REVIEW ARTICLE

ENGLISH VERSION

Non-exercise models for prediction of aerobic fitness and applicability on epidemiological studies: descriptive review and analysis of the studies

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ABSTRACT

A low cardiorespiratory fitness is an independent risk factor for mortality from all causes, but mainly for coronary heart disease. Nevertheless, there are many difficulties to evaluate it by exercise testing in the epidemiological context. Alternative forms of evaluation have therefore been suggested using non-exercise regression models. This study aimed to review and critically analyze these models and their applicability in epidemiological studies. A systematic review was conducted considering papers published between 1966 and 2002. There were selected 24 studies attending the inclusion criteria. Only five of them related the standard error of estimation (SEE), the equation fully reported, present a higher sample size and made the cross-validation. These studies presented a higher adjusted R^2, what mean the quality and the prediction power of them. The authors conclude that cardiorespiratory evaluation by non-exercise models in epidemiological studies could be feasible. However, few models seem to fulfill the minimum external validation requirements to provide data that could be generalized for large populations.

Key words: Physical fitness. Regression analysis. Epidemiology.

INTRODUCTION

Cardiorespiratory fitness is considered a health-related fitness component that indicates the capability of cardiovascular and respiratory systems in providing oxygen during a continuous physical activity[1,2]. Morbidity and mortality risks of chronic-degenerative diseases, among them coronary artery disease, systemic high blood pressure, *diabetes mellitus* and some types of cancer have been associated to low cardiorespiratory fitness and physical activity[3-9]. It would be important to assess cardiorespiratory capability on a general population.

The use of cardiorespiratory fitness as an exposure variable in epidemiological studies is limited by the high costs, by technical operational difficulties, and by the time spent to measure it[10,11]. These facts have fostered the development of more simple methods, where the maximal and submaximal exercise tests have been replaced by multiple linear regression models to predict cardiorespiratory fitness from physical features and living habits[11-14]. This type of techniques, more simple, less costly, and easy to apply, favors the use of cardiorespiratory fitness as an exposure variable in epidemiologic studies, particularly in low-infrastructure sites[12,15]. Thus, the purpose of this investigation was to assess studies on non-exercise cardiorespiratory fitness predictive models, to describe the evolution of this type of technique, and to assess the developed models, particularly in regard to their quality.

METHODOLOGY

The potentially useful articles were retrieved from references of published articles and books (manually) and by research in databanks *Medlars online* (Medline) *Silver Plat-*

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ter, and *Lilacs* ("Latin America and the Caribbean Literature on Health Sciences Information"). The review was limited from January 1966 until December 2002 in the Medline; and in Lilacs from 1982 until 2002.

All potentially useful articles retrieved from electronic media had their abstracts downloaded and were independently assessed by two reviewers, one, a health-applied physical fitness specialist, knowledgeable on the theme under study, and the other an epidemiologist experienced in systematic reviews. The main inclusion criteria was collecting studies that focused non-exercise prediction of cardiorespiratory fitness, based on easy-to-measure useful variables for populational studies, such as weight, height, anthropometric measures, and fitness status. From the collection and reading of the articles, their references were tracked in search of other potentially useful articles. This task was repeated as many times as necessary until one believed that none of the references presented studies was not yet identified.

THE HISTORY OF NON-EXERCISE MODELS

The reviewing stage allowed the finding of 24 articles that met inclusion criteria, all of them original studies published since 1967. The development of the definition of purposes and methodological features of the studies made evident the efforts toward more accurate cardiorespiratory capability models. Thus, the studies will be presented chronologically. In order to enhance discussion on them, during the study description process one saw fit to present other investigations that, at some time, had contributed to the knowledge on the issue or cross-validated original predictive models.

The first investigations to suggest assessment of maximum oxygen uptake through variables other than exercise tests were carried out at the end of the 60s. At that time, research focused on measuring the amount to potassium in the body through a radio-diagnostic technique of muscular tissue[16,17]. This technique accepts that potassium levels in fat-free mass to be constant. Thus, once the amount of potassium in the body is established, it is possible to make predictions regarding lean mass. The rationale to assess lean mass is that a physically active individual would present a positive relation between cardiorespiratory fitness and muscular mass.

