Assessing Cardiorespiratory Fitness Without Performing Exercise Testing

Radim Jurca, PhD, Andrew S. Jackson, PED, Michael J. LaMonte, PhD, MPH, James R. Morrow Jr., PhD, Steven N. Blair, PED, Nicholas J. Wareham, MBBS, PhD, William L. Haskell, PhD, Willem van Mechelen, MD, PhD, Timothy S. Church, MD, MPH, PhD, John M. Jakicic, PhD, Raija Laukkanen, PhD

Background: Low cardiorespiratory fitness (CRF) is associated with increased risk of chronic diseases and mortality; however, CRF assessment is usually not performed in many healthcare settings. The purpose of this study is to extend previous work on a non–exercise test model to predict CRF from health indicators that are easily obtained.

Methods: Participants were men and women aged 20 to 70 years whose CRF level was quantified with a maximal or submaximal exercise test as part of the National Aeronautics and Space Administration/Johnson Space Center (NASA, n =1863), Aerobics Center Longitudinal Study (ACLS, n =46,190), or Allied Dunbar National Fitness Survey (ADNFS, n =1706). Other variables included gender, age, body mass index, resting heart rate, and self-reported physical activity levels.

Results: All variables used in the multiple linear regression models were independently related to the CRF in each of the study cohorts. The multiple correlation coefficients obtained within NASA, ACLS, and ADNFS participants, respectively, were 0.81, 0.77, and 0.76. The standard error of estimate (SEE) was 1.45, 1.50, and 1.97 metabolic equivalents (METs) (1 MET=3.5 ml O_2 uptake · kilograms of body mass^{-1} · minutes^{-1}), respectively, for the NASA, ACLS, and ADNFS regression models. All regression models demonstrated a high level of cross-validity (0.72<R<0.80). The highest cross-validation coefficients were seen when the NASA regression model was applied to the ACLS and ADNFS cohorts (R=0.76 and R=0.75, respectively).

Conclusions: This study suggests that CRF may be accurately estimated in adults from a non–exercise test model including gender, age, body mass index, resting heart rate, and self-reported physical activity.

(Am J Prev Med 2005;29(3):185–193) © 2005 American Journal of Preventive Medicine

Introduction

Low cardiorespiratory fitness (CRF) is associated with adverse metabolic risk factor profiles,[1–3] increased risk of cardiovascular disease, type 2 diabetes, and mortality.[4–10] The strength of association between low CRF and mortality is comparable to that between mortality and conventional health indicators such as body weight, blood pressure, cholesterol level, and smoking.[8,9,11] Although CRF is an important health indicator, fitness assessment is usually not performed in many healthcare settings.

The decision to measure and evaluate health indicators in most settings is likely influenced by the feasibility and cost of measuring the parameter. Assessments of body weight, blood pressure, cholesterol levels, and smoking habits are relatively easy to obtain, and are routinely obtained and used in patient counseling. Absence of feasible assessment methods and consensus guidelines for interpreting health-related CRF levels may contribute to the lack of fitness evaluation in most settings. Incorporation of CRF into individual risk assessment might be more feasible if simple CRF assessments are available.

The gold standard measure of CRF is maximal oxygen uptake ($\dot{V}O_{2max}$), typically expressed as follows: milliliters of O_2 uptake · kilograms of body mass^{-1} · minutes^{-1}, or

From The Cooper Institute (Jurca, LaMonte, Morrow, Blair, Church), Dallas, Texas; Department of Health and Human Performance, University of Houston (Jackson), Houston, Texas; Department of Kinesiology, Health Promotion, and Recreation, University of North Texas (Morrow), Denton, Texas; Department of Public Health and Primary Care, Institute of Public Health (Wareham), Cambridge University, Cambridge, United Kingdom; Department of Medicine, Stanford University (Haskell), Stanford, California; Institute for Research in Extramural Medicine and Department of Public and Occupational Health (van Mechelen), VU University Medical Center, Amsterdam, The Netherlands; University of Pittsburgh, Physical Activity and Weight Management Research Center (Jakicic), Pittsburgh, Pennsylvania; and Polar Electro (Laukkanen), Kempele, Finland

Address correspondence and reprint requests to: Radim Jurca, PhD, The Cooper Institute, 12330 Preston Road, Dallas TX 75230. E-mail: djurca@cooperinst.org.

The full text of this article is available via AJPM Online at www.ajpm_online.net.

doi:10.1016/j.amepre.2005.06.004

metabolic equivalents (METs), where 1 MET = 3.5 ml O_2 uptake · kilograms of body mass^{-1} · minutes^{-1}.

$\dot{V}O_{2max}$ can be assessed with direct or indirect procedures.[12,13] Direct measures provide the most precise assessment of CRF and are obtained by ventilatory gas analysis at maximal exertion during a graded exercise ergometry test.[12,14] Indirect methods estimate $\dot{V}O_{2max}$ from maximal exercise duration, the peak workload and/or heart rate (HR) responses achieved during submaximal or maximal exercise ergometry, or the amount of time required to walk, jog, or run a specified distance.[13,14] However, both direct and indirect methods of assessing CRF may be impractical for regular use in most settings.

