Is predicted body-composition and relative fat mass an alternative to body-mass index and waist circumference for disease risk estimation

Cichosz, Simon Lebech; Rasmussen, Nicklas Højgaard-Hessellund; Vestergaard, Peter; Hejlesen, Ole

Published in:
Diabetes & Metabolic Syndrome: Clinical Research & Reviews

DOI (link to publication from Publisher):
10.1016/j.dsx.2022.102590

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Diabetes & Metabolic Syndrome: Clinical Research & Reviews 16 (2022) 102590

Contents lists available at ScienceDirect

Diabetes & Metabolic Syndrome: Clinical Research & Reviews

journal homepage: www.elsevier.com/locate/dsx

Is predicted body-composition and relative fat mass an alternative to body-mass index and waist circumference for disease risk estimation?

Simon Lebech Cichosz [a, *], Nicklas H. Rasmussen [b], Peter Vestergaard [b], Ole Hejlesen [a]

[a] *Department of Health Science and Technology, Aalborg University, Denmark*
[b] *Steno Diabetes Center North Denmark, Aalborg University Hospital, Aalborg, Denmark*

A R T I C L E I N F O

Article history:
Received 22 April 2021
Received in revised form
29 July 2022
Accepted 31 July 2022

Keywords:
Diabetes
Coronary heart disease
High blood pressure
Hospitalization
Cancer
Arthritis
Predicted body composition
Body mass index
Waist circumference

A B S T R A C T

Background and aims: New methods to estimate body-composition have recently been proposed, but their relation to diseases, such as diabetes and coronary heart disease, needs further investigation. The purpose of this study was to investigate the association between proposed prediction of body-composition (PBC); Relative Fat Mass (RFM), Body Mass Index (BMI), Waist Circumference (WC) and disease.

Methods: In a cross-sectional cohort (NHANES) the association between the four body measures and diabetes, high blood pressure, coronary heart disease, cancer, arthritis, and hospitalization were assessed. A total of 13,348 people was included in this study. Receiver operating characteristic (ROC), Area Under Curve (AUC) and statistical testing were used to evaluate the differences.

Results: PBC/RFM had significant higher AUC than BMI or WC for diabetes, high blood pressure, hospitalization, and arthritis. PBC had a significant higher AUC than RFM, BMI, WC for Cancer and coronary heart disease.

Conclusions: RFM and PBC could be a better indicator to distinguish amongst people with a risk of diseases compared to traditional measures such as BMI and WC. However, future studies need to investigate the longitudinal association between RFM, PBC and the risk of disease development to assess if these measures are better suited for risk-stratification.

1. Introduction

Commonly used body metrics such as body mass index (BMI) and waist circumference (WC) does not sufficiently describe the association between the fat mass distribution and the lean body mass and the potential risk of developing diseases [1,2]. Currently, the gold standard is a dual energy x-ray absorptiometry (DXA) scan, [3,4]. With DXA scans it is possible to divide fat mass into Subcutaneous Adipose Tissue (SAT) and Visceral Adipose Tissue (VAT) [5]; However, DXA scans require a comprehensive set-up and access to hospital equipment.

Therefore, alternative and simpler methods have been proposed to measure body fat percentage, fat mass, muscle mass and distribution of fat [6]. Orison et al. proposed equation to estimate the Relative Fat Mass (RFM), as a measurement of whole-body fat percentage, and found a better correlation with DXA scans than BMI [6]. Furthermore, Cichosz et al. proposed a method to predict body fat, trunk fat and lean mass from anthropometric measurements [7,8]. The predicted results were highly associated with whole body DXA scan estimates. However, the accuracy of these alternative methods to determine the correlation between body composition and diseases is still unknown.

Therefore, the purpose of this study was to investigate PBC, RFM, BMI, WC, and their association to diseases such as type 2 diabetes (T2D), hypertension, coronary heart disease (CHD), cancer, and hospitalization.

2. Subjects, materials and methods

2.1. Data material

The study cohort was derived from participants in the cross-sectional National Health and Nutrition Examination Survey (NHANES) 1999–2006. The survey included home interviews of participants followed by physical examinations with additional laboratory measurements.

* Corresponding author. Fredrik Bajers Vej 7D2, DK-9220, Aalborg, Denmark.
E-mail address: simcich@hst.aau.dk (S.L. Cichosz).

https://doi.org/10.1016/j.dsx.2022.102590

2.2. Study population

The inclusion criteria for the cohort were people of age 18 ≥ who had anthropometric assessment (body measurements), answered the demographic questionnaire, a diabetes questionnaire, and a general medical conditions questionnaire. A detailed description of the NHANES procedure is available online [9]. A total of 13,348 people was eligible for inclusion in the cohort.

