ORIGINAL ARTICLE

NON-EXERCISE PREDICTION MODEL TO ESTIMATE CARDIORESPIRATORY FITNESS IN BRAZILIAN ADULTS

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Highlights: (1) A practical non-exercise model was developed to estimate cardiorespiratory fitness (VO_2peak) in adults. (2) The prediction equation was derived from a large sample of 8,293 adults using simple resting clinical variables. (3) The model demonstrated good predictive performance (R = 0.74; adjusted R^2 = 0.56; SEE = 6.11–6.93 $mL \cdot kg^{-1} \cdot min^{-1}$). (4) Cross-validation confirmed the model's robustness and reproducibility in an independent cohort. (5) The model provides a feasible alternative for estimating CRF in epidemiological studies and settings without access to CPET.

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(as accepted)

This is a preliminary, unedited version of a manuscript that was accepted for publication in Revista Contexto & Saúde. As a service to our readers, we are making this initial version of the manuscript available, as accepted. The article will still be reviewed, formatted and approved by the authors before being published in its final form.

http://dx.doi.org/10.21527/2176-7114.2026.51.15412

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How to cite:
Ulbrich AZ, Cáceres JMS, Araujo LFR, Perez LHG, Franzoni NR, Bertin RL. et al. Non-exercise prediction model to estimate cardiorespiratory fitness in brazilian adults. Rev. Contexto & Saúde. 2026;26(51):e15412

ABSTRACT

The most accurate tool to assess cardiorespiratory fitness (CRF) is cardiopulmonary exercise testing (CPET). However, for its use it is required expensive equipment, trained technicians and considerable time, restricting its use in large population studies. Given these limitations, this study aims to develop and cross-validate a prediction model for estimating CRF in adults using simple resting outcomes. The study used data from 8,526 subjects, aged between 18 and 65 years, consisting of 5,291 men and 3,235 women divided into development group (G1) and cross validation group (G2). To develop models to estimate the CRF, the variables analysed were gender, conditioning, age, pre-exercise heart rate, body mass index, hypertension, diabetes, dyslipidaemia and smoking. Using multiple linear regression, a model was developed to estimate oxygen uptake peak (VO_{2peak}) based on age, gender, body mass index (BMI), Heart rate Pre-effort ($HR_{pre\text{-}esf}$) conditioning, smoking, dyslipidaemia, hypertension, and diabetes. This predictive model showed a coefficient correlation (r) = 0.74, and explained 55.5% of the variation of VO_{2peak}, with standard error of estimate (SEE) indicating 6.93 $ml.kg^{-1}.min^{-1}$ variation. Cross-validation using other subjects confirmed these statistics with correlation of (r) = 0.75, adjusted R^2 of 0.56, and SEE of 6.11 $ml.kg.^{-1}min^{-1}$. The model developed to predict CRF is feasible and practical for prediction of VO_{2peak} in epidemiological studies or when a CPET cannot be performed. These models, which do not involve physical exercise, can serve as a tool to guide exercise prescription strategies.

Keywords: Regression analysis; cardiorespiratory fitness; prediction algorithms

Introduction

Cardiorespiratory fitness (CRF) can reflect an individual's past physical activity and their capacity to engage in physical activity[1]. However, its usefulness is not restricted to sports performance, as it can also be used as a diagnostic measure of health and to guide exercise prescription [1,2].

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Population studies demonstrated that low levels of CRF are associated with higher risk of cardiovascular disease, diabetes, certain cancers, and all-cause mortality, supporting its assessment at the population level[3-5]. Maranhão Neto[6] showed that low fitness was associated with a 33% higher risk of cardiovascular disease, an 89% higher risk of diabetes mellitus, and a 67% higher risk of hypertension, regardless of sex, age, or presence of obesity.

