Use of Health-Related, Quality-of-Life Metrics to Predict Mortality and Hospitalizations in Community-Dwelling Seniors

David A. Dorr, MD, MS,† Spencer S. Jones, MStat,†‡ Laurie Burns, PT, MS,† Steven M. Donnelly, PhD,§ Cherie P. Brunker, MD,‡ Adam Wilcox, PhD,†‡ and Paul D. Clayton, PhD†‡*

OBJECTIVES: To investigate whether health-related quality-of-life (HRQoL) scores in a primary care population can be used as a predictor of future hospital utilization and mortality.

DESIGN: Prospective cohort study measuring Short Form 12 (SF-12) scores obtained using a mailed survey. SF-12 scores, age, and a comorbidity score were used to predict hospitalization and mortality rate using multivariable logistic regression and Cox proportional hazards during the ensuing 28-month period for elderly patients.

SETTING: Intermountain Health Care, a large integrated-delivery network serving a population of more than 150,000 seniors.

PARTICIPANTS: Participants were senior patients who had one or more chronic diseases, were community dwelling, and were initially treated in primary care clinics.

MEASUREMENTS: SF-12 survey Version 1.

RESULTS: Seven thousand seventy-six surveys were sent to eligible participants; 3,042 (43%) were returned. Of the returned surveys, 2,166 (71%) were complete and scoreable. For the respondent group, a multivariable analysis demonstrated that older age, male sex, higher comorbidity score, and lower mental and physical summary measures of SF-12 predicted higher mortality and hospitalization. On average, nonresponders were older and had higher comorbidity scores and mortality rates than responders.

CONCLUSION: The SF-12 survey provided additional predictive ability for future hospitalizations and mortality. Such predictive ability might facilitate preemptive interventions that would change the course of disease in this segment of the population. However, nonresponder bias may limit the utility of mailed SF-12 surveys in certain populations. **J Am Geriatr Soc 54:667–673, 2006.**

Key words: quality of life; health status; hospitalizations; mortality; SF-12

Measures of self-perceived health status can be used to evaluate multiple dimensions of the burden of disease and the effect of specific treatments over time. Health-status measures can also play a role in patient assessment. Measurement tools such as the Short Form 12 (SF-12) or Short Form 36 (SF-36) are widely used, because they are brief yet comprehensive, readily available, psychometrically sound, and of proven usefulness in measuring and monitoring health status in general and specific populations.[1]

As the average age of the population increases and healthcare costs rise, there has been increased consideration of how to predict which segments of the population might benefit from focused allocation of resources to mitigate worsening health status. Health-related quality-of-life (HRQoL) surveys have been found to be useful in predicting costs,[2] future mortality, and hospitalization[3–8] in specific patient populations. In these studies, the predictive value of HRQoL extended beyond traditional models of prediction, including comorbidity and case-mix scores. Whether administration of HRQoL survey might further identify individuals at risk for death and hospitalization within a large, general population of seniors who had at least one chronic illness was questioned.

Questions also remain about the best way to distribute such surveys across a large population. One study compared administration of the SF-36 test via telephone, face-to-face interviews, and a mailing.[9] Mailing the self-administered surveys provided the ability to reach a widely dispersed population sample simultaneously at a relatively low cost. Some authors have found that face-to-face administration results in higher scores, possibly from the subjects' desire to please, and have concluded that individuals will be more honest in their answers when the survey is self-administered.[10] If prediction across a broad population is to be successful, respondents must provide accurate answers, and any biases in nonrespondent groups must be understood.

From the *Department of Medical Informatics and Clinical Epidemiology, Oregon Health and Science University, Portland, Oregon; †Intermountain Health Care, Salt Lake City, Utah; ‡Department of Medical Informatics, University of Utah, Salt Lake City, Utah; and §HealthInsight, Inc., Salt Lake City, Utah.

