Risk Screening in a Medicare/Medicaid Population

Administrative Data versus Self Report

Christopher L. Vojta, MD, MBA, Deneen D. Vojta, MD, Thomas R. TenHave, PhD, Miguel Amaya, MPH, Risa Lavizzo-Mourey, MD, MBA, David A. Asch, MD, MBA

OBJECTIVE: To compare the abilities of two validated indices, one survey-based and the other database-derived, to prospectively identify high-cost, dual-eligible Medicare/Medicaid members.

DESIGN: A longitudinal cohort study.

SETTING: A Medicaid health maintenance organization in Philadelphia, Pa.

PARTICIPANTS: HMO enrollees ($N = 558$) 65 years and older eligible for both Medicare and Medicaid.

MEASUREMENTS AND MAIN RESULTS: Two hundred ninety six patients responded to a survey containing the Probability of Repeat Admission Questionnaire (Pra) between October and November 1998. Using readily available administrative data, we created an administrative proxy for the Pra. Choosing a cut point of 0.40 for both indices maximized sensitivity at 55% for the administrative proxy and 50% for the survey Pra. This classification yielded 103 high-risk patients by administrative proxy and 73 by survey Pra. High-cost patients averaged at least 2.3 times the resource utilization during the 6-month follow-up. Correlation between the two scores was 0.53, and the scales disagreed on high-cost risk in 78 patients (54 high-cost by administrative proxy only, and 24 high-cost by survey Pra only). These two discordant groups utilized intermediate levels of resources, \$2,171 and \$2,794, that were not statistically significantly different between the two groups (probability $> \chi^2 = .66$). Receiver operating characteristic curve areas (0.68 for survey Pra and administrative proxy for respondents, and 0.67 by administrative proxy for non-respondents) revealed similar overall discriminative abilities for the two instruments for costs.

CONCLUSIONS: The Medicaid/Medicare dual-eligible population responded to the survey Pra at a rate of 53%, limiting its practical utility as a screening instrument. Using a cut

point of 0.40, the administrative proxy performed as well as the survey Pra in this population and was equally applicable to nonrespondents. The time lag inherent in database screening limits its applicability for new patients, but combining database-driven and survey-based approaches holds promise for targeting patients who might benefit from case management intervention.

KEY WORDS: geriatrics; risk screening; Medicaid; dual eligible; health maintenance organization.

J GEN INTERN MED 2001;16:525-530.

Approximately 6 million "dually-eligible" patients in the United States receive both Medicare and Medicaid benefits. This group consumes 30% of the Medicare budget and 35% of Medicaid expenditures, while representing only 17% of the 37 million Medicare beneficiaries and 16% of the Medicaid population.¹

With the number of elderly Americans expected to double to approximately 70 million by 2030, and the number of frail elderly increasing at an even faster rate, providers are searching for ways to improve patients' health outcomes while containing costs.² In the last 10 years, many health plans have begun to focus on identifying those at greatest risk of poor outcomes with the goal of intervening to prevent or slow clinical deterioration.

Since its publication in 1993, the Probability of Repeat Admission Questionnaire (Pra) has become a cornerstone of these efforts (available at www.blackwellscience.com/jgi). This 8-question survey, which yields a risk score between 0.07 and 0.80, has been found valid and acceptable in many different populations of community-dwelling elderly, including Medicaid, fee-for-service, and managed care patients.³⁻⁵

The Pra, however, has several drawbacks. First, although one of its putative strengths has been ease of administration, in published studies it generally achieves response rates of only 50% to 60%.⁶⁻⁸ Second, those who do not respond to health surveys are often older and sicker than respondents,^{9,10} and as a result, these survey-based screening efforts may be missing those who would benefit most from targeted interventions. Third, the Medicaid population can represent an even more challenging group. Transiency and lower levels of literacy, for example, can lead to even lower response rates.^{11,12} Finally, administration of the Pra or any other survey can be expensive. In Philadelphia, costs have been as high as \$11.00 per survey (D. Vojta, personal communication).

