



Risk Factors for Hospitalization Among Community-Dwelling Primary Care Older Patients

Citation

Inouye, Sharon K., Ying Zhang, Richard N. Jones, Peilin Shi, L Adrienne Cupples, Harold N. Calderon, and Edward R. Marcantonio. 2008. "Risk Factors for Hospitalization Among Community-Dwelling Primary Care Older Patients." Medical Care 46 (7): 726–731. doi:10.1097/mlr.0b013e3181649426.

Published Version

doi:10.1097/MLR.0b013e3181649426

Permanent link

http://nrs.harvard.edu/urn-3:HUL.InstRepos:33750349

Terms of Use

This article was downloaded from Harvard University's DASH repository, and is made available under the terms and conditions applicable to Other Posted Material, as set forth at http://nrs.harvard.edu/urn-3:HUL.InstRepos:dash.current.terms-of-use#LAA

Share Your Story

The Harvard community has made this article openly available. Please share how this access benefits you. <u>Submit a story</u>.

Accessibility



NIH Public Access

Author Manuscript

Med Care. Author manuscript; available in PMC 2008 August 15.

Published in final edited form as: *Med Care*. 2008 July ; 46(7): 726–731.

Risk Factors for Hospitalization Among Community-Dwelling Primary Care Older Patients: Development and Validation of a Predictive Model

Sharon K. Inouye, M.D., MPH¹, Ying Zhang, M.D., MPH², Richard N. Jones, Sc.D.³, Peilin Shi, PhD⁴, L. Adrienne Cupples, PhD⁵, Harold N. Calderon, BBA⁶, and Edward R. Marcantonio, M.D., SM⁷

1 Department of Medicine, Harvard Medical School, Boston, MA, Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife, Boston, MA

2 Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife, Boston, MA

3 Department of Medicine, Harvard Medical School, Boston, MA, Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife, Boston, MA

4 Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife, Boston, MA

5 Departments of Biostatistics and Epidemiology, School of Public Health, Boston University, Boston, MA

6 Department of Finance, Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA

7 Department of Medicine, Harvard Medical School, Boston, MA, Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife, Boston, MA

Abstract

Background—Unplanned hospitalization often represents a costly and hazardous event for the older population.

Objectives—To develop and validate a predictive model for unplanned medical hospitalization from administrative data.

Research Design—Model development and validation.

Subjects—3919 patients aged \geq 70 years who were followed for at least one year in primary care clinics of an academic medical center.

Measures—Risk factor data and the primary outcome of unplanned medical hospitalization were obtained from administrative data.

Results—Of 1932 patients in the development cohort, 299 (15%) were hospitalized during one year follow up. Five independent risk factors were identified in the preceding year: Deyo-Charlson comorbidity score ≥ 2 (adjusted relative risk [RR]=1.8, 95% confidence interval [CI] 1.4–2.2), any prior hospitalization (RR=1.8, 95% CI 1.5, 2.3), 6 or more primary care visits (RR=1.6, 95%, 95% CI 1.3–2.0), age \geq 85 years (RR=1.4, 95% CI 1.1, 1.7), and unmarried status (RR=1.4, 95% CI 1.1, 1.7). A risk stratification system was created by adding 1 point for each factor present. Rates of hospitalization for the low- (0 factor), intermediate- (1–2 factors) and high-risk (\geq 3 factors) groups were 5%, 15%, and 34% (P<0.0001). The corresponding rates in the validation cohort, where 328/1987 (17%) were hospitalized, were 6%, 16%, and 36% (P<0.0001).

Conclusions—A predictive model based on administrative data has been successfully validated for prediction of unplanned hospitalization. This model will identify patients at high risk for hospitalization who may be candidates for preventive interventions.

predictive model; geriatrics; acute care; hospitalization

INTRODUCTION

Hospitalization is common among older persons, and results in substantial morbidity and costs¹. The Medicare-age population experiences a rate of hospitalization of 17.5% or 6.4 million per year², comprising over 49% of acute hospital days³, and resulting in over \$148.2 billion of annual Medicare expenditures⁴. Frequently, hospitalization can initiate the terminal downward spiral for an older person. Hazards of hospitalization for the elderly are myriad, and include delirium, falls, functional decline, institutionalization, and death^{1,5, 6}. The rate of serious iatrogenic hospital complications in older patients range from 29–38%^{7–9}, and are at least 3–5 fold higher in older compared with younger patients with similar diagnoses^{6, 10}. Moreover, these complications are often unrelated to admitting diagnoses, and more directly related to aspects of hospitalization itself, such as immobilization, dehydration, malnutrition, nosocomial infections, and psychoactive medications^{1,11}.

