

An Early Warning Tool for Predicting at Admission the Discharge Disposition of a Hospitalized Patient

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Although the Department of Veterans Affairs (VA) health system is not necessarily reimbursement-based, it strives to achieve high quality care and efficient resource utilization via evidence-based practice and continuous measurement and improvement. Effectively managing patient flow through VA medical centers requires the proactive identification of appropriate level of care and services. Early planning and coordination by the healthcare team, including physicians, social workers, rehabilitation specialists, and postacute care services, improves inpatient care quality and access while reducing costs.^{1,2} The ability to predict discharge disposition—whether a patient can return home or requires placement in a care facility—could expedite rehabilitation, improve coordination of care among consultants, prepare caregivers, and help community agencies plan for needed resources. It also helps reduce length of hospital stay, which, in turn, may mitigate the risks of hospitalization and improve patient recovery.³⁻⁷ Consequently, early, accurate, and effective discharge planning has emerged as a high priority for both patients and hospital systems.⁸

The primary objective of this study was to develop an approach that could serve as an early warning decision aid to care providers for predicting, within 24 hours of admission, the discharge disposition of hospitalized veterans based on the available clinical and health utilization factors at index and previous hospitalizations.

METHODS

Setting

The study setting was the inpatient medical service at the West Roxbury campus of the VA Boston Healthcare System (VA-BHS). At the time of the study, discharge planning occurred within an interdisciplinary group consisting of a nurse case manager, a social worker, and a clinician representing the medical team. Consultations with other services, such as physical and/or occupational therapy, were made based on the individual assessments of these groups, mostly prompted by clinical judgment.

ABSTRACT

OBJECTIVES: To develop an early warning discharge disposition prediction tool based on clinical and health services factors for hospitalized patients. Recent study results suggest that early prediction of discharge disposition (ie, whether patients can return home or require placement in a facility) can improve care coordination, expedite care planning, and reduce length of stay.

STUDY DESIGN: Retrospective analysis of inpatient data; development of multiple logistic regression model and an easy-to-use score.

METHODS: We used retrospective data from all patients who were admitted in 2013 to the general medical service at the Veterans Affairs Boston Healthcare System and discharged alive. A derivation-validation approach was used to build a multiple logistic regression model, which was transformed into a score for potential implementation.

RESULTS: Of the 4760 patients discharged in 2013, 485 (10.2%) were discharged to a facility other than home. Correlates of discharge to a facility included a primary admission diagnosis of neoplasm [odds ratio [OR], 2.71; 95% CI, 1.73-4.25], diseases of the nervous system (OR, 2.53; 95% CI, 1.26-5.08), and musculoskeletal diseases (OR, 2.55; 95% CI, 1.52-4.27), as well as discharge to a facility during previous hospitalization. Patients with a prior primary diagnosis of circulatory disorder and those with comorbidity of hypertension, either complicated or uncomplicated, were less likely to be discharged to a facility. A value of 5 or greater on the 20-point scale indicated discharge to a facility with 83% sensitivity and 48% specificity.

CONCLUSIONS: A validated, easy-to-use score can assist providers in identifying upon admission those patients who may not be able to go directly home after hospitalization, thus facilitating early discharge planning and coordination, potentially reducing length of hospital stay and improving patient experience.

Am J Manag Care. 2018;24(10):e325-e331

TAKEAWAY POINTS

We developed an early warning discharge disposition prediction tool to facilitate discharge planning and coordination, potentially reducing length of hospital stay and improving patient experience.

- ▶ Our tool can be used within 24 hours of a patient's admission to a general internal medicine unit.
- ▶ The tool is a scoring system that has been derived from a statistical model.
- ▶ It will help care managers in effectively classifying, at the point of admission, patients requiring disposition to facilities other than home.

Main outcome measure. The main outcome was the patient's discharge disposition, home versus facility. Patients discharged to the community, including those who were homeless and referred to a shelter, were considered discharged to "home." Facility locations included VA nursing home care units (NHCUs), also known as Community Living Centers, and non-VA nursing homes.

Data Collection

We obtained 4817 records (3187 were unique patients) from the corporate data warehouse of the VA-BHS for January 1, 2013, through December 31, 2013. After excluding 57 records (1.18%) with missing discharge disposition, the final data set consisted of 4760 records. We considered factors for inclusion in this study that would be readily available to the care team within 24 hours of admission.

Index admission. For the index admission, we ascertained demographic information (ie, age, sex, race, presence of non-VA health insurance, and marital status), clinical factors (primary diagnosis, number of diagnoses), source of admission, and specialty of the admitting ward. The primary diagnosis at the time of admission is not an available field in VA administrative data; however, the primary hospitalization diagnosis, recorded clinically at the time of discharge, is routinely transcribed from the admission history and physical notes and thus represents the likely primary diagnosis at the time of admission. These diagnoses were grouped into 19 categories based on *International Classification of Diseases, Ninth Revision* standard code groups. We counted all recorded discharge diagnoses associated with that admission and included this sum as the number of diagnoses. Admission sources included VA nursing home, VA domiciliary, transfer from other VA hospital, outpatient treatment, and other direct admissions (eg, walk-ins, directly admitted from home, transfers from non-VA facilities). Admitting ward specialties included general (acute medicine), cardiac intensive care unit (ICU), medical ICU, medical step down, telemetry, and hospice for acute care. We included ICU patients because the variables considered in predicting their disposition are comparable with those of patients admitted to non-critical care units. We further derived the 31 Elixhauser comorbidities using the updated *International Classification of Diseases, Ninth Revision, Clinical Modification* coding schema of Quan et al.⁹ This study was approved by the VA-BHS Institutional Review Board.