Shephard *et al*.[18] published, in 1971, the first study aiming to predict cardiorespiratory fitness through multiple regression and without the use of exercise tests. Thirty-seven anthropometric measures and body strength indices were collected from 46 children and adolescents of both genders, as part of a randomized sample of Toronto (Canada) students. The most promising and applicable models for other studies were those based on body area (calculated through weight and height measures), in addition to skinfold of the thigh and age. The authors concluded that, for children, cardiorespiratory fitness could be conveniently predicted according to the proposed method. Two years later, Bruce *et al*.[19] established some cardiorespiratory fitness predictive models with and without exercise tests, demonstrating that it could be predicted through variables such as gender, age, weight and the habit of practicing physical exercise, by the use of stepwise multiple regression analysis. This was the first study to use adults and to demonstrate that cardiorespiratory fitness could be predicted not only through anthropometric data, but also from behavioral variables, such as the practice of daily physical activity.

Among the studies that used anthropometric variables following the line of Shephard *et al*.[18], Mayhew and Gifford's[20] in 1975, and Bonen's *et al*.[21] in 1979 stand out. In the former[20], 31 boys age 7 to 9 years were studies, and $\dot{V}O_{2max}$ was estimated through a number of anthropometric measurements. Initially, just the simple correlation of $\dot{V}O_{2max}$ with the measurements was performed. Next, the stepwise multiple regression analysis was used to select the most representative models. Again, the most significant measurements were related to lower limbs: volume and skinfold of leg and thigh presented higher coefficient of explanation ($R^2 = 0.64$). In the later[21], also with children and adolescents, the authors checked the predictive power of age, weight and height of 100 boys age 7 to 15 years. According to the authors, the high coefficient presented ($R^2 = 0.88$) and the fact that children did not adapt well to most exercise tests would strengthen even more the idea that predictive models with easy-to-measure variables would be an excellent alternative to an indirect calculation of aerobic power. Finally, in 1978, Taylor *et al.* [22] tried to predict the total time spent in minutes during a treadmill stress test through the total of scores from the *Minnesota Leisure Time Physical Activity* (MLTPA) developed at the University of Minnesota. The MLTPA seeks to assess physical activities practiced over the past year. This model did not present a very strong association ($R^2 = 0.27$), which could indicate that just the history of physical activity should not be used to predict.

In the 80s, only three studies carried out in India sought to predict cardiorespiratory fitness using anthropometric variables only. In the first[23], 27 anthropometric measurements using the stepwise multiple regression analysis were performed, to check which variables could significantly predict $\dot{V}O_{2max}$ of 120 women and men. Four variables remained in the final model: weight, height, elbow diameter and chest skinfold. In another study with 70 male subjects age 11 to 18 years, Verma *et al*.[24] found a $\dot{V}O_{2\,max}$ relationship with age, weight and height, identifying a higher explanation power (R^2 = 0.81) in a regression model based only on weight. Finally, in 1998, with a sample of 146 men, Verma *et al*.[25] checked how cardiorespiratory fitness could be predicted from age, height and weight. A model including age and weight was then designed. The two Indian studies with adult subjects had similar coefficients of explanation in their models (respectively, 0.29 and 0.35), suggesting that the use of anthropometric variables was not as suitable for adults as it was for children and adolescents. One possibility to consider, which would justify the relative success of the use of only anthropometric variables in models for children and adolescents, is the fact that biological age in childhood is directly related to body proportions. However, we do not have data to confirm this hypothesis.

In 1981, Leon *et al*.[26] predicted the time spent on a maximum treadmill test by 175 middle-age men, using both anthropometric and behavioral variables. This was the first study to suggest the use of cardiorespiratory fitness prediction without exercise tests for epidemiological studies, based on the increase in number of evidences of a low cardiorespiratory fitness and the risk of dying from coronary artery disease. Eleven predictive variables were selected: age, rate of intense activities according to MLTPA, body mass index (BMI), past or current smoking, typical performance on a sweat- or dyspnea-causing occupational activity, amount of coffee, tea, or cola-type soft drink drank a week, habit of smoking pipe or cigar, leisure activities that caused sweat or dyspnea, average hours of sleep, and heart rate at rest. The authors concluded that a good cardiorespiratory capability could be predicted from standardized questionnaires, along with simple physical measurements, in spite of the determination coefficient value be moderate (R^2 = 0.53).

Using self-reported physical activity to predict maximum oxygen uptake, Siconolfi *et al*.[27] observed, in 36 men and 32 women, that the predictive power of the models was higher if they checked the intensity of the physical activity performed, rather than just checking whether subjects performed them or not. From this study on, the intensity of physical activity became a constant and very important variable in predictive studies. For instance, two years later Milesis[28] estimated the time of performance in a maximum stress test of 126 men and 70 women, based on the variables gender, age, reciprocal weight index (height divided by the cubic root of weight), level of physical activities according to categories 1 to 5 (sedentary, little active, active, highly active, and athlete), background of smoking, according to categories 0 to 2 (never smoked, smoker of less than 20 cigarettes/day, and smoker of more than 20 cigarettes/day), and heart rate at rest. Kohl *et al*.[15], through a questionnaire sent by mail, predicted the maximum performance time (in minutes) in a stress test applied to 375 subjects with mean age of 47.1 years. The predictive model included age and physical activity-related variables, such as a score for participating in activities such as walking and running, and the frequency these activities were performed under intensity enough to cause sweating.

