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Orginal Research Article

Discriminant Function Analysis Predicts Three Different Obesity Measures Using Fitness Scores

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Abstract: Background: The relationship between obesity and fitness among generally healthy adults is unclear. The purpose of this study was to determine if a set of fitness test scores can reasonably predict obesity membership better than chance. **Methods**: Data used for this study came from a fitness assessment of N=87 male college students. Fitness scores included bench press (BP), leg press (LP), push-up (PU), maximal oxygen consumption (VO2max), sit-and-reach (SNR), vertical jump (VJ), curl-up (CU), and grip strength (GS). Three different body composition (BC) measures were used to create obesity categories: waist circumference (WC), body mass index (BMI), and percent body fat (PBF). Discriminant function analysis was used to find linear algorithms that best separate obesity groups. **Results**: Discriminant functions included VO2max, BP, and VJ as predictors for the BMI analysis (r_{can} = .59, p < .001) and LP, PU, and VO2max as predictors for both the PBF (r_{can} = .63, p < .001) and WC (r_{can} = .55, p < .001) analyses. All three discriminant functions significantly predicted obesity membership better than chance (BMI = 83.9%, PBF = 94.3%, WC = 94.3%, ps < .001). **Conclusion**: Results from this study indicate that fitness attributes can be used to successfully predict obesity in generally healthy males.
Keywords: Health-related fitness, Obesity, Discriminant function analysis.

INTRODUCTION

Obesity is a major health problem with negative associations to several chronic diseases and many debilitating illnesses (Lundeen, E. A. *et al.*, 2018; Shakiba, M. *et al.*, 2019). Recent findings estimate over 90 million American adults and over 15 million American youth are obese (Quick Stats. 2018). Despite the over-preponderance of research supporting obesity as a public health problem, the obesity paradox has appeared in the literature to counter such negative relationships in certain health outcomes (Oesch, L. *et al.*, 2017; McAuley, P. A. 2018, June). One theoretical explanation for the obesity paradox is the increased muscle mass that correlates with increased body mass in obese individuals (Wannamethee, S. G. *et al.*, 2014). Additionally, higher physical fitness may be associated with increased muscle mass, also supporting the paradox (Boo, S. H. *et al.*, 2019). In light of these contradictions, few studies have examined various attributes of fitness simultaneously in relation to obesity in generally healthy adults. Therefore, the purpose of this study was to determine if a set of field-based fitness test scores could predict obesity, using three different body composition measures, in adult male participants.

METHODS

Participants and Design

Data for this research came from a cross-sectional fitness assessment where N=87 college males attending a rural public university volunteered to participate in a series of health-related fitness tests. Students were recruited by campus flyers and word-of-mouth and offered free fitness evaluation in exchange for their participation. Study components and protocols were reviewed and approved by the university system's institutional review board (IRB).

Body Composition (BC) and Obesity Measures

BC was assessed using three different methods: 1) body mass index (BMI), 2) percent body fat (PBF) by handheld bioelectric impedance technique, and 3) waist circumference (WC). BMI (kg/m^2) was assessed by measuring height with a wall-mounted stadiometer and measuring weight with an electronic floor scale (American College of Sports Medicine.

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2013). PBF was assessed with an Omron handheld device and followed manufacturer's procedures (Omron Fat Loss Monitor. 2012). Finally WC was measured at the narrowest location between the umbilicus and xiphoid process (American College of Sports Medicine. 2013). Obesity classification was determined if participants had a BMI > 30 kg/m^2, PBF ≥ 25%, or WC > 102 cm.

Physical Fitness Test Battery

Eight different fitness tests were used in this study, including: 1RM bench press test (BP) (American College of Sports Medicine. 2013), 1RM leg press test (LP) (American College of Sports Medicine. 2013), maximal repetition push-up test (PU) (American College of Sports Medicine. 2013), maximal oxygen consumption (VO2max) by multi-stage fitness (beep) test (Ramsbottom, R. *et al.,* 1988), sit-and-reach test (SNR) (American College of Sports Medicine. 2013), vertical jump test (VJ) (Haff, G., & Triplett, N.T. 2016), maximal repetition curl-up test (CU) (American College of Sports Medicine. 2013), and maximal grip strength test (GS) (Suni, J. *et al.,* 2009).

