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Comparison of simple efficient clinical and self-reported predictors of mortality in a National United States Cohort

Robert M. Kaplan*[1], Virginia J. Howard[2], Jennifer J. Manly[3], George Howard[4]

[1] *Clinical Excellence Research Center, Department of Medicine, Stanford University, Stanford, CA, United States*
[2] *Department of Epidemiology, School of Public Health, University of Alabama at Birmingham, Birmingham, AL, United States*
[3] *Department of Neurology, G.H. Sergievsky Center and Taub Institute for Research on Alzheimer's Disease and the Aging Brain, Columbia University, New York, NY, United States*
[4] *Department of Biostatistics, School of Public Health, University of Alabama at Birmingham, Birmingham, AL, United States*

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ABSTRACT

Purpose: To compare the relative value of simple efficient methods for predicting mortality.
Methods: We compared three clinical (blood pressure, blood glucose, and low density lipoprotein cholesterol [LDL] cholesterol) and three self-reported (smoking, educational attainment and self-reported health) prospectively measured predictors of mortality in a cohort of 30,239 white and black adults who were 45 years of age or older at enrollment between 2003-2007. Survival was modeled using proportional hazards analysis and the c-statistic was used to evaluate information provided by each measure.
Results: Information on all variables and follow up was available for 27,482 (91%), and among these, there were 4,409 (16%) deaths over an average of 7.6 years. The clinical measures of blood pressure, blood glucose, and cholesterol were modestly good predictors of short-term survival (for each, $p < .01$). However, simple one-item self-reports provided better prediction of mortality than the clinical indicators. The Age-Sex Race (ASR) adjusted Hazard Ratios (HR) for self-reported current smoking in contrast to not smoking (2.43, CI: 2.25-2.63) self-rating of health as poor in contrast to excellent (HR = 6.26, CI: 5.42-7.23), and less than high school education versus collage graduation (HR = 2.21, CI: 2.01-2.42) were all highly significant.
Conclusion: Simple one-item self-reports may be undervalued as meaningful predictors of longevity.

Key Words: Self report, Clinical epidemiology, Longevity prediction

1. INTRODUCTION

Health planners, actuaries, and clinical providers need estimates of how long people are expected to live. Often these individuals have limited resources, are given little space on questionnaires, and have little time for assessment.[1] These challenges raise an important question. If one wanted to predict mortality risk at the individual level and were only able to ask a few questions, what would they be?

Health related information in a typical clinical setting usually comes from three sources: 1) medical history and physical examination taken by a healthcare provider, 2) results from instrumentation and laboratory findings, and 3) self-reports

*Correspondence: Robert M. Kaplan; Email: bob.kaplan@stanford.edu; Address: CERC, Stanford University, 75 Alta Road, Stanford, CA 94305, United States.

from the patient. Information collected in epidemiologic studies and in clinical practice usually emphasizes clinical or laboratory findings, such as blood pressure, serum cholesterol, or fasting plasma glucose. Physician notes typically include diagnoses and general health appraisals. However, some evidence suggests that clinician and patient overall ratings of health are often discordant. Physicians give greater weight to clinical measures and risk factors while patient judgments are weighted more by functional limitations and psychological well-being.[2] Although patient self-reports are often not captured in the electronic health record,[3] a growing literature suggests that simple self-reported variables also contribute important information.[4–10] These simple self-reports might not provide guidance for clinical intervention, but they may offer important information about the determinants of health.[11] In actuarial studies, self-reports are low cost and simply acquired. Simple self-ratings of health have been shown to predict remaining life expectancy in a variety of studies. In the most widely cited paper, Idler and Benyamini reviewed 27 community studies and found self-reported health to predict mortality in 23 of the 27 studies.[4] The review was updated by Benyamni and Idler to include 19 additional studies published between 1995 and 1998.[12] Although studies consistently (17 of the 19 newer studies) show self-rated health is a significant predictor of longevity, few studies have directly compared self rated health with objectively measured biological variables. In the Benyamni and Idler review 3 of 19 studies included independently measured cardiovascular risk factors. In the Idler and Benyamni review only one study appeared to have provider measures of risk factors while another study used interviewer-measured blood pressure. Some of these studies were small and had a relatively limited number of deaths. When cardiovascular risk factors were measured, they are typically used for statistical adjustment, but were not compared directly to self-report measures as predictors of longevity.[13] As a result, the value of self-reports remains undervalued in health research and health care practice.

