American Journal of Applied Mathematics and Statistics, 2018, Vol. 6, No. 6, 224-231
Available online at http://pubs.sciepub.com/ajams/6/6/2

DOI:10.12691/ajams-6-6-2

A New and Simple Prediction Equation for Health-Related Fitness: Use of Honest Assessment Predictive Modeling

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Received September 19, 2018; Revised October 23, 2018; Accepted November 07, 2018

Abstract **Background**: The five components of health-related fitness are cardiorespiratory endurance, muscular strength, muscular endurance, body composition, and flexibility. To assess an individual on all five components can be time consuming. Thus, it would be useful to fitness specialists if a simpler and valid fitness assessment was available to measure overall health-related fitness. The purpose of this study was to employ honest assessment predictive modeling to find a parsimonious set of variables that can predict overall health-related fitness. **Methods**: Data used for this study came from college students who completed a fitness test battery. An overall health-related fitness score (T-score) was constructed using maximal oxygen consumption (VO2, ml/kg/min), 1RM bench press (BP, lb), maximal push-up repetition (PU, #), and percent body fat (PBF, %). The set of possible predictor variables consisted of participant age (yr), sex (male/female), body mass index (BMI, kg/m^2), waist circumference (WC, cm), 1RM leg press (LP, lb), countermovement vertical jump (VJ, in), flexed arm hang (FAH, sec), physical activity rating (PAR, 0 thru 10), and sit-and-reach (SNR, cm). The honest assessment predictive modeling procedure comprised three steps: 1) development of competing models using a TRAINING dataset, 2) selecting an optimal model using a separate VALIDATION dataset, and 3) assessing fitness score construct validity using a final SCORING dataset. **Results**: Stepwise model selection with Schwarz Bayesian criterion (SBC) on the TRAINING data resulted in five possible models including sex, VJ, PAR, and WC. Results on the VALIDATION data indicated a three-variable model had the lowest average squared error (ASE) and consisted of sex, VJ, and PAR (F=107.8, p<.001, R^2=.82, SEE=3.09). Finally, predicted values from the SCORING data showed that athletes ($Mean$=54.9, SD=5.1) had a significantly (p<.001) greater mean fitness score than non-athletes ($Mean$=39.8, SD=4.8). **Conclusion**: This study presents a valid equation that can simply predict overall health-related fitness in college students.

Keywords: *physical fitness, vertical jump, predictive modeling, regression, honest assessment*

Cite This Article: Peter D. Hart, "A New and Simple Prediction Equation for Health-Related Fitness: Use of Honest Assessment Predictive Modeling." *American Journal of Applied Mathematics and Statistics*, vol. 6, no. 6 (2018): 224-231. doi: 10.12691/ajams-6-6-2.

1. Introduction

The five components of health-related fitness are cardiorespiratory endurance, muscular strength, muscular endurance, body composition, and flexibility [1]. These fitness components are considered health-related because of their strong ties to health outcomes, such as coronary heart disease [2,3,4,5,6], cancer [7,8,9], stroke [10], and all-cause mortality [11,12,13]. Despite the strong connections between health-related fitness and health, many adults remain unfit [14,15,16]. One potential reason preventing adults from meeting higher levels of fitness, is the difficulty involved in baseline and follow-up fitness assessment. For example, a common assessment for cardiorespiratory endurance in adults is the one-mile walk test [17]. This test, typically considered a relatively simple field test to administer, requires the participant to walk at a maximal speed for a one-mile distance while recording their exercise heart rate before crossing the one-mile mark. For the average adult, these steps may be too difficult to follow which could then hinder the assessment process.

Several professional organizations exist which certify fitness professionals and focus specifically on the technical aspects of assessment and evaluation [18].Many of these certifying bodies require specific degrees and/or coursework as a prerequisite before qualifying to take such certification exams [19]. This type of specialized training is not practical for the average adult interested in assessing their own fitness status. Furthermore, seeking the help from a fitness professional to gain an assessment requires motivation and often resources. On top of these barriers, obtaining a complete health-related fitness profile requires the administration of several different time-consuming tests [20]. Therefore, a need exists for a simpler approach to overall health-related fitness assessment. Thus, the purpose of this study was to build a valid equation that can easily predict overall health-related fitness. Specifically, this study employed honest assessment predictive modeling to find a parsimonious set of variables that can predict overall health-related fitness.