Therefore, the determination of peak oxygen uptake (VO_2peak) is the primary outcome for quantifying CRF[7]. The cardiopulmonary exercise test (CPET) is a valuable tool for the assessment of physical performance and health status [8,9]. Nevertheless, its use in clinical and research contexts is limited by several factors [10]. First, the test requires specialised equipment and trained personnel, which can often be costly and not easily accessible[11-14]. Second, the complexity of the procedure may pose challenges for certain participants, while its technical demands can restrict its broader applicability. These limitations have prompted research into alternative approaches for determining CRF. Among these, non- exercise prediction models testing have been developed and validated as feasible, cost-effective, and time-efficient strategies, making them particularly suitable for large-scale epidemiological studies. [13,15,16]

Several mathematical models identified in international studies are considered valid, employing multiple variables such as age, gender, body mass index (BMI), body fat percentage, resting heart rate, and levels of physical activity, in addition to their own specific variables. [12,14,17]. Sloan et al.[14] used a large dataset comprising 5,293 Japanese adults, employing supervised machine learning with elastic net regression to derive sex-specific CRF prediction equations. This approach entailed the rigorous process of data pre-processing including outlier removal and variable standardization [14]. Additionally, the researchers employed a sophisticated nonlinear augmentation technique to enhance the predictive capabilities of the model[14]. The efficacy of these methodologies was evaluated through a rigorous 10-fold cross-validation procedure, with the aim of optimising model performance and minimising the mean squared error[14]. Even with an accuracy of 90% among them in the relationship of physical inactivity[12] , when associated with equations based on submaximal and maximal exercises respectively, there was a low degree of accuracy (51% - 59%) in categorizing participants into fitness terciles[12,13.]

It is therefore evident that there is a paucity of national studies adressing alternative methods for determining CRF. This highlights the need to develop and validate prediction

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models based on simple, routinely collected clinical and anthropometric variables. It is hypothesised that such models may provide a feasible and scalable approach for estimating CRF in large populations, supporting epidemiological surveillance and clinical decision-making in resource-constrained settings.[11]

Methods

The development of CRF prediction equations that do not require exercise testing was facilitated by employing a database comprising 8,526 cardiopulmonary exercise tests (CPETs), after excluding irrelevant records. The process entailed the elimination of cases characterised by missing values, inconsistent entries (*e.g.*, implausible physiological measurements), duplicated or incomplete variables, and participants with documented cardiovascular, metabolic, or respiratory diseases. These potential sources of bias could have introduced errors into the results. To create the predictive model, the database was divided into two groups: G1, the development group, comprising 6,526 CPETs, and G2, the cross-validation group, comprising 2,000 CPETs.

Subjects

Data from 8,526 subjects "apparently healthy" were analysed. Patients with cardiovascular disease or other relevant comorbidities were excluded from the study based on information obtained from their medical records. This number was used in subsequent phases of the study, encompassing 5,730 active participants (2,019 women and 3,711 men) and 2,796 sedentary subjects (1.238 women and 1.558 men). Data were drawn from a database at Cardiosport Clinic in Florianópolis, Santa Catarina, Brazil. Evaluations were performed between January of 2004 and December of 2010. All subjects provided written informed consent for the use of their data in population-based studies. The study was approved by the Human Ethics and Research committee of the State University of Santa Catarina under protocol nº 97/2010.

Measurements

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Body mass, height and body mass index

Body mass (BM) was measured with a Filizola® scale with 100 grams resolution and height with a Sanny® stadiometer with 0.1 cm precision. This data was obtained to calculate the body mass index (BMI). BMI was calculated as body mass divided by height squared.[18]

Pre-exercise heart rate

Pre-exercise heart rate ($HR_{pre\text{-}exerc}$) was measured during five minutes rest in a sitting position, which preceded the CPET, with an Elite 3-lead electrocardiogram (ECG) (Micromed - Brazil). This measurement was considered the lowest heart rate during the evaluation period[19].

Medical record data

The gender (male and female), smoking (yes or no), age and physical activity status (sedentary or active) were recorded through a questionnaire. Subjects were considered physically active if they met the criteria established by Blair et al.[20].