In this study we consider the information provided by traditional indicators such as blood pressure, cholesterol, and glucose in comparison to simple self-reported questions about education, self-rated health, and cigarette smoking. The three traditional indicators were selected because, on the basis of substantial evidence, they are routinely used in clinical practice to assess risk for heart disease which is the most common cause of premature death.[14] Our goal was to assess the relative predictive utility provided by biologic tests versus simple self-reports. The analysis used data from a national, population-based cohort study of 30,239 community-dwelling individuals, blacks and whites, aged 45 or older at enrollment in 2003-2007, the REasons for Geographic and Racial Differences in Stroke (REGARDS) study.[15] We believe this is the largest national sample that has been used to compare biological and self reported variables as predictors of longevity.

2. METHODS

REGARDS is a prospective cohort study focused on racial and geographic differences in stroke mortality.[15] The study focused on contributors to stroke incidence and mortality from both ischemic stroke and intracerebral hemorrhage. In addition to stroke outcomes, the data set can be used to evaluate predictors of all-cause mortality. The methodology for to study is described in detail in other REGARDS publications.[15]

2.1 Study population

Between January 2003 and October 2007, 30,239 black and white adults, who were 45 years of age or older were recruited. A commercially available list was used to identify community-dwelling residents. Individuals on the list received a solicitation through the mail and were later contacted by telephone. Adults were oversampled from eight states comprising the geographic region known as the stroke belt.[15] About 56% of the participants resided in these states, including: North Carolina, South Carolina, Georgia, Tennessee, Alabama, Mississippi, Arkansas, and Louisiana. The other 44% were sampled from the other 40 contiguous US states. The sampling design included oversampling of black participants. The final sample comprised 42% black and 55% women. Among those who responded to the telephone inquiry and were eligible, 49% agreed to participate. The initial consent to participate was secured verbally during the telephone contact. As part of the in-home physical exam, written informed consent was obtained. The study involved multiple institutions and IRBs at each of these institutions independently approved the study protocol.

2.2 Demographic assessment

An initial telephone interview was used to obtain information on demographic characteristics, including age, race, sex.

2.3 Cardiovascular risk assessment

We *a priori* selected three cardiovascular risk factors as biological measures. Cardiovascular risk factors were chosen because heart and vascular diseases remain the most common cause of death in the US and because the importance of screening for CVD risk factors is uncontroversial. We focused on three biological risk factors: blood pressure, LDL cholesterol, and blood glucose. These three measures were chosen because: 1) they have been the most consistent predictors of major health events, including death, in major epidemiological studies,[16] 2) the United States Preventive Services Taskforce rates screening for each of these three variables as supported by the highest level of evidence (see http://www.uspreventiveservicestaskforce.org), and 3) they are routinely used in the clinical practice of medicine.[17]

An assessment of cardiovascular risk was based on a telephone interview, self-administered questionnaires, an in-home physical examination conducted 3-4 weeks after the telephone interview and the analysis of blood samples collected during the in-home exam. Blood pressure was measured after the participant had been seated for five minutes. The average of two blood pressures was used in the analysis. High blood pressure was defined as SBP greater or equal than 140 mmHg. Clinical hypertension was defined as SBP greater than or equal to 140 mmHg, or diastolic blood pressure greater or equal than 90 mmHg, or self-reported use of antihypertensive medications. The difference between high blood pressure and clinical hypertension was, in part, attributable to self-reported medication use.

A fasting blood panel was used to estimate blood glucose, and low density lipoprotein cholesterol. The Friedewald formula was used to calculate low-density–lipoprotein cholesterol.[18] All blood samples were sent to a central laboratory. Fasting glucose greater than 126 mg/dl were considered high. For cases in which participants failed to fast prior to the examination (14% of those evaluated), the threshold of 200 mg/dl was used. We used a similar definition for clinical Diabetes Mellitus. Subjects were also considered to have diabetes if they met the definition of high blood glucose, or if they self-reported using medication to control blood sugar. The difference between high glucose and Diabetes Mellitus in this analysis was the self-report of medicine use. It was necessary to keep these variables separate because fasting blood glucose can be normal for people with diabetes when they are well controlled on medication. In the analysis, we consider both high measured blood glucose and Diabetes Mellitus by this definition.