Previous studies examining risk factors for hospitalization^{12, 13} have focused on specific populations (e.g., nursing home, home care, frail elders)^{13–18}, specific diagnoses (e.g., anemia, depression)^{19,20}, and often use intensive data collection methods to identify risk factors, such as interview or functional assessment^{21–27}. The present study was intended to provide a predictive model that would estimate the risk for hospitalization using administrative data.

Specific objectives were to: (1) identify risk factors for acute, unplanned medical hospitalization from administrative data in a community-dwelling older population followed in primary care medical clinics; (2) develop a predictive model for hospitalization in an initial cohort; and (3) validate the model in a separate cohort. Our hypotheses were that factors such as older age and higher comorbidity would predict the risk of hospitalization. Our goal was to create a parsimonious model based on clinically important risk factors._ Ultimately, we hoped that we could design a predictive system that would be useful to proactively identify high-risk patients for preventive interventions or planning purposes.

METHODS

Study design

The study followed a prospective validation design. The predictive model was developed in an initial cohort, then tested in a validation cohort.

Study setting and sample

Beth Israel Deaconess Medical Center (BIDMC) is a 585-bed academic acute-care hospital affiliated with Harvard Medical School with over 40,000 admissions and 750,000 outpatient visits each year. Health Care Associates and Senior Health represent two primary care clinics at the BIDMC. Referrals to both clinics come primarily from the emergency department, hospital attendings and housestaff, subspecialist physicians, and from family or other patients. Patients followed in these clinics tend to receive the majority of their healthcare within the BIDMC system. The patients served are primarily fee-for-service, with <1% enrolled in Medicare managed care plans. For Health Care Associates, founded in the early 1970s, the staff includes 50% residents, and patients are followed for a median of 10 years or greater longitudinally. For Senior Health, founded in 2003, the staff includes 20% fellows, and patients

have been followed for a median of 3–4 years longitudinally. These two clinics serve a diverse sample of elders in terms of educational and socioeconomic background, primary language and country of origin, and regional representation from throughout the greater Boston area.

The sample included all patients age \geq 70 year who were seen at least once in primary care clinics (Health Care Associates or Senior Health) at the BIDMC during July 1, 2003 through June 30, 2004, and at least once during the subsequent year from July 1, 2004 through June 30, 2005. This criterion was selected to ensure that patients had been followed for an adequate time period to maximize the chances that relevant data would be available in the administrative database. All patients who died before June 30, 2005 were excluded, since they died prior to the period where the outcomes were ascertained (July 1, 2005 to June 30, 2006). A total sample of 3919 patients met these eligibility criteria. A split sample was created using a random selection process; half the sample (N=1932) was used as the initial cohort to develop the prediction model, and the remaining half (N= 1987) was used as the validation cohort. Once the sample was selected, all data were de-identified for all Health Insurance Portability and Accountability Act (HIPAA) identifiers by the BIDMC Information Technology department before analyses were performed. This study was conducted under a waiver of the Health Insurance Portability and Accountability Act from the BIDMC Institutional Review Board.

Risk factor variables

The data source was an administrative database called the BIDMC casemix_tsi data repository, which includes information on date and type of inpatient and outpatient visits, demographics, billing diagnoses, and charges. The diagnosis codes were those used for billing purposes on hospital discharges, clinic visits, and other claims (radiologic procedures, laboratory tests). These codes were compiled for each patient across the one year prediction period. Additional relational databases contain further details on each visit, such as laboratory results. Data from the electronic medical record were not obtained for this study or utilized for these analyses.

We identified potential risk factor variables based on the medical literature 12,19,21-22,25-26,27-29 and expert opinion. Risk factor variables considered included age, gender, ethnicity, marital status, insurance type, Deyo-adapted Charlson comorbidity score²⁷, number of diagnoses, any previous hospitalization, any nursing home stay, number of primary care physician visits, receipt of any surgical procedure, receipt of any hemodialysis, and abnormal laboratory values. These variables were identified from all inpatient and outpatient visits during the prediction interval from 7/1/04 through 6/30/05.