An international group of experts in the areas of physical activity and fitness assessment, epidemiology, preventive medicine, and clinical exercise testing reviewed the precision and feasibility of a variety of methods that might be used to quantify CRF in healthcare settings. Based on the review of the literature and the clinical expertise of these experts, it was concluded that the prediction of CRF from non–exercise test regression models would be most appropriate for widespread use in many healthcare settings if sufficient validity was obtained with this method of assessment. Non–exercise test models estimate $\dot{V}O_{2max}$ from the regression of measured maximal oxygen uptake on independent variables known to be predictive of CRF, such as gender, age, body size, resting HR, and self-reported habitual physical activity levels. This method avoids the burden of exercise testing, while providing a reasonably accurate estimation of CRF.[15–17] The purpose of this report is to extend a previous non–exercise test model[15] for estimating CRF. Additional analyses were conducted, including cross-validation studies, in expanded and new data sets.

Methods

Secondary analyses were performed on data previously obtained in three large cohorts of adults. The samples were from the National Aeronautics and Space Administration/Johnson Space Center (NASA; Houston TX), collected from 1971 to 2002[18,19]; the Aerobics Center Longitudinal Study (ACLS), collected from 1985 to 2000[9,10]; and the 1990 Allied Dunbar National Fitness Survey (ADNFS).[20] Participants provided informed consent to participate in their respective cohort studies.

NASA Participants and Test Method

The NASA[18,19] participants include 1458 men and 405 women aged 20 to 70 years who elected to have a maximal graded exercise stress test as part of their annual health examination. All tests were performed on a treadmill using the Bruce protocol. Maximal oxygen uptake was measured with ventilatory gas analysis procedures that are described elsewhere.[15] The highest minute $\dot{V}O_{2max}$ observed during the test was accepted as the $\dot{V}O_{2max}$ and then divided by 3.5 to express CRF as METs. Participants were not using chronotropic medication, and none had an abnormal ECG during exercise. Participants are representative of the general NASA/Johnson Space Center workforce, that is, college educated and largely comprised of non-Hispanic whites.

ACLS Participants and Test Method

The ACLS[9,10] participants included 35,826 men and 10,364 women aged 20 to 70 years who had a preventive medical examination at the Cooper Clinic in Dallas TX. CRF was quantified as maximal METs estimated from the final treadmill speed and grade[14] of a symptom-limited maximal exercise test using a modified Balke protocol.[21] ACLS men and women are predominantly non-Hispanic whites, well educated, and of middle and higher socioeconomic status.

ADNFS Participants and Test Method

The ADNFS[20] participants were 853 men and 853 women aged 20 to 70 years. The sample is representative of the 30 parliamentary constituencies of England. CRF was estimated during a submaximal treadmill test with ventilatory gas analysis of submaximal $\dot{V}O_{2max}$ and a test endpoint of at least 85% of age-predicted maximum HR.[20] Submaximal $\dot{V}O_{2max}$ and HR were used to extrapolate $\dot{V}O_{2max}$, which was converted to METs for use in the current analysis.

Non–Exercise Model Variables

All three databases include gender, age, measured height and weight to compute body mass index (BMI; kg/m^2), resting HR, and self-reported physical activity levels (SR-PA). Physical activity was assessed with different instruments in each study sample. The ACLS SR-PA scale consists of five categories, while the ADNFS and NASA SR-PA scales have six and eight categories, respectively. The NASA and ADNFS SR-PA scales were collapsed into five categories to provide a common metric across the three databases (Table 1). The original eight-category non–exercise test model[15] was reanalyzed with five-category scale data, and a slightly lower standard error of estimate (SEE; 1.45 vs 1.49 METs) was found. Table 1 lists a description of each of the five physical activity categories that were used to guide the development of the SR-PA used in the current analysis. Resting HR was obtained from the ECG after 5 minutes of rest in the recumbent or supine position.

Statistical Analysis

Multiple linear regression was used to develop a non–exercise prediction model in each database. The dependent variable was CRF expressed as METs. The independent variables were gender (0=female, 1=male), age (years), BMI, resting HR (beats · minutes^{-1}), and the dummy-coded five-category SR-PA scale according to the Pedhauzur method.[22] Congruence of the prediction models was examined by comparing the regression parameters and model fit statistics.[22] Congruence was further examined by cross-validating each regression equation within the other databases. Each regression equation was applied to the independent variables of the other two databases to produce a non–exercise estimated measure of CRF. Pearson product-moment correlations were used to

Table 1. Description of five-category self-reported physical activity scale for each database