2.4 Self-report variables

We focused on three a priori selected self-reported variables. Telephone interview was used to assess smoking status categorized as smoking versus past/never, This was determined by a yes response to the question, Do you smoke cigarettes now, even occasionally? The question was asked to those who admitted to smoking more than 100 cigarettes in their lifetimes. During the phone interview, each participant was asked to rate their own health as either excellent, very good, good, fair, or poor. Respondents were also asked to report their highest level of education and were classified as completing less than high school, high school graduation, some college, or college graduation. The three self-report variables were selected because previous published suggested that they were related to health outcome and because they offered information often not requested by health care providers.[5,6]

2.5 Vital status

After the baseline assessment, participants were followed by telephone every six months. When participants could not be reached by telephone, we contacted a proxy respondent who had been identified when the participant enrolled in the study. For deceased patients, the date of death was confirmed through several sources, including Social Security Index, death certificates, or the National Death Index. For this analysis, follow-up was through November 21, 2015.

2.6 Analysis methods

Each predictor of death was evaluated with linear adjustments for age, sex and race (ASR). Odds of survival through the follow up period were estimated using Kaplan-Meier product limit proportional hazard functions. Information provided by each ASR adjusted measure was evaluated using the c-statistic.[19] This measure considers two people chosen at random from the study. These two people will have predicted scores from the proportional hazards model. If both people died, then we can know the order. If the person with the higher predicted risk from the model died before the low risk person, then the observed outcome is concordant with the predicted risk, otherwise it is discordant. The concordance/discordance can also be established if one of the two participants had died, and the death occurred at a shorter time than the follow-up up of the other participant (i.e., time to death was shorter than time to censoring). However, the concordance/discordance cannot be established for the pair where the follow-up time of the person not dying is shorter than the time to death (i.e., time to censoring was shorter than time to death), or in the case where neither person died (i.e., both participants were censored). The c-statistic is the likelihood that the person with the higher predicted risk will have a shorter time to death, and is calculated as the proportion of concordant pairs among all pairs of participants where the concordance/discordance can be established. In the case of no differences in the value of two predictors, then the likelihood of a pair being concordant is 50-50, and the expected value of the c-statistic is 0.50. Alternatively, in the case where one predictor is consistently better than the alternative predictor, all of the pairs will be concordant and the expected value of the c-statistic is 1.00. Examination of deviations in time-dependent covariates was used to test the proportional hazards assumption. Computations were performed using SAS version 9.4.

Through a computational model, the c-statistic considered each possible pairing of two people in which concordance/discordance could be established and sums up these pairs. In studies of mortality in humans, a variable with a c-statistic above 0.70 is considered a good predictor of morality.[20] The $p < .05$ (95% confidence interfal) threshold was used for declaring statistical significance.

3. RESULTS

Of the 30,239 participants, data from follow-ups were available on all variables for 27,482 (91%). During a mean follow-up of 7.6 ± 2.9 years, there were 4,409 (16%) deaths. With 27,482 participants, there are 377,616,421 pairs of participants, and with the 4,409 deaths the concordance/discordance could be established in 93,642,182 pairs of participants (9,717,436 pairs where both participants died and 83,924,746 where one participant died prior to the other being censored). The concordance/discordance could not be established in 283,974,239 of the pairs of participants: 17,804,111 where one participant was censored prior to the other dying, and 266,170,128 where neither participant died. Baseline characteristics are shown in Table 1 and the primary results from the analysis are presented in Table 2. The coefficients in Table 2 are each after adjustment for age, race and sex (the "base model") and then each of the other variable one at a time. The first model includes age, race, sex, and high glucose, while the second model includes age, race, sex, and diabetes. The models were run separately because of the potential co-linearity between diabetes and high glucose. By separating the models, the correlation between high glucose and diabetes is not an issue.

Any model must adjust for the three demographic variables known to have a significant impact on life expectancy: age, race, and sex. The base model included these demographic factors, which were entered in the same block. As expected, age has a strong influence on life expectancy, HR = 2.33 (95% CI: 2.25-2.41). Similarly, black race (in comparison to white race) was associated with a 40% hazard ratio for death within the study interval (HR = 1.40, CI: 1.32-1.49), and male sex (in comparison to female sex) was associated with a 64% increased risk of death, (HR = 1.64, CI: 1.54-1.74). Each of the analyses presented below adjusts for age, race, and sex (ASR adjusted).