Address correspondence to David A. Dorr, 3181 SW Sam Jackson Park Road, Mailcode: BICC, Portland, OR 97239. E-mail: address: dorrd@ohsu.edu

DOI: 10.1111/j.1532-5415.2006.00681.x

0002-8614/06/$15.00

At Intermountain Health Care, a large integrated-delivery network serving a population of more than 1 million Utahans and more than 150,000 seniors, interventions designed to improve the care of seniors and patients with chronic illnesses are being evaluated. (See www.intermountainhealthcare.org/cmt for details.) As part of efforts to focus resources on at-risk patients, the SF-12 survey was mailed to a set of community-dwelling elderly patients with at least one chronic disease to assess their current health status. It was hypothesized that lower mental and physical SF-12 scores would predict higher hospital utilization and mortality rates in this broad population over the following 2 years, even after adjusting for important predictor covariates. This study provides information about the diagnostic usefulness of the SF-12 as a predictor of future utilization and the potential response bias from mailing SF-12 surveys to seniors.

METHODS

Patient Selection and Eligibility Criteria

To help select community-dwelling patients with one or more chronic illnesses who would receive a survey, a comorbidity-scoring algorithm based upon billing codes associated with ambulatory visits for senior patients from 1998 to 2001 was used. The comorbidity score was generated by adapting methods of Charlson[11] and Deyo[12] to an administrative data set with the study population through revalidation. Initial score creation took place by identifying the combined set of conditions used by both groups; detecting the presence of the conditions in patients by matching a set of predefined *International Classification of Diseases, Ninth Revision*, codes[11] to Medicare billing data generated in 2 years; and weighted calculation by determining the odds of death for a randomly selected half of the population during the following year and using the rounded odds ratio (OR) as a weight. Multivariable logistic regression was used to create the weights and account for multiple co-occurring conditions. Validation took place by weighting conditions in the other half of the population and testing for relationship to death and hospital admission. There were 152,163 beneficiaries with 2,525,663 encounters in the data set used to create the weights for the comorbidity score. A monotonic relationship between comorbidity score and both death and hospitalization was found in the validation set. The comorbid conditions and their weights are as follows: peripheral vascular disease, rheumatic disease, myocardial infarction, chronic obstructive pulmonary disease, and diabetes mellitus without complications received a weight of one; acute liver disease, diabetes mellitus with complications, malignancy (excluding solid tumor), hemi/paraplegia, and renal disease were weighted as two; chronic liver disease, congestive heart failure, and solid tumor were weighted as three; and dementia was weighted as four. Comorbid scores ranged from 1 to 13, with a higher score representing a greater burden of disease.

Patients who received the survey met the following eligibility criteria. They had seen their primary care provider within 14 months, had a comorbidity score of 1 or higher, were enrolled in Medicare, and were living outside of an institution as of September 2002. Surveys were sent out in May 2002, and the survey return period ended September 2002. Addresses were rechecked in 2004, and those who had moved or died before the end of the survey return period were excluded from analysis. From a set of 96,950 patients aged 65 and older, 7,076 surveys were sent to eligible patients. Figure 1 displays response rates and reasons for exclusion. Patients were encouraged to ask family members for help in filling out the survey. The mailed survey was formatted for senior patients, and the patient received only one mailing or contact, as mandated by the local administration. The local institutional review board approved the study, and consent was obtained from patients in the course of mailing the survey.

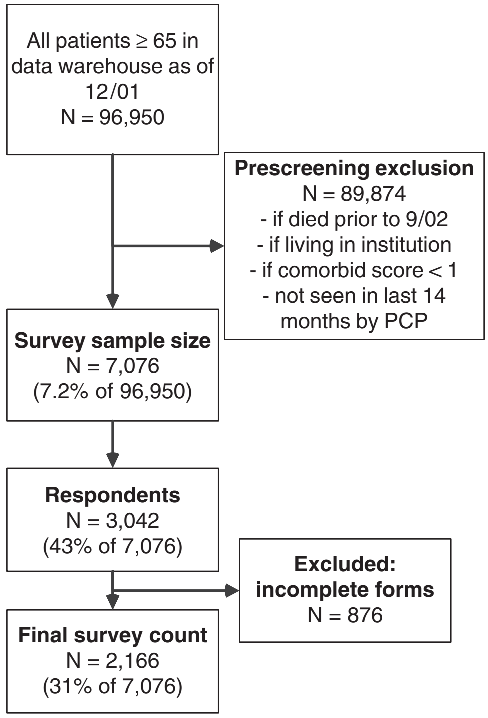

Figure 1. Population screening and survey return rates.