Activity Level	NASA	ACLS	ADNFS
Level 1 (SR-PA-0)	Little activity other than walking for pleasure (0, 1, 2)[a]	No activity	From 0 to 4 occasions of at least moderate activity in past 4 weeks (1, 2)[b]
Level 2 (SR-PA-1)	Some regular participation in modest physical activities involving sports, recreational activities (3, 4)[a]	Participated in sporting or leisure-time physical activity other than walking, jogging, or running	From 5 to 11 occasions of at least moderate activity in past 4 weeks (3)[b]
Level 3 (SR-PA-2)	Aerobic exercise such as run/walk for 20 to 60 minutes per week (5)[a]	Walk, jog, or run up to 10 miles per week	≥12 Occasions of moderate activity in past 4 weeks (4)[b]
Level 4 (SR-PA-3)	Aerobic exercise such as run/walk for 1 to 3 hours per week (6)[a]	Walk, jog, or run from 10 to 20 miles per week	≥12 Occasions of a mix of moderate and vigorous activities in past 4 weeks (5)[b]
Level 5 (SR-PA-4)	Aerobic exercise such as run/walk for >3 hours per week (7)[a]	Walk, jog, or run >20 miles per week	≥12 occasions of vigorous activity in past 4 weeks (6)[b]

[a]Original eight-category scale used by Jackson et al.[15]
[b]Original ADNFS 6-category scale.[20]
ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; NASA, National Aeronautics and Space Administration/Johnson Space Center; SR-PA, self-reported physical activity.

examine the relationship between maximal METs estimated from the regression equation and the criterion measure of CRF within each database. The distribution of residual scores (i.e., the difference between measured and estimated CRF) was obtained for each equation and applied to the other databases. The mean residual score was examined to identify systematic errors in the CRF prediction. Data were analyzed in 2004.

Results

Demographic and SR-PA data that describe all cohorts are shown in Tables 2 and 3. The men and women in the three samples were similar in age, BMI, and resting HR. The mean CRF of the NASA men was lower than the ACLS and ADNFS men by about 0.59 and 1.63 METs, respectively. The SR-PA profile of the NASA and ADNFS men showed they were more likely to be in the higher SR-PA categories than the ACLS men. The measured mean CRF of the NASA women was lower than in ACLS and ADNFS women, but the difference was small: 0.57 and 0.66 METs, respectively. The SR-PA profiles of the ACLS and ADNFS women were similar, whereas a higher proportion of NASA women reported ratings in the high and very high categories.

Table 4 presents Pearson correlations between CRF and all independent variables within each database. All correlations were statistically significant ($p<0.01$), indicating that each independent variable was related to CRF. The highest correlations were found between CRF and SR-PA.

Table 5 shows multiple regression analysis for each database. All variables used in the model were independently related to CRF in each of the study cohorts. The multiple correlation coefficients (SEE) obtained within

Table 2. Demographic descriptive statistics (mean±SD) of men in each database and level of self-reported physical activity

Variable	NASA	ACLS	ADNFS
Sample size (n)	1458	35,826	853
Age (years)	45.9±7.8	43.3±9.6	41.6±13.3
Height (cm)	177.2±6.3	178.7±6.5	175.8±6.9
Weight (kg)	80.2±11.1	83.5±12.7	77.9±10.8
BMI (kg/m^2)	25.5±3.1	26.3±3.7	25.2±3.2
Resting HR (beats/min)	64.9±10.5	60.9±11.0	69.2±10.8
Maximal METs	10.98±2.30	11.57±2.17	12.61±2.94
Maximal HR (beats/min)	176.4±11.4	178.8±12.8	
RER	1.23±0.11		
SR-PA-0 (inactive)	16.1%	37.2%	24.3%
SR-PA-1 (low)	29.6%	18.2%	21.3%
SR-PA-2 (moderate)	20.5%	27.2%	23.9%
SR-PA-3 (high)	17.8%	11.4%	15.4%
SR-PA-4 (very high)	16.0%	6.0%	15.1%

ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; BMI, body mass index; HR, heart rate; MET, metabolic equivalent; NASA, National Aeronautics and Space Administration/Johnson Space Center; RER, respiratory exchange ratio; SD, standard deviation; SR-PA, self-reported physical activity.

Table 3. Demographic descriptive statistics (mean±SD) of women in each database and level of self-reported physical activity

Variable	NASA	ACLS	ADNFS
Sample size (n)	401	10,364	853
Age (years)	39.5±9.6	42.4±10.3	41.4±13.2
Height (cm)	164.0±6.2	164.5±6.1	162.2±6.3
Weight (kg)	64.1±11.5	61.7±11.3	64.9±11.3
BMI (kg/m^2)	23.8±4.0	22.8±3.9	24.7±4.1
Resting HR (beats/min)	60.0±10.4	64.3±11.0	72.3±10.5
Maximal METs	9.03±2.35	9.60±2.39	9.69±2.38
Maximal HR (beats/min)	178.4±12.0		
RER	1.26±0.10		
SR-PA-0 (inactive)	22.2%	33.9%	25.3%
SR-PA-1 (low)	21.9%	21.6%	27.9%
SR-PA-2 (moderate)	19.4%	28.7%	29.8%
SR-PA-3 (high)	21.5%	11.1%	11.5%
SR-PA-4 (very high)	15.0%	4.7%	5.5%

ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; BMI, body mass index; HR, heart rate; MET, metabolic equivalent; NASA, National Aeronautics and Space Administration/Johnson Space Center; RER, respiratory exchange ratio; SD, standard deviation; SR-PA, self-reported physical activity.