A year later, in an important study because of the size of the sample, Blair *et al*.[12] developed a model to predict the time of a maximum stress test on a treadmill, with 15.627 men (42.5 ± 9.5 years) and 3.943 women (42.1 ± 10.7 years). The subjects were divided in five groups according to age range, from those 20 to 29 years until those over 60 years, and got predictive models with explication coefficients ranging from 0.49 to 0.60 for males and 0.20 to 0.49 for females. The models included the following variables: BMI, heart rate at rest, rate of physical activity and leisure at the past month (being 1 equal to no physical activity practiced at the past month, and 5 to walking, running or jogging more than 32 km a week), and smoking (whether the subject smoked or not). In this study there is an additional evidence: alterations in BMI and rest were accountable for 14 to 19% of changes treadmill time.

Studies to predict cardiorespiratory fitness in subjects with heart condition were pioneered by Lee *et al*.[29], at the end of the 80s, through the *Specific Activity Scale – SAS*[30]. Lee *et al*.[29] demonstrated, in 36 heart-condition patients and healthy subjects that the self-reported ability in performing daily-life activities (such as putting on clothes, taking a shower or going up a flight of stairs) could add to the stress test in predicting cardiorespiratory capability. This could even enable the health team to decide whether or not the subject should undertake the test, depending on the reported limitations. Soon after, in order to use longitudinal epidemiological studies, Hlatky *et al*.[31] validated a cardiorespiratory fitness predictive model without the use of exercise test in heart-condition patients. Initially, maximum oxygen uptake was correlated to functional capability of 50 patients according to the Duke University's *Duke Activity Status Index – DASI*). This index included 12 items, comprising activities related to personal care, home-making activities, sex, and recreational activities, weighted according to their individual metabolic expenditure measured in METs. Spearman's correlation was high (0.80). However, this first group was interviewed, but other 50 subjects filled out a questionnaire, and correlation was lower (0.58). At the end of the process, a simple regression model was generated from data of the first and second groups. According to the authors, further studies are necessary to check whether *DASI* is sensitive to detect longitudinal changes. Moreover, they do not believe that the questionnaire may replace the stress test, even being a good tool to assess the autonomy of coronary artery disease patients.

In 1990, Jackson *et al.*[13] developed two models to predict cardiorespiratory fitness using variables gender, age, body composition and self-reported physical activity practice (from 0 to 7 according to intensity, being 0 for the person who did not take part in any physical activity or sports over the past month, and 7 for ones who run more than 10 miles or spent more than 3 hours per week practicing a physical activity similar to running). One of the models used BMI as measure of body composition, and the other the amount of fat (%F) predicted by skinfold measurements. Both, the %F ($R^2 = 0.66$) and the BMI ($R^2 = 0.62$) models showed, according to the authors, good predictive values for 1.393 males and 150 females age ranging from 20 and 70 years. The model's accuracy was confirmed when it was applied in the cross-validation sample with 423 males and 43 females, healthy and with high blood pressure. Pearson's correlation coefficients between predicted and observed values in the model including %F and BMI were of 0.82 and 0.79, respectively. Only in subjects with high level of fitness ($\dot{V}O_{2\,max} \geq 55$ ml.kg^{-1}.min^{-1}) the models tended to underestimate fitness. However, this type of people is high above the average of the population, and does not affect applicability of the models for a large sample. These models showed to be more accurate than Åstrand's and Ryhming's[32] predictive treadmill model, that used heart rate measured at submaximal exertion on the treadmill. These results confirmed the ideas advocated by Shephard *et al.*[18] that non-exercise models could be more accurate that submaximal physical tests. Moreover, this was the first study the investigators had special concern with cross-validation procedures.