Predictor and Outcome Variables

Several hypothesized predictor variables in the model were identified. For HRQoL, the two summary scores from the SF-12 (the Mental Component Score (MCS) and Physical Component Score (PCS)) were used.[13,14] The PCS and MCS summary scores were created using norm-based methods that standardize the scores to a mean of 50 and a standard deviation of 10 in the general 1998 U.S. population, with higher scores indicating better self-perceived health. Other predictive covariates in the analysis were age at survey mailing (May 1, 2002), sex, and comorbidity score. Outcomes were death within 28 months as reported in the Utah Bureau of Vital Statistics and first hospitalization within 28 months as billed to Medicare. For logistic analyses, both were measured dichotomously. For the survival analyses, both were measured as time until outcome (if present) from the date of survey mailing. Population norms for death rate were generated from age- and sex-specific summary data at the Utah Department of Health.[15]

Statistical Analyses

To address the possibility of response bias, responders and nonresponders were compared using Student t test for continuous variables (age and comorbidity score) and chi-square test for dichotomous variables (sex, hospitalization, and death).

Single-variable analyses were used to evaluate the ability of each covariate to predict mortality or hospitalization. All variables that were significant in single-variable testing or are common important covariates (e.g., sex) were entered into the multivariable model. For the continuous variable age, the respondents were grouped in 5-year age intervals, PCS and MCS scores were grouped based on the quartiles of the 1998 U.S. aged 65 to 74 scoring distribution, and comorbidity scores were grouped into four categories (low, low-moderate, high-moderate, and high) based on the distribution of the sample population. The multivariable logistic regression allowed adjusted ORs to be computed for each of the covariates. Survival analysis using Cox proportional hazards methods was used to build survival curves and compute hazard rate ratios for the predictive value of the SF summary scores and other covariates for mortality and hospitalizations over time. No therapeutic interventions based on predictive measures were performed on the study population during the period of investigation. Calibration and discrimination of the logistic regression models were tested using the c statistic and the Hosmer-Lemeshow (H-L) test. Cox models were evaluated by assessing the proportional hazards assumption using a supernum test based on cumulative sums of Martingale residuals. SAS software version 9.1 was used to perform all statistical analyses (SAS Institute, Inc., Cary, NC).

RESULTS

Response Rates and Responder Bias

Of the 7,076 surveys mailed to eligible patients, 3,042 (43%) were returned. Excluding incomplete forms (n = 876), 2,166 (31%) eligible forms could be scored. The number of incomplete forms included respondents who did not completely fill out the survey and those who completely filled out the survey but did not sign the necessary consent form.

To better understand the nonresponders, an analysis based on data from Medicare records was performed to compare the results of nonresponders and responders. Table 1 contains a comparison of their demographics, comorbidity scores, and subsequent deaths and hospitalizations. Nonresponders had a significantly higher burden of disease, were older, and had higher odds of death in the subsequent period than responders. The mortality rates for the responder group (15.3%, $P = .07$) and the nonresponder group (20.1%, $P < .001$) were higher than the age- and sex-adjusted death rate at 28 months for Utahans as a whole (13.7%). The higher rate is likely due to a utilization bias, with patients seeking health care being more likely to be ill than the general population, even those aged 65 and older.

Table 1. Characteristics of the Responder and Nonresponder Groups

Chracteristic	Responder (n = 3,042)	Nonresponder (n = 4,034)
Age		
Mean ± SD	77.9 ± 6.8	78.3 ± 7.3*
≥85, %	15.8	20.1*
Male, %	45.1	45.7
Comorbidity score, mean ± SD	3.5 ± 1.7	3.7 ± 1.9*
Died (at 28 months), %	15.3	20.4*
Hospitalized (at 28 months), %	44.5	45.2

* Statistically significant ($P < .05$) differences between the two groups.
SD = standard deviation.

Prediction of Death: Single-Variable and Multivariable Models

In single-variable logistic analysis for death, each of the covariates (age group, comorbidity score, and the two SF-12 summary scores) was statistically significant, with the exception of sex ($P = .36$), although sex was entered into the multivariable model and proved to be significant in the multivariable case. A multivariable logistic analysis controlling for age, sex, and comorbidity score demonstrated persistence of the predictive value of the physical and mental subscores for death or hospitalization over the 28-month study period. Table 2 shows the adjusted ORs computed for the covariates used in the multivariable model. For the SF-12 subscores, the OR for death in the lowest PCS group versus the highest PCS group was 6.25 (95% confidence interval (CI) = 1.95–20.06). The OR for respondents in the lowest MCS group versus the highest MCS group was 2.52 (95% CI = 1.74–3.64). For covariates, men's odds of death over the study period were 1.40 times (95% CI = 1.06–1.84) the odds of women, whereas respondents with comorbidity scores of 6 or higher had 2.12 times (95% CI = 1.39–3.23) the odds of death as those with a comorbidity score of 2 or less.