NASA, ACLS, and ADNFS participants, respectively, were 0.81 (1.45 METs), 0.77 (1.50 METs), and 0.76 (1.97 METs). Table 5 includes regression weights of each independent variable, which were identical for BMI, while SR-PA demonstrated the greatest variance among the three cohorts. Although the regression weights were similar between the NASA and ACLS model, the ANDFS regression weights for SR-PA were consistently lower compared with the other two models. The NASA and ACLS differences in SR-PA categories ranged from 0.02 METs for SR-PA-4 to 0.49 METs for SR-PA-1.

To further examine the cross-validity of each of the regression models, correlations were computed between estimated MET levels of CRF from each model and the measured MET value within each cohort (Table 6). The mean residual score for each regression model applied within each of the cohorts (Table 6) was also computed. The cross-validation correlations were lower than the multiple regression correlations reported in Table 5. When the NASA regression model was applied to the ACLS and ADNFS data, Pearson product-moment correlations of 0.76 and 0.75, respectively, were observed. These correlations were 0.01 correlation units less than the respective multiple regression correlations observed in each cohort. Each of the regression models demonstrated reasonably high levels of validity as seen by relatively small prediction errors when a given regression model was applied within the other two cohorts. The NASA regression model underestimated CRF in the ACLS and ADNFS cohorts by 0.67 and 1.37 METs, respectively. In contrast, the ADNFS model systematically overestimated CRF in the NASA and ACLS cohorts by 1.03 and 0.56 METs, respectively. The NASA model showed the highest cross-correlations and lowest SEE. Thus, a score sheet (Figure 1) was developed to predict CRF from the regression coefficients of the NASA prediction model (Table 5).

Table 4. Pearson correlations between cardiorespiratory fitness and nonexercise independent variables

Variable	NASA	ACLS	ADNFS
Gender (F=0; M=1)	**0.32***	**0.35***	**0.48***
Age (years)	**−0.35***	**−0.33***	**−0.51***
BMI (kg/m^2)	**−0.33***	**−0.26***	**−0.28***
Resting HR (beats/min)	**−0.39***	**−0.42***	**−0.23***
SR-PA	**0.58***	**0.48***	**0.32***

*$p < 0.01$ (bolded).
ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; BMI, body mass index; F, female; HR, heart rate; M, male; NASA, National Aeronautics and Space Administration/Johnson Space Center; SR-PA, self-reported physical activity.

Discussion

CRF is a strong independent predictor of all-cause and cause-specific mortality in asymptomatic individuals as well as in individuals with existing metabolic or cardiovascular disease.[8,9,11] In spite of having a similar relative and attributable risk of mortality as regularly monitored health indicators,[8,11] feasibility issues limit assessment of CRF in many healthcare settings. The purpose of the current study was to expand previous work[15] on a non–exercise test model to predict CRF. Jackson et al.[15] reported the precision of a non–exercise prediction model based on gender, age, BMI, and SR-PA in a homogeneous cohort of men and women. This model was cross-validated on a cohort of hypertensive men and women.[15] In the current study, data were used from three cohorts, including a larger group of individuals from the NASA cohort where the original regression model was developed. Resting HR was added as an independent variable and the original eight-category SR-PA scale was collapsed into a simpler five-category scale with more generalizable categories. Each of the three non–exercise models was congruent

Table 5. Non-exercise regression analysis with MET levels of maximal cardiorespiratory fitness as dependent variable for each database

	NASA	ACLS	ADNFS
Dependent variable	**Measured METs**	**Estimated METs**	**Estimated METs**
Exercise test protocol	**Maximal**	**Maximal**	**Submaximal**
Intercept	**18.07***	**18.81***	**21.41***
Gender (F=0; M=1)	**2.77***	**2.49***	**2.78***
Age (years)	**−0.10***	**−0.08***	**−0.11***
BMI (kg/m^2)	**−0.17***	**−0.17***	**−0.17***
Resting HR (beats/min)	**−0.03***	**−0.05***	**−0.05***
SR-PA-1 (low)	**0.32***	**0.81***	**0.35***
SR-PA-2 (moderate)	**1.06***	**1.17***	**0.29***
SR-PA-3 (high)	**1.76***	**2.16***	**0.64***
SR-PA-4 (very high)	**3.03***	**3.05***	**1.21***
R	**0.81***	**0.77***	**0.76***
R^2	0.65	0.60	0.58
SEE	1.45	1.50	1.97

*$p < 0.01$ (bolded).
ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; BMI, body mass index; F, female; HR, heart rate; M, male; MET, metabolic equivalent (1 MET=3.5 ml O_2 uptake · kg body mass^{-1} · min^{-1}); NASA, National Aeronautics and Space Administration/Johnson Space Center; R, multiple correlation coefficient; SEE, standard error of estimate; SR-PA, self-reported physical activity.

and generalizable within each of the cohorts. The current NASA regression model showed a slightly better model fit compared with the previously reported prediction equation[15] (R=0.81 vs R=0.78).