The interest for the models proposed by Jackson *et al.*[13] lead to the carrying out of two studies, whose purpose was to check the accuracy of the proposed models in two samples of different features: Kolhorst and Dolgener[33] checked model validity in 69 physically active university students. The study included 28 men and 41 women, mean age of 21 ± 2 years. Upon applying Pearson's correlation to compare results of measured and predicted cardiorespiratory fitness, the authors observed that the two models of Jackson *et al.*[13] did not present good correlation ($r = 0.72$), confirming the conclusion of the original study that their applicability was limited to highly fit subjects. In 1996, Williford *et al.*[34] checked cross-validation of non-exercise models[13] in a sample of 165 women, as the cross-validation sample in the original study was small ($n = 43$). Both, the BMI and the %F models showed good correlation ($r = 0.81$ and 0.86 respectively), confirming accuracy of these models also in women aged 18 to 45 years. The model was able to predict fitness of 87% of the women with $\dot{V}O_{2max} < 32$ ml.kg^{-1}.min^{-1}, a value with higher association to mortality risk from all causes[12], suggesting its use in epidemiological investigations.

In 1992, Ainsworth *et al.*[13] developed a model to predict cardiorespiratory fitness by asking the frequency a subject would perform intense physical activities for over 15 minutes, in addition to other easy-to-assess variables, such as age, gender and BMI. For that, they had a somewhat small sample of 27 men and 47 women, age between 21 and 59 years. An interesting feature of this study is that for the authors to reach the most suitable question on the physical activity, they applied a number of physical activity questionnaires used in epidemiological investigations[35-39]. At the end, just one question on the regular practice of more intense physical activities remained in the model[37], strengthening the idea that the variable physical activity could be assessed in a simple way, to inform on cardiorespiratory fitness, as long as the intensity of the activity was taken into consideration, along with other variables. Two years later, Myers *et al.*[40] developed a model to predict performance in a maximum stress test on a treadmill, in 207 men and 5 women (62 ± 8 years) with heart condition, through the *Veteran Specific Activity Questionnaire – VSAQ* and age. The study subjects informed in the questionnaire which physical activity they were able to perform without exertion limiting symptoms (fatigue, uneasiness in the chest, dyspnea). Through the multiple regression model generated, the authors developed a nomogram in which, from the number of METs defined at the questionnaire, and the age of the subject, his/her performance on the treadmill was predicted. According to the authors, the model did not have the purpose of replacing the ergometric test, but would enable the health team to have an idea of the subject's physical fitness, and would adjust the test to this status.

Whaley *et al.*[41] developed another fitness prediction model with variables gender, age, heart rate at rest, weight, proportion of fat, smoking (from 1 to 8 according to the frequency and number of cigarettes smoked, 1 being for non-smokers, and 8 to smoking more than two packs a day), and self-reported physical activity (from 1 to 6 according to the intensity, 1 being for the sedentary subject, and 6 for the highly fit subject, who runs, cycles or swims more than 20 miles a week). Seven hundred and two males and 473 females took part in the study, and the predictive model presented good accuracy ($R^2 = 0.72$). Like Jackson's *et al.*[13] study, this one also carried out a cross-validation of the model. Pearson's correlation between predicted and measured values ($r = 0.85$) led the authors to consider the model valid. Still in that year, Heil *et al.*[14] validated a non-exercise model with variables gender, age and age^2, proportion of fat, and the score of Jackson's *et al.*[13] physical activity levels in 229 women and 210 men aged 20 to 79 years ($R^2 = 0.77$). Cross-validation was carried out in 65 subjects with features similar to the group to which the model was validated. According to the authors, Pearson's correlation was good ($r = 0.85$); however, the small sample somewhat limits the results of the cross-validation. Notwithstanding, the generated model reinforces the idea that it is actually possible to predict cardiorespiratory fitness from some variables suggested by Jackson *et al.*[13].

In 1996, another predictive questionnaire was validated, based on functional impairment of heart-condition patients: the *Specific Activity Questionnaire* – *SAQ*, with 13 questions related to daily-life[42]. Ninety-seven patients (being 12 females) had their fitness predicted through SAQ score, height, age and weight ($R^2 = 0.50$). Pearson's correlation was calculated between SAQ and other questionnaires in regard to cardiorespiratory fitness, and the following results were found: SAQ ($r = 0.71$), SAS[29] ($r = 0.35$), DASI[31] ($r = 0.62$) and VSAQ[40] ($r = 0.66$). For the authors, this evidenced the potential use of SAQ in studies with heart-condition subjects if the stress test was costly or unfeasible. In that same year, Cardinal[43] published a study in which he checked whether the models proposed by Jackson *et al.*[13] and Ainsworth *et al.*[10] were associated between themselves and with other physical activity indices, in 123 healthy women (age = 38.8 ± 8.4 years). The conclusion was that both, the models ($r = 0.80$) and the physical activity indices (0.26 a 0.74), had an overall good correlation between themselves, and followed similar classification criteria. A year later, George *et al.*[44] established a predictive model adjusted for young, physically active students, in a sample of 50 males and females aged 18 to 29 years. To increase accuracy of the final model ($R^2 = 0.72$), as attempts to predict fitness of highly fit individuals had failed so far, new variables were added. Among them, there was a question on the perceived fitness to perform activities such as walking and running, in which people should inform at what pace they could move without become extremely tired. Another question was related to the history of physical activity practice, ranging from 0 to 10 over a six-month period, rather than from 0 to 7 over one month, as proposed in Jackson's *et al.*[13] study. The authors considered this to be the first model with no need for any measuring, as weight and height to calculate BMI were self-reported. In this study, the process of cross-validation was different than the prior ones. Instead of using a sub-sample of the whole group under investigation, which, according to the authors, would limit the sample, it was used the method of adding the square of the predicted residues *(PRESS)*. This method allows the use of all subjects in the sample, in both validation and cross-validation. For this purpose, it is based on the calculation of the predicted residues for each subject, while he/she is excluded from the original model[45]. From adding the square of these residues it is possible to calculate R^2 (0.71) and the standard error of the estimate, evidencing the good accuracy of the model.