Because of these concerns, Coleman et al. created a proxy for the Pra using many of the same demographic and clinical variables as the survey Pra. Within a group of

Received from the Division of Geriatrics (CLV, RL-M), the Center for Clinical Epidemiology and Biostatistics (TRT, DAA), the Institute on Aging (CLV, RL-M, DAA), Department of Medicine at the University of Pennsylvania; the Leonard Davis Institute of Health Economics (DDV, RL-M, DAA); the Division of Medical Affairs (DDV, MA), Health Partners; and the Philadelphia Veterans Affairs Medical Center (DAA, RL-M), Philadelphia, Pa.

Dr. Deneen D. Vojta is now Assistant Medical Director at Frankford Health Care System, Philadelphia, Pa.

Mr. Amaya is now an independent consultant.

Dr. Risa Lavizzo-Mourey is now Senior Vice President and Director of the Health Care Group at the Robert Wood Johnson Foundation, and Sylvan Eisman Professor of Medicine at the University of Pennsylvania.

Address correspondence and reprint requests to Dr. Vojta: 226 Ralston House, 3615 Chestnut St., Philadelphia, PA 19104 (e-mail: chris.vojta@uphs.upenn.edu).

2,174 community-dwelling Medicare HMO members, Coleman et al. reported that their instrument worked well as a close substitute for the survey Pra in predicting hospitalizations and functional decline (in restricted activity days) over a 4-year period.¹³ In this study, we sought to extend Coleman et al.'s work to a frail Medicaid population and to test the administrative proxy against a true survey Pra. The specific aims were to analyze the results of the survey Pra administered in a community-dwelling Medicare/Medicaid population, to develop a model using administrative data that predicts dual-eligible patients at risk for high resource use as measured by total costs over a short outcome period, and to formally test the administrative Pra on survey nonrespondents.

METHODS

Setting

We selected 558 members of Health Partners of Philadelphia (a Medicaid HMO) who met the following criteria: age 65 years or older, continuous membership of Health Partners for 18 months (12 months prior to the survey and 6 months after), and dual-eligible Medicare/Medicaid recipients (Figure 1). The Institutional Review Board of the University of Pennsylvania and the HMO approved the study. Continuous membership was required in order to mirror the two longitudinal questions on the survey Pra: number of doctors visits and hospitalizations over the previous year.

Survey

Between October and November 1998, all 558 subjects received the survey Pra. Nonrespondents received a second questionnaire and finally a phone call encouraging them to participate in the health screening. Survey Pra scores were calculated as described by Pacala et al.¹⁴

Creation of the Administrative Proxy

The administrative proxy consisted of 7 of the 8 survey Pra items as shown in Table 1. Following Coleman et al.'s

Table 1. Survey Pra and Administrative Proxy Items and Database Sources

Survey Pra	Administrative Proxy Source
Age	Demographics database
Gender	Demographics database
Doctor visits in past 12 mo	Claims database: specialist visits Encounter database: primary care doctor visits
Hospitalizations in past 12 mo	Claims database
Diabetes	Claims database: ICD-9 codes Encounter database: ICD-9 codes Pharmacy database: text search
Heart disease	Claims database: ICD-9 codes Encounter database: ICD-9 codes Pharmacy database: text search
Self-rated health	Deyo index Claims database: ICD-9 codes Encounter database: ICD-9 codes
Temporary caregiver	Dropped

methods, we dropped the item pertaining to patient support system.¹⁵ The remaining items were extracted from four different Health Partners' databases including a general demographics database that contains basic demographic information as well as enrollment status, an inpatient claims database that contains all hospital and laboratory information as well as visits to specialists, an encounters database that encompasses primary care physician visits, and a pharmaceutical database. The combinations of databases used to create each item are also delineated in Table 1. During the study period, primary care physicians received capitated payments from Health Partners; however, they were required to complete encounter forms and reimbursed \$0.50 per form. Administrative databases generally capture simple demographic items and billing-related claims with high degrees of accuracy.^{16,17}

We assigned diagnoses of diabetes or heart disease based on the presence of an appropriate International Classification of Diseases, 9th revision (ICD-9) code in the claims or encounter databases. The specific ICD-9 codes are detailed in Table 2. Two or more instances were required to establish a diagnosis of diabetes or heart disease.¹⁸ In addition, we assigned a diagnosis of diabetes to patients receiving more than one month's supply of oral hypoglycemic or insulin-based drugs, and a diagnosis of coronary artery disease for patients receiving multiple months of nitroglycerin-containing compounds (see Table 2).