Historical factors. We also derived several historical clinical and health services factors using a 12-month "look back" into 2012 records of each of the unique patients. The clinical factors included the primary diagnosis of the immediately preceding hospital admission, the number of diagnoses on the immediately preceding admission, and the discharge disposition for the immediately preceding admission. The health services/utilization factors included the number of admissions in the 12 months prior to the index admission and an indicator of whether the index admission was an all-cause readmission within 30 days.

Data Analysis

Due to pragmatic limitations to conducting a prospective validation, we adopted the standard derivation-validation approach. Accordingly, we split the records randomly into 2 subsets of 70% and 30%. Using the 70% data subset (the derivation set; $n = 3351$), we built a case-mix-adjusted multiple logistic regression model of discharge to facility (using backward stepwise selection; $P = .05$), with sex forced into the model. Robustness of the selected predictors was confirmed through combined backward-forward and forward-only stepwise methods, and other P values.

After the first model was built, admission from a VA NHCUs was found to have a disproportionately large odds ratio (OR) of approximately 145 for facility discharge, attributable to the fact that nearly all patients admitted from an NHCUs (40/42; 95%) were discharged to a facility. Consequently, admission from an NHCUs was deemed the major, and sufficient, factor for the hospital care team to deem a facility discharge. The final multiple logistic regression model we present next does not include NHCUs admission as a predictor.

Once the final model was derived, we used the remaining 30% of the data (the validation data set; $n = 1409$) to estimate the model's predictive power based on area under the operating curve (AUC) values. A score for clinical application was derived from the final model. Using the standardized logistic regression coefficients, each factor in the final model was assigned a relative weight on a 20-point scale; the score for a patient would then be the sum of these weights, if the corresponding factors were present for that patient. The 20-point scale was chosen as the best balance between discrimination (to allow enough separation between factors) and ease of use. These weights were rounded to integer values for ease of addition in practice. In deciding whether to round each weight up or down, our objective was to maximize the correlation between the total score for a patient and the predicted probability of discharge to facility for that patient from the logistic regression model (across all records in the derivation data set). Continuous predictors (age and number of diagnoses) were separated into categories based on the distribution of the data; the weight assigned to each of these was divided among the corresponding categories, and these divisions were considered as additional decision variables in the optimization. The sum of all the weights in the score was constrained to be 20 (ie, if a patient exhibited all predictors from the final model, then the patient would be assigned a score of

20). Details of the scoring methodology and optimization are presented in **eAppendix A** (eAppendices available at ajmc.com).

Because the coefficients in the logistic regression model, and the corresponding factor score weights, could be either positive (predictive of discharge to a facility) or negative (protective factors), we separated them into 2 positive additive subtotals in the scoring tool, 1 for the predictive factors and 1 for the protective factors. The latter was then subtracted from the former to get the final score for a patient. Clinical practitioners were consulted in order to ensure that the questions relating to each factor from the model were phrased in a way that would make sense to a care provider. We then determined a threshold value beyond which the patient was likely to go to a facility, considering an acceptable sensitivity and specificity of the score suggested by our medical collaborators. SAS version 9.4 (SAS Institute; Cary, North Carolina) was used for all statistical analyses.

RESULTS

Of the 4760 patients in the full data set, 485 (10.2%) were discharged to a facility, which included a VA nursing home (n = 301), VA medical center (n = 129), community nursing home (n = 53), VA domiciliary (n = 1), and other government hospital (n = 1).

Table 1 indicates that demographic variables such as age, marital status, and white race were independent predictors of the patient's disposition location. Several other factors related to admitting source, admitting ward, clinical diagnosis, and comorbidities were also significant.

Table 2 highlights that a previous admission diagnosis of diseases of the nervous system, diseases of the circulatory system, or external causes of injury and supplemental classification, as well as total number of diagnoses, were independent historical clinical predictors of the discharge disposition for the index admission. Number of previous admissions in the past 6 months and previous discharge to a community hospital, VA medical center, or VA NHCU were independent health services predictors of the discharge disposition for the index admission.