The comorbidities (hypertension, diabetes and dyslipidemia) were assessed through tests requested by specialists from Cardiosport Clinic. Hypertension was defined as values higher than 130mmHg for systolic blood pressure or/and 90 mmHg for diastolic blood pressure. Diabetes was defined as values equal or higher than 100 mg/dL. Dyslipidemia was defined as cholesterol values higher than 200 mg/dL.

Cardiorespiratory fitness test

The VO_{2peak} was determined by a ramp protocol, according to *Diretrizes sobre teste ergométrico*[21] guidelines from the Brazilian Cardiology Society. For testing, a motorized treadmill (Imbrasport-ATL®, Brazil 1999) with an Elit three leads ECG (ECG Digital; Micromed® - Brasília, DF - Brazil) were used. The analysis of VO_{2peak} was determined by "mixing chamber" gas analyzer (Metalyzer ll Cortex®, Germany, 2003), using the bundled software Ergo Elite PC Version 3.3.6.2 (Micromed®, Brazil).

Ventilatory thresholds were identified by analyzing ventilatory responses during the CPET. The first ventilatory threshold (VT1) was determined by an increase in VE/VO_2 without

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a concomitant change in VE/VCO_2, while the second ventilatory threshold (VT2) was identified by a simultaneous increase in VE/VO_2 and VE/VCO_2, associated with a decrease in $PetCO_2$. The highest VO_{2peak} peak value was determined in the final 30 seconds of the test. The test was considered maximal when the participant reached voluntary exhaustion and exhibited a respiratory exchange ratio (RER) greater than 1.10. The CPET was terminated due to voluntary exhaustion, inability to maintain the workload, the onset of limiting signs or symptoms, clinically relevant cardiovascular or respiratory changes, or based on safety criteria established by international guidelines for cardiopulmonary exercise testing.

Data analysis

Data was analyzed using the statistical package SPSS version 17.0 for Windows®. Kolmogorov-Smirnov test was carried out to determine the normality of independent variables. Descriptive analysis was used to characterize the sample (mean, standard deviation, minimum and maximum values of each variable). Chi-square test (χ^2) verified the dispersions between categorical variables.

The data of the individuals considered able to participate in the study (n = 8293) were randomly divided into development group (G1, n = 6293) and cross-validation group (G2, n = 2000) using the Bland and Altman analysis.

In this research VO_{2peak} was considered the dependent variable. Gender, conditioning, age, BMI, $HR_{pre\text{-}exerc}$, smoking, diabetes, hypertension, and dyslipidemia were considered independent variables.

The prediction model was developed through multiple linear regression analysis with stepwise forward method. To verify the validity of the developed equation, the Pearson correlation (r), coefficient of determination (adjusted R^2) and standard error of estimate (SEE) were calculated. The beta body mass (β-weight) of each independent variable was also examined to verify their predictive strength. The variables used in the model were coded as follows: age expressed in completed years; conditioning expressed in: sedentary (0) or active (1); dyslipidaemia, smoking, hypertension and diabetes were each expressed according to its presence: no (0) or yes (1). Statistical analysis adopted the significance of $p<0.05$ and confidence interval of 95%.

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Finally, the validity of the predictive non-exercise model was examined through the application of the equation developed from the cross-validation group data (G2) and then comparing the predicted values with those obtained directly by the CPET.

Results

The descriptive statistics of the sample (G1 and G2 groups) are presented in **Table 1**.

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Table 1- Descriptive statistics for the validation (G1) and cross-validation (G2) groups.