Among the three prediction models in the current study, the NASA model showed the highest multiple correlation and lowest standard error compared with the equations derived in the ACLS and ADNFS. This is likely explained by differences in the dependent variable for each database. In the NASA cohort, CRF was measured with the gold standard method of ventilatory gas analysis at maximal exertion during a graded treadmill exercise test. In the other two cohorts, CRF was estimated from the maximal workload achieved (ACLS) or from submaximal responses (ADNFS) during treadmill exercise testing. Nonetheless, the cross-cohort validity and generalizability of each regression model within the two remaining cohorts were reasonably high, and indicate that a good estimate of CRF can be obtained from the independent variables of gender, age, BMI, resting HR, and SR-PA habits, whether measured or estimated CRF was used as the dependent variable in developing the prediction model. Because each of these predictor variables is easily obtained, it is believed that non–exercise test methods of predicting CRF should become a routine component of primary healthcare examinations.

If CRF were to be assessed in healthcare settings, there must be a meaningful way to interpret the results for the purposes of risk stratification and individual counseling. Clinical measurements are more useful as prognostic indicators when a specified level of the parameter being measured identifies a threshold of increased risk for adverse health outcomes.[23] Currently, there is no complete consensus on a level of CRF that classifies an asymptomatic individual as high risk, nor is there agreement as to what level of CRF is sufficient in the context of health and disease prevention. However, results from four large prospective studies suggest that 9 to 10 METs for men and 7 to 8 METs for women is a MET level associated with a ≥50% reduction in mortality risk.[10,24–27] Identification of clinically useful CRF values for detecting individuals with elevated mortality risk can not be based solely on a relative measure of association,[23] but such observations may reveal a fitness level that can be subjected to more rigorous and clinically relevant sensitivity and specificity assessment such as receiver-operating char-

Table 6. Cross-validation analysis of nonexercise equations applied to other databases

Regression model	Data source	Cross-validity correlation	95% CI	Residual score (METs)	95% CI
NASA	ACLS	0.76	0.75–0.77	0.67	0.66–0.69
NASA	ADNFS	0.75	0.72–0.78	1.37	1.26–1.48
ACLS	NASA	0.80	0.77–0.82	−0.45	−0.54 to −0.36
ACLS	ADNFS	0.74	0.71–0.77	1.06	0.95–1.17
ADNFS	NASA	0.76	0.74–0.80	−1.03	−1.11 to −0.95
ADNFS	ACLS	0.72	0.71–0.73	−0.56	−0.58 to −0.55

ACLS, Aerobics Center Longitudinal Study; ADNFS, Allied Dunbar National Fitness Survey; CI, confidence interval; MET, metabolic equivalent; NASA, National Aeronautics and Space Administration/Johnson Space Center.

Name:______________________________ Date:___________________

STEP 1

<u>Physical activity score</u>: Choose <u>one</u> activity category that best describes your usual pattern of daily physical activities, including activities related to house and family care, transportation, occupation, exercise and wellness, and leisure or recreational purposes.

	Score
Level 1: Inactive or little activity other than usual daily activities.	0.00
Level 2: Regularly (≥5 d/wk) participate in physical activities requiring low levels of exertion that result in slight increases in breathing and heart rate for at least **10 minutes** at a time.	0.32
Level 3: Participate in aerobic exercises such as brisk walking, jogging or running, cycling, swimming, or vigorous sports at a comfortable pace or other activities requiring similar levels of exertion for **20 to 60 minutes** per week.	1.06
Level 4: Participate in aerobic exercises such as brisk walking, jogging or running at a comfortable pace, or other activities requiring similar levels of exertion for **1 to 3 hours** per week.	1.76
Level 5: Participate in aerobic exercises such as brisk walking, jogging or running at a comfortable pace, or other activities requiring similar levels of exertion for **over 3 hours** per week.	3.03

STEP 2

<u>Estimate MET level of cardiorespiratory fitness</u>

Enter 0 for women or 1 for men	[ ]	x 2.77	=	[ ]
				minus
Enter **age** in years	[ ]	x 0.10	=	[ ]
				minus
Enter **body mass index**[a]	[ ]	x 0.17	=	[ ]
				minus
Enter **resting heart rate**	[ ]	x 0.03	=	[ ]
				plus
Enter **physical activity score** from step 1	[ ]	x 1.00	=	[ ]
				plus
Constant				18.07
				=
Estimated MET value				[ ]

<u>Clinical relevance of selected maximal MET levels of cardiorespiratory fitness</u>[b]