Table 3 shows the case-mix-adjusted logistic regression model, along with the ORs and 95%

TABLE 1. Characteristics of the Patients at Admission*

Characteristic	Home n = 4275 (90%)	Facility n = 485 (10%)
Age, years, mean ± SD***	70.29 ± 13.43	73.64 ± 12.72
Female, n (%)	171 (4)	20 (4)
Married, n (%)*	1597 (37)	135 (28)
Race, n (%)		
White, not of Hispanic origin**	1764 (41)	244 (50)
Black, not of Hispanic origin	157 (4)	12 (2)
Hispanic, white	21 (<1)	1 (<1)
Asian or Pacific Islander	7 (<1)	0 (0)
Hispanic, black	4 (<1)	0 (0)
American Indian or Alaska Native	2 (<1)	1 (<1)
Insurance coverage, n (%)	3333 (78)	364 (75)
Primary diagnosis, n (%)		
Infectious and parasitic diseases	131 (3)	23 (5)
Neoplasms***	176 (4)	47 (10)
Endocrine, nutritional, and metabolic diseases and immunity disorders	225 (5)	15 (3)
Diseases of the blood and blood-forming organs	84 (2)	7 (1)
Mental disorders	392 (9)	29 (6)
Diseases of the nervous system**	55 (1)	13 (3)
Diseases of the sense organs	19 (<1)	2 (<1)
Diseases of the circulatory system**	1037 (24)	80 (16)
Diseases of the respiratory system*	564 (13)	80 (16)
Diseases of the digestive system	378 (9)	31 (6)
Diseases of the genitourinary system	299 (7)	26 (5)
Diseases of the skin and subcutaneous tissue	160 (4)	14 (3)
Diseases of the musculoskeletal system and connective tissue**	136 (3)	29 (6)
Congenital anomalies	7 (<1)	0 (0)
Symptoms, signs, and ill-defined conditions	401 (9)	43 (9)
Injury and poisoning***	194 (5)	43 (9)
External causes of injury and supplemental classification	17 (<1)	3 (1)
Number of diagnoses, mean ± SD***	10.19 ± 3.75	11.65 ± 3.28
Elixhauser comorbidities, n (%)		
Congestive heart failure	867 (20)	109 (22)
Cardiac arrhythmia*	1321 (31)	170 (35)
Valvular disease	316 (7)	31 (6)
Pulmonary circulation disorders	170 (4)	19 (4)
Peripheral vascular disorders	367 (9)	42 (9)
Hypertension, uncomplicated*	1910 (45)	186 (38)
Hypertension, complicated*	614 (14)	49 (10)
Paralysis**	55 (1)	16 (3)
Other neurological disorders***	288 (7)	58 (12)
Chronic pulmonary disease	1254 (29)	146 (30)
Diabetes, uncomplicated	1198 (28)	132 (27)
Diabetes, complicated	304 (7)	38 (8)
Hypothyroidism	217 (5)	32 (7)
Renal failure	859 (20)	91 (19)

(continued)

TABLE 1. (Continued) Characteristics of the Patients at Admission*

Characteristic	Home n = 4275 (90%)	Facility n = 485 (10%)
Liver disease	505 (12)	59 (12)
Peptic ulcer disease, excluding bleeding	28 (1)	2 (<1)
AIDS/HIV	16 (<1)	4 (1)
Lymphoma	68 (2)	8 (2)
Metastatic cancer***	124 (3)	37 (8)
Solid tumor without metastasis***	353 (8)	71 (15)
Rheumatoid arthritis/collagen vascular disease	58 (1)	11 (2)
Coagulopathy	162 (4)	11 (2)
Obesity	238 (6)	30 (6)
Weight loss	82 (2)	18 (4)
Fluid and electrolyte disorders	587 (14)	81 (17)
Blood loss anemia	18 (<1)	2 (<1)
Deficiency anemia*	208 (5)	35 (7)
Alcohol abuse**	809 (19)	69 (14)
Drug abuse	261 (6)	26 (5)
Psychoses***	192 (4)	52 (11)
Depression	848 (20)	105 (22)
Source of admission, n (%)		
From home or other non-VA community location**	3392 (79)	347 (72)
From VA outpatient clinic	856 (20)	90 (19)
Transfer from another VA hospital**	22 (1)	7 (1)
VA nursing home care unit***	2 (<1)	40 (8)
Transfer from non-VA hospital	2 (<1)	0 (0)
VA domiciliary	1 (<1)	1 (<1)
Nursing unit on admission, n (%)		
General medicine, without telemetry implemented***	2297 (54)	319 (66)
General medicine, with telemetry implemented***	1494 (35)	118 (24)
Cardiac ICU	242 (6)	18 (4)
Medical step down ^b	128 (3)	14 (3)
Medical ICU	113 (3)	18 (4)
Hospice for acute care	1 (<1)	0 (0)

ICU indicates intensive care unit; VA, Veterans Affairs.

* $\alpha = .05$; ** $\alpha = .01$; *** $\alpha = .001$ in bivariate analysis using the derivation set.

*Some categories may not add up to 100% due to missing values not reported here.

^bThe medical step down unit is principally intended for patients requiring more frequent nursing contact and/or more intensive respiratory monitoring than the general medical units but not requiring 1-to-1 nursing care or other intensive care of the critical care units.

CI) based on the derivation data set; ORs greater than 1 indicate higher chance of discharge to a facility, whereas ORs less than 1 indicate higher chance of going home. The AUC of this model was 0.75 for the derivation data set; using the validation set, the AUC was 0.74.