In 1999, Mathews *et al*.[11] proposed a model and examined its sensitivity to rate cardiorespiratory fitness. The authors considered that not doing this would limit the application of the models in epidemiological studies. The rating would enable disease-risk estimates to be compared among different fitness levels. Following the example of George *et al*.[44], only self-reported variables were included in the model: age, age^2, gender, reported physical activity (as proposed by Jackson *et al.*[13]), height and weight, ($R^2 = 0.74$). Rating accuracy of the model was assessed by tabulating data into age and gender categories, and distributing them in fifths of measured and predicted cardiorespiratory fitness. The overall accuracy rating of the model was modest (36%). However, 83% of all subjects were appropriately classified, or in the closest fifth. The extreme error in classifying from the lowest to the highest fifth was seldom observed (0.13%), leading to the conclusion that the predicted fitness values could be used as an exposure variable in epidemiological studies when the stress test was not a feasible option. For the process of cross-validation, the PRESS method was also used, confirming the validity of the model ($R^2 = 0.74$).

In a study that seems to be, until the writing of this text, the last on non-exercise models to predict cardiorespiratory fitness, Wu e Wang[46] established a model from the observation of 24 workers of both genders living in Taiwan. The significant variables in the regression model were gender, age and BMI ($R^2 = 0.77$), confirmed by the cross-validation process in a small sample (N = 6). The authors believed that the model could suit an occupationally active population. However, extrapolation of the results is obviously impaired by the very small sample.

CRITICAL ANALYSIS OF THE REVIEWED MODELS

Tables 1 and 2 present the studies, their country of origin, sample, gender, age group, and predictive models with adjusted R^2 and standard error of estimation (SEE). Table 1 presents all studies that used $\dot{V}O_{2\,max}$ as a dependent variable, both in relative ($ml.kg^{-1}.min^{-1}$) and absolute ($l.min^{-1}$) terms. In table 2, the dependent variable was the time spent performing a maximum stress test on treadmill (in minutes) or its maximum intensity (in METs).