2. Methods

2.1. Participants and Design

The current study used two independent cross-sectional sets of data. The first dataset contained fitness test battery scores from *N*=95 college students attending a rural public university. The second dataset was developed after the main analysis of the current study was complete and consisted of a smaller set of fitness tests from *N*=24 college students attending the same university. Students were included in this study if they completed all pertinent fitness assessments. College students were recruited by public flyers and word-of-mouth. The university system's institutional review board (IRB) approved all study methods and procedures.

2.2. Variables Utilized

The dependent variable in this study was a constructed score representing overall health-related fitness that used participant maximal oxygen consumption (VO2), 1RM bench press (BP), maximal push-up repetition (PU), and percent body fat (PBF). The independent variables were age (yr), sex (male/female), body mass index (BMI), waist circumference (WC), 1RM leg press (LP), countermovement vertical jump (VJ), flexed arm hang (FAH), physical activity rating (PAR), and sit-and-reach (SNR).

2.3. Assessment of Fitness Tests

A total of three body composition measures were collected. PBF (%) was assessed using the sum of three skinfold sites for males (chest, abdomen, thigh) and females (triceps, suprailiac, thigh) and density with body fat percentage equations [21]. BMI (kg/m^2) was assessed using a wall mounted stadiometer and digital floor scale [22]. WC (cm) was assessed using an elastic tape and measuring the narrowest point between the participant's umbilicus and xiphoid process [23]. Three muscular strength measures were collected. BP (lb) and LP (lb) were assessed by the heaviest load successfully lifted according to ACSM guidelines [24]. VJ (inches) was assessed by marking a solid wall with chalked fingers [25]. VJ scores were computed as the differences between participant jump height and reach. Two muscular endurance measures were collected. Using ACSM guidelines, PU was assessed where the total number of push-up repetitions completed with proper form was the participant's score [23]. FAH (sec) was assessed by participants hanging from a pull-up bar where the total time the participant kept their chin above the bar with an underhand grip was their score [26].

Two cardiorespiratory measures were collected. Maximal VO2 (ml/kg/min) was assessed by a 20-meter run test cued by audio beeps [27]. The VO2 test was stopped when the participant failed to reach a 20-meter mark before the ending beep twice in a row. PAR (0 thru 10) was assessed by a single response to a physical activity scenario describing the participant's overall level of activity [28]. PAR responses ranged from 0 (avoid walking or exertion) to 10 (run over 25 miles per week or equivalent). SNR was assessed using a standard trunk flexion box [29].

2.4. Assessment of Overall Health-related Fitness

Four different fitness scores representing four fitness components were used to compute the overall health-related fitness score. There were three reasons driving the decision to leave out a measure of flexibility from the overall fitness score. One, the inter-item test correlations for the study SNR variable across all other study variables were generally weak and non-significant for both males and females (see Table 2). Two, prior research does not support flexibility as a predictor of health outcomes like it does the other four components of health-related fitness [30,31]. And three, anecdotal evidence suggests that flexibility is not a trait necessarily possessed by individuals who are fit and not necessarily absent from those who are unfit. Consequently, the overall health-related fitness score was built with measures of cardiorespiratory endurance, muscular strength, muscular endurance, and body composition. The selection of test variables as outcome or predictor was based on including the more established test scores for the constructed outcome variable and leaving the fitness scores that were easier to administer as predictor variables. The constructed health-related fitness score was developed by taking the average of the four selected fitness tests after converting them to sex-specific T-scores [32]. Body composition T-scores were reversed coded so large T-scores represented greater (better) health-related fitness.