Continuous variables were examined continuously and with cutpoints selected by previous studies, clinical judgment, and data distributions. Advanced age was defined as age \geq 85 years representing the oldest-old and comprising the highest 20th percentile in the sample. Male gender, nonwhite race, Medicaid or uninsured status, and unmarried status have been used previously^{21,28}. The Deyo-adapted Charlson score \geq 2 is a commonly used cutpoint to indicate high comorbidity³⁰, 31. An individual with a Deyo-Charlson score of \geq 2^{30,31} would have either 2 or more of these conditions [myocardial infarct, congestive heart failure, peripheral vascular disease, cerebrovascular disease, dementia, chronic pulmonary disease, connective tissue disease, ulcer disease, mild liver disease, or diabetes] or any one of these conditions [hemiplegia, moderate or severe renal disease, diabetes with end organ damage, any tumor, leukemia, lymphoma, moderate or severe liver disease, metastatic solid tumor, or AIDS]. Number of diagnoses with a cut-point of \geq 10 was used, since it represented the sample median and was used previously³². However, this score was highly correlated with number of clinic visits (i.e., more diagnoses assigned at each visit), Pearson's r = 0.70; thus, given the collinearity, we opted to use the Deyo-adapted Charlson score in the final model. Cut-points for laboratory values were selected based on previous studies³³⁻³⁵. Missing laboratory values

were assigned a "normal" value, as done previously^{33,36}, since most physicians do not order laboratories in the absence of a clinical indication.

Study outcome

The outcome was any unplanned medical hospitalization at the BIDMC during the one year period from 7/1/05 through 6/30/06. An unplanned hospitalization was coded as an urgent or emergent admission type in the administrative data.

Model development

Potential risk factor variables were first examined in bivariable analyses. The variables were selected by meeting all of the following criteria identified *a priori*: (1) prevalence of >15%; (2) relative risk (RR) > 1.5 for categorical outcomes; (3) P<0.05; and (4) clinical relevance. For closely related variables, one variable was selected according to best fulfillment of the *a priori* criteria. The panel of selected variables was further evaluated in multivariable analyses to yield the final independent predictor variables.

Statistical analysis and model validation

Baseline characteristics of the development and validation cohorts (Table 1) were compared using t-test statistics for continuous variables or chi-square statistics for categorical variables. For bivariable and multivariable analyses, logistic regression analysis was used. Model-based estimates were applied (i.e., log-binomial model) to calculate adjusted relative risks (RRs) and confidence intervals (CIs) from the parameter estimates and standard errors³⁷. To address missing data, we first verified that the missing data were not biased in their distribution between outcome groups. Then, we used SAS PROC MI to impute missing values for race and marital status. Sensitivity analyses were conducted to verify that imputation of missing values did not affect the results³⁸. Calibration of the model was evaluated with the Hosmer-Lemeshow test of goodness-of-fit statistic, and with analysis of residuals, including the inspection of residual plots (delta chi-square residual, delta deviance residual, and Cook's distance).

The predictive model created in the initial cohort was subsequently tested in the validation cohort. Model performance in both cohorts was assessed using the C statistic, approximating the area under a receiver-operating characteristic curve³⁹, and ranging from 0.5 (no discrimination above chance) to 1.0 (perfect discrimination). A risk stratification system was developed by assigning one point to each of the final risk factors present. Based on distributional characteristics (i.e., groups with similar hospitalization rates were combined), we created 3 strata representing low-, intermediate-, and high-risk groups. Overall chi-square and Cochran-Armitage trend tests were used to compare hospitalization rates by risk strata in both cohorts. All analyses were conducted using SAS Version 9.1 (SAS Institute, Cary, NC).

RESULTS

Baseline characteristics of the initial cohort appear in Table 1. Of 1932 patients, 299 (15.4%) had at least 1 urgent or emergent hospitalization during the outcome interval. The mean length of hospital stay was 8.3 ± 10.4 days, median 4.0 days (range, 1.0–93 days).

Development of the predictive model

The 16 candidate risk factor variables considered for the predictive model appear in Table 2. Using the *a priori* selection criteria above, these variables were narrowed based on bivariable results. Five potential risk factors were selected and all were retained in the final predictive model (Table 3). These included Deyo-Charlson comorbidity score \geq 2, any hospitalization in the prior year, 6 or more primary care visits in the previous year, age \geq 85 years, and unmarried

status. These factors were entered into a single predictive model to provide an overall estimate of the independent contribution of each variable to subsequent hospitalization. While any abnormal laboratory result met selection criteria for inclusion, this variable was found to be collinear with any hospitalization in the prior year (Pearson r=0.45, P<0.001), and may not be readily available in administrative databases at all hospitals. In addition, the inclusion of this variable did not substantively improve the performance of the model. For these reasons, this variable was not included in the final model.