		G1 group (n=6.526)		
	Variable	**Minimum**	**Maximum**	**Mean ±SD**
Females N=2,464	Age (yr)	18.02	64.95	40.18 ± 12.4
	Height (cm)	142.50	185	162.56 ± 6.5
	BM (kg)	39	111	62.44 ± 10.6
	BMI ($kg.m^{-2}$)	15.99	39.84	23.65 ± 3.9
	$HR_{pre\text{-}exerc}$($beats.min^{-1}$)	41	129	83.88 ± 13.9
	VO_{2peak} ($ml.kg^{-1}.min^{-1}$)	16	62.84	31.53 ± 7.6
Males N=3,962	Age (yr)	18.04	65	40.56 ± 10.4
	Height (cm)	145	208	176.35 ± 7.2
	BM (kg)	46	145	81.33 ± 12.6
	BMI ($kg.m^{-2}$)	16.98	39.89	26.13 ± 3.6
	$HR_{pre\text{-}exerc}$($beats.min^{-1}$)	41.00	130	77.31 ± 13.3
	VO_{2peak} ($ml.kg^{-1}.min^{-1}$)	16.05	75.57	40.56 ± 10.4
		G2 group (n=2.000)		
	Variable	**Minimum**	**Maximum**	**Mean ±SD**
Females N=793	Age (yr)	18.1	65	41.3 ± 12.1
	Height (cm)	145	190	163.2 ± 6.4
	BM (kg)	43	107	63.2 ± 10.2
	BMI ($kg.m^{-2}$)	16.6	39.8	23.8 ± 3.9
	$HR_{pre\text{-}exerc}$($beats.min^{-1}$)	47	130	83.9 ± 13.6
	VO_{2peak} ($ml.kg^{-1}.min^{-1}$)	16	60.39	30.9 ± 7.6
Males N=1.307	Age (yr)	18	64.93	39.3 ± 12.4
	Height (cm)	146	203	176.1 ± 7.0
	BM (kg)	42.2	133	80.7 ± 12.4
	BMI ($kg.m^{-2}$)	16.7	39.5	25.9 ± 3.6
	$HR_{pre\text{-}exerc}$($beats.min^{-1}$)	41	130	77.6 ± 13.3
	VO_{2peak} ($ml.kg^{-1}.min^{-1}$)	16.5	71.1	40.9 ± 10.5

N= number of subjects; SD: standard deviation; BM= body mass; BMI= body mass index; HR: heart rate pre-exercise test; VO2 peak: peak oxygen uptake. yr: years old; cm: centimeter; kg: kilogram; $kg.m^{-2}$: kilogram per square meter; $beats.min^{-1}$: beats per minute; $ml.kg^{-1}.min^{-1}$: milliliter per kilogram per minute.

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Regarding comorbidities in the G1 group, women had lower percentages of diabetes and dyslipidaemia than men. In G2, this pattern was not observed, as men and women showed similar percentages of the four comorbidities analysed (**Supp. Table S1**).

As all independent variables were valid predictors ($p < 0.001$) of CRF, they were all selected to compose the predictive model developed. The algorithm for predicting VO_2 is as follows:

$VO_2peak = 71.147 – 0.338$ (age) + 10.081 (gender) – 0.766 (BMI) – 0.103 (pre-exercise HR) + 1.452 (fitness) – 3.150 (smoking) – 1.962 (dyslipidaemia) – 1.585 (hypertension) – 2.134 (diabetes).

Values to be used in the model: age expressed in completed years; conditioning expressed as: sedentary (0) or active (1); dyslipidaemia, smoking, hypertension and diabetes each expressed according to its presence: no (0) or yes (1).; HRpre-exerc: beats per minutes (bpm).

The model demonstrated a substantial degree of fit, evidenced by an R^2 value of 0.55 and a standard error of estimate (SEE) of 6.93 ml.kg-1min-1, accompanied by a notable effect size (f2 = 1.22). The stepwise procedure performed nine steps (Table 3). In the last, the highest value of adjusted R square was obtained.

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Table 3. Results of regression analyses for the total population sample.

