	40 (98)	137 (96)
Coronary artery disease *	93 (51)	29 (71)	64 (45)
Prior PCI *	25 (14)	9 (22)	16 (11)

	All participants (n=183)	Readmitted (n=41)	Not readmitted (n=142)
Aortic stenosis *	16 (9)	3 (7)	13 (9)
Stroke *	25 (14)	7 (17)	18 (13)
COPD *	17 (9)	3 (7)	14 (10)
<i>Admission exam and diagnostics</i>			
In-hospital cardiac arrest *	0	0	0
Systolic blood pressure, mmHg *	130 (113, 149)	128 (118, 139)	132 (112, 151)
Heart rate, beats/min *	82 (71, 92)	81 (70, 92)	82 (71, 93)
Respiratory rate, breaths/min *	20 (18, 20)	19 (18, 20)	20 (18, 20)
Body mass index, kg/m ²	32.9 (27.3, 40.9)	30.3 (25.8, 38.3)	33.2 (28.5, 41.6)
Sodium, mg/dL *	138 (136, 140)	137 (135, 139)	138 (136, 140)
Blood urea nitrogen, mg/dL *	26.0 (17.0, 41.0)	36.5 (21.5, 51.8)	24.0 (16.8, 37.0)
Creatinine, mg/dL *	1.41 (1.02, 1.93)	1.54 (1.16, 2.27)	1.31 (0.99, 1.81)
Hematocrit, % *	36.0 (31.0, 41.0)	36.0 (30.5, 40.0)	36.5 (32.0, 41.5)
Glucose, mg/dL *	114 (97, 164)	105 (93, 131)	118 (98, 169)
Left ventricular ejection fraction, % *	35 (20, 55)	31 (19, 46)	35 (20, 55)
<i>Hospital admissions in previous year</i>			
Any cause, #	2 (1, 4)	2 (1, 3.5)	2 (0, 4)
Heart failure cause, #	1 (0, 3)	1.5 (0, 3)	1 (0, 3)
Predicted readmission risk, % †	24.6 (21.5, 28.5)	27.5 (23.7, 31.0)	23.9 (21.0, 26.9)

PCI, percutaneous coronary intervention; COPD, chronic obstructive pulmonary disease

* Included in the Krumholz et al.⁵ readmission risk model for heart failure.

† Predicted readmission risk calculated using the Krumholz et al.⁵ readmission risk model for heart failure.

Table 2

Characteristics and patient-centered factors by cluster. “Low” corresponds to not a problem or a minor problem. “Moderate” corresponds to a minor-moderate problem. “High” corresponds to a moderate-major problem.

Cluster	Characteristics*	Following instructions	Management strategies	Financial effects	Daily activities	Physical effects	Emotional effects	Social support and relationships
Cluster 1 n=87	More likely male, retired, good-to-excellent self-rated health, fewest prior hospitalizations	Low	Low	Low	Low	Moderate	Low	Low
Cluster 2 n=62	More likely female, disabled, fair self-rated health	Low	Low	Moderate	High	High	Moderate	Low
Cluster 3 n=34	More likely unemployed, poor self-rated health, most prior hospitalizations	High	High	Moderate	High	High	High	Moderate

* Characteristics are numerically summarized in the online-only Data Supplement Table 1.