Performance of the predictive model

Development cohort—The final model generated a C-statistic of 0.72, indicating good prediction above chance³⁹. The Hosmer-Lemeshow goodness-of-fit test chi-square= 4.7 (7 degrees of freedom, P=0.70) indicates that the model fits the data well. Inspection of residuals revealed 4 influential outlier data points; the results were not appreciably different with exclusion of these patients; thus, all patients were retained in the final model. A risk stratification system was created by assigning 1 point to each of the final risk factors present during the prediction interval. Three risk groups were created: low risk (0 factors), intermediate risk (1–2 factors), and high-risk (3–5 factors) groups. Rates of hospitalization increased from 5% to 15% to 34% across risk groups (χ^2 trend = 115.6, P <0.0001), with the corresponding risk gradient extending from 1.0 (referent) to 3.1 to 7.0 (Table 4).

Validation cohort—The validation cohort was similar to the development cohort in all baseline characteristics (Table 1). Of 1987 patients, 329 (16.6%) had an urgent or emergent hospitalization during the outcome interval. Mean length of hospital stay was 8.0 ± 10.1 days, median 5.0 days (range, 1.0–92 days).

The predictive model yielded a C-statistic of 0.73, demonstrating good prediction above chance. The Hosmer-Lemeshow goodness-of-fit test chi-square= 6.32 (6 degrees of freedom, P=0.39) indicates that the model fits the data well. Applying the risk stratification system (Table 4), rates of hospitalization increased from 6% to 16% to 36% across groups (χ^2 trend = 111.3, P <0.0001), representing a 6-fold increased risk of hospitalization between low- and high-risk groups.

DISCUSSION

We developed and successfully validated a predictive model for acute medical hospitalization in a primary care community-dwelling cohort. The overall rates of hospitalization in our cohorts (15–17%) are directly comparable to the 17% rate for Medicare patients nationally². Five factors that independently contribute to risk of hospitalization were identified in the preceding year: Deyo-Charlson comorbidity score ≥ 2 , any prior hospitalization, ≥ 6 primary care visits, age ≥ 85 years, and unmarried status. Thus, we confirmed our hypothesis that both demographic and comorbidity factors would contribute to the risk of hospitalization. In patients identified as high risk, the rate of hospitalization was 34–36% in the following year.

This study serves to confirm risk factors identified in previous studies¹², 19, 21, 25–28, yet allows us to extend this work to facilitate risk stratification from administrative data, which may enhance identification of high risk patients. While laboratory results were predictive, these results may not be readily available in all administrative databases, and thus, were not included in the final model. Similar to previous studies, our work again confirms the importance of comorbidity or casemix in prediction of future resource utilization $^{40-41}$. Similar to the Probability of Repeated Admission (Pra) questionnaire^{22,25,26}, our study identified prior hospitalization and more than 6 physician visits in the previous year as important risk factors. Moreover, the unmarried variable may also reflect the lack of an informal caregiver, similar to the Pra questionnaire. Our goal in this study was to create a parsimonious model, based on

Med Care. Author manuscript; available in PMC 2008 August 15.

clinically important risk factors, and not primarily to maximize prediction. Thus, we did not choose to include all possible variables which may have improved prediction, variables with low prevalence in the sample, or variables which were highly collinear. Prediction may have been improved with inclusion of more variables, however, we wanted to develop a model based on a smaller number of clinically important risk factors.

Strengths of this study include the availability of a large sample of primary care patients, who are representative of the older population in one metropolitan area. The sample is diverse in terms of race, ethnicity, and socioeconomic status. The development and validation of the predictive model in two separate groups (randomized split sample) is another important strength, which lends support for the robustness and generalizability of the model⁴². However, future studies will be needed to verify transportability of the model to other populations.

Several caveats deserve comment. First, given the nature of administrative data, some data were missing for risk factors such as race and marital status; however, sensitivity analyses reveal that imputation of these missing values did not affect the results. Second, we were unable to examine many risk factors identified in previous studies (e.g., self-rated health, physical functioning). While including these factors may have led to better prediction, this would contradict our goal of identifying factors via administrative data. Third, we did not examine specific diagnoses, which will be an important area for future research. Moreover given the nature of our administrative data, we were unable to distinguish which diagnoses codes were for "rule-out" conditions, rather than existing diagnoses. Fourth, we required that patients be followed in their primary care clinics for at least one year to ensure that adequate information in our administrative data. Thus, while prediction would be useful for primary care patients followed longitudinally, applying this model would be more difficult for patients who are new to a healthcare system or followed elsewhere and may affect the generalizability of the model. Fifth, since this was a single-site study, we may have missed hospitalizations that occurred at other hospitals; however, it is important to note that the vast majority of patients receiving their primary care at the BIDMC also choose to be hospitalized there. Finally, our model would not apply to prediction of all types of hospitalization (e.g., surgical, gynecological), since we restricted ourselves to only medical hospitalizations. Generalizability may have been limited by inclusion of only medical hospitalizations at a single site, and future studies will be needed to verify effectiveness in other populations and for other types of hospitalizations.