Finally, we used the Deyo-Charlson comorbidity index as a proxy for self-rated health status. This index is an ICD-9-based version of the well-known Charlson comorbidity index and has been shown to correlate strongly with patient-reported health.^{19,20} As in the Charlson index, the Deyo modification assigns comorbidity points based on the presence of clinical conditions (as defined by presence of ICD-9 codes), such as congestive

FIGURE 1. Study flow diagram.

Table 2. ICD-9 Codes and Pharmaceutical Search Criteria for Diabetes and Heart Disease

Condition	Pharmaceutical	ICD-9 Codes
Diabetes	Glimepiride, glipizide, glyburide, acarbose, insulin, metformin, miglitol, repaglinide, troglitazone	250*
Coronary artery disease	Nitro*, Isosorbide*	410*, 411*, 412*, 413*, 414.0, 414.8, 414.9

*Wildcard, any combination of letters or numbers thereafter.

heart failure and renal disease. These points are then totaled to yield an overall comorbidity score. We assigned Deyo scores of "0" a proxy response of "excellent," "1-2" a response of "fair," and "3-4" a response of "poor." Using the coefficients derived by Coleman et al. for scoring the administrative proxy, we calculated scores for the 558 patients. This yielded scores between 0.15 and 0.83, similar to the survey Pra.

Our outcome of interest was total claims costs over the 6 months' follow-up from July 1, 1998, to December 31, 1998. These data were extracted from the claims database with the exception of drug costs that were extracted from the pharmacy database. We took the perspective of the health plan in calculating costs as the actual dollars paid by the HMO. We then defined high-cost patients as those in the top quartile of total costs to the health plan.

We used logistic regression to test for differences in the age, gender, and costs for respondents and nonrespondents. We used κ statistics to test the relationship between individual items on the survey Pra and administrative proxy, and then compared the sensitivity and specificity of each instrument at cut points from 0.40 to the traditional 0.50 to determine the optimal cut point for identifying high-cost patients. We then calculated total costs for groups designated as "high risk" and "low risk" based on cut point and used logistic regression to test for differences in costs between the two groups. To explore differences in patients identified as high risk by each scale, we divided patients into four groups: "concordant low risk" (both scales rating a patient as low risk); discordant "administrative proxy only high risk"; discordant "survey Pra only high risk"; and concordant high risk (both scales rating a patient as high risk). We used nonparametric Kruskal-Wallis tests to test for overall cost differences among the groups and then to compare differences between individual groups correcting for multiple comparisons. To further explore the predictive accuracy of the survey Pra and administrative proxy for total costs, we then used logistic regression to compare scale risk scores to actual outcomes (high or low total cost groups). We measured areas under receiver

operating characteristic curves (AUCs) to quantify this discriminative ability. An AUC of 0.5 represents discriminative capacity no greater than pure chance, and a value of 1.0 represents perfect predictive accuracy. After testing the administrative proxy in the respondent population, we tested its predictive ability in the nonrespondent population.

We used STATA version 5.0 (Stata Corp., College Station, Tex) for all statistical calculations except for AUC analyses for which we used the statistical program ROCKIT.²¹

RESULTS

Overall, response rate for the survey Pra was 54%. Respondents and nonrespondents did not differ significantly in age (71.1 years vs 71.7 years, $P = .20$); gender (24% male vs 28% male, $P = .22$); and total costs during follow-up (\$2,106 vs \$1,538, $P = .07$). Comparison of survey Pra scores to administrative proxy scores showed a correlation of 0.53, and distribution of these scales is shown in Figure 2. Comparison of self-report to database responses for items yielded a κ of 0.75 or better for age, gender, hospitalization and diabetes, and kappas of 0.37 and 0.17 for heart disease and number of doctor visits respectively (Table 3). Comparison of the indices' sensitivities and specificities at cut points from 0.40 to 0.50 are shown in Table 4. Because the intent of these indices is to screen for high-cost patients, we chose the cut point with the maximum sensitivity as the cutoff for predicted high-cost patients. The cost of false positives and false negatives is not available and therefore was not considered for this analysis.

Based on the chosen cut point of 0.40, the "high risk group" of respondents utilized 2.7 times as many resources as the "low risk group" (\$3,844 vs \$1,417, $P = .00$) based on survey Pra stratification, and 2.3 times as much resource use (\$3,212 vs \$1,377, $P = .00$) based on administrative proxy scoring. AUCs testing for the ability of each index to predict patient in the top quartile of total costs were 0.68 (95% confidence interval [CI] 0.64 to 0.72).