Prediction of Hospitalization: Single-Variable and Multivariable Models

All survey respondents who died before September 9, 2004, (n = 267) were removed from the logistic analyses for hospitalizations. Single-variable and multivariable analyses demonstrated increasing odds of hospitalization as the mental and physical scores decreased and the comorbidity score increased. The increase in odds of hospitalization for the SF-12 PCS and MCS scores was less than that for death, but both were significant when comparing the lowest and highest PCS and MCS score groups. Patients with comorbidity scores of 6 or higher had 1.94 times the odds of admission as those in the lowest group. Higher odds of mortality and hospitalization were observed in the older age groups, whereas sex was a significant predictor for death but not for hospitalization. Model calibration and discrimination were acceptable for both models (death: c = 0.77; H-L $P = .98$; hospitalization: c = 0.64; H-L $P = .46$).

Survival Analysis for Death and Hospitalization

Survival analysis using Cox proportional hazards revealed significant differences in mortality and hospitalization over time between the different PCS and MCS groups, as shown in Figure 2. For those in the low PCS group, the risk of death was 5.99 times (95% CI = 1.90–18.95) as great as that of those in the high PCS group (Figure 2A). Respondents in the

Table 2. Multivariable Logistic Analyses for Prediction of Death or Hospitalization in Community-Dwelling Older People

	Outcome			
	Death (n = 2,166)		Hospitalization (n = 1,899)	
Variable	Adjusted Odds Ratio	*P*-value	Adjusted Odds Ratio	*P*-value
Primary association testing: Medical Outcomes Survey Short Form-12 Scale				
Physical Component Score Quartile				
4 (>53.16)	1.0 (referent)		1.0 (referent)	
3 (45.55–53.16)	1.34	.67	2.06	.002
2 (36.83–45.54)	3.23	.06	2.20	<.001
1 (<36.83)	6.25	.002	3.03	<.001
Mental Component Score Quartile				
4 (>58.46)	1.0 (referent)		1.0 (referent)	
3 (53.99–58.46)	1.21	.44	1.05	.73
2 (45.15–53.98)	1.75	.01	1.20	.20
1 (<45.15)	2.52	<.001	1.55	<.001
Important covariates				
Male	1.40	.02	1.14	.18
Age				
65–69	1.0 (referent)		1.0 (referent)	
70–74	1.15	.66	0.83	.23
75–79	2.21	.007	1.12	.47
80–84	2.98	<.001	1.14	.42
≥85	4.93	<.001	1.32	.15
Comorbidity score				
Low (≤2)	1.0 (referent)		1.0 (referent)	
Low-moderate (3)	1.30	.20	1.37	.01
High-moderate (4–5)	1.85	.001	1.46	.004
High (≥6)	2.12	<.001	1.94	<.001

low MCS group had 2.30 times (95% CI = 1.64–3.22) as great a risk of death as those in the high MCS group (Figure 2B). The PCS groupings reveal virtually no difference in the hazard functions of the two highest PCS quartile groups, although individuals with PCS scores in the range of the first and second quartiles had a greater risk of mortality over time than those with PCS scores in the first two quartiles. Like the PCS curves, the third and fourth MCS quartile groups appear to merge in Figure 2B, indicating poor discrimination between the hazard functions of these two groups, although they are separate from the first and second MCS quartile groups. As with the logistic analysis, the difference in MCS mortality was clear in the fourth quartile versus the first and second quartiles but not in the fourth versus the third quartile.

Low PCS and MCS scores and high comorbidity scores predicted shorter time until hospitalization, as shown in Figure 2C and D. The lowest PCS score group had 2.64 times the hazard rate ratio of hospitalization as the highest PCS score groups ($P<.001$), whereas the lowest MCS group had 1.40 times the hazard rate of the highest group ($P<.001$). The group with the highest comorbidity scores had 1.68 times the hazard rate ratio as the group with the lowest ($P<.001$). Figure 2C, the survival curve for the three PCS groups, shows a stable distribution of hospitalizations over time; the four groups separate almost immediately and remain so throughout the study period. For Figure 2D, there is little differentiation between the third and fourth quartiles but obvious separation from the lower two quartiles.