Among diagnoses on admission of the index hospitalization, neoplasms (OR, 2.71; 95% CI, 1.73-4.25), diseases of the nervous system (OR, 2.53; 95% CI, 1.26-5.08), and diseases of the musculoskeletal system and connective tissue (OR, 2.55; 95% CI, 1.52-4.27) were associated with discharge to a facility. In contrast, historical primary diagnosis of circulatory system disease was associated with lower likelihood of discharge to a facility (OR, 0.54; 95% CI, 0.35-0.83),

as were the presence of both uncomplicated hypertension (OR, 0.62; 95% CI, 0.47-0.80) and complicated hypertension (OR, 0.31; 95% CI, 0.20-0.48) during prior hospitalization. The previous primary diagnosis of external causes of injury and supplemental classification indicated a higher likelihood of patient discharge to a facility (OR, 2.58; 95% CI, 1.73-3.84), as did the comorbidity of other neurological disorders (OR, 1.70; 95% CI, 1.16-2.50).

The 3 previous discharge disposition locations of community hospital, VA medical center, and VA NHCU were associated with high ORs (10.33, 4.21, and 3.59, respectively), indicating that if the patient had been discharged to one of these locations after the prior admission, then this patient was very likely to go to a facility again upon discharge from the index hospitalization.

The score developed for clinical application is shown in **eAppendix B**. The weights assigned to the factors in the score achieved an 84% correlation with the logistic regression model probabilities for the derivation set. At a classification threshold of 5 points, the score achieved a sensitivity (number of discharges to a facility correctly identified as such) and specificity (number of home discharges correctly identified as such) of 83% and 46%, respectively (**Figure**). When tested on the validation set, the score with this threshold achieved 82% sensitivity and 48% specificity, suggesting that the score is robust in predicting discharge to a facility.

DISCUSSION

In this retrospective study of an entire year's acute care hospitalizations at a tertiary care VA medical center, we identified variables that predict, at the time of admission, a patient's likely discharge to a facility. We found that

nearly all patients admitted from a VA NHCU were discharged to a facility. Using a derivation-validation approach, we determined that older patients; those admitted with neurologic, oncologic, and musculoskeletal primary diagnoses; those with higher numbers of diagnoses; and those previously hospitalized and discharged to a VA medical center were more likely to be discharged to a facility during the index hospitalization. In contrast, those with hypertension and those with a prior hospitalization with a primary diagnosis of a circulatory disorder were less likely to be discharged to a facility in the index hospitalization. These findings, validated in a subsequent logistic regression model, led to the creation of a clinically relevant

score that can be used to predict at the time of admission, with good sensitivity and acceptable specificity, discharge to a facility.

Several studies have focused on predicting discharge among specific patient populations, such as stroke, traumatic brain injury, total joint arthroplasty, geriatric, trauma, or cardiac surgery^{2,10-14}; some have proposed various prediction tools.¹⁵⁻¹⁸ The Barthel scale¹⁹ was developed to assess improvement of stroke patients throughout rehabilitation by periodic repetitions of the test, whereas the Blaylock Risk Assessment Screening Score index²⁰ was developed for use in elderly patients within 48 hours of admission. Recently, Simonet et al developed a validated score predicting risk of discharge to a postacute care facility for general medicine patients, both on day 1 (admission) and day 3 of hospital stay.⁵ Although their study had fewer than 400 patients, most likely due to its prospective nature, 3 of 5 significant factors in their day 1 model were similar to our findings: age, number of diagnoses, and admission source. Unlike the present study, they did not find historical health utilization factors (ie, hospital and emergency department visits in the past 3 months) to be independent predictors. In further contrast, they used an aggregate comorbidity index (Charlson index) not found to predict discharge disposition, whereas we used the more granular set of 31 Elixhauser comorbidities, 3 of which were part of the final adjusted model. We acknowledge that some of the comorbid conditions occurred with relatively low prevalence in this population and, as such, the comorbid conditions in the final model should be validated in future study.

Our study is among the first to predict discharge disposition among general internal medicine VA patients. It is also among only a few to deliver an implementable predictive tool based on the statistical analysis conducted in the study. Although current clinical factors, such as diagnosis and comorbidities, typically form the basis of a care provider's instinctive prediction of the eventual disposition location, we uncovered a few historical clinical and health utilization factors that also seem to play an important role in this decision-making process in practice.

This tool could be used by the patient's care team at admission to classify the patient as one to potentially be discharged to a facility. This information would provide an early indicator to the patient and the care team at the beginning phase of the patient's stay, when

clinical information is sparse and before other clinical bedside data and functional status assessments have been collected. Having this "early warning" would facilitate discharge planning, as the discharge coordinator could initiate discussion with the patient soon after admission regarding the potential for placement in a facility and begin evaluating alternatives. It is worth noting that the purpose of such an early warning system is to help the care team anticipate the potential workload of discharge planning, to promote and enhance communication between providers and the patient, and to expedite overall care coordination associated with discharge to