FIGURE 2. Distribution of survey Pra and administrative proxy risk scores.

Table 3. Comparison of Survey-based Responses and Database Items

Item	Self-report (n = 296)	Database (n = 296)	κ (95% CI)
Mean age, y	71.7	71.1	0.83 (0.75 to 0.92)
Gender, % male	23	23	0.99 (0.88 to 1.00)
One or more inpatient stays, %	27	27	0.75 (0.64 to 0.80)
Six or more doctor visits, %	46	82	0.17 (0.09 to 0.25)
Diabetes, % affected	35	39	0.86 (0.75 to 0.97)
Heart disease, % affected	26	28	0.37 (0.36 to 0.58)

CI, confidence interval.

The survey Pra and administrative proxy agreed on the classification of 216 of 296 patients; 169 were low risk by both scales, and 49 were high risk by both scales. Overall κ was 0.37. Resource use was lowest among patients identified as low risk by both scales (\$1,176), highest among those identified as high risk by both scales (\$4,359), and intermediate for those patients for whom the indices differed (Table 5). Kruskal-Wallis testing for differences across all groups was significant (χ^2 57.7, probability $> \chi^2 = .0001$); and pairwise comparisons of total costs by group were significant except for comparisons between the two discordant groups, and the “high-risk survey Pra only” group versus the “concordant high-risk” group.

Finally, application of the administrative proxy to survey nonrespondents demonstrated stability in the index’s performance. High-risk patients experienced total costs 2.1 times ($P = .00$) that of low-risk patients, and the AUC for the model was 0.67 (95% CI, 0.63 to 0.71).

DISCUSSION

The development of an administrative version of the Pra by Coleman et al. advanced our ability to identify the frail elderly. In this study, we sought to extend this work to a particularly vulnerable population of dual-eligible Medicare/Medicaid members with the goal of identifying patients at higher risk for significant resource utilization in the ensuing 6 months.

Of the 558 Health Partners members eligible for the study, 296 responded to the survey Pra. This 54% response rate was consistent with the response rates in other published studies of the Pra.^{22–25} In this group of dual-eligible patients, the survey Pra appeared to work as effectively as in other populations. Resource utilization was at least double across all groups tested, and overall AUCs were 0.67 to 0.68. Interestingly, respondents tended towards being sicker than nonrespondents, averaging \$477 more in costs.

This study has several limitations. First, using resource utilization as the metric to identify high-risk elders

may not be ideal. Although costs are a readily measurable outcome of strategic importance for the ongoing operations of health plans, an ideal screening tool would also identify enrollees at risk for functional decline, and allow risk stratification and targeting of an appropriate level of intervention. Although Coleman et al. did validate the Pra against a measure of functional decline (restricted activity days), further research is clearly needed to evaluate the ability of claims-based risk stratification to predict patients’ functional status. Second, the time lag inherent in any database-driven instrument such as the administrative proxy precludes its use as a screening tool for new members of a health plan. Our validation study required a full year’s continuous membership for calculation of an administrative proxy score. Third, this analysis required the combination of information from multiple databases. Within Health Partners, this task is much simpler due to a unique identifier assigned to each patient; however, a significant number of dual-eligible patients do have split coverage such that one provider manages their Medicare benefits and a second manages their Medicaid benefits. In this case, calculation of an administrative proxy is not possible. Fourth, the AUCs and sensitivities of both the survey Pra and administrative proxy continue to leave substantial room for improvement. Fifth, the Philadelphia Medicare/Medicaid population may not be generalizable. Medicaid members in this region must choose from one of four health maintenance organizations, and benefit shopping occurs. To the extent that Health Partners’ package of benefits and perceived service differs from that of its competitors, it may attract a unique population of patients, thus limiting the application of these findings to other dual-eligible populations. Finally, the costs of false

Table 4. Comparison of Sensitivity and Specificity of Survey Pra and Administrative Proxy at Selected Cut Points