Statistical Analyses

Descriptive statistics were computed and exploratory analyses conducted on all independent variables. Skewness and kurtosis values (reported as *Z* statistics) smaller than |3.30| were considered acceptable (Kim, H.Y. 2013). Discriminant function analysis procedures included a series of five analytical steps. First, a stepwise discriminant analysis was performed for each obesity dependent variable using PROC STEPDISC to find parsimonious sets of fitness score predictors. Second, each specific obesity measure model was inspected for assumptions related to discriminant function analysis. Specially, multivariate normality, lack of outliers, linearity, homogeneity of covariance matrices between groups, and lack of multicollinearity were checked for each of the three discriminant function models. Multivariate normality was checked using the %MULTNORM SAS macro (Liu, M. 2015). Each model showed slight tendency toward non-multivariate normality due to the non-normal nature of PU, BP, and LP. However, after log transformations showed appropriate multivariate normality but no differences in either discriminant function results, analyses on the original variables were reported. This decision also made sense since discriminant function analysis is robust to failures of normality if violations are caused by skewness rather than outliers (Tabachnick, B.G. *et al.,* 2013). Continuing assumption checking, outliers were checked using the SAS %OUTLIER macro (McQuown, G. 2000), linearity was assessed by inspecting Pearson correlation coefficients, homogeneity of covariance matrices was checked using Box's M test, and multicollinearity was assessed by inspecting each variable's variance inflation factor (VIF) using PROC REG. Third, analysis of variance (ANOVA) was run to examine mean fitness score differences across obesity groups. Fourth, discriminant functions were computed for each obesity measure model along with associated statistics, such as the discriminant function z-score cutoff and the canonical correlation coefficient (r_{can}). Fifth, classification functions were computed and subsequently used to validate the discriminant functions in terms of the percentage of participants correctly placed into their actual obesity classification by the functions. All analytical steps followed general multivariate data analysis recommendations (Tabachnick, B.G. *et al.,* 2013; Hair, J.F. *et al.,* 2006). All statistical analyses were performed using SAS version 9.4 (SAS Institute. 2008).

RESULTS

All N=87 male participants (Mean age 21.2 yr.) had complete fitness and body composition data. Table 1 contains descriptive statistics on all possible independent variables in the study. For samples of medium size, skewness and kurtosis values were all acceptable. As seen in Table 1, both muscular endurance tests (PU & CU) showed the greatest amount of variability among male participants.

Table 2 contains ANOVA results for each of the three obesity measures and associated best predictors from the stepwise discriminant analyses. Within each model, each predictor saw a significant ($p < .05$) difference across obesity classification. Moreover, each difference indicated inferior fitness in obese participants, with exception of both BP and LP, where obese individuals showed superior muscular strength.

Table 3 contains results from each discriminant function analysis. The structure column contains total canonical structure values which are simply bivariate correlation coefficients between each fitness attribute and the discriminant function fitness scores (i.e., *Z* scores). In this analysis, positive discriminant function *Z* scores represent greater fitness. For example, structure coefficients for the BMI discriminant function analysis are .70, -.51, and .48 for VO2max, BP, and VJ, respectively. Therefore, VO2max and VJ are both directly related and BP indirectly related to the discriminant function fitness scores. The pattern of structure coefficients follow similarly to the ANOVA analyses, where BP and LP are both indirectly related to fitness scores. The DF column consists of the canonical discriminant function, discriminant function group means, and the discriminant function cutoff value which is the weighted average of the two group means. Each of the three analyses shows good discriminant function means separation. Additionally, all three discriminant function analyses were significant (*p*s < .05) with moderately strong effects (r_{can}s). Finally, in Table 3, obese and non-obese columns contain the classification functions, where the larger of the two scores would indicate participant obesity membership. The classification functions can be used to validate the discriminant functions, reported in the following section.

Table 4 contains results from the discriminant function classification functions, used on the current study sample. The overall percentage correct (percentage of participants who were correctly placed into their current obesity group by the discriminant function) was acceptable (> 83%) across all three analyses. Additionally, three separate statistical tests were conducted to validate the classification accuracy. The binomial test, using a null value of chance (50% correct classification), was significant (*ps* < .05) across each of the three analyses. Press's *Q* test, also using a null value of chance (50% correct classification), was significant (*ps* < .05) across each of the three analyses. Finally, the McNemar chi-square test, with a null hypothesis of no change in predicted from observed obesity classification, was not significant (*ps* ≥ .05) across each of the three analyses.