TABLE 2. Historical Clinical and Health Services Variables for the Cohort

Characteristic	Home n = 4275 (90%)	Facility n = 485 (10%)
Previous primary diagnosis, n (%)		
Infectious and parasitic diseases	64 (1)	7 (1)
Neoplasms	131 (3)	25 (5)
Endocrine, nutritional, and metabolic diseases and immunity disorders	132 (3)	11 (2)
Diseases of the blood and blood-forming organs	54 (1)	7 (1)
Mental disorders	485 (11)	64 (13)
Diseases of the nervous system*	44 (1)	11 (2)
Diseases of the sense organs	19 (<1)	2 (<1)
Diseases of the circulatory system***	664 (16)	47 (10)
Diseases of the respiratory system	309 (7)	24 (5)
Diseases of the digestive system	228 (5)	22 (5)
Diseases of the genitourinary system	167 (4)	9 (2)
Diseases of the skin and subcutaneous tissue	87 (2)	10 (2)
Diseases of the musculoskeletal system and connective tissue	91 (2)	12 (2)
Congenital anomalies	2 (<1)	0 (0)
Symptoms, signs, and ill-defined conditions	268 (6)	35 (7)
Injury and poisoning	102 (2)	16 (3)
External causes of injury and supplemental classification***	160 (4)	83 (17)
Previous discharge disposition, n (%)		
Return to community/independent	2730 (64)	294 (61)
VA medical center***	135 (3)	43 (9)
Community nursing home	38 (1)	8 (2)
VA nursing home care unit***	24 (1)	11 (2)
Community hospital*	6 (<1)	6 (1)
VA domiciliary	1 (<1)	0 (0)
Other government hospital	0 (0)	1 (<1)
Other placement/unknown (not specified)	0 (0)	1 (<1)
Previous number of diagnoses, mean ± SD***	9.93 ± 4.30	11.10 ± 3.40
Current admission is an all-cause readmission within 30 days, n (%)*	1255 (29)	175 (36)
Number of admissions in past 6 months, mean ± SD*	1.42 ± 2.10	1.59 ± 1.84
Number of admissions in past 12 months, mean ± SD	2.27 ± 3.39	2.33 ± 2.45

VA indicates Veterans Affairs.

* $\alpha = .05$; ** $\alpha = .01$; *** $\alpha = .001$ in bivariate analysis using the derivation set.

*Some categories may not add up to 100% due to missing values not reported here.

TABLE 3. Case-Mix-Adjusted Model for Disposition Prediction of Patients Not Admitted From Nursing Home Care Units, Using the Derivation Data Set

Predictor	Odds Ratio (95% CI)	P
Age	1.02 (1.01-1.03)	.0001
Female sex	0.84 (0.43-1.65)	.6094
Primary diagnosis		
Neoplasms	2.71 (1.73-4.25)	<.001
Diseases of the nervous system	2.53 (1.26-5.08)	.0094
Diseases of the musculoskeletal system and connective tissue	2.55 (1.52-4.27)	.0004
Number of diagnoses*	1.15 (1.11-1.20)	<.001
Previous primary diagnosis		
Diseases of the circulatory system	0.54 (0.35-0.83)	.0047
External causes of injury and supplemental classification	2.58 (1.73-3.84)	<.001
Previous discharge disposition		
Community hospital	10.33 (2.07-51.63)	.0045
VA medical center	4.21 (2.60-6.83)	<.001
VA nursing home care unit	3.59 (1.49-8.67)	.0044
Comorbidities		
Hypertension, uncomplicated	0.62 (0.47-0.80)	.0003
Hypertension, complicated	0.31 (0.20-0.48)	<.001
Other neurological disorders	1.70 (1.16-2.50)	.0069

VA indicates Veterans Affairs.

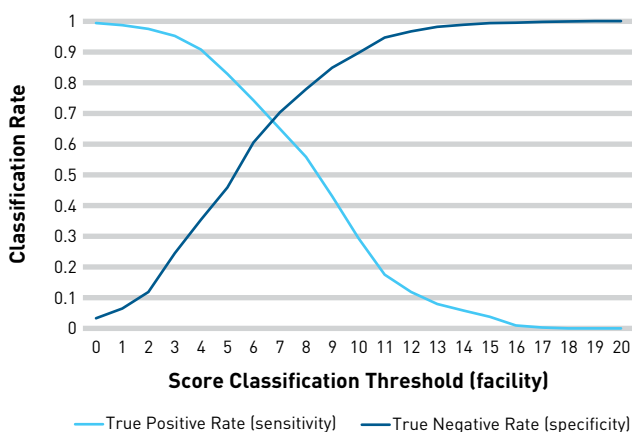
*Because discharge diagnosis by definition is not available on admission, the scoring system uses the active diagnoses being addressed on admission as a proxy.

a facility, and not to identify an optimal discharge within those 24 hours upon admission.

In terms of the diagnoses found in this study to be significantly associated with discharge to a facility, many were consistent with what clinicians would expect among very ill patients who would likely need postacute care in a nursing, rehabilitation, or specialized facility, such as those with metastatic cancer, paralysis, and psychoses. Conversely, the factors that seemed to be protective (ie, predictive of a discharge to home)—for example, having a diagnosis of hypertension, either complicated or uncomplicated—may simply be an indicator of the absence of more serious or complicated diagnoses.