After adjusting for ASR, having high blood pressure increased the hazard of death by 43%, (CI: 1.34-1.53) and clinical hypertension increased the risk only slightly to 46% (HR = 1.46, CI: 1.36-1.56). Fasting plasma glucose > 126 mg/dl or non-fasting > 200 mg/dl increased the risk of death by 68%, (HR = 1.68, CI: 1.55-1.83), while meeting the clinical definition of diabetes increased the hazard by 89% (HR = 1.89, CI: 1.77-2.01). Unexpectedly, having LDL-cholesterol greater than 130 mg/dl did not increase the HR, and appears to have a slight protective effect HR = 0.91 (0.85-0.97).

Table 1. Baseline characteristics based on 27,482 participants with follow-up

			Description*
Base model	Age		64.9 ± 9.4
	Race	White	59%
		Black	41%
	Sex	Female	55%
		Male	45%
High BP	No		79%
	Yes		21%
Hypertension	No		41%
	Yes		59%
High Glucose	No		89%
	Yes		11%
Diabetes	No		79%
	Yes		21%
LDL Cholesterol > 130 mg/dl	No		70%
	Yes		30%
Current Smoker	No		86%
	Yes		14%
Self-reported health	Excellent		16%
	Very good		31%
	Good		35%
	Fair		15%
	Poor		4%
Education	College Grad		35%
	Some College		27%
	HS Grad		26%
	LT HS		12%

Note. BP = blood pressure; LDL = Low density lipoprotein; mg/dl = milligrams/deciliter.
* The entry for age is the mean ± one standard deviation. All other entries are in percentages.

Self-report items

Each of the self-reported items was strongly associated with life expectancy. In comparison to non-smokers, ASR adjusted self-reported current smokers were 2.43 times more likely to die (CI: 2.25-2.63) during the follow-up period. In contrast to those who rated their health as excellent, a simple self-rating of health as very good was associated with a 29% increase in the hazard of death (HR = 1.29, CI: 1.15-1.44), while participants self-rating their health as poor were 626% higher in deaths during the study follow-up (HR = 6.26, CI: 5.42-7.23).

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Table 2. Summary of base model and age-sex-race adjusted models for clinical and self-reported predictors

			Deaths/N (%)	HR (95% CI)	C-statistic
Base model	Age (per 10 years)		Age 45-64 1,029/13,902 (7%)	2.33 (2.25-2.41)	0.721 (0.713-0.729)
			Age 65+ 3,380/13,580 (25%)		
	Race	White	2,531/16,296 (16%)	1.00 (ref)	
		Black	1,878/11,187 (17%)	1.40 (1.32-1.49)	
	Sex	Female	1,848/15,052 (12%)	1.00 (ref)	
		Male	2,561/12,430 (21%)	1.64 (1.54-1.74)	
+High BP	No		3,061/21,845 (14%)	1.00 (ref)	0.726 (0.719-0.734)
	Yes		1,348/5,637 (24%)	1.43 (1.34-1.53)	
+Hypertension	No		1,264/11,325 (11%)	1.00 (ref)	0.727 (0.719-0.734)
	Yes		3,145/16,157 (19%)	1.46 (1.36-1.56)	
+High Glucose	No		3,709/24,530 (15%)	1.00 (ref)	0.726 (0.719-0.734)
	Yes		700/2,952 (24%)	1.68 (1.55-1.83)	
+Diabetes	No		2,993/21,786 (14%)	1.00 (ref)	0.734 (0.726-0.741)
	Yes		1,416/5,696 (25%)	1.89 (1.77-2.01)	
+LDL > 130	No		3,317/19,187 (17%)	1.00 (ref)	0.721 (0.714-0.729)
	Yes		1,092/8,295 (13%)	0.91 (0.85-0.97)	
+Smoking	No		3,568/23,560 (15%)	1.00 (ref)	0.738 (0.730-0.745)
	Yes		841/3,922 (21%)	2.43 (2.25-2.63)	
+Self-reported health	Excellent		407/4,437 (9%)	1.00 (ref)	0.755 (0.748-0.763)
	Very good		1,001/8,518 (12%)	1.29 (1.15-1.44)	
	Good		1,641/9,599 (17%)	2.01 (1.80-2.24)	
	Fair		1,017/4,004 (25%)	3.38 (3.00-3.80)	
	Poor		343/924 (37%)	6.26 (5.42-7.23)	
+Education	College Grad		1,121/9,658 (12%)	1.00 (ref)	0.733 (0.725-0.740)
	Some College		1,151/7,366 (16%)	1.49 (1.37-1.62)	
	HS Grad		1,198/7,094 (17%)	1.59 (1.46-1.73)	
	LT HS		939/3,364 (28%)	2.21 (2.01-2.42)	

Note. BP = blood pressure, LDL = Low density lipoprotein, mg/dl = milligrams/deciliter, HR = Hazard Ratio.