2.5. Statistical Analyses

Data analysis for this study began by first screening all relevant variables for outliers and removing observations with incomplete data. After data were cleaned, a total of *N*=95 observations were included in the main analysis. After the main analysis was complete, follow-up data were collected on *N*=24 participants specifically aimed at validating the fitness scores from the newly developed prediction equation. With exception of Table 6, all reported results were from the main dataset. Descriptive statistics with independent t-tests were computed for all study variables by sex. Bivariate Pearson correlation coefficients with Student's t-tests were computed to examine the inter-relationships across study variables by sex. For an alternative model building approach, an all subsets multiple regression analysis was run using the coefficient of determination (R^2) as criteria. The honest assessment predictive modeling procedure was run in three stages. First, using PROC GLMSELECT, the main dataset was randomly split into TRAINING (*N*=75) and

VALIDATION (N=20) sets. During this stage, a stepwise model selection option was used on the TRAINING data using Schwarz Bayesian criterion (SBC) as the stopping criterion. The SBC has the following formula n*log(SSE/n)+p*log(n), where lower values indicate less unexplained model variance (error) with fewer predictors. Second, using the set of competing models from the first step, an optimal model was selected using the VALIDATION dataset and average squared error (ASE) as criterion. ASE is the sum of squared differences between the observed value and predicted value divided by the number of cases, where lower values are optimal. Third, using the best fitting model resulting from the VALIDATION data and the follow-up SCORING dataset, scores were computed and compared between groups of known trait differences as a means to validate the new overall health-related fitness scores. Model post-fitting was performed and reported, including checks on linear regression assumptions, influential observations, and multicollinearity. All analyses were performed using SAS version 9.4 [33,34]. All p-values were reported as 2-sided and statistical significance was defined as p-values < 0.05.

3. Results

Table 1 contains descriptive statistics of all study variables for the combined N=95 sample by sex. Significant (ps<.05) sex differences were seen for all study variables, except age (p=.142) and PU (p=.070). Table 2 contains bivariate correlation coefficients among study variables for both males (lower portion) and females (upper portion). Most notable, SNR was significantly (ps<.05) related to only PU, FAH, and PAR among males and only BP among females. Additionally, SNR correlations were all weak (rs<.40).

Table 3 contains descriptive results from a traditional all subsets model selection procedure using R^2 criteria. The table shows an apparent trend of top performing models excluding the variables age and BMI. Table 4 contains results from the honest assessment on TRAINING and VALIDATION datasets. Stepwise model selection on the TRAINING data resulted in five possible models, where a model including only sex, VJ, and PAR was indicated by an optimal SBC value (SBC=182.62). Results on the VALIDATION data indicated the same three variable model had the lowest ASE (see Figure 1). Table 5 contains the coefficients for the best fitting and validated three variable model predicting overall health-related fitness. All model coefficients were significant (ps<.05) and the overall model explained a large percentage of variance in health-related fitness scores (F=107.8, p<.001, R^2=.82, SEE=3.09).

Table 6 contains construct validity evidence for the newly predicted overall health-related fitness scores using the SCORING data. Specifically, this table displays mean fitness scores from the new prediction equation on two groups that theoretically have different levels of fitness. Results showed that athletes ($Mean$=54.9, SD=5.1) had a significantly (p<.001) greater mean fitness score than non-athletes ($Mean$=39.8, SD=4.8). Therefore, these results indicate that the new fitness score can discriminate between two groups with known differences in health-related fitness.