Equation components	R	R^2	R^2adjusted	*P*-value	SEE
Age	**0.516**	**0.266**	**0.266**	**<0.001**	**8.904**
Age, Gender	**0.661**	**0.436**	**0.436**	**<0.001**	**7.806**
Age, Gender, BMI	**0.722**	**0.521**	**0.521**	**<0.001**	**7.195**
Age, Gender, BMI, HRpre-exerc	**0.735**	**0.540**	**0.540**	**<0.001**	**7.052**
Age, Gender, BMI, HRpre-exerc, Conditioning,	**0.739**	**0.546**	**0.546**	**<0.001**	**7.006**
Age, Gender, BMI, HRpre-exerc, Conditioning, Smoking	**0.741**	**0.550**	**0.549**	**<0.001**	**6.979**
Age, Gender, BMI, HRpre-exerc, Conditioning, Smoking, Dyslipidemia	**0.744**	**0.553**	**0.552**	**<0.001**	**6.954**
Age, Gender, BMI, HRpre-exerc, Conditioning, Smoking, Dyslipidemia, Hypertension	**0.745**	**0.555**	**0.555**	**<0.001**	**6.937**
Age, gender, BMI, HRpre-exerc, Conditioning, Smoking, Dyslipidemia, Hypertension, Diabetes	**0.746**	**0.556**	**0.555**	**<0.001**	**6.932**

R, multiple correlation coefficient; R^2, squared multiple correlation coefficient; adjusted R^2, adjusted squared multiple correlation coefficient; SEE, standard error of estimate.

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When conducting cross-validation in the G2 group a significant correlation of r = 0.75 ($p<0.001$), adjusted R^2 of 0.56 and SEE of 6.11 $ml.kg^{-1}.min^{-1}$ was verified. Therefore, the model was considered valid for estimating cardiorespiratory fitness for this group. According to **Table 4**, it is observed that gender, age and BMI had a higher contribution in the VO_{2peak} prediction.

Table 4. β- weight from the variables used in the study.

Variable	β-weight
Gender	0.472*
Age	-0.407*
BMI	-0.289*
HRpre-exerc	-0.138*
Conditioning	0.076*
Smoking	-0.060*
Dyslipidemia	-0.049*
Hypertension	-0.048*
Diabetes	-0.029*

HRpre-exerc: heart rate pre-exercise; BMI: body mass index; * $P < 0.001$

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Discussion

This study aimed to develop and cross-validate an equation to predict cardiorespiratory fitness using simple measurement variables, without performing physical exercise tests. Obtaining such data via regression equations without exercise testing is an economical, practical and efficient alternative and can be used in epidemiological studies[8,10].

Our results suggest that the prediction model of CRF without exercise testing can provide valid estimates of VO_{2peak} for men and women “apparently healthy”, active or

sedentary, aged between 18 and 65. Classic studies estimating VO_2 max using regression have indicated consistent levels of accuracy and explained variability. Nes et al.[22] (HUNT Study) applied multivariate regression in 4,637 healthy individuals and obtained $R^2 = 0.61$ (SEE = 5.70 $ml \cdot kg^{-1} \cdot min^{-1}$) for men and $R^2 = 0.56$ (SEE = 5.14 $ml \cdot kg^{-1} \cdot min^{-1}$) for women, with the strongest predictors being age, waist circumference, physical activity, and resting heart rate. Jackson et al.[23] developed two non-exercise models, using variables such as gender, age, body composition, and self-reported physical activity, achieving multiple correlations of R = 0.81 (SEE = 5.3 $ml \cdot kg^{-1} \cdot min^{-1}$) in the model with fat percentage and R = 0.78 (SEE = 5.6 $ml \cdot kg^{-1} \cdot min^{-1}$) in the BMI-based model [23]. These results are consistent with other reported regressions[19,20], which show adjusted R^2 values close to 0.50–0.60 and standardized errors in the range of 5.0 to 5.7 $ml \cdot kg^{-1} \cdot min^{-1}$. Regardless of the method used (BMI model or otherwise) or the population studied, a convergence is observed: the models explain approximately half of the variation in VO_2max and have a typical estimation error of about 5 $ml \cdot kg^{-1} \cdot min^{-1}$. This consistency suggests that these non-exercise or submaximal prediction models can be useful tools for broad estimates in population studies or clinical contexts. Furthermore, one study showed that this method of assessing CRF is feasible and practically useful in primary care for identification of apparently healthy individuals at increased risk of premature cardiovascular disease and all-cause mortality.[24]