DISCUSSION

This study has demonstrated that self-reported health status independently predicts hospitalization and mortality in patients. When used in conjunction with other predictors, the SF-12 provided additional value in the prediction of outcomes. A significant response bias was not found; on average, responders were younger and healthier than nonresponders and therefore less likely to die over the follow-up period. Despite this bias, the results are useful, because even the responders were at higher risk of death and hospitalization than the general population of seniors, and the power of the SF-12 to detect increased risk within this population was substantial.

Currently, health-status surveys are rarely used in clinical practice, especially for prediction of utilization. In part because of the fragmented and reactive nature of the U.S. healthcare system, population management through predictive models is still rare. With specific feedback on patients' physical and mental performance, it might become much easier for healthcare providers to focus a care-management system, such as geriatric care teams, on populations at risk of hospitalization or death. Because resources are limited, focusing the intervention on the

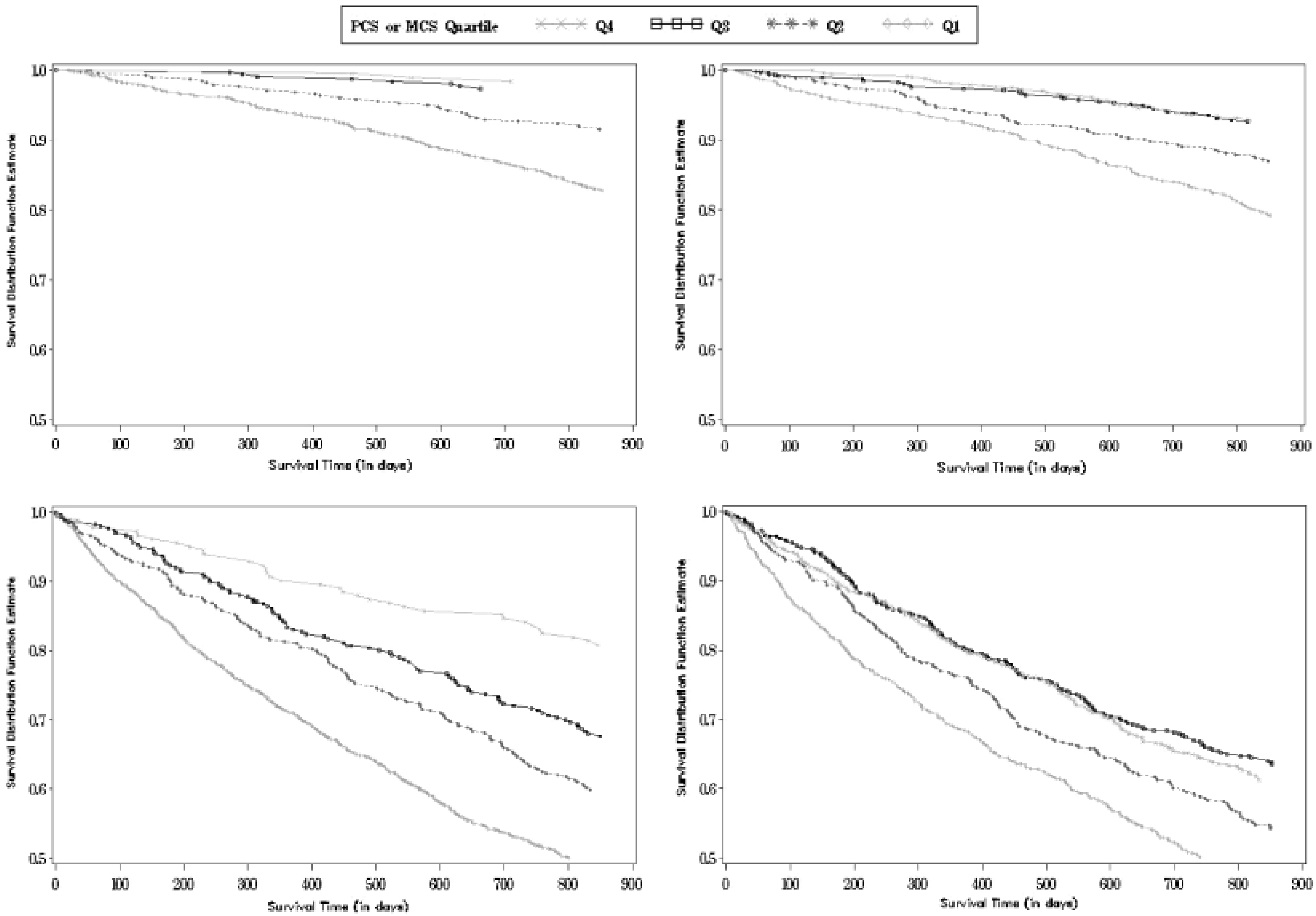

Figure 2. Survival distribution function for death as predicted by Short Form-12 quality-of-life (A) physical component score groups and (B) mental component score groups. Survival distribution function for hospitalization as predicted by Short Form-12 quality-of-life (C) physical component score groups and (D) mental component score groups.

population most likely to benefit is an important first step. It remains to be seen whether improved resource allocation efficiency could forestall death or hospitalization, but the sharpened focus may produce significant benefits. For instance, patients not able to complete regular daily activities as a result of emotional or physical problems (as recorded on the SF-12) might be proactively triaged into a care-management system, which could mitigate the functional problem. In addition, quality-of-life measures may help clinicians address issues beyond the scope of usual care that interfere with patients' social and physical wellness.

The results also indicate the potential power of the quality-of-life survey in prediction, even above conventional measures. In single-variable modeling, low physical SF-12 scores were powerful predictors of death and hospitalization. In multivariable modeling, low physical scores were stronger predictors of death and hospitalization than any other variable. Although a certain amount of correlation (Pearson correlation coefficient = 0.10–0.27) exists between the SF-12 scores and other variables, interaction terms did not alter the overall model. Thus, these results suggest that physical SF-12 scores can provide significant value, alone and when combined with traditional measures. Mental SF-12 score had significant effect, although of smaller magnitude. The comorbidity score also was a significant predictor of death and hospitalization. Age and sex were significant only for death, not hospitalization, as other researchers have found.[16] Thus, these results indicate that appropriate measurement of SF-12 may be important in disease and population management.