Table 1. Descriptive statistics of all study variables

	Male (N=62)		Female (N=33)	
Variable	*Mean*	*SD*	*Mean*	*SD*
Age (yr)	20.9	3.70	22.6	6.10
VJ (in)	23.4	3.84	15.2	3.33
PBF (%)	14.1	6.51	23.3	4.85
BMI (kg/m^2)	27.1	4.56	24.2	3.34
WC (cm)	84.9	8.00	74.1	7.71
BP (lb)	216.4	46.89	95.2	19.55
LP (lb)	564.6	143.97	310.7	101.40
PU (#)	32.0	13.28	27.3	10.68
FAH (sec)	34.5	19.34	22.9	16.93
VO2 (ml/kg/min)	36.8	7.88	30.1	6.78
PAR (0 thru 10)	6.8	2.47	5.2	2.75
SNR (cm)	27.8	7.96	34.1	7.02

Note. VJ is vertical jump. PBF is percent body fat. BMI is body mass index. WC is waist circumference. BP is bench press. LP is leg press. PU is push-up. FAH is flexed arm hang. VO2 is oxygen consumption. PAR is physical activity rating. SNR is sit-and-reach. Significant (ps<.05) mean sex differences were seen on all variables, except Age (p=.142) and PU (p=.070).

Table 2. Correlation matrix of all dependent variables for males (bottom) and females (top)

Variable	Age	VJ	PBF	BMI	WC	BP	LP	PU	FAH	VO2	PAR	SNR
Age (yr)	1	**-.429**	**.389**	.302	.208	-.085	.113	**-.372**	-.272	**-.374**	**-.382**	.011
VJ (in)	**-.298**	1	**-.721**	**-.534**	**-.377**	**.355**	.209	**.447**	**.761**	**.704**	**.650**	.087
PBF (%)	.107	**-.399**	1	**.583**	**.347**	-.203	-.070	-.238	**-.606**	**-.629**	**-.627**	-.046
BMI (kg/m^2)	.185	**-.347**	**.817**	1	**.842**	.316	.328	-.211	**-.648**	**-.418**	-.304	.074
WC (cm)	**.278**	**-.458**	**.644**	**.762**	1	.343	**.479**	-.250	**-.528**	-.271	-.262	.091
BP (lb)	-.214	**.465**	.158	**.359**	.154	1	**.505**	**.470**	.147	**.450**	**.624**	**.373**
LP (lb)	.186	-.038	**.314**	**.531**	**.536**	**.454**	1	.195	.192	.284	.279	.296
PU (#)	-.229	**.456**	**-.397**	**-.260**	**-.399**	**.378**	.071	1	**.491**	**.549**	**.656**	.146
FAH (sec)	-.204	**.390**	**-.608**	**-.582**	**-.611**	-.064	**-.288**	**.556**	1	**.590**	**.565**	.172
VO2 (ml/kg/min)	**-.389**	**.448**	**-.522**	**-.504**	**-.530**	.088	-.233	**.349**	**.376**	1	**.834**	.138
PAR (0 thru 10)	**-.279**	**.331**	**-.544**	**-.408**	**-.360**	**.266**	-.016	**.660**	**.467**	**.628**	1	.278
SNR (cm)	-.117	.215	-.130	.002	-.128	.225	.185	**.316**	**.278**	.239	**.285**	1

Note. N=62 for males (below the diagonal). N=33 for females (above the diagonal). VJ is vertical jump. PBF is percent body fat. BMI is body mass index. WC is waist circumference. BP is bench press. LP is leg press. PU is push-up. FAH is flexed arm hang. VO2 is oxygen consumption. PAR is physical activity rating. SNR is sit-and-reach. Bold values are significant (p < .05).