Cut Points	Total Costs, %	Inpatient Stays, %
Cut point = 0.40		
Administrative proxy		
Sensitivity	55	60
Specificity	72	68
Survey Pra		
Sensitivity	50	57
Specificity	83	79
Cut point = 0.45		
Administrative proxy		
Sensitivity	28	30
Specificity	87	84
Survey Pra		
Sensitivity	39	54
Specificity	89	87
Cut point = 0.50		
Administrative proxy		
Sensitivity	21	27
Specificity	89	92
Survey Pra		
Sensitivity	32	48
Specificity	91	90

Table 5. Comparison of Costs for Concordant and Discordant Grouping

Agreement	Total Costs (\$D)
Concordance	
Survey Pra and administrative proxy low risk (n = 169)	\$1,176 (\$2,018)
Discordance	
Administrative proxy high risk only (n = 54)	\$2,171 (\$3,522)
Survey Pra high risk only (n = 24)	\$2,794 (\$3,344)
Concordance	
Survey Pra and administrative proxy high risk (n = 49)	\$4,359 (\$5,120)

positives and false negatives are impossible to assess at this point.

The common response to identification of high-risk patients in a managed care organization is to begin intensive case management of these members. Studies of these interventions in elders have met with mixed results thus far. While some targeted case management programs have been shown to reduce expenditures by decreasing hospitalizations, a recent social worker-based case management program failed to show reductions in health care costs for seniors.²⁶⁻²⁸ Thus, although one might hypothesize that the cost of a false negative could be high in terms of increased morbidity and mortality, the cost of a false positive could also be high in exposing patients to increased testing and interventions without improving outcomes or quality of life. Given that the relative cost of false positive and false negative assessments is unknown, we cannot determine the optimal operating point on a receiver operating characteristic curve.

Despite these limitations, the administrative proxy discriminated between groups of high and lower resource utilizers over a shorter follow-up period than Coleman et al.'s work and worked equally well in the 50% of Medicaid patients unwilling or unable to respond to survey-based screening. This finding is particularly important in the Medicaid population in which transiency, lower literacy rates, and mistrust of the health system already create significant barriers to health care access. Despite its time lag, if the administrative proxy maintains this performance, it presents an opportunity to identify frail managed care members at minimal incremental cost. In addition, continuous calculation of the risk score may allow more timely intervention for patients whose risk scores change dramatically even in the absence of a full year of data.

REFERENCES

1. Waid MO. Brief summaries of Medicare & Medicaid. Title XVIII and Title XIX of The Social Security Act as of June 25, 1998. Baltimore, Md: Health Care Financing Administration [online] 1998 June 25 [cited 2000 mar 22]; [21 screens]. Available from URL:<http://www.hcfa.gov/medicare/>
2. Coleman EA, Wagner EH, Grothaus LC, Hecht J, Savarino J, Buchner DM. Predicting hospitalization and functional decline in health plan enrollees: are administrative data as accurate as self-report? *J Am Geriatr Soc.* 1998;46:419-25.
3. Boulton C, Dowd B, McCaffery D, Boulton L, Hernandez R, Krulewicz H. Screening elders at risk for hospital admission. *J Am Geriatr Soc.* 1993;41:811-7.
4. Pacala JT, Boulton C, Boulton L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. *J Am Geriatr Soc.* 1995;43:374-77.
5. Pacala JT, Boulton C, Reed R, Aliberti E. Predictive validity of the Pra instrument among older recipients of managed care. *J Am Geriatr Soc.* 1997;45:614-7.
6. Pacala JT, Boulton C, Boulton L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. *J Am Geriatr Soc.* 1995;45:373-7.
7. Pacala JT, Boulton C, Reed R, Aliberti E. Predictive validity of the Pra instrument among older recipients of managed care. *J Am Geriatr Soc.* 1997;45:614-7.
8. Fillit HM, Picariello G, Warburton SW. Health risk appraisal in the elderly: results from a survey of 70,000 Medicare HMO members. *J Clin Outcomes Manage.* 1997;4:23-9.
9. Hertzog AR, Rodgers WL. Age and response rates to interview sample surveys. *J Gerontol.* 1988;43S:200-5.
10. Launer LJ, Wind AW, Deeg DJ. Nonresponse pattern and bias in a community-based cross-sectional study of cognitive functioning among the elderly. *Am J Epidemiol.* 1994;139:803-12.
11. Vojta CL, Amaya M, Browngohl K, Coburn K, Vojta DD. A home-based asthma education program in managed Medicaid. *J Clin Outcomes Manage.* 1999;6:30-4.
12. Root J, Stableford S. Easy-to-read consumer communications: a missing link in Medicaid managed care. *J Health Polit Policy Law.* 1999;24(1):1-26.
13. Coleman EA, Wagner EH, Grothaus LC, Hecht J, Savarino J, Buchner DM. Predicting hospitalization and functional decline in health plan enrollees: are administrative data as accurate as self-report? *J Am Geriatr Soc.* 1998;46:419-25.
14. Pacala JT, Boulton C, Boulton L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. *J Am Geriatr Soc.* 1995;45:373-7.
15. Coleman EA, Wagner EH, Grothaus LC, Hecht J, Savarino J, Buchner DM. Predicting hospitalization and functional decline in health plan enrollees: are administrative data as accurate as self-report? *J Am Geriatr Soc.* 1998;46:419-25.
16. Chao J, Gillanders WG, Flocke SA, Goodwin MA, Kikano GE, Strange KC. Billing for physician services: a comparison of actual billing with CPT codes assigned by direct observation. *J Fam Pract.* 1998;47(5):335-6.
17. Robinson JR, Young TK, Roos LL, Gelskey DE. Estimating the burden of disease. Comparing administrative data and self-reports. *Med Care.* 1997;35(9):932-47.
18. Herbert PL, Geiss LS, Tierney EF, Engellau MM, Yawn BP, McBean AM. Identifying persons with diabetes using Medicare claims data. *Am J Med Quality.* 1999;14(6):270-7.
19. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chron Dis.* 1987;40(5):373-83.
20. Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. *J Outcomes Clin Epidemiol.* 1992;45(6):613-9.
21. Metz CE, Herman BA, Roe CA. Statistical comparison of two ROC curve estimates obtained from partially-paired datasets. *Med Decis Making.* 1998;18:110-21.
22. Pacala JT, Boulton C, Boulton L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. *J Am Geriatr Soc.* 1995;45:373-7.