As indicated by the β-weight (table 3 and 4), the variable that showed the highest impact in the CRF prediction, in the equation developed, was gender (β-weight = 0.472). These values are like those found by Mailey et al.[25] (β-weight = 0.500) and George et al.[26] (β-weight = 0.530 and 0.500), and higher than the values found by Heil et al.[27] (β-weight = 0.180) and Whaley et al.[28] (β-weight = 0.260). The extant literature suggests that, in general, males tend to exhibit higher levels of CRF in comparison to females, a phenomenon that can be primarily attributed to disparities in body composition and higher haemoglobin concentration. [29-30] When haemoglobin levels are equalised, the discrepancy in VO_2max is significantly diminished. [29] However, even after normalisation by lean mass, men maintain higher maximal cardiac output and oxygen delivery capacity, largely explained by lower haemoglobin levels in women. [30]

A substantial body of research has consistently demonstrated that age is a significant negative predictor of CRF. In the present study, the β-weight was -0.407, a value very similar to that reported by Mailey et al. [25] (β = -0.450). The findings of the present study (tables 3 and

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4) demonstrate that the results are slightly higher than those previously reported by Heil et al. [27] , Whaley et al. [28] and Bradshaw et al. [31]. However, it is noteworthy that all these studies support the inverse relationship between age and VO_2. [19-22] This consistency underscores the well-established physiological decline in maximal oxygen uptake with advancing age, largely explained by reductions in maximal heart rate, stroke volume, and peripheral oxygen utilization [19-22].

Regarding body composition, the present study used BMI as a marker, resulting in a β-weight of -0.289. This finding agrees with Bradshaw et al. [31] (β = -0.270) and Mailey et al. [25] (β = -0.330), while diverging from the values reported by Whaley et al. [28] and George et al. [26], who observed weaker or inconsistent associations. Although BMI cannot distinguish between lean and fat mass, it remains a practical and accessible surrogate marker. It effectively reflects the adverse impact of excess body weight on aerobic efficiency and oxygen cost during physical exertion. [29,30]

Regarding smoking, we found a β-weight of -0.060 in the predictive model, a value similar to that reported by Whaley et al.[28] (β-weight -0.064). Blair et al.[20] developed ten equations for males and females. Their models presented β-weight values ranging from -0.03 to -0.09 for women and -0.04 to -0.13 for men which shows that smoking subtly contributes to the prediction[20]. According to Conklin et al.[32] individuals who use tobacco have a reduced CRF, mainly due to changes in lung function. Abstinence from smoking for only 24 hours provides better exercise tolerance.[32]

Blair et al.[20] found that resting heart rate (HR_{res}) contributed to their CRF prediction models presenting β-weight ranging between -0.177 and -0.273. Those values are higher than that found in this study (-0.138). However, in the study by Mailey et al. [25], which aimed to validate the prediction models originally developed by Jurca et al. [33], HR_{res} was not significantly associated with CRF. This finding stands in contrast to the conclusions drawn in the original study by Jurca et al. [33], wherein HR_{res} exhibited a moderate negative correlation with CRF, with β-weight values ranging from -0.23 to -0.42. These findings suggest that, while HR_{res} may be a meaningful predictor in some populations, its predictive value for CRF may vary depending on sample characteristics, such as age, gender distribution, and baseline fitness level. Indeed, a reduced HR is characteristic of subjects with better CRF, due to increased stroke volume and thus increased cardiac output under normal physiological conditions.