Lowering the threshold, or cut point, in the prediction model allows for increased sensitivity at the expense of decreased specificity. The implications of these trade-offs are worth considering further. For instance, although an increase in sensitivity would predict accurately at admission a larger proportion of patients to be discharged to a facility, a number of these would also be false positives (predicting discharge to a facility when actually the patient goes home). This may be due to the evolving clinical and functional status information, along with other factors (eg, patient/family choice, patient's social network, availability of beds at postacute care settings, etc), during the patient's stay. In all of those false-positive cases, the care provider team would have begun planning for a discharge to a facility on day 1 and continued their effort until it became apparent that the patient may be able to realize a discharge to home. This process induces overutilization of scarce resources, including expert discharge planning and physical therapy consultations. In general, however, our sense is that most clinicians and case managers would favor being surprised by a patient going home rather than being surprised by a patient requiring discharge to a rehabilitation or skilled nursing facility, as planning for the latter normally requires a longer lead time.

FIGURE. Effect of Classification Threshold on Score Sensitivity and Specificity



Limitations

Our study findings must be viewed in the context of several limitations. First, although we accessed rich clinical data from the corporate data warehouse, this data source did not include patients' activities of daily living, income level, or level of social support. We used the number of diagnoses as a proxy to estimate patient acuity and marital status as a proxy to estimate available social support. Second, in determining the primary diagnosis and number of diagnoses for a patient admission, the recorded discharge diagnoses associated with that admission were used. At this facility, the primary diagnosis at admission is routinely transcribed as the discharge diagnosis; however, this approach may have resulted in our using some diagnoses that were not actually known at the time of admission. Because discharge diagnosis by definition is not available on admission, the model and scoring system use the active diagnosis identified on admission as a proxy. Third, although we could not identify the eventual disposition of 129 patients transferred to another VA medical center, we classified them as discharged to a facility, as the eventual disposition was not

germane to the disposition outcome of the index hospitalization. Finally, to develop and validate our early warning approach, we focused on a specific cohort of veterans hospitalized on a general medicine unit at one VA facility. We believe that the tool may be potentially generalizable to similarly sized VA hospitals, but further study is needed for validation in this population as well as for generalizability to other settings and populations.

CONCLUSIONS

In order to preempt potential delays in discharging patients from an acute inpatient facility, we attempted to identify factors apparent at the time of a patient's admission to a general medicine unit that are statistically significant predictors of eventual discharge to a facility, as opposed to discharge to home. Using a year's worth of clinical data from a tertiary care VA medical center, we used a derivation-validation approach and identified several such factors. From the final model, we developed a point-based scoring tool that can be readily implemented in clinical practice with minimal disruption.

Our study is both confirmatory and exploratory. We confirm previous research conducted on nonveteran populations and among patients with specific medical conditions that demonstrated the ability to develop a model to predict discharge disposition at admission using readily available factors. We explored the statistical significance of several historical clinical and health services factors that are frequently considered in clinical practice; many of these variables were independent predictors, and 2 were indeed part of the final adjusted model. We also developed a predictive score; future study should explore the validation of this score in actual clinical practice. ■

Acknowledgments

This research was supported by a contract from the New England Veterans Engineering Resource Center (NE-VERC). The authors appreciate the support from Maria Lebedeva, PhD, who was the primary contact at NE-VERC and facilitated data collection and collaborations with the VA Boston collaborators.

Coauthor Michael Donlin, MSN, ACNP-BC, FHM, died April 3, 2017.

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Source of Funding: New England Veterans Engineering Resource Center.

Author Disclosures: The authors report no relationship or financial interest with any entity that would pose a conflict of interest with the subject matter of

this article. The views expressed in this article are those of the authors and do not necessarily represent the views of the Department of Veterans Affairs.

Authorship Information: Concept and design (NB, PJP, MD, EKM, SRS); acquisition of data (NB, MD, EKM, SRS); analysis and interpretation of data (NB, PJP, MD, EKM); drafting of the manuscript (NB, PJP, MD); critical revision of the manuscript for important intellectual content (NB, PJP, SRS); statistical analysis (NB, PJP); obtaining funding (PJP); administrative, technical, or logistic support (SRS); and supervision (PJP).

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eAppendix A. Derivation of a Score from the Logistic Regression Model

A score for practical use was derived from the final logistic regression model. Comparing relative values of the coefficient of the variables in the logistic model have been used to assign points. For instance, in the study by Simonet et al.⁵, out of 5 variables, 4 of the coefficients were roughly 4 times larger than the remaining coefficient, so these 4 variables were assigned 4 points each and the fifth was assigned 1 point in the scoring system. However, coefficients which are standardized to the scale of their respective variables are generally regarded as more meaningful than unstandardized coefficients. The scoring system developed by Beaulieu¹⁷ uses a methodology relying on standardized coefficients to assign weights to the final variables. Several approaches to standardizing coefficients in logistic regression exist; Menard et al. list 6 different methods, all of which rely in some manner on the variance of their respective variables.

SAS statistical software, which was used in this study, provides standardized estimates of the coefficient β_i by $\hat{\beta}_i/(s/s_i)$, where s_i is the total sample standard deviation for the i th explanatory variable and $s = \pi/\sqrt{3}$. Using the standardized logistic regression coefficients ($\hat{\beta}_i^*$) provided by SAS, each factor in the final model was assigned a relative weight w_i out of a 20-point scale, using the following formula:

$$w_i = 20 * \hat{\beta}_i^* / \sum \hat{\beta}_i^*$$

While any scale could have been used, a 20-point scale was chosen as the best balance between discrimination (to allow enough separation between factors) and ease-of-use; a smaller scale might not ensure that all coefficients could be rounded to representative integers, whereas a larger scale might be cumbersome to use. Beaulieu¹⁷ also used a 20-point scale.