While the identified risk factors are not necessarily directly amenable to intervention, they do serve to identify a highly vulnerable group that is old, frail, with considerable comorbidity, and high health care utilization. Thus, this predictive model may serve the important role of risk stratification, to identify a group at high risk for future hospitalization who might be candidates for preventive interventions. Such interventions might span a broad array of interventions, such as care coordination, intensive case management, preventive home visits, or optimization of transitional care^{43–47}. The high-cost area of unplanned hospitalization represents an area of particular importance for cost containment. Moreover, given the high impact and substantial rates of adverse outcomes associated with hospitalization, targeting the identified high risk group for preventive interventions makes sense from both clinical and policy perspectives.

Acknowledgements

The authors thank Ms. Elizabeth Wood for assistance with obtaining and interpreting the administrative data, and Ms. Sarah Dowal for assistance with manuscript preparation. This work is dedicated to Benjamin and Jordan Helfand.

Funding sources: Funded in part by grants from the National Institute on Aging (R21AG025193 and K24AG00949), the Harvard Older Americans Independence Center (P60AG00812), and the Aging Brain Center, Institute for Aging Research, Hebrew SeniorLife. Dr. Inouye holds the Milton and Shirley F. Levy Family Chair. Dr. Marcantonio is a Paul Beeson Physician Faculty Scholar in Aging Research

Med Care. Author manuscript; available in PMC 2008 August 15.

References

- Inouye SK, Schlesinger MJ, Lydon TJ. Delirium: a symptom of how hospital care is failing older persons and a window to improve quality of hospital care. Am J Med 1999;106:565–573. [PubMed: 10335730]
- 2. Van de Water, PN. Medicare finances: Findings of the 2007 Trustees report Medicare brief. 2007 Apr; 17. p. 1-7.
- 3. A profile of older Americans. Washington, D.C: Department of Health and Human Services; 2000. Administration on Aging.
- 4. National Center for Health Statistics. Health, United States, 2006. Hyattsville, Maryland: Public Health Service; 2006.
- Creditor MC. Hazards of hospitalization of the elderly. Ann Intern Med 1993;118:219–223. [PubMed: 8417639]
- Gillick MR, Serrell NA, Gillick LS. Adverse consequences of hospitalization in the elderly. Soc Sci Med 1982;16:1033–1038. [PubMed: 6955965]
- Reichel W. Complications in the care of five hundred elderly hospitalized patients. J Am Geriatr Soc 1965;13:973–981. [PubMed: 5843927]
- Steel K, Gertman PM, Crescenzi C, et al. Iatrogenic illness on a general medicine service at a university hospital. New Engl J Med 1981;304:638–642. [PubMed: 7453741]
- Becker PM, McVey LJ, Saltz CC, et al. Hospital-acquired complications in a randomized controlled clinical trial of a geriatric consultation team. JAMA 1996;275:852–857. [PubMed: 8596223]
- Brennan TA, Leape LL, Laird NM, et al. Incidence of adverse events and negligence in hospitalized patients. New Engl J Med 1991;324:370–376. [PubMed: 1987460]
- Rothschild JM, Bates DW, Leape LL. Preventable medical injuries in older patients. Arch Intern Med 2000;160:2717–2728. [PubMed: 11025781]
- Miller EA, Weissert WG. Predicting elderly people's risk for nursing home placement, hospitalization, functional impairment, and mortality: A synthesis. Med Care Res Rev 2000;57:249– 297.
- Fortinsky RH, Madigan EA, Sheehan TJ, et al. Risk factors for hospitalization among Medicare home care patients. West J Nurs Res 2006;28:902–917. [PubMed: 17099104]
- Fried TR, Mor V. Frailty and hospitalization of long-term stay nursing home residents. J Am Geriatr Soc 1997;45:265–269. [PubMed: 9063269]
- 15. Satish S, Winograd CH, Chavez C, Bloch DA. Geriatric targeting criteria as predictors of survival and health care utilization. J Am Geriatr Soc 1996;44:914–918. [PubMed: 8708300]
- Murtaugh CM, Freiman MP. Nursing home residents at risk of hospitalization and the characteristics of their hospital stays. The Gerontologist 1995;35:35–43. [PubMed: 7890201]
- 17. Kiel DP, Eichorn A, Intrator O, et al. The outcomes of patients newly admitted to nursing homes after hip fracture. Am J Public Health 1994;84:1281–1286. [PubMed: 8059886]
- Freiman MP, Murtaugh CM. The determinants of the hospitalization of nursing home residents. J Health Econ 1993;11:349–359. [PubMed: 10129842]
- 19. Pennix BW, Pahor M, Woodman RC, et al. Anemia in old age is associated with increased mortality and hospitalization. J Gerontol A Biol Sci Med Sci 2006;61:474–479. [PubMed: 16720744]
- 20. Brown SL, Salive ME, Guralnik JM, et al. Antidepressant use in the elderly: Association with demographic characteristics, health-related factors, and health care utilization. J Clin Epidemiol 1995;48:445–453. [PubMed: 7897465]
- 21. Dorr DA, Jones SS, Burns L, et al. Use of health-related, quality-of-life metrics to predict mortality and hospitalizations in community-dwelling seniors. J Am Geriatr Soc 2006;54:667–673. [PubMed: 16686880]
- 22. Wagner JT, Bachmann LM, Boult C, Harari D, von Renteln-Kruse W, Egger M, Beck JC, Stuck AE. Predicting the risk of hospital admission in older persons--validation of a brief self-administered questionnaire in three European countries. J Am Geriatr Soc 2006;54:1271–6. [PubMed: 16913998]
- Studenski S, Perera S, Wallace D, et al. Physical performance measures in the clinical setting. J Am Geriatr Soc 2003;51:314–322. [PubMed: 12588574]