Table 1. Descriptive statistics for all fitness variables (N=87).

Variable	*Mean*	*SD*	*Median*	*Min*	*Max*	*CV*	*Skewness*	*Kurtosis*
BP	235.23	64.04	225.00	115.00	450.00	27.22	2.75	1.17
LP	593.51	165.24	550.00	270.00	900.00	27.84	1.47	-1.69
PU	35.43	15.89	32.00	8.00	83.00	44.85	2.31	-0.52
VO2max	36.85	8.01	35.80	20.20	57.50	21.72	0.84	-0.65
SNR	28.99	8.83	29.00	9.00	49.00	30.45	-0.19	-0.51
VJ	23.53	4.34	23.50	13.00	36.50	18.46	0.25	-0.21
CU	54.16	21.58	61.00	13.00	75.00	39.84	-1.27	-2.99
GS	54.74	8.63	53.30	32.00	77.50	15.77	1.14	-0.90

Note. BP is bench press. LP is leg press. PU is push-up. VO2max is maximal oxygen consumption. SNR is sit-and-reach. VJ is vertical jump. CU is curl-up. GS is grip strength. Skewness and kurtosis are reported as *Z* statistics where *Z* values smaller than |3.30| were considered acceptable.

Table 2. Comparison of fitness test performance across obesity groups.

Method	Non-Obese			Obese			
Variable	*N*	*Mean*	*SD*	*N*	*Mean*	*SD*	*p*
BMI	66			21			
VO2max		38.70	7.62		31.04	6.58	<.001
BP*		224.55	56.10		268.81	77.78	.005
VJ		24.23	4.09		21.36	4.60	.008
PBF	72			15			
LP*		570.76	158.35		702.67	164.60	.005
PU*		38.07	15.69		22.73	10.59	.001
VO2max		38.88	7.11		27.14	4.42	<.001
WC	79			8			
LP*		572.78	158.01		798.13	92.04	<.001
PU*		36.58	15.85		24.00	13.14	.033
VO2max		37.90	7.52		26.49	5.61	<.001

Note. BMI is body mass index. PBF is percent body fat. WC is waist circumference. Actual obesity classification was determined if participants had a BMI > 30 kg/m^2, PBF ≥ 25%, or WC > 102 cm. *Log transformed variables showed similar results as original variables, therefore, analyses with original variables is reported.

Table 3. Discriminant function analysis results for obesity grouping from fitness attributes (N=87).

BMI					PBF					WC				
Variable	Structure	DF	Non-obese	Obese	Variable	Structure	DF	Non-obese	Obese	Variable	Structure	DF	Non-obese	Obese
VO2max	.698	.0804	0.4904	0.3560	LP*	-.480	-.0032	0.0236	0.0303	LP*	-.722	-.0048	0.0265	0.0372
BP*	-.505	-.0141	0.0128	0.0364	PU*	.580	.0314	0.0063	-0.0601	PU*	.419	.0244	-0.0327	-0.0872
VJ	.482	.1499	0.9666	0.7161	VO2max	.881	.1034	0.8709	0.6523	VO2max	.755	.0734	0.7396	0.5758
Constant		-3.1645	-22.9129	-19.4914	Constant		-3.0476	-23.9640	-20.5549	Constant		-.7178	-21.1059	-23.8241
Means					Means					Means				
Non-obese		0.4034			Non-obese		0.3644			Non-obese		0.2050		
Obese		-1.2680			Obese		-1.7491			Obese		-2.0246		
Cutoff		-0.8645			Cutoff		-1.2389			Cutoff		-1.4865		
r_{can}	.586				r_{can}	.628				r_{can}	.546			
F, λ, p	14.49, .656, <.001				F, λ, p	18.05, .605, <.001				F, λ, p	11.75, .702, <.001			
χ^2, p	10.51, .1046				χ^2, p	7.66, .264				χ^2, p	4.86, .562			