Table 3. Traditional Model Selection by R-square Criteria

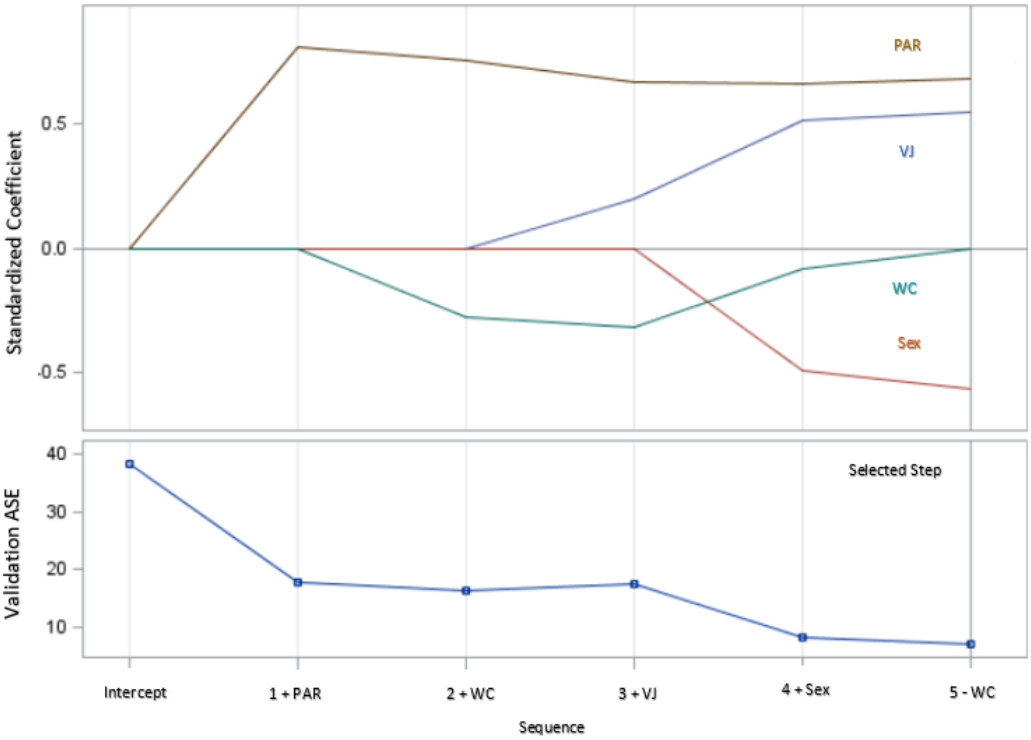
# of Variables	Adj R^2	R^2	Variable(s)
1	.638	.642	PAR
1	.288	.295	FAH
2	.698	.705	WC,PAR
2	.689	.696	Sex, PAR
3	.815	.821	VJ, Sex, PAR
3	.718	.727	FAH, Sex, PAR
4	.816	.824	VJ, Sex, PAR,FAH
4	.815	.823	VJ, Sex, PAR, SNR
5	.818	.827	VJ, Sex, PAR, FAH, LP
5	.816	.826	VJ, Sex, PAR, FAH, SNR

Note. Outcome variable was overall fitness score (mean T-score) constructed from VO2, BP, PU, and PBF. Only the top two models from each set of *p* predictors is shown.

Table 4. Honest assessment predictive modeling using both training and validation data

Step	Entered	Removed	#	SBC	ASE	ASE'
0	Intercept		1	298.2953	50.3855	38.2666
1	PAR		2	222.625	17.3432	17.6759
2	WC		3	209.1686	13.6838	16.3037
3	VJ		4	204.5163	12.1414	17.2988
4	Sex		5	185.412	8.8847	8.0197
5		WC	4	**182.6243**	9.0678	**6.9848**

Note. Outcome variable was overall fitness score (mean T-score) constructed from VO2, BP, PU, and PBF. Bold values are optimal. # indicates number of parameters in model. SBC is Schwarz Bayesian criterion. SBC (n*log(SSE/n)+p*log(n)) is criterion used by the stepwise procedure on training data. A lower SBC is optimal. ASE is average squared error (sum of squared differences between the observed value and predicted value divided by number of cases) based on training data. A lower ASE is optimal. ASE' is on validation data and used to select the final model.



Note. Steps 1 thru 4 variables were added (+). Step 5 WC was removed (-) due to drop in validation ASE.