For the 14 variables included in the final model, eAppendix Table 1 summarizes the original coefficient estimates, the standardized coefficient estimates provided by SAS, and the assigned weights.

eAppendix Table 1. Historical Clinical and Health Services Variables for the Cohort

Variable	Coefficient Estimate ($\hat{\beta}_i$)	Standardized Coefficient Estimate ($\hat{\beta}_i^*$)	Weight (w_i)
Age	0.019	0.142	4.255
Sex (Female)	-0.176	-0.019	-0.570
Current Diagnosis: Neoplasms	0.998	0.114	3.432
Current Diagnosis: Diseases of the Nervous System	0.926	0.063	1.904
Current Diagnosis: Diseases of the Musculoskeletal System and Connective Tissue	0.936	0.095	2.858
Number of Diagnoses (Current)	0.141	0.290	8.692
Previous Diagnosis: Diseases of the Circulatory System	-0.615	-0.120	-3.591
Previous Diagnosis: External Causes of Injury and Supplemental Classification	0.947	0.113	3.396
Previous Discharge Disposition: Community Hospital	2.335	0.059	1.775
Previous Discharge Disposition: VA Medical Center	1.439	0.148	4.429
Previous Discharge Disposition: VA Nursing Home Care Unit	1.279	0.062	1.868
Comorbidity: Hypertension, Uncomplicated	-0.486	-0.133	-3.981
Comorbidity: Hypertension, Complicated	-1.175	-0.225	-6.765
Comorbidity: Other Neurological Disorders	0.530	0.077	2.300

The score for a patient would then be the sum of these weights (if the corresponding factors were present for that patient). These weights were rounded to integer values for ease of addition in practice. Instead of an ad hoc approach, we performed this rounding using an optimization approach. In deciding whether to round each weight up or down to the nearest integer value, our objective was to maximize the correlation between the total score for a patient and the predicted probability of discharge to a facility for

that patient from the logistic regression model (across all records in the derivation data set). This was chosen as the objective to ensure that the score was as faithful a representation of the logistic regression model as possible. Due to rounding, some inherent loss of accuracy is unavoidable in the score; however, in general, a higher score should correlate with a higher underlying probability of discharge to a facility and vice-versa. This can be captured by maximizing the correlation between the 2, measured using the Pearson correlation coefficient, ρ .

In developing the score, continuous predictors (age and number of diagnoses) were separated into sub-categories based on the distribution of the data. In both cases, 4 sub-categories were formed; the division points were created following the standard deviations of the underlying variables ($x \leq \mu - 2\sigma$, $x \leq \mu - \sigma$, $x \leq \mu + \sigma$, $x \geq \mu + 2\sigma$). This resulted in the 4 mutually exclusive sub-categories shown in the score in Appendix A. The rounded weight assigned to each parent continuous predictor was then divided among the sub-categories; these divisions were considered as additional decision variables in the optimization. For example, if age was rounded to 5 points, then the 4 sub-categories of age must be assigned some combination of the weights 1, 1, 1, and 2 (summing up to 5). The sum of all the rounded weights in the score was constrained to be 20, ensuring that if a patient exhibited all predictors from the final model, they would be assigned a score of 20.

The optimization is presented below with notations and bounds summarized in eAppendix Tables 2 and 3.

eAppendix Table 2. Notation for the Optimization Model

Decision Variable	Description
w_i^*	Rounded weight assigned to each final predictor i
w_{age}^*	Rounded weight assigned to the final predictor <i>age</i>
w_{diag}^*	Rounded weight assigned to the final predictor <i>number of diagnoses</i>
y_j^*	Weight assigned to each of the 4 age sub-categories
z_k^*	Weight assigned to each of the 4 number of diagnoses sub-categories
S_p	Score for patient p
\hat{S}	Vector comprising of scores, S_p , across all patients p
Parameter	Description
I	Set of final predictors; $i \in I$
J	Set of sub-categories for age; $j \in J$
K	Set of sub-categories for number of diagnoses; $k \in K$
P	Set of patient records; $p \in P$
u_i	Upper limit of each rounded weight i^{**}
l_i	Lower limit of each rounded weight i^{**}
u_{age}	Upper limit of the rounded weight for age ^{**}
l_{age}	Lower limit of the rounded weight for age ^{**}
u_{diag}	Upper limit of the rounded weight for number of diagnoses ^{**}
l_{diag}	Lower limit of the rounded weight for number of diagnoses ^{**}
α_{ip}	Indicator if predictor i is present for patient p
β_{jp}	Indicator if patient p falls into age sub-category j
γ_{kp}	Indicator if patient p falls into number of diagnoses sub-category k
P_p	Predicted probability of patient discharge to a facility from the final regression model
\hat{P}	Vector comprising of predicted probabilities, P_p , across all patients p

^{**} See eAppendix Table 3 for upper and lower bounds on the rounded weights. Notice that these were set to the nearest integer values bounding each fractional weight w_i , w_{age} , or w_{diag} .