2.3. Predictors

Our data set included four different types of predictors for classification of disease;

BMI was derived from weight and height of individuals.

WC was measured accordingly to the NHANES procedure. RFM was calculated from height, WC and sex, based on equation (1) (sex = 0 for male, sex = 1 for female). Predicted body composition (PBC) (predicted total lean body mass, total fat mass and fat mass of the trunk) were based on neural network prediction using demographic information and anthropometric measurements (age, sex and ethnicity, height, weight, BMI, upper leg length, maximal calf circumference, upper arm length, arm circumference, WC, thigh circumference, triceps skinfold, and subscapular skinfold). The procedure for calculating the predicted value were published elsewhere [7].

$$RFM = 64 - \left(20 \times \left(\frac{\text{height}}{\text{waist}}\right)\right) + (12 \times \text{ sex}) \tag{1}$$

Equation 1 – calculation of RFM from height, waist circumference and sex.

2.4. Outcome

The outcome was the ability of the different predictor types to distinguish between people with and without diseases. The simple approaches were compared as BMI and WC to the novel proposed body estimators from RFM and PBC. Predicted total lean body mass, total fat mass and fat mass of the trunk required measurement of several body anthropometrics and were calculated by a computer. The outcome was assessed by comparison of receiver operating characteristic Area Under the Curve (AUC) between the simple predictors and novel predictors. The following diseases was investigated: diabetes, High blood pressure (HBP), Coronary heart disease (CHD), Cancer, Arthritis, Hospitalization.

2.5. Statistical analysis and modeling approach

To investigate the potential of PBC (predicted total lean body mass, total fat mass, and fat mass of the trunk) to discriminate between people with and without a disease we constructed logistic regression models. Predicted total lean body mass, total fat mass and fat mass of the trunk were used as independent variables and the morbidities were used as dependent variables. The output from the logistic regression models and the three remaining predictors (BMI, WC, RMF) were separately used to derive receiver operating characteristic (ROC) curve and corresponding areal under the curve (AUC) value for each morbidity.

The dataset was split into 50%/50% for training and testing of the model's predictors. A cross-validation approach was utilized such that the 50% of data were used for training, the remaining 50% were used for testing and then vice versa. Significance of the difference between the areas under independent ROC curves were tested using a Bonferroni corrected significance level of 0.05/number of tests [10].

3. Results

3.1. Cohort and study population characteristics

A total of 13,348 people were included in the study, which represented the analytic cohort (characteristics: Table 1). The ROC analysis is presented in Fig. 1.

3.2. Diabetes

A significant difference in AUC was seen between each method - between PBC vs. RFM ($p = 0.0088$), between RFM vs. WC ($p = 0.0112$), and WC vs. BMI ($p = 0.0019$).

3.3. High blood pressure

A significant difference in AUC was seen between each method - between PBC & RFM vs. WC ($p = 0.0006$), and WC vs. BMI ($p < 0.0001$).

3.4. Hospitalization

A significant difference in AUC (was seen between PBC vs. RFM ($p = 0.0086$), between RFM vs. WC ($p = 0.0085$), but not between WC vs. BMI ($p = 0.0777$).

3.5. Cancer

A significant difference in AUC was seen between PBC vs. RFM ($p < 0.0001$), and WC vs. BMI ($p < 0.0001$).

3.6. Coronary heart disease

A significant difference in AUC was seen between PBC vs. WC ($p = 0.0012$), and RFM vs. BMI ($p < 0.0001$).

3.7. Arthritis

A significant difference in AUC was seen between each method - between PBC vs. RFM ($p = 0.0002$), between RFM vs. WC ($p = 0.0003$), and WC vs. BMI ($p = 0.0004$).

Tabel 1
Characteristics of the participants in the dataset. Presented as mean (standard deviation) or as percentage of the population.