Figure 1. Variable progression for stepwise selection based on SBC and validation ASE

Table 5. Final prediction equation from honest assessment procedure

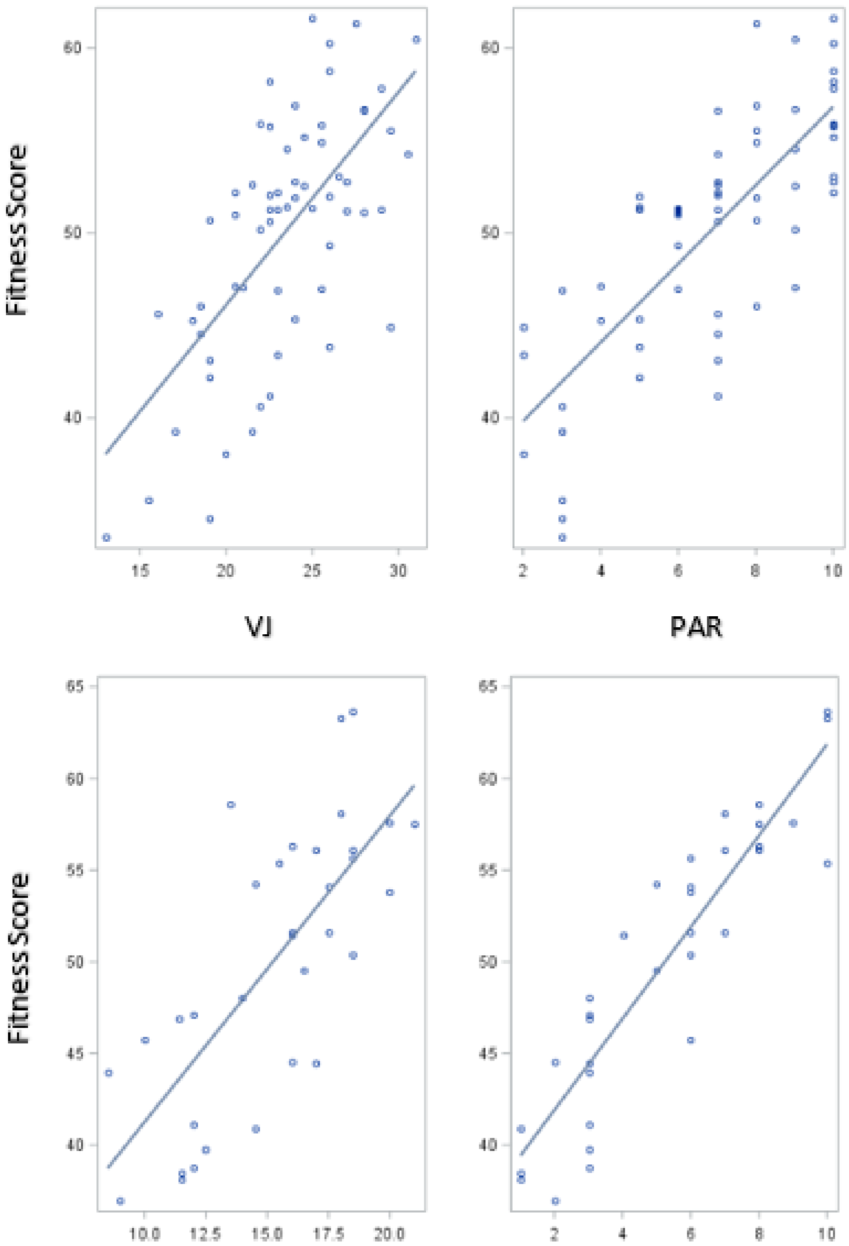
Variable	*DF*	*Estimate*	*Beta*	*SE*	*t*	*p*
Intercept	1	28.452	0.000	1.660	17.14	<.001
VJ (in)	1	0.760	0.548	0.109	6.99	<.001
Sex (1/0)	1	-8.733	-0.567	1.121	-7.79	<.001
PAR (0 thru 10)	1	1.819	0.679	0.150	12.14	<.001

Note. Equation is from training data predicting overall health-related fitness score (T-score). Sex is 1 for male or 0 for female. VJ is in inches. PAR ranges from 0 to 10. Model statistics: F=107.8, p<.001, R^2=.82, *SEE*=3.09.