Education was also a significant predictor of life expectancy. In comparison to college graduates, the chances of death were 49% higher during the follow-up (HR = 1.49, CI: 1.37-1.62) and, those with less than a high school education had a 221% higher mortality (HR = 2.21, CI: 2.01-2.42).

Figure 1 is a plot of the c-statistics for the various ASR adjusted models. The base model that includes only age, race and sex, has a c-statistic of 0.721 for death. High LDL was not associated with an increase in the c-statistic. High blood pressure, hypertension, and high fasting glucose, all increase the c-statistic to about 0.725. Diabetes, smoking and education each increased the c-statistic to about 0.735, and the general health question increased the c-statistic to 0.755. Overall, adding the three simple self-reported variables provides more information about the probability of dying during the study than do the clinical and laboratory measures.

4. Discussion and conclusion

How might we most efficiently achieve the goal of estimating how long someone will live? If allowed only a few data points, what would they be? Our analysis suggests that after age, race, and sex are taken into account, simple self-reports about educational attainment, self-rated health, and cigarette smoking each provide more information than individual traditional measures such as blood pressure, cholesterol, or blood glucose levels. Further, adding self-reported medication use to measures of blood glucose improves the prediction of mortality. The results stand in contrast to suggestions that self-reported information is unreliable, and of little value in research and clinical practice.[21]

Several other studies have produced similar results. For example, a substantial number of studies now indicate that years of education completed is a very good predictor of longevity.[1,4,12,22–25] This effect remains graded after adjustments for demographic factors, income, biological risk factors, and health behaviors. Our analysis extends earlier studies because it includes a larger representative sample from the US population and because it offers direct comparisons between self-reported variables and the best biological predictors of longevity.