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Few developing CRF prediction equation studies were performed in the Brazilian population[11,34]. The importance of this study to Brazil, and possibly to other countries is due to the large sample size (8293 individuals, 3157 women and 5136 men), wide range of age (18 to 65 years) and range level of CRF (16 to 75.57 $ml.kg^{-1}.min^{-1}$). These characteristics strengthen the external validity of the findings and increase the potential for generalizing the equations developed to different populations and clinical and epidemiological contexts.

However, this study showed lower accuracy because the algorithm was more general in nature compared to the study by Policarpo-Barbosa[35], which demonstrated a higher adjusted R^2 (0.90) and a lower SEE (3.44 $ml \cdot kg^{-1} \cdot min^{-1}$). Furthermore, the difference can be explained by the sample size (n = 8,293), the wide age range (18–65 years), and the classification of CKD into four categories.

The independent variables included in this study have been widely used in research on CRF prediction, with their relevance supported by established statistical analyses[11–14,22,24–27,34,36]. Although the variables traditionally used to predict cardiorespiratory fitness (CRF) are well established in the literature, no study has consistently evaluated the influence of important cardiovascular risk factors such as diabetes mellitus, dyslipidaemia and hypertension on VO_2 estimates. This gap is particularly relevant, since individuals with these conditions are at higher cardiovascular risk and often have reduced CRF. In this context, obtaining more accurate estimates of VO_2 has high clinical value for risk stratification, monitoring cardiovascular health, and prescribing physical exercise. Our results demonstrate that the inclusion of these cardiometabolic variables improves the accuracy of predictive models, reinforcing their importance in the development of equations that are more applicable to clinical practice.

In the cross-validation analysis, the correlation between predicted values and the reference method (CPET) was confirmed, explaining 56% of the variation in VO_2peak and exhibiting a standard error of 6.11 $ml \cdot kg^{-1} \cdot min^{-1}$. These results are analogous to those reported by Jackson et al.[23] in their cross-validation for apparently healthy subjects in the model that uses BMI (r = 0.79 and SEE = 5.3 $ml.kg^{-1}.min^{-1}$). However, the findings demonstrate greater stability compared to those reported by Eldridge[36], who obtained an *r* value of 0.68 and a standard error of the estimate (SEE) of 3.74 ml kg^{-1} min^{-1}. Moreover, these results are lower than those attained by Bradshaw et al.[37], who reported a substantially higher correlation (r = 0.91 and SEE = 3.63 ml kg-1 min-1) using the *Pess* method which incorporates variables such

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as perceived exertion, speed (velocity), and slope (inclination) into the prediction model.

The study limitations include a retrospective database, which limits control over potential unrecorded confounding factors and the standardization of all collected variables. Furthermore, the sample consisted of individuals aged 18 to 65 years of both sexes with cardiovascular risk factors, which may limit the generalizability of the results to populations without risk factors, older adults over 65 years of age, or individuals with established cardiovascular disease. Finally, although the model demonstrated good predictive performance, future studies with external validation in different populations and clinical contexts are needed to confirm its applicability and robustness.

Conclusion

The non-exercise prediction model developed in this study demonstrated satisfactory predictive performance and reliability, as evidenced by cross-validation procedures, providing a practical approach for estimating CRF using readily available resting parameters. The model developed provides a satisfactory degree of accuracy comparable to exercise models already established and may be employed in epidemiological studies. However, future cross validation of the present model is recommended prior to its use in other populations and countries.

Acknowledgements

We would like to thank the collaboration of Cardiosport Clinic and Nucleous of Cardiology and Exercise Medicine from the Center of Health Sciences and Sports of the State University of Santa Catarina. The authors also tank Dr. Tim Takken for their critical review of the manuscript.

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Submitted: December 16, 2023

Accepted: August 11, 2026

Published: October 26, 2026

PRE-PROOF

NON-EXERCISE PREDICTION MODEL TO ESTIMATE CARDIORESPIRATORY FITNESS IN BRAZILIAN ADULTS

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Conflict of interest:	There are no disclosures to report and no conflicts of interest.

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