Note. r_{can} is the canonical correlation coefficient. *F* statistic is for Wilks' Lambda (λ). χ^2 statistic is for Anderson's test for homogeneity of variance-covariance matrices. The largest *VIF* in all models was 1.42, ensuring lack of multicollinearity. *Log transformed variables showed similar results as original variables, therefore, analyses with original variables is reported. Structure column is total canonical structure (bivariate correlations between each fitness attribute and the discriminant function *Z* scores, where positive Z scores represent greater fitness). DF column is the canonical discriminant function. DF cutoff is the weighted average of the two group means. Obese and non-obese columns are the classification functions, where larger of the two scores would indicate membership. Actual obesity classification was determined if participants had a BMI > 30 kg/m^2, PBF ≥ 25%, or WC > 102 cm.

Table 4. Classification results from use of discriminant functions (N=87).

BMI	Predicted		PBF	Predicted		WC	Predicted	
Observed	Non-obese	Obese	Observed	Non-obese	Obese	Observed	Non-obese	Obese
Non-obese	61	5	Non-obese	71	1	Non-obese	78	1
%	92.4	7.6	%	98.6	1.4	%	98.7	1.3
Obese	9	12	Obese	4	11	Obese	4	4
%	42.9	57.1	%	26.7	73.3	%	50.0	50.0
Overall % correct	83.9	<.001	Overall % correct	94.3	<.001	Overall % correct	94.3	<.001
Press's *Q*	40.0	<.001	Press's *Q*	68.2	<.001	Press's *Q*	68.2	<.001
χ^2_M	1.14	.285	χ^2_M	1.80	.180	χ^2_M	1.80	.180

Note. Binomial test used to test the overall % correct as compared to chance. Press's *Q* is a test of discriminatory power as compared to chance. χ^2_M is McNemar chi-square test. Classification analyses with log transformed variables showed similar results as classification analyses with original variables, therefore, analyses with original variables is reported. Actual obesity classification was determined if participants had a BMI > 30 kg/m^2, PBF ≥ 25%, or WC > 102 cm.

DISCUSSION

The primary purpose of this study was to determine if a set of field-based fitness test scores could predict obesity classification in generally healthy adult males. After beginning the research with a set of eight fitness test scores spanning several different components of fitness, results indicate that three fitness scores can successfully and accurately predict obesity classification. These results were consistent across each of the three obesity measures (BMI, PBF, and WC). Several aspects of these results are noteworthy. Firstly, given that a stepwise selection procedure was used to determine the best and most parsimonious set of predictors, it is worth highlighting that VO2max was a final predictor in each obesity measure model. Additionally, VO2max, a measure of cardiorespiratory fitness, was directly related to the discriminant function scores and saw greater values in non-obese males.

Secondly, similarly to the previous comment, it is worth underscoring that a measure of muscular strength (LP or BP) was in each of the three discriminant function models. However, unlike VO2max, muscular strength measures were indirectly associated with discriminant function scores but saw greater values in obese males. This noteworthy finding may suggest that slow maximal strength may be more so a predictor of obesity and less so a predictor of overall fitness. This point is also emphasized by the fact that the PBF and WC discriminant function models each included a measure of muscular endurance (PU) and the BMI model included a measure of high speed strength (VJ), each showing greater values in non-obese males. These comments in summary suggest further research is needed to examine the extent to which muscular strength contributes to health-related fitness and/or determining if a ceiling effect exists in the relationship between slow speeds muscular strength and health outcomes such as obesity.

Results from this research should be considered along with its limitations. One limitation of this study is the use of field-based body composition measures to assess obesity. Despite these limitations, measures were taken to minimize measurement error during data collection. Additionally, body composition measures used in this study were previously found to be both valid and reliable among the study population (Hart, P. D. 2017; Hart, P. D. 2017). A final limitation of this study is the fact that only generally healthy males were used as participants. Therefore, results from this study should not be confused as pertaining to other populations.

CONCLUSIONS

Results from this research indicate that fitness attributes of generally healthy males can be used to successfully predict obesity. Discriminant function fitness scores were greater (indicating greater fitness) for non-obese males than for obese males. Additionally, fitness measures of slow speed maximal strength were indirectly associated with discriminant function fitness scores. Although further research is warranted, slow speed maximal strength may not provide benefit in obesity prevention.

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