Table 6. Known-groups validity of new fitness scores from new sample

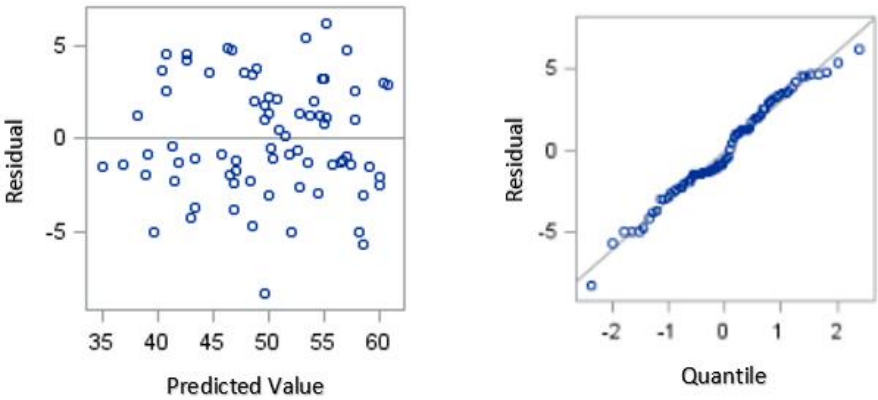
	Athlete (N=16)		Non-Athlete (N=8)	
Variable	*Mean*	*SD*	*Mean*	*SD*
Fitness Score	54.9	5.12	39.8	4.77

Note. Mean fitness scores (T-scores) were significantly (p<.001) different.



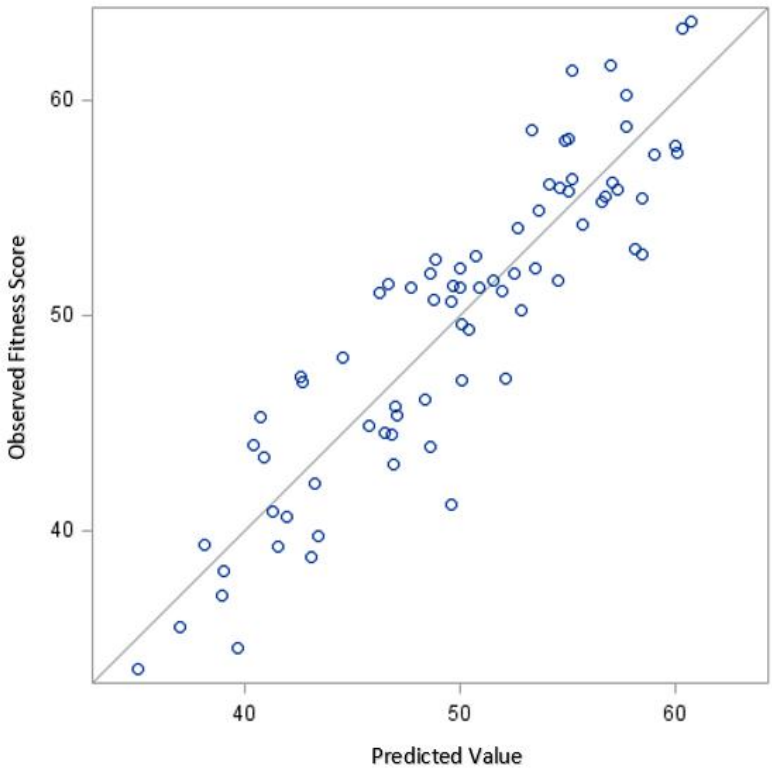
Note. Plots of fitness score by VJ (left) and PAR (right) confirm that the linearity assumption is met for males (above) and females (bottom). Data in graphs are from the training dataset.

Figure 2. Predictive model post-fitting: Check on assumptions



Note. Residual by predicted value plot (left) and normal quantile plot (right) confirm that the normal errors with mean of zero, equal variance, and independence assumptions are met. Data in graphs are from the training dataset.

Figure 3. Predictive model post-fitting: Check on assumptions



Note. Data in graph are from the training dataset.