Med Care. Author manuscript; available in PMC 2008 August 15.

- 24. Kennedy BS, Stanislav VK, Vaccarino V. Repeated hospitalizations and self-rated health among the elderly: A multivariate failure time analysis. Am J Epidemiol 2001;153:232–241. [PubMed: 11157410]
- Pacala JT, Boult C, Boult L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. J Am Geriatr Soc 1995;43:374–7. [PubMed: 7706626]
- Boult C, Dowd B, McCaffrey D, Boult L, Hernandez R, Krulewitch H. Screening elders for risk of hospital admission. J Am Geriatr Soc 1993;41:811–7. [PubMed: 8340558]
- Prabhakaran VM, Pujara S, Mills AJ, et al. Can nutritional criteria help predict outcome in hospitalized patients? Clin Chem 1986;32:2077–2079. [PubMed: 3096596]
- Landi F, Onder G, Cesari M, et al. Comorbidity and social factors predicted hospitalization in frail elderly patients. J Clin Epidemiol 2004;57:832–836. [PubMed: 15551473]
- 29. de Boer AG, Wijker W, de Haes HC. Predictors of health care utilization in the chronically ill: a review of the literature. Health Policy 1997;42:101–115. [PubMed: 10175619]
- Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. J Clin Epidemiol 1992;45:613–619. [PubMed: 1607900]
- Charlson ME, Pompei P, Ales KL, et al. A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. J Chron Dis 19876;40:373–383. [PubMed: 3558716]
- Desai MM, Bogardus ST, Williams CS, et al. Development and validation of a risk adjustment index for older patients: The High-Risk Diagnoses for the Elderly Scale. J Am Geriatr Soc 2002;50:474– 481. [PubMed: 11943043]
- Inouye SK, Charpentier PA. Precipitating factors for delirium in hospitalized elderly persons: predictive model and inter-relationship with baseline vulnerability. JAMA 1996;275:852–857. [PubMed: 8596223]
- Walter LC, Brand RJ, Counsell SR, et al. Development and validation of a prognostic index for 1year mortality in older adults after hospitalization. JAMA 2001:2987–2994. [PubMed: 11410097]
- 35. Inouye SK, Bogardus ST, Vitagliano G, et al. Burden of illness score for elderly persons (BISEP): Risk adjustment incorporating the cumulative impact of diseases, physiologic abnormalities and functional impairments. Med Care 2003;41:70–83. [PubMed: 12544545]
- Wagner DP, Knaus WA, Draper EA. Statistical validation of a severity of illness measure. Am J Public Health 1983;73:878–884. [PubMed: 6408937]
- 37. Greenland S. Model-based Estimation of Relative Risks and Other Epidemiologic Measures in Studies of Common Outcomes and in Case-Control Studies. Am J Epidemiol 2004;160:301–305. [PubMed: 15286014]
- Carpenter JR. Sensitivity analysis after multiple imputation under missing at random: a weighting approach. Statistical Methods in Medical Research 2007;16:259–275. [PubMed: 17621471]
- Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 1982;143(1):29–36. [PubMed: 7063747]
- Petersen LA, Pietz K, Woodard LD, Byrne M. Comparison of the predictive validity of diagnosisbased risk adjusters for clinical outcomes. Med Care 2005;43:61–7. [PubMed: 15626935]
- 41. Wahls TL, Barnett MJ, Rosenthal GE. Predicting resource utilization in a Veterans Health Administration primary care population: comparison of methods based on diagnoses and medications. Med Care 2004;42:123–8. [PubMed: 14734949]
- Justice AC, Covinsky KE, Berlin JA. Assessing the generalizability of prognostic information. Ann intern Med 1999;130:515–524. [PubMed: 10075620]
- 43. Coleman EA, Boult C. Improving the quality of transitional care for persons with complex care needs. J Am Geriatr Soc 2003;51(4):556–557. [PubMed: 12657079]
- 44. Rahkonen T, Eloniemi-Sulkava U, Paanila S, et al. Systematic intervention for supporting community care of elderly people after a delirium episode. Inter Psychogeriatr 2001;13:37–49.
- 45. Dalby DM, Sellors JW, Fraser FD, et al. Effect of preventive home visits by a nurse on the outcomes of frail elderly people in the community: A randomized controlled trial. Can Med Assoc J 2000;162:497–500. [PubMed: 10701382]