This study reaffirms others that have demonstrated that health status independently predicts mortality in patients. One study that found self-reported functional impairment is an independent predictor of death in seniors.[17,18] Functional status assessments in hospitalized patients have also been reported as a predictor of many poor outcomes, including mortality.[19–23] The current study validates previous findings of the ability to predict male veterans' future mortality and hospitalizations from the SF-36, extending it to a different population (community-based primary care clinic) and with a different instrument (the SF-12).[4] In the current study, there was a much larger female population (55%) and an older population. Other notable differences between the current and previous studies include the use of administrative (specifically clinic billing) data for assessing comorbidities versus previous use of self-reported diseases and use of Medicare data to account for all hospitalizations. Because veterans may have multiple sources for payment, using only Department of Veterans Affairs data likely undercounts the number of total hospitalizations for Medicare-eligible patients.[24]

The current study indicates that response rate biases might influence outpatient assessment through a mailed survey. In addition to the differences in adjusted death rates, the samples of nonresponders had significantly more comorbidities and were older than the responders. In this study and others, there was a tendency for persons with dementia, higher risk or comorbidity scores, and greater age not to respond.[25,26] The survey administration technique had several factors associated with stimulating return rates, as demonstrated in a recent systematic review,[27] including short length, personalization, stamped return envelopes, and being sent via first-class mail. It was felt that the interest to participants would be maximized by the choice of scales, but this is debatable. Nevertheless, significant constraints prevented the use of money (both ethical and scarce resources) and repeat questionnaires (the administration felt this was burdensome to the patients, based on a recent series of complaints), concerns that plague a number of large institutions. The response group adequately represents a population of moderately ill cohorts in primary or geriatric care practices for which this predictive tool may be useful in allocating resources.[28] Nonetheless, self-administration in an office setting may be preferred to increase sample size and reach a broader population.[29]