Figure 4. Graph of observed fitness score by model predicted fitness score

Model post-fitting was conducted to ensure the quality of the selected prediction equation. Specifically, quantitative predictors were found to satisfy the assumption of linearity (see Figure 1). Additionally, residuals were found to be approximately normal with mean of zero and constant variance (see Figure 3). Finally, other regression diagnostics indicated an adequate final model, such as checks on COOK's *D* values (all *D*s<0.04), *DFFITS* values (all *DFFITS*<0.41), *DFBETA*s (all *DFBETA*s<0.21), and *VIF*s (all *VIF*s<5).

4. Discussion

The purpose of this study was to build a valid equation that can easily predict overall health-related fitness using honest assessment predictive modeling. Results from the assessment proved successful in that a parsimonious model was identified using a training dataset and then validated using a hold-out dataset. The independent variables in the final model predicting overall health-related fitness were VJ, sex, and PAR. Additionally, the final three-predictor model explained a large percentage of variance in overall health-related fitness. Moreover, these predictors are easily measured by participants. For example, a VJ test can be administered using any wall with high ceilings, chalk for participant fingers, and a tape measure. More simply, sex and PAR can be assessed easily by asking two questions. Therefore, the modeling process to find a simpler set of variables that can predict overall health-related fitness was effective. These findings are consistent with a recent study that showed VJ scores were related to other health-related fitness scores from a fitness test battery [35].

A secondary objective of this study was to provide construct validity evidence for the new overall health-related fitness score. This objective was assessed by using the new prediction equation to create fitness scores from individuals in a follow-up dataset and comparing the scores between athletes and non-athletes. Results from this part of the study was also successful since athletes in the sample had a significantly greater health-related fitness score than the non-athletes. This evidence suggests that the new fitness score is sensitive enough to detect fitness differences between two groups of individuals that theoretically possess different fitness levels.

To date, the evidence supporting parsimonious health-related fitness prediction equations is sparse. There are, however, published studies that have built prediction equations for specific fitness components. For example, one such study developed a set of regression equations capable of predicting maximal oxygen consumption in men using only non-exercise variables such as age, BMI, smoking status, resting heart rate, physical activity, and race [36]. A similar study on adults built a non-exercise equation predicting maximal oxygen consumption using only sex, age, BMI, perceived functional ability, and a rating of physical activity [37]. Finally, a study more similar to the current research, built valid equations predicting peak power and mean power using only sex, body mass and a participant estimate of relative jumping ability [38]. Although these studies sought to build parsimonious prediction equations using variables that were easy to assess, their equations were only predicting a specific fitness component. Therefore, the results from this study are novel.

The strengths of this study are worth mentioning. As previously stated, a major strength in this study was its use of several different fitness tests in building the complete prediction equation. Specifically, the computed outcome variable contained relative values of cardiorespiratory endurance, muscular strength, muscular endurance, and body composition and therefore represented an overall health-related fitness construct. A second strength of this study was its use of the honest assessment procedures. The use of honest assessment ensured that the final model was valid based on statistical criteria applied to an independent hold-out sample. Furthermore, the addition of the construct validity portion of the study provided another source of evidence supporting the legitimacy of the prediction equation.

The limitations in this study should be mentioned. The most important limitation to discuss regarding these findings is the generalizability of the final prediction equation. That is, the final model resulting from this research was developed using college students attending a smaller rural public university. Therefore, as in any regression equation scenario, the final model in this study should not necessarily be used on individuals outside the population from which it was built [39]. A second limitation regarding the findings from this study is the use of field test scores for constructing the outcome variable in the model. Although laboratory tests may have added a greater degree of control over the assessment procedures, the tests used to compute the outcome variable in this study are considered criterion field tests [40,41,42,43].

5. Conclusions

This study presents a valid equation that can simply predict overall health-related fitness in college students. The novel aspect of the prediction equation is the simplicity of its inputs which include a VJ score, sex, and an answer to a single PAR question. Fitness professionals should consider promoting VJ testing as a simple correlate to overall health-related fitness.

Acknowledgements

No financial assistance was used to assist with this project.

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