TABLE 1
Models to predict $\dot{V}O_{2\,max}$ without performing exercises

Authors (year/country)	Gender	Age	N	Model	R^2 adjusted	ESE (±)
Shephard *et al.*[18] (1971/Canada)	M F	9-13	22 23	0.0216 (body surface) + 0.0117 (age) + 0.125 (sf thigh) – 1.19 0.0480 (body surface) + 0.0050 (age) + 0.043 (sf thigh) – 0.89	0.54 0.84	0.25 $l.min^{-1}$ 0.128 $l.min^{-1}$
Bruce *et al.*[19] (1973/USA)	M F	29-73	138 157	85.42 – 13.73 (gender 1-2) – 0.409 (age) – 3.24 (physical activity 1-2) – 0.114 (weight)	0.66	4.84 $ml.kg^{-1}.min^{-1}$
Mayhew, Gifford[20] (1975/USA)	M	8.7 ± 0.9	31	0.448 + 0.4463 (volume of left leg) – 0.0088 (sf thigh) – 0.0332 (sf leg)	0.62	0.152 $l.min^{-1}$
Bonen *et al.*[2] (1979/USA)	M	6.7-14.8	100	– 1.543 + 0.051 (age) + 0.014 (height) + 0.023 (weight)	0.87	0.162 $l.min^{-1}$
Verma *et al.*[23] (1980/India)	M	19-34	120	126.810 – 0.3577 (weight) – 0.4996 (height) – 0.4972 (sf chest) + 4.2539 (diameter of elbow)	0.34	5.07 $ml.kg^{-1}.min^{-1}$
Sciconolfi *et al.*[27] (1985/USA)	M F	41 ± 14 42 ± 15	36 32	1.92 (number of days practicing sweat-causing activities) + 23.76	0.22	8.63 $ml.kg^{-1}.min^{-1}$
Verma *et al.*[24] (1986/India)	M	11-18	70	0.109 + 0.03833 (body weight)	0.81	0.218 $l.min^{-1}$
Lee *et al.*[29] (1988/USA)	M	50-67	36	25.9 – 4.76 (SAS)	0.52	NR
Hlatky *et al.*[31] (1989/USA)	NR	NR	50	0.43 (DASI) + 9.6	0.34	NR
Jackson *et al.*[13] (1990/USA)	M F	20-70	1.393 150	N-Ex %F = 50.513 + 1.589 (history of physical activity 0-7) – 0.289 (age) – 0.552 (%F) + 5.863 (gender 0-1) N-Ex BMI = 56.363 + 1.921 (history of physical activity 0-7) – 0.381 (age) – 0.754 (BMI) + 10.987 (gender 0-1)	0.66 0.62	5.35 $ml.kg^{-1}.min^{-1}$ 5.70 $ml.kg^{-1}.min^{-1}$
Ainsworth *et al.*[10] (1992/USA)	M F	21-59	27 47	65.0 + 1.8 (frequency of exercise times/week) – 10.0 (0-1 gender) – 0.3 (age) – 0.6 (BMI)	0.74	4.46 $ml.kg^{-1}.min^{-1}$
Whaley *et al.*[41] (1995/USA)	M F	41.8 ± 11 41.6 ± 12	702 473	61.66 – 0.328 (age) + 5.45 (gender 0-1) + 1.832 (physical activity 1-6) – 0.436 (%F) – 0.143 (FC rep) – 0.446 (smoking 1-8)	0.73	5.38 $ml.kg^{-1}.min^{-1}$
Heil *et al.*[14] (1995/USA)	M F	20-79	210 229	36.580 – 0.541 (%fat) + 1.347 (physical activity 0-7) + 0.558 (age) – 7.81 (age^2) + 3.706 (gender 0-1)	0.77	4.90 $ml.kg^{-1}.min^{-1}$
Rankin *et al.*[42] (1996/Australia)	M F	59 ± 10	85 12	(2.36) SAQ + (0.35) height – (0.19) age – (0.16) weight – 33.89	0.49	5.43 $ml.kg^{-1}.min^{-1}$
George *et al.*[44] (1997/USA)	M F	18-29	50 50	44.895 + 7.042 (gender 0-1) – 0.823 (BMI) + 0.738 (perceived functional capability 1-13) + 0.688 (history of physical activity 0-10)	0.71	5.64 $ml.kg^{-1}.min^{-1}$
Verma *et al.*[25] (1998/India)	M	21-58	146	52.66 – 0.328 (age) – 0.436 (body weight)	0.29	NR
Mathews *et al.*[11] (1999/USA)	M F	20-79	390 409	34.142 + 0.133 (age) – 0.005 $(age)^2$ + 11.403 (gender 0-1) + 1.463 (physical activity 0-7) + 9.170 (height) - 0.254 (weight)	0.74	5.64 $ml.kg^{-1}.min^{-1}$
Wu, Wang[46] (2002/Taiwan)	M F	20-30	12 12	3.127 + (0.980 gender 0-1) (0.115 age) + (0.084 BMI)	0.75	0.432 $l.min^{-1}$

ESE – Estimate standard error; # – Calculated from R; M – male; F – female; sf – skinfold; Gender – 1 Female; 2 – Male or 0 – Female, 1 – Male; SAS – Specific Activity Status; DASI – Duke Activity Status Index; SAQ – Specific Activity Questionnaire; BMI – Body mass index; %F – Percentage of fat.

TABLE 2
Models to predict duration of maximum intensity of non-exercise stress test