Characteristics	
n	13,348
Males,%	54
Age, yr	47.8 (19.2)
Mexican American	23
Other Hispanic	4
Non-Hispanic White	51
Non-Hispanic Black	19
Other Race - Including Multi-Racial	4
Weight, kilogram	75 (16)
Height, centimeter	168.3 (10.1)
Body mass index, w/h^2	26.4 (4.7)
Diabetes, %	5
High blood pressure, %	19
Hospitalized <1 year, %	11
Cancer, %	8
Coronary heart disease, %	4
Arthritis, %	23

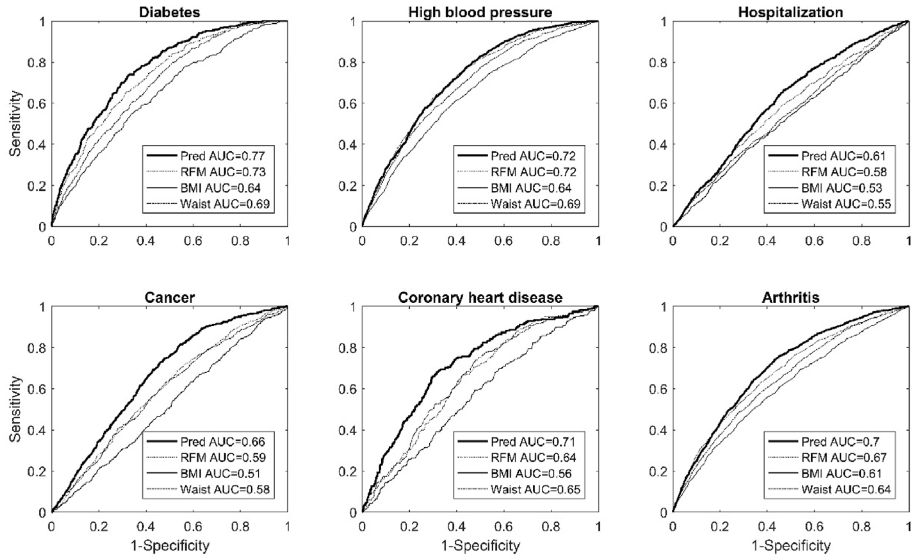

Fig. 1. ROC and AUC for decriminating between disease and no disease using waist circumference (Waist), body mass index (BMI), relativ fat mass (RFM) and predicted body composition (Pred).

4. Discussion

This study investigated the association between commonly used measures of body composition, two newer proposed estimates for body composition and the association to the risk of certain diseases and hospitalization. We compared ROC curves and AUC between the four methods to differentiate five diseases and participants who experienced hospitalization within the last year. A BMI in the range of overweigh and obesity has been associated with an increased risk of T2D and CVD [11]. BMI and WC are easy obtainable measurements, however [12,13], their ability to estimate the risk of developing diseases, is questionable [6,14]. The results from this study showed that BMI has a poor ability to predict the prevalence of T2D, high blood pressure and arthritis. Furthermore, the ability to predict cancer, CHD and hospitalization was insignificant (AUC of 0.5 represents the predictive capability at random) [15,16]. The measurement of WC was superior to differentiate between people with and without disease. However, the ability was poor for all the prediction of WC. These findings could indicate that BMI and WC are poor choices to discriminate disease prevalence without taking additional risk factors into account.

In general, both PBC and RFM predicted the disease prevalence better compared with the traditional measurements. In several cases the PBC approach did also improve the AUC beyond the improvement from RFM. PBC predicted the prevalence of T2D with a high AUC and was superior to RFM, WC and BMI. Furthermore, The PBC approach also predicted the risk of CVD and cancer. In general, the results from this study indicate that predicted body composition measurements could be a beneficial tool to assess the risk of diseases. However, the RFM also added additional information compared to the traditional measurements. Furthermore, it is simple to use with few measurements, as height, weight and waist, often are at hand. On the contrary, PBC requires additional body measurements and a computer program to calculate the prediction. This could be a hurtle if implemented in a clinical set-up, as time-consuming procedures might be deselected.

In general, increasing weight is a proposed increasing problem in modern countries. Obese people or people with elevated BMI in the range of overweight are recommended to lose weight to reduce the risk of disease. However, with insight in Risk Factors and Public health in Denmark developed by the National Board of Health overweight is far from the leading cause of death [17]. Nor the leading cause of disease or early death. Other factors as cancer, smoking, alcohol, loneliness, physical inactivity and poor eating habits are more pronounced. The reason – overweight itself when stratified from the above-mentioned causes only contributes to few causes of death each year. However, identifying the right people at risk with e.g. elevated SAT or PBC is crucial to avoid stigmatization of overweight people and unnecessary examinations and weigh loss procedures. A weight loss could be beneficial in several cases but not only based on an elevated BMI. Both, PBC or RFM could be new and easier methods to identify this specific group of people.