There are several other limitations of this study. The primary drawback of using the SF-12 is that there is a much smaller set of validation literature. Although it was attempted to use similar measures, such as comorbidity, to see whether the results generated were from other confounders, further validation should occur to solidify the usefulness of the SF-12 as a predictor. Nevertheless, the SF-36 summary scores—a scale with much broader prediction literature—have been mapped onto the SF-12 scores with good correlation. The SF-12 is easier for older people to understand and complete. Indeed, other large assessment efforts are switching to the SF-12 from the SF-36, including the Health Outcome Survey administered by Centers for Medicare and Medicaid Services. Selection of the population of interest for prediction would still be important; administration of the survey to healthy older people as a predictive tool may not be useful or cost effective. Finally, the data on chronic conditions were identified from administrative data and did not formally include the severity of these conditions or a detailed analysis of previous hospitalizations or procedures. Because severity is expensive to measure for each disease, the combination of the SF summary scores and the comorbidity score may provide a useful surrogate for the severity of all diseases combined. The upside of this approach is that the administrative data are easier for many researchers to acquire than self-reported date. Finally, when the comorbidity score was revalidated, dementia was the most strongly weighted diagnosis, outweighing usual causes of death such as ischemic heart disease or cancer. Other studies have also found cognitive decline to be a strong predictor, attributing its predictive strength to late diagnosis and multifactorial etiologies.[30]

In summary, a simple, noninvasive, self-reported quality-of-life survey was more useful in predicting death and utilization than traditional measures used alone. This finding reflects common knowledge; people with disease and infirmities are more likely to die or become hospitalized than those who are not so burdened, but for those who wish to intervene proactively, an easy-to-implement predictive tool that can be applied to populations of patients could be valuable. Although the exact populations and techniques appropriate for this survey are unclear, these results can help guide groups attempting to manage resources and maximize population-based care. It should be emphasized that the elderly study population had at least one comorbid illness and at least one visit to an ambulatory care provider in the year before they were mailed the questionnaire. To fully realize value from a predictive tool, it will be necessary to assess whether provider practice patterns change given feedback about the emotional and physical function of the patient, to determine what interventions aimed specifically at these populations work, and to maximize the efficiency and effectiveness of those interventions.

ACKNOWLEDGMENTS

Financial Disclosure: This study was supported by Grant 2001–0456 from the John A. Hartford Foundation. David A. Dorr was supported through a grant from the National Library of Medicine (Training Grant 5T15LM007124–07). The analyses upon which this publication is based were performed under Contract 500–02-UT01, funded by the Centers for Medicare and Medicaid Services, an agency of the U.S. Department of Health and Human Services. The content of this publication does not necessarily reflect the views or policies of the Department of Health and Human Services, nor does mention of trade names, commercial products, or organizations imply endorsement by the U.S. government. The authors assume full responsibility for the accuracy and completeness of the ideas presented. (Publication 7SOW-UT-30–101/7–05)

No consultantships, stocks, or patents are held by any authors in any companies related to this research.

Author Contributions: Dorr, Jones, Burns, Wilcox, and Clayton: study concept and design. Burns, Donnelly, Wilcox, and Brunker: acquisition of subjects and/or data. Dorr, Jones, Donnelly, and Brunker: analysis and interpretation of data. All: preparation of manuscript.

Sponsor's Role: The sponsor had no role in the design, methods, subject recruitment, data collections, analysis, or preparation of the manuscript. The investigators had unfettered access to the data at all times and made all decisions related to the analysis and interpretation of the data.

REFERENCES

1. Ware JEJ, Kosinski M, Turner-Bowker DM et al. How to Score Version 2 of the SF-12 Health Survey With a (Supplement Documenting Version 1). Lincoln, RI: QualityMetric Inc., 2002.
2. Chern JY, Wan TT, Begun JW. A structural equation modeling approach to examining the predictive power of determinants of individuals' health expenditures. J Med Syst 2002;26:323–336.
3. Jordan K, Ong BN, Croft P. Previous consultation and self reported health status as predictors of future demand for primary care. J Epidemiol Community Health 2003;57:109–113.
4. Fan VS, Au D, Heagerty P et al. Validation of case-mix measures derived from self-reports of diagnoses and health. J Clin Epidemiol 2002;55:371–380.
5. Fan VS, Au DH, McDonell MB et al. Intraindividual change in SF-36 in ambulatory clinic primary care patients predicted mortality and hospitalizations. J Clin Epidemiol 2004;57:277–283.
6. Ethgen O, Kahler KH, Kong SX et al. The effect of health related quality of life on reported use of health care resources in patients with osteoarthritis and rheumatoid arthritis: A longitudinal analysis. J Rheumatol 2002;29:1147–1155.
7. Ethgen O, Tellier V, Sedrine WB et al. Health-related quality of life and cost of ambulatory care in osteoporosis: How may such outcome measures be valuable information to health decision makers and payers? Bone 2003;32:718–724.