Authors	Gender	Age (years)	N	Model	R^2 adjusted	ESE (±)
Taylor *et al.*[22] (1975/USA)	M	48.4 ± 6.1	175	NR	0.27	NR
Leon *et al.*[26] (1981/USA)	M	48.5 ± 6.1	175	15,583 + 0.235 (intense leisure physical activity) – 0.051 (age) – 6.72 (BMI) – 0.405 (smoking 1 to 3) + 0.353 (dyspnea and sweat at work 1-0) – 0.008 (dyspnea and sweat at work) + 0.012 (handgrip power-) + 0.316 (cigar or pipe 1 to 3) + 0.395 (dyspnea and sweat at leisure 1-0) – 0.189 (average sleep hours) – 0.015 (heart rate at rest)	0.53	NR
Milesis[28] (1987/USA)	M F	42.7 ± 10.5 42.1 ± 11.8	126 70	– 275.7 + 155 (gender 0-1) + 61.53 (reciprocate of weight index) + 72.36 (physical activity 1-6)	0.76	71.4 seg
Kohl *et al.*[15] (1988/USA)	M	47.1 ± 9.6	375	Age, running and walking index, and frequency of practice of sweat-causing activities (the model was not presented in full)	0.42	NR
Blair *et al.*[12] (1989/USA)	M F	42.5 ± 9.5 42.1 ± 10.7	15.627 3.943	Women 20-29 years 1.619.7 – 395.5 (relative weight) – 6.8 (heart rate at rest) + 110.6 (rating of physical activity 1-5) – 36.4 (smoking 0-1) Men 20-29 years 2.092.8 – 591.7 (relative weight) – 5.4 (heart rate at rest) + 106.6 (rating of physical activity 1-5) – 82.0 (smoking 0-1)	0.48 0.57	NR NR
Myers *et al.*[40] (1994/USA)	M F	207 5	62 ± 8	4.7 + 0.97 (VSAQ) – 0.06 (age)	0.67	1.43 METs

VSAQ – Veterans Specific Activity Questionnaire

Multiple linear regression has been the statistical analysis most often used to predict cardiorespiratory fitness without exercise test. It is to be used when the investigator intends to explain which variables add to the prediction of the dependent variable (cardiorespiratory fitness), and the magnitude of their role[47]. In some studies, only simple linear regression was studied[24,27,29,31]. All articles presented the equation's R (multiple correlation coefficient) or R^2 (explication coefficient) related to the explanatory capability of the model. The presentation of these data is according to the recommendations found in the literature[48]. The adjusted R^2 can be easily calculated and is useful for a better analysis of the models, as it is not influenced by the number of independent variables. On the other hand, R^2 tends to inflate as a function of the amount of variables included in the model. The adjusted R^2 is calculated through the formula[48]

$$\text{adjusted } R^2 = 1 - [(1 - R^2)\ n\text{-}1/n\text{-}p],$$

where n is the number of subjects in the sample and p the number of parameters: the rationale for calculating R^2 is to analyze and compare the quality of the adjustment of predictive models with different amounts of variables. Based on this calculation, one can state that models that present value higher than the adjusted R^2 are those with higher explanatory capability in the sample for which they were validated. As to the SEE, it indicates the variation not explained by the regression line, being a discrepancy measure among the observed and predicted variables. Some authors consider that non indicating SEE lessens the quality of the study, particularly if they do not present the complete model[48,49]. The fact that some studies did not predict maximum oxygen uptake (table 2) implies that the models relate to a doubly-indirect independent variable, which would affect even more the quality of the models, for the time spent on a maximum test is already an indirect indicator of cardiorespiratory fitness. Mechanical efficiency is also a factor that interferes in the result, regardless of $\dot{V}O_2$. Furthermore, other studies[21,23-25] have reported that the maximum oxygen intake was predicted rather than measured, which affect even more the quality of these predictions.

The five studies with the higher adjusted R^2 value (table 1) and among the most recent are those that include SEE and the model, had higher number of subjects in the sample, and performed cross-validation. Some considerations must be made as to advantages and disadvantages of these studies: a tendency in the two most recent predictive studies[11,44] was the use of only self-reported variables in the prediction model, in order to further decrease time of application. This tendency made models with measured predictive variables, such as heart rate at rest[41], to be hampered. The reason being that, in spite of the measures seeming to be simple to assess, they may require some time to be assessed. For instance, it takes from 5 to 10 minutes to accurately assess heart rate, which is longer than the time required for some submaximal tests. Variables that need well-trained personnel to properly assess them, such as skinfold measures, may also be of disadvantage to be applied in models for the study of big samples. In some studies[13,14,41] the skinfold method was used to predict the percentage of body fat through another model, which may include errors from restrictions proper to this type of prediction.

An interesting point that should be reviewed in George's *et al*.[44] study is that, as the authors mentioned, it would be specific for well-fit individuals. If this is to be true, it can be argued that its application is for a small portion of the population. On the other hand, individuals with low cardiorespiratory fitness present higher risk to develop cardiovascular and metabolic diseases. This considered, this model could be regarded as detrimental for epidemiological research. Another important factor to be taken into consideration in any study aiming to predict non-exercise cardiorespiratory fitness is the influence of genetics in the level of fitness. Some studies showed that this could influence about 30 to 40% of the magnitude of results[50]. Notwithstanding, variables related to perceived exertion in daily activities, such as walking and running, used by George *et al*.[44], may be an alternative for cardiorespiratory fitness not related to physical activity history, as a subject may present a good cardiorespiratory fitness without necessarily practicing exercises regularly.