- 46. Stuck AE, Egger M, Hammer A, Minder CE, Beck JC. Home visits to prevent nursing home admission and functional decline in elderly people. JAMA 2002;287:1022–1028. [PubMed: 11866651]
- 47. Naylor MD, Brooten D, Campbell R, et al. Comprehensive discharge planning and home follow-up of hospitalized elders: A randomized clinical trial. JAMA 1999;281:613–620. [PubMed: 10029122]

Table 1

Baseline Patient Characteristics in the Two Cohorts*

| Characteristics | Development Cohort(N =1932) [†] | Validation Cohort [†] (N = 1987) |
|--|--|---|
| Age, y (mean \pm SD) | 78.5 ± 6.0 | 78.7 ± 6.0 |
| Male, No. (%) | 737 (38.1) | 774 (39.0) |
| Nonwhite, No. (%) | 405 (23.1) | 408 (22.2) |
| Married, No. (%) | 887 (46.1) | 918 (46.4) |
| Medicaid or uninsured, No. (%) | 53 (2.7) | 49 (2.5) |
| Enrolled from: | | |
| Health Care Associates, No. (%) | 1567 (81.1) | 1609 (81.0) |
| Senior Health, No. (%) | 365 (18.9) | 378 (19.0) |
| Deyo-Charlson score, mean \pm SD | 1.60 ± 1.99 | 1.59 ± 2.02 |
| Score ≥ 2 , No. (%) | 759 (39.3) | 745 (37.5) |
| Number of medical diagnoses, mean \pm SD | 13.6 ± 10.2 | 14.0 ± 11.1 |
| Number ≥ 10 , No. (%) | 1099 (56.9) | 1147 (57.7) |
| Any hospitalization in previous year, No. (%) | 434 (22.5) | 451 (22.7) |
| Any nursing home stay in previous year, No. (%) | 89 (4.6) | 119 (6.0) |
| Primary care visits in past year, mean \pm SD | 5.7 ± 4.1 | 5.8 ± 4.4 |
| Primary care visits ≥ 6 in previous year, No. (%) | 796 (41.2) | 829 (41.7) |

 \tilde{M} Missing values were present for some variables as follows. In the development cohort, race data (missing n=178), marital status (n=11); in the validation cohort, race data (n=151), marital status (n=9).

 † No statistically significant differences in baseline characteristics between the two cohorts.

Table 2

Variables Considered as Risk Factors for Hospitalization in the Development Cohort*