1 MET	Resting metabolic rate; sitting quietly in a chair
<3 METs	Severely limited functional capacity; a criteria for placement on a heart transplant list
3–5 METs	Poor prognosis in coronary patients; highly deconditioned individual
10 METs	Good prognosis in coronary patients on medical therapy; approximate maximal capacity expected in regularly active middle-aged men and women
13 METs	Excellent prognosis regardless of disease status
18 METs	Elite endurance athletes
20 METs	World-class athletes

Figure 1. Worksheet for estimating maximal MET levels of cardiorespiratory fitness from routinely collected clinical data. [a]Body mass index=(weight in lbs × 703)/(height in inches)^2 or (weight in kilograms)/(height in meters)^2. [b]Adapted from the American Heart Association.[45,46] MET, metabolic equivalent.

acteristic analysis.[28] Additional work is needed to place CRF levels into clinical relevance similar to guidelines that currently exist for blood pressure, lipids, glucose, and body weight.[29–32]

There are three reasons for establishing a criterion level of CRF. First, low CRF carries the same or higher strength of association and attributable risk for mortality as routinely measured clinical risk factors.[8,9,11] Second, because increases in CRF are often accompanied by favorable changes in other health indicators such as blood pressure, triglycerides, glycemic control, and body fat distribution,[33,34] identifying and intervening on low CRF may have additional health benefits beyond the attributable fraction of mortality risk that has been reported for low fitness. Third, there is a growing urgency for additional clinical measures to improve traditional approaches of identifying the high-risk asymptomatic patient who would benefit from intensive primary preventive therapy.[35] Three recent studies showed that measures of CRF provided added prognostic value to conventional clinical risk assessment methods such as the Framingham risk score and echocardiography.[36–38] However, the actual feasibility for use of predicting CRF from non–exercise testing methods in a variety of healthcare settings needs to be determined.

To help facilitate an efficient use of the non–exercise test prediction model reported here, a worksheet was developed to compute an individual's CRF level (Figure 1). The worksheet can serve as the focus of individual counseling on improving or maintaining CRF. Because the NASA equation had a slightly lower SEE, the regression coefficients from the NASA model were used in the worksheet. Suppose one is interested in quantifying the CRF level of a 45-year-old male who weighs 193 pounds (87.7 kg), is 68 inches (172 cm) tall, and has a resting HR of 72 beats per minute with a usual pattern of daily physical activity reported as Level 2. After entering all values in the worksheet, the estimated maximal MET level of CRF for this person is 9.02 METs. Based on available data,[10,24–27] this man likely has an acceptable level of CRF in terms of risk for premature mortality.

When a concerningly low level of CRF is identified, the following counseling should be considered. The major determinant of CRF is the degree to which one is regularly active over recent weeks and months, although a genetic component also exists.[39,40] Indeed, in each cohort of the current analysis the independent variable with the strongest association with CRF determined from exercise testing was SR-PA level (Table 5). Current public health[6,41] and clinical guidelines[42] recommend the accumulation of ≥30 minutes of at least moderate-intensity physical activity on ≥5 days of the week, and this is sufficient to improve low CRF. However, physical activity is similar to other therapeutic agents with dose–response characteristics, wherein a minimal dose that has proven efficacy and safety is typically prescribed as the initial dose. Interindividual responses and differences in the specificity and severity of the risk factor being addressed often dictate that the dose of the therapeutic agent be titrated to maximize its effectiveness. These considerations also apply for physical activity interventions, to which interindividual physiological responses are documented.[43] Thus, more physical activity may be required for some individuals to improve their CRF or other risk factor levels. It might be argued that solely a measure of physical activity may be more feasible to identify high-risk patients than the non-exercise estimate of CRF given the limited time for counseling. No compelling data was found to evaluate which exposure, physical activity or estimated CRF, is a more important determinant of health outcomes. However, steeper gradients or stronger associations have been shown between measured CRF, as compared with SR-PA, and health outcomes.[44] It was assumed that the stronger association for CRF was due primarily to less misclassification than on the activity measure. However, the precision of non–exercise test estimates of CRF as predictors of health outcomes has yet to be examined.

Limitations of this study include population characteristics, such as heterogeneity in race/ethnic distributions, cross-sectional design that prevents an analysis of whether changes in CRF can be detected, and lack of consensus in the literature regarding definition of an acceptable level of CRF for risk reduction. Strengths of the study include compelling data on the importance of CRF for risk assessment, use of three different populations to test the model, and acceptable cross-validation of the model.

Data presented here indicate that CRF may be assessed from a non–exercise test model including gender, age, BMI, resting HR, and SR-PA. Such a model is valid across diverse population cohorts. Additional work is needed to assess the actual feasibility of this approach in primary care and other settings, to verify the validity of non-exercise estimates of CRF as predic-

What This Study Adds . . .

Precise assessment of cardiorespiratory fitness is obtained by ventilatory gas analysis at maximal exertion.

However, the prediction of fitness from non-exercise models seems most appropriate for widespread use in many healthcare settings.

This study expanded previous work on non–exercise test model to predict fitness by conducting additional analyses on large cohorts.