8. Rumsfeld JS, MaWhinney S, McCarthy M Jr et al. Health-related quality of life as a predictor of mortality following coronary artery bypass graft surgery. Participants of the Department of Veterans Affairs Cooperative Study Group on Processes, Structures, and Outcomes of Care in Cardiac Surgery. JAMA 1999;281:1298–1303.
9. Weinberger M, Oddone EZ, Samsa GP et al. Are health-related quality-of-life measures affected by the mode of administration? J Clin Epidemiol 1996;49:135–140.
10. Cook DJ, Guyatt GH, Juniper E et al. Interviewer versus self-administered questionnaires in developing a disease-specific, health-related quality of life instrument for asthma. J Clin Epidemiol 1993;46:529–534.
11. Charlson ME, Pompei P, Ales KL et al. A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. J Chronic Dis 1987;40:373–383.
12. 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.
13. Ware J Jr, Kosinski M, Keller SD. A 12-Item Short-Form Health Survey: Construction of scales and preliminary tests of reliability and validity. Med Care 1996;34:220–233.
14. Reuben D, Valle L, Hays R et al. Measuring physical function in community-dwelling older persons: A comparison of self-administered, interviewer-administered, and performance based measures. J Am Geriatr Soc 1995;43:17–23.
15. Utah Department of Health. 2004 IBIS Query System (IBIS-PH) [on-line]. Available at http://health.utah.gov/ibis-ph Accessed December 7, 2005.
16. Hardy SE, Gill TM. Recovery from disability among community-dwelling seniors. JAMA 2004;29:1596–1602.
17. Manton KG. A longitudinal study of functional change and mortality in the United States. J Gerontol 1988;43:S153–S161.
18. Reuben DB, Rubenstein LV, Hirsch SH et al. Value of functional status as a predictor of mortality: Results of a prospective study. Am J Med 1992;93:663–669.
19. Inouye SK, Peduzzi PN, Robison JT et al. Importance of functional measures in predicting mortality among older hospitalized patients. JAMA 1998;279:1187–1193.
20. Winograd CH, Gerety MB, Chung M et al. Screening for frailty: Criteria and predictors of outcomes. J Am Geriatr Soc 1991;39:778–784.
21. Narain P, Rubenstein LZ, Wieland GD et al. Predictors of immediate and 6-month outcomes in hospitalized elderly patients. The importance of functional status. J Am Geriatr Soc 1988;36:775–783.
22. Gillick MR, Serrell NA, Gillick LS. Adverse consequences of hospitalization in the elderly. Soc Sci Med 1982;16:1033–1038.
23. Davis RB, Iezzoni LI, Phillips RS et al. Predicting in-hospital mortality. The importance of functional status information. Med Care 1995;33:906–921.
24. General Accounting Office. Use of VA Services by Medicare-Eligible Veterans [on-line]. Washington, DC: Available at www.gao.gov/cgi-bin/getrpt?HEHS-95–13 Accessed December 7, 2005.
25. Hayes V, Morris J, Wolfe C et al. The SF-36 health survey questionnaire: Is it suitable for use with older adults? Age Ageing 1995;24:120–125.
26. Wagner EH, LaCroix AZ, Grothaus LC et al. Responsiveness of health status measures to change among older adults. J Am Geriatr Soc 1993;41:241–248.
27. Edwards P, Roberts I, Clarke M et al. Increasing response rates to postal questionnaire: Systemic review. BMJ 2002;324:1183–1185.
28. Scholes D, LaCroix AZ, Wagner EH et al. Tracking progress toward national health objectives in the elderly: What do restricted activity days signify? Am J Public Health 1991;81:485–488.
29. Sherbourne CD, Meredith LS. Quality of self-report data: A comparison of older and younger chronically ill patients. J Gerontol 1992;47:S204–S211.
30. Bassuk SS, Wypij D, Berkman LF. Cognitive impairment and mortality in the community dwelling elderly. Am J Epidemiol 2000;151:676–688.