| | | (N=1932) Hospitalization | n When Factor | |
|--|---------|-----------------------------|-----------------|----------------|
| Factor | Prev(%) | Present No. (%), | Absent, No. (%) | RR (95% CI) |
| Age \geq 85 years | 19.6 | 87/378 (23) | 212/1554 (14) | 1.7 (1.4, 2.1) |
| Male gender | 38.2 | 116/737(16) | 183/1195(15) | 1.0 (0.8, 1.3) |
| Nonwhite race | 23.1 | 67/405(17) | 207/1349(15) | 1.1 (0.8, 1.4) |
| Unmarried | 53.9 | 195/1034(19) | 103/887(12) | 1.6 (1.3, 2.0) |
| Medicaid or uninsured | 2.7 | 6/53 (11) | 293/1879 (16) | 0.7 (0.3, 1.6) |
| Devo-Charlson score ≥ 2 | 39.3 | 184/759(24) | 115/1173(10) | 2.5 (2.0, 3.1) |
| Number of medical diagnoses ≥ 10 | 56.9 | 244/1099(22) | 55/833(7) | 3.4(2.5, 4.5) |
| Any hospitalization in previous year | 22.5 | 130/434(30) | 169/1498(11) | 2.7 (2.2, 3.3) |
| Any nursing home stay in previous year | 4.6 | 33/89(37) | 266/1843(14) | 2.6 (1.9, 3.4) |
| Primary care visits ≥ 6 in previous year | 41.2 | 180/796(23) | 119/1136(10) | 2.2(1.7, 2.7) |
| Any surgery in previous year | 4.4 | 18/85(21) | 281/1847(15) | 1.4(0.9, 2.1) |
| Hemodialysis in previous year | 0.4 | 5/7(71) | 294/1925(15) | 4.7 (2.9, 7.6) |
| Hematocrit < 30 ml/dL | 9.8 | 72/190(38) | 227/1742(13) | 2.9 (2.3, 3.6) |
| Serum albumin < 3.0 mg/dL | 2.5 | 18/49(37) | 281/1883(15) | 2.5 (1.7, 3.6) |
| Serum creatinine >1.5 mg/dL | 12.5 | 72/241(30) | 227/1691(13) | 2.2 (1.8, 2.8) |
| Any abnormal laboratory result ^{\dagger} | 18.8 | 116/363(32) | 183/1569(12) | 2.7 (2.2, 3.4) |

^{*}Prev=prevalence; RR=relative risk; CI=confidence interval. Missing values were present for some variables as follows: race data (missing n=178), marital status (n=11).

 $\dot{\tau}$ Abnormal laboratory results included hematocrit < 30 ml/dL, serum albumin < 3.0 mg/dL, or serum creatinine > 1.5 mg/dL in previous year. The most abnormal result during the previous year was used to score this variable.

Table 3

Independent Risk Factors for Hospitalization*

| Risk Factor | (N = 1932) | Adjusted $\mathbf{RR}^{\dot{\mathcal{T}}}$ (95% CI) |
|--|------------|---|
| Deyo-Charlson score ≥ 2 (n = 759) | | 1.8 (1.4, 2.2) |
| Any hospitalization in previous year $(n = 434)$ | | 1.8 (1.5, 2.3) |
| Primary care visits ≥ 6 in previous year (n = 796) | | 1.6 (1.3, 2.0) |
| Age $\ge 85 \ (n = 378)$ | | 1.4 (1.1, 1.7) |
| Age ≥ 85 (n = 378) Unmarried (n = 1040) ^{\neq} | | 1.4 (1.1, 1.7) |

* RR=relative risk; CI=confidence interval. n=number of patients with the risk factor present.

 † Adjusted relative risk derived from multivariable models in PROC GENMOD.

Includes imputed values for 11 missing subjects.

| 7 |
|-------------------|
| ~ |
| = |
| T |
| Τ. |
| T |
| \mathbf{v} |
| |
| 2 |
| $\mathbf{\Sigma}$ |
| ~ |
| 5 |
| = |
| 2 |
| utho |
| - |
| - |
| \leq |
| 5 |
| Man |
| 2 |
| |
| S |
| ×. |
| <u> </u> |
| <u> </u> |
| |
| 0 |

Table 4 Performance of the Predictive Model in the Two Cohorts *

| | | Development Cohort (N=1932) | t (N=1932) | Validation Cohort (N=1987) | t (N=1987) |
|-----------------------------|---------------------------|---|---|---|--|
| Risk Group | Number of risk factors | Hospitalization n/N (%) | RR (95% CI) | Hospitalization n/N (%) | RR (95% CI) |
| Low Intermediate High | 0 - 2 > 3 | $\begin{array}{c} 22/461 \left(4.8\right) ^{\dagger} \\ 167/1143 \left(14.6\right) ^{\dagger} \\ 110/328 \left(33.5\right) ^{\dagger} \end{array}$ | 1.0 (referent) 3.1 (2.0, 4.8) 7.0 (4.5, 11.1) | $30/473 (6.3)^{\sharp}$ 184/1191 (15.5)^{\sharp} 115/323 (35.6) ^{\sharp} | 1.0 (referent) 2.4 (1.7, 3.6) 5.6 (3.8, 8.4) |

Inouye et al.

* RR=relative risk; CI=confidence interval. Includes imputed values for marital status for 11 subjects in development cohort and 9 subjects in validation cohort.

 $f_{\chi^2 \text{trend}} = 115.6, \text{P} < 0.0001$

 $\sharp^2_{\chi^2 \text{trend}} = 1151.3, P<0.0001$