Results suggest that fitness may be assessed from a non-exercise model, including gender, age, body mass index, resting heart rate, and self-reported physical activity.

tors of health outcomes and to establish a target level of CRF for primary prevention.

This workshop was supported in part by Masterfoods Incorporated. We are grateful to Melba Morrow for editorial assistance.

No financial conflict of interest was reported by the authors of this paper.

References

1. LaMonte MJ, Eisenman PA, Adams TD, Shultz BB, Ainsworth BE, Yanowitz FG. Cardiorespiratory fitness and coronary heart disease risk factors: the LDS Hospital Fitness Institute cohort. Circulation 2000;102:1623–8.
2. Jurca R, LaMonte MJ, Church TS, et al. Associations of muscle strength and aerobic fitness with metabolic syndrome in men. Med Sci Sports Exerc 2004;36:1301–7.
3. Wong SL, Katzmarzyk P, Nichaman MZ, Church TS, Blair SN, Ross R. Cardiorespiratory fitness is associated with lower abdominal fat independent of body mass index. Med Sci Sports Exerc 2004;36:286–91.
4. Lynch J, Helmrich SP, Lakka TA, et al. Moderately intense physical activities and high levels of cardiorespiratory fitness reduce the risk of non–insulin-dependent diabetes mellitus in middle-aged men. Arch Intern Med 1996;156:1307–14.
5. Lakka TA, Venalainen JM, Rauramaa R, Salonen R, Tuomilehto J, Salonen JT. Relation of leisure-time physical activity and cardiorespiratory fitness to the risk of acute myocardial infarction in men. N Engl J Med 1994;330:1549–54.
6. U.S.Department of Health and Human Services. Physical activity and health: a report of the Surgeon General. Atlanta GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, 1996.
7. Ekelund LG, Haskell WL, Johnson JL, Whaley FS, Criqui MH, Sheps DS. Physical fitness as a predictor of cardiovascular mortality in asymptomatic North American men: the Lipid Research Clinic's mortality follow-up study. N Engl J Med 1988;319:1379–84.
8. Laukkanen JA, Kurl S, Salonen R, Rauramaa R, Salonen JT. The predictive value of cardiorespiratory fitness for cardiovascular events in men with various risk profiles: a prospective population-based cohort study. Eur Heart J 2004;25:1428–37.
9. Blair SN, Kohl HW III, Paffenbarger RS Jr, Clark DG, Cooper KH, Gibbons LW. Physical fitness and all-cause mortality: a prospective study of healthy men and women. JAMA 1989;262:2395–401.
10. Blair SN, Kampert JB, Kohl HW, et al. Influences of cardiorespiratory fitness and other precursors on cardiovascular disease and all-cause mortality in men and women. JAMA 1996;276:205–10.
11. Wei M, Kampert JB, Barlow CE, et al. Relationship between low cardiorespiratory fitness and mortality in normal-weight, overweight, and obese men. JAMA 1999;282:1547–53.
12. Davis JA. Direct determination of aerobic power. In: Maud PJ, Foster C, eds. Physiological assessment of human fitness. Champaign IL: Human Kinetics, 1995:9–17.
13. Ward A, Ebbeling CB, Ahlquist LE. Indirect methods for estimation of aerobic power. In: Maud PJ, Foster C, eds. Physiological assessment of human fitness. Champaign IL: Human Kinetics, 1995:37–56.
14. American College of Sports Medicine. ACSM's guidelines for exercise testing and prescription. 6th ed. Philadelphia: Lippincott Williams & Wilkins, 2000.
15. Jackson AS, Blair SN, Mahar MT, Wier LT, Ross RM, Stuteville JE. Prediction of functional aerobic capacity without exercise testing. Med Sci Sports Exerc 1990;22:863–70.
16. Williford HN, Scharff-Olson M, Wang N, Blessing DL, Smith FH, Duey WJ. Cross-validation of non-exercise predictions of $\dot{V}$O2peak in women. Med Sci Sports Exerc 1996;28:926–30.
17. George JD, Stone WJ, Burkett LN. Non-exercise $\dot{V}$O2max estimation for physically active college students. Med Sci Sports Exerc 1997;29:415–23.
18. Jackson AS, Beard EF, Wier LT, Ross RM, Stuteville JE, Blair SN. Changes in aerobic power of men, ages 25–70 yr. Med Sci Sports Exerc 1995;27:113–20.
19. Jackson AS, Wier LT, Ayers GW, Beard EF, Stuteville JE, Blair SN. Changes in aerobic power of women, ages 20–64 yr. Med Sci Sports Exerc 1996;28:884–91.
20. Sports Council and Health Education Authority. Allied Dunbar Fitness Survey: a report on activity patterns and fitness levels. London: The Sports Council and Health Education Authority, 1994.
21. Balke B, Ware RW. An experimental study of physical fitness in Air Force personnel. US Armed Forces Med J 1959;10:675–88.
22. Pedhazur EJ. Multiple regression in behavioral research: explanation and prediction. 3rd ed. New York: Wadsworth, 1997.
23. Wald NJ, Hackshaw AK, Frost CD. When can a risk factor be used as a worthwhile screening test? BMJ 1999;319:1562–5.