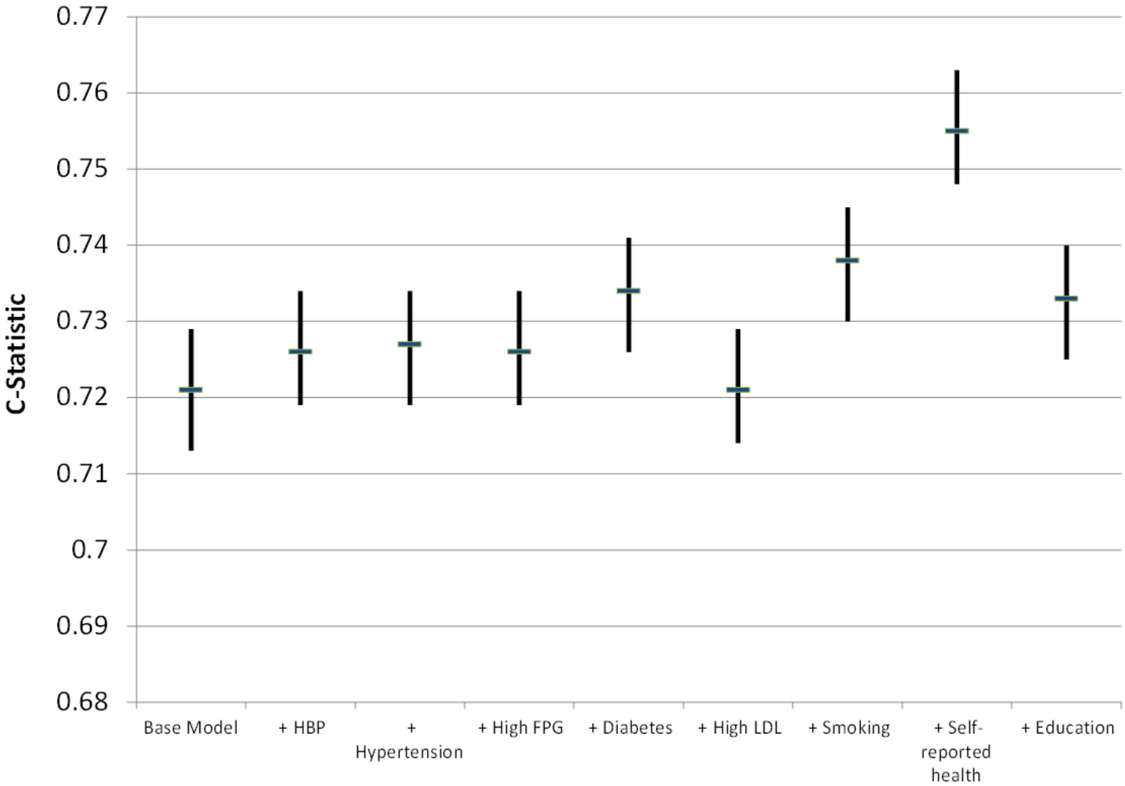

Figure 1. Plot of c-statistics for base model and ASR adjusted clinical and self-reported predictors

Self-reported smoking, not validated by cotinine or other biological tests remains a very strong predictor of near term mortality.[26] It is no surprise that self-reported tobacco use predicts survival in the REGARDS cohort. An enormous amount of evidence documents the relationship between tobacco smoking and longevity.[27] However, patients are rarely asked about cigarette smoking in clinical practice. A recent analysis of the Medical Expenditure Panel Survey (MEPS)[17] suggested that physicians ask about current cigarette smoking only about half the time. The current study adds evidence to suggest that the policy issue should no longer be whether smoking should be assessed, but why information is not consistently collected. It is possible that some providers avoid asking questions that patients may perceive as personal or that might lead patients to feel their providers are judgmental. But, if health care providers are not even asking about smoking, intervention is unlikely. It seems less likely that clinicians would fail to act on clinical observations of hypertension, high cholesterol, and diabetes.

Patient's self-reported health status is either rarely asked or rarely recorded in medical records. Our results, and those of a variety of other studies,[5,7] indicate that a simple rating of health status provides better prediction of longevity than information about cardiovascular risk factors, including cigarette smoking, age, race, and years of education. We recognize that fair or poor self-rated health does not offer specific intervention directions for clinicians. However, given the strength of the relationship between self-rated health and mortality, the ratings may alert clinicians to patients who need greater surveillance. In addition, self-rated health is also a very reliable predictor of health care expenditure and the utilization of health care services.[6,8] We believe that self-reported health takes disease status into consideration in addition to subjective evaluation of intangible aspects of wellness. Self-reported health has been shown to predict current life expectancy for people with or without multiple diagnoses in several other studies.[4]

We recognize that there are challenges with self-reported health measures. Often these variables offer little information to clinicians. For example, it is difficult to know what action a provider should take when he or she learns that a patient has less than a high school education. Although we do not know the mechanism, low education is an important risk factor for premature mortality. Blood pressure, which yields less information about the hazard of death, is assessed in nearly all primary care visits, and there are national guidelines and recommendations to guide what the provider actions should be. We evaluated a limited set of self-report variables and it is likely that other simple questions might also predict outcome. For example, we did not evaluate self-reports of serious illnesses, such as heart disease or cancer because they typically depend on information reported to a patient by a health care provider.

Our analysis comes with several important limitations. A variety of other factors are known to affect health outcomes. We did not include measures of alcohol consumption, income, and marital status. Other studies have shown these to be important social predictors or health outcome.[28–30] Future studies may explore how simple measures of these social determinants may predict current life expectancy.

Patient reported health was the strongest predictor of near term death. It is possible that this reflects the integration of several sources of information: that provided by the physician, by the laboratory and by the experience of the patient. Some recent evidence suggests that the correlation between this one item and more complex measures of health status can be very high ($r = 0.81$).[31]

In summary, information about patient wellness typically comes from three sources: 1) physician acquired history and physical examination, 2) laboratory and clinical tests, and 3) patients. Among the three sources, laboratory measures of cardiovascular risk factors are often considered to be the most important variables that should be gathered in epidemiologic studies and in clinical practice. Physician examination and history is also considered to be invaluable, while patient self-reports are usually considered to be unreliable or meaningful only if they confirm clinical impressions or laboratory tests. Our analysis suggests that simple one item patient reports provide superior prediction of probability of survival. These simply acquired data should be given greater attention in actuarial practice, epidemiologic research, and clinical medicine.

CONFLICTS OF INTEREST DISCLOSURE

The authors declare that they have no competing interests.

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