The methodological progress of the studies and the high accuracy of the established models, most of them for healthy subjects, suggests this type of prediction to be a good alternative to rate cardiorespiratory fitness. However, these models are still little used in epidemiological investigations. The models proposed by Jackson *et al*.[13] are the only ones used so far by other studies[51,52]. However, the testing of model applicability is still deficient. Some reasons may be pointed out: first, most models have been developed using sample of subjects of high or average social, economic and cultural levels. As this profile does not match the social features of most of the population, the extrapolation potential of the models is being limited, and they should not be broadly applied.

Another aspect is that the self-reported physical activity is limited, in most studies, to leisure activities [11,13-15]. Only Whaley's *et al*. study[41] included occupational tasks in their model, in addition to leisure activities. In Ainsworth's *et al.*[10] study, occupational activity was also assessed. However, as the sample subjects had sedentary or extremely light occupational activities, this variable did not add to the final predictive model. By the way, populations of low occupational-level activities are found in a number of studies[11,13-15,34]. Even the population of Blair's *et al*. study[12], with 15,627 males and 3,943 females could not be considered as representative of the American population, as they performed low-intensity occupational activities, had high educational level, and were from average to high social-economic level. This limitation was acknowledged by the authors themselves[12]. Finally, Wu and Wang's study[46], in spite of proposing to apply the model to subjects occupationally active, does not include any physical activity-related activity, which may be necessary in a higher, more heterogeneous group. As to the existing models to predict fitness in heart-condition patients, one may say that they provide additional information on the autonomy of the subjects. However, they typically do not dare to predict a cardiorespiratory fitness.

The non-exercise studies may be compared to some submaximal tests used in epidemiological investigations. If some submaximal tests showed an R^2 value higher than those without exercise (0.81; 0.85), SEE values are comparable ($\pm$ 4 $ml.kg^{-1}.min^{-1}$)[53], or are not reported[54], which limits their use. Moreover, in some submaximal tests[54], validation was performed in a very narrow age group, which hampers a comprehensive use of the models. Another interesting issue is related to the comparison of the models with the questionnaire of physical activity history, often used in epidemiological research. It is a fact that nature and intensity of daily activities may influence the subject's cardiorespiratory fitness[56,57]. Therefore, it should not be ignored as a dependent variable in the development of predictive models. On the other hand, the correlation between physical activity and cardiorespiratory fitness tends to be small when based on information from questionnaires. High correlation is connected to intense physical activities. In spite of physical activity be considered the main determinant of cardiorespiratory fitness, physical activity information given on an interview or self-reported, with average duration between 15 to 45 minutes, does not seem suitable to assess cardiorespiratory fitness[39]. However, this may be an interesting aspect to be studied, as many a time predictive models derive from simple questionnaires, whose predictive power is enhanced as one adds easy-to-measure variables in more complex models. The strategies used by Mathews *et al.*[11] of considering self-reported variables only, even for weight and height, for not requiring long measuring time nor trained evaluators, seem to be quite appropriate to apply in epidemiological studies, and future studies should consider these principles.

FINAL CONSIDERATIONS

Non-exercise predictive models are a subject of interest for investigators worldwide. In principle, non-exercise models may be a feasible alternative to assess cardiorespiratory fitness in epidemiological studies. The fact that only a few models exist whose validity allows for an acceptable degree of generalization shows that this area has been scarcely explored, and new investigations on the theme should be carried out.

Some prospective issues should be addressed. First, for further applicability in epidemiological studies, the new investigations should not limit themselves to validation and cross-analysis only, but should tackle longitudinal sensitivity of $\dot{V}O_{2max}$ prediction. This means, so far, one does not know if changes in predictive variables over time (changes due to training) may be detected by non-exercise models. Moreover, one must acknowledge that there are few studies that focus the development of models to be applied to special groups, such as (particularly) the elderly, children, adolescents, women, or heart-condition patients. Those that exist have low generalization capability, due to the small sample used in their development. Another important aspect is the role of social, economic and cultural components: the designing of regression models to predict cardiorespiratory fitness should take into consideration the characteristics of the population under investigation, particularly in the selection of predictive variables. It is clear the need to include, in studies to be validated, subjects of average and low social-economic status, as well as the physical activity required by their occupation. These features tend to be specific for the observed region or population. This evidences the need for studies that develop models suited to the different Brazilian regions and social status of their population, or, at least, to check the validity of the existing models in the Brazilian scenario.

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