24. Kampert JB, Blair SN, Barlow CE, Kohl HW III. Physical activity, physical fitness, and all-cause and cancer mortality: a prospective study of men and women. Ann Epidemiol 1996;6:452–7.
25. Myers J, Prakash M, Froelicher V, Do D, Partington S, Atwood JE. Exercise capacity and mortality among men referred for exercise testing. N Engl J Med 2002;346:793–801.
26. Laukkanen JA, Lakka TA, Rauramaa R, et al. Cardiovascular fitness as a predictor of mortality in men. Arch Intern Med 2001;161:825–31.
27. Gulati M, Pandey DK, Arnsdorf MF, et al. Exercise capacity and the risk of death in women: the St James Women Take Heart Project. Circulation 2003;108:1554–9.
28. Zweig MH, Campbell G. Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine. Clin Chem 1993;39:561–77.
29. Chobanian AV, Bakris GL, Black HR, et al. The seventh report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure: the JNC 7 report. JAMA 2003;289:2560–72.
30. Adult Treatment Panel III. Executive summary of the third report of the National Cholesterol Education Program (NCEP) Expert Panel on Detection, Evaluation, and Treatment of High Blood Cholesterol in Adults (Adult Treatment Panel III). JAMA 2001;285:2486–97.
31. American Diabetes Association. Physical activity/exercise and diabetes mellitus. Diabetes Care 2003;26(suppl 1):S73–7.
32. National Institutes of Health, National Heart, Lung, and Blood Institute. Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults: the evidence report. Rockville MD: National Institutes of Health, National Heart, Lung, and Blood Institute, 1998.
33. Duncan JJ, Farr JE, Upton J, Hagan RD, Oglesby ME, Blair SN. The effects of aerobic exercise on plasma catecholamines and blood pressure in patients with mild essential hypertension. JAMA 1985;254:2609–13.
34. Dunn AL, Marcus BH, Kampert JB, Garcia ME, Kohl HW III, Blair SN. Comparison of lifestyle and structured interventions to increase physical activity and cardiorespiratory fitness: a randomized trial. JAMA 1999;281:327–34.
35. Smith SC Jr, Greenland P, Grundy SM. AHA Conference Proceedings. Prevention conference V: Beyond secondary prevention: identifying the high-risk patient for primary prevention: executive summary. American Heart Association. Circulation 2000;101:111–6.
36. Balady GJ, Larson MG, Vasan RS, Leip EP, O'Donnell CJ, Levy D. Usefulness of exercise testing in the prediction of coronary disease risk among asymptomatic persons as a function of the Framingham risk score. Circulation 2004;110:1920–5.
37. Aktas MK, Ozduran V, Pothier CE, Lang R, Lauer MS. Global risk scores and exercise testing for predicting all-cause mortality in a preventive medicine program. JAMA 2004;292:1462–8.
38. Elhendy A, Mahoney DW, McCully RB, Seward JB, Burger KN, Pellikka PA. Use of a scoring model combining clinical, exercise test, and echocardiographic data to predict mortality in patients with known or suspected coronary artery disease. Am J Cardiol 2004;93:1223–8.
39. Bouchard C, Malina RM, Perusse L. Genetics of fitness and physical performance. Champaign IL: Human Kinetics, 1997.
40. Stofan JR, DiPietro L, Davis D, Kohl HW III, Blair SN. Physical activity patterns associated with cardiorespiratory fitness and reduced mortality: the Aerobics Center Longitudinal Study. Am J Public Health 1998;88:1807–13.
41. Pate RR, Pratt M, Blair SN, et al. Physical activity and public health: a recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine. JAMA 1995;273:402–7.
42. Thompson PD, Buchner D, Pina IL, et al. Exercise and physical activity in the prevention and treatment of atherosclerotic cardiovascular disease: a

statement from the Council on Clinical Cardiology (Subcommittee on Exercise, Rehabilitation, and Prevention) and the Council on Nutrition, Physical Activity, and Metabolism (Subcommittee on Physical Activity). Circulation 2003;107:3109–16.
43. Bouchard C, Rankinen T. Individual differences in response to regular physical activity. Med Sci Sports Exerc 2001;33:S446–51.
44. Blair SN, Cheng Y, Holder JS. Is physical activity or physical fitness more important in defining health benefits? Med Sci Sports Exerc 2001;33:S379–99.
45. Fletcher GF, Balady G, Froelicher VF, Hartley LH, Haskell WL, Pollock ML. Exercise standards. A statement for healthcare professionals from the American Heart Association Writing Group. Circulation 1995;91:580–615.
46. Fleg JL, Pina IL, Balady GJ, et al. Assessment of functional capacity in clinical and research applications: an advisory from the Committee on Exercise, Rehabilitation, and Prevention, Council on Clinical Cardiology, American Heart Association. Circulation 2000;102:1591–7.