eAppendix Table 3. Upper and Lower Bounds on Rounded Weights

Variable	Upper Bound on Rounded Weight (u_i)	Lower Bound on Rounded Weight (l_i)
Age	5	4
Sex (Female)	0	-1
Current Diagnosis: Neoplasms	4	3
Current Diagnosis: Diseases of the Nervous System	2	1
Current Diagnosis: Diseases of the Musculoskeletal System and Connective Tissue	3	2
Number of Diagnoses (Current)	9	8
Previous Diagnosis: Diseases of the Circulatory System	-3	-4
Previous Diagnosis: External Causes of Injury and Supplemental Classification	4	3
Previous Discharge Disposition: Community Hospital	2	1
Previous Discharge Disposition: VA Medical Center	5	4
Previous Discharge Disposition: VA Nursing Home Care Unit	2	1
Comorbidity: Hypertension, Uncomplicated	-3	-4
Comorbidity: Hypertension, Complicated	-6	-7
Comorbidity: Other Neurological Disorders	3	2

Objective: $\max \rho(\hat{S}, \hat{P})$

Subject to:

$$S_p = \sum_{i \in I} \alpha_{ip} w_i^* + \sum_{j \in J} \beta_{jp} y_j^* + \sum_{k \in K} \gamma_{kp} z_k^* \quad \forall p$$

$$l_i \leq w_i^* \leq u_i \quad \forall i$$

$$l_{age} \leq w_{age}^* \leq u_{age}$$

$$l_{diag} \leq w_{diag}^* \leq u_{diag}$$

$$\sum_{j \in J} y_j^* = w_{age}^*$$

$$\sum_{k \in K} z_k^* = w_{diag}^*$$

$$\sum_{i \in I} w_i^* + w_{age}^* + w_{diag}^* = 20$$

$$w_i^*, w_{age}^*, w_{diag}^*, y_j^*, z_k^* \in Z \quad \forall i, j, k$$

The objective, as noted previously, is to maximize the Pearson correlation between the assigned scores and the predicted probabilities from the final logistic regression model. The first constraint defines the score for each patient; the next 3 bound each rounded weight. The fifth and sixth constraints ensure that the combined weights allocated to the sub-categories within the 2 continuous predictors must equal the total rounded weight allocated to the parent continuous predictor (i.e., age and number of diagnoses). The seventh constraint ensures that the rounded weights assigned to all the final predictors sum to 20, keeping to the 20-point scale. The last constraint ensures that the rounded weights for predictors and sub-categories to take on positive or negative integer values (i.e., they belong to the set of integers, Z).

Since the coefficients in the logistic regression model (and the corresponding factor score weights) could be either positive (predictive of discharge to a facility) or negative (protective factors), we separated them into 2 positive additive subtotals in the scoring tool, 1 for the *predictive* factors and 1 for the *protective* factors. The latter is then subtracted from the former to get the final score for a patient. Clinical practitioners were consulted in order to ensure that the questions relating to each factor from the model were phrased in a way that have clinical and practical relevance to the care providers on the unit.

We then determined a threshold value beyond which the patient was likely to be discharged to a facility, considering an acceptable sensitivity and specificity of the score suggested by our medical collaborators. SAS v9.4 was used for all statistical analyses.

Reference

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eAppendix B. A Score for Determination of Discharge to a Facility within 24 Hours of Admission to General Medicine

Was patient admitted from a VA Nursing Home Care Unit (NHCU)?
 If YES, patient should be treated as a **discharge to a facility**
 If NO, use the score below:

<i>Factors predicting discharge to a facility</i>		Points	
How old is the patient?			
56 or younger		1	_____
57 to 70		2	
71 to 84		3	
85 or older		4	
Does the patient's current primary diagnosis fall into one of the following categories?			
Diseases of the nervous system		2	_____
Neoplasms		3	
Diseases of the musculoskeletal system and connective tissue		3	
How many active diagnoses are being addressed on admission?			
5 or fewer		1	_____
6 to 10		3	
11 to 14		6	
15 or more		8	
If the patient was discharged from the hospital within the last 12 months was the primary diagnosis "external causes of injury and supplemental classification" (E and V ICD-9 codes)?			
		4	_____
If the patient was discharged from the hospital within the last 12 months, were they discharged to one of the following?			
Community hospital		1	_____
VA nursing home care unit		1	
VA medical center		5	
Does the patient currently exhibit the comorbidity of "other neurological disorders" (ELX 9)?			
		2	_____
Subtotal A (sum up the points for the predictive factors)			_____
<i>Factors predicting discharge to home (protective factors)</i>			
Is the patient female?			
		1	_____
When the patient was last admitted, did the primary diagnosis fall under the category of "diseases of the circulatory system"?			
		3	_____
Does the patient currently exhibit one of the following comorbidities?			
Hypertension, Uncomplicated (ELX 6)		3	_____
Hypertension, Complicated (ELX 7)		6	_____
Subtotal B (sum up the points for the protective factors)			_____
_____	-	_____	= _____
Subtotal A	-	Subtotal B	= Final Score

If Final Score is 5 or greater,
the patient is more likely to be discharged to a Facility.