23. Fillit HM, Picariello G, Warburton SW. Health risk appraisal in the elderly: results from a survey of 70,000 Medicare HMO members. *J Clin Outcomes Manage.* 1997;4:23-39.
24. Robinson JR, Young TK, Roos LL, Gelskey DE. Estimating the burden of disease. Comparing administrative data and self-reports. *Med Care.* 1997;35(9):932-47.
25. Boulton C, Boulton L, Murphy C, Ebbitt B, Luptak M, Kane RL. A controlled trial of outpatient geriatric evaluation and management. *J Am Geriatr Soc.* 1994;42:465-70.
26. Burns LR, Lamb GS, Wholey DR. Impact of integrated community nursing services on hospital utilization and costs in a Medicare risk plan. *Inquiry.* 1996;33:30-41.
27. Forman SA, Kelliher M, Wood G. Clinical improvement with bottom-line impact. Custom care planning for patients with acute and chronic illness in a managed care setting. *Am J Managed Care.* 1997;3:1039-48.
28. Boulton C, Rassen J, Rassen A, Moore RJ, Robison S. The effect of case management on the costs of health care for enrollees in Medicare Plus Choice plans: a randomized trial. *J Am Geriatr Soc.* 2000;48:996-1001.

APPENDIX

The Probability of Repeat Admission Questionnaire

Survey Questions:

1. In general would you say your health is: (Excellent, Very good, Fair, Poor)?
2. In the previous 12 months, have you stayed overnight as a patient in a hospital? (Not at all, One time, Two or three times, More than three times.)
3. In the previous 12 months, how many times did you visit a physician or clinic? (Not at all, One time, Two or three times, Four to six times, More than six times.)
4. Have you ever had:
 - A. Coronary heart disease? (Yes, No, Don't know.)
 - B. Angina pectoris? (Yes, No, Don't know.)
 - C. A myocardial infarction? (Yes, No, Don't know.)
 - D. Any other heart attack? (Yes, No, Don't know.)
5. In the previous 12 months did you have diabetes? (Yes, No.)
6. Is there a friend, relative or neighbor who would take care of you for a few days, if necessary?
7. Are you: (Male, Female)?
8. What is your date of birth?

Source: Pacala JT, Boulton C, Boulton L. Predictive validity of a questionnaire that identifies older persons at risk for hospital admission. *J Am Geriatr Soc.* 1995;43:374-7.