4.1. Strengths

Several strengths should be considered in this study. Among these are aging, which was included in the PBC method. Age is an important factor when estimating body composition. More people are getting older, and BMI is an insufficient measurement when examining the aging population. Studies have found that even though BMI remains relatively stable during aging, there is an increase of fat mass with a redistribution of VAT as well as a decrease of lean mass [18]. Especially, the amount of VAT is associated with developing of disease, hence the BMI could be misleading compared to the PBC method, even at more normal ranged BMI. Furthermore, the PBC method uses neural network prediction with demographic information and anthropometric measurements. Whereas DXA scars are limited due to its levels of radiation (although a small dose), poor availability and it is costly to operate. Furthermore, different ethnicities were included in the PBC method. Even though DXA has been used to examine body composition in recent years, there is still a lack of reference values in the general population from different countries as body composition differs between different ethnic groups [19,20].

4.2. Limitations

This cohort used in this study were a wide representative sample of people with multiple ethnic origin and people with a large anthropometric range. However, some limitations should be addressed. First, a cross-section study does not address the development of diseases and how they progress based on body composition measurements. Several previous studies have shown an association between BMI and WC and the development of diabetes, hypertension and coronary heart disease [21]. A prospective study design could be a better option, in order to recommend RFM and predicted body composition as potential better alternatives to risk stratification of diseases. Secondly, the definition of diseases in the analyzed cohort was based on self-reported current health-status. This might include some uncertainty into labeling of people with and without diseases and also classifying people into disease subclasses. E.g. differentiation between people with T1D/T2D and type of arthritis.

4.3. Conclusion

In general, both PBC and RFM predicted the disease prevalence better compared with the traditional measurements (BMI, WC). The results from this study indicate that predicted body composition measurements could be a beneficial tool to assess the risk of diseases when DXA scan is not available. However, future studies need to investigate the longitudinal association between RFM, PBC and disease development to assess if these measurements are better suited for risk-stratification.

Funding/support

None to disclose.

Data availability

The study cohort was derived from participants in the cross-sectional National Health and Nutrition Examination Survey (NHANES) 1999–2006. Data are available from the Center for Disease Control and Prevention website.

Declaration of competing interest

None to disclose.

Acknowledgements

N/A.

References

[1] Lee DH, Keum N, Hu FB, Orav EJ, Rimm EB, Sun Q, et al. Development and validation of anthropometric prediction equations for lean body mass, fat mass and percent fat in adults using the National Health and Nutrition Examination Survey (NHANES) 1999-2006. Br J Nutr 2017;118:858–66. Cambridge University Press.

[2] Lee DH, Keum NN, Hu FB, Orav EJ, Rimm EB, Willett WC, et al. Predicted lean body mass, fat mass, and all cause and cause specific mortality in men: prospective US cohort study. BMJ 2018 Jul 3;362. k2575.

[3] Buckinx F, Landi F, Cesari M, Fielding RA, Visser M, Engelke K, et al. Pitfalls in the measurement of muscle mass: a need for a reference standard. J. Cachexia, Sarcopenia. Muscle 2018;9(2):269–78.

[4] Erlandson MC, Lorbergs AL, Mathur S, Cheung AM. Muscle analysis using pQCT, DXA and MRI. Eur J Radiol 2016;85(8):1505–11.

[5] Kaul S, Rothney MP, Peters DM, Wacker WK, Davis CE, Shapiro MD, et al. Dual-energy X-ray absorptiometry for quantification of visceral fat. Obesity 2012 Jun;20(6):1313–8.

[6] Woolcott OO, Bergman RN. Relative fat mass (RFM) as a new estimator of whole-body fat percentage – A cross-sectional study in American adult individuals. Sci Rep 2018;8(1):1–11.

[7] Cichosz SL, Rasmussen NH, Vestergaard P, Hejlesen O. Precise prediction of total body lean and fat mass from anthropometric and demographic data: development and validation of neural network models. J. Diabetes Sci. Techn. 2021 Nov;15. https://doi.org/10.1177/1932296820971348.

[8] Cichosz S., Vestergaard P., Hejlesen O. Body composition prediction—BOMP: a new tool for assessing fat and lean body mass. J. Diabetes Sci. Tech.. doi: 10.1177/19322968221076560. In press.

[9] NHANES 1999-2006. Centers for disease Control and prevention (CDC). National center for health statistics (NCHS). National health and nutrition examination survey data. Hyattsville, MD: U.S. Department of health and human services, centers for disease con [Internet]. [cited 2019 Dec 1]. Available from: https://wwwn.cdc.gov/nchs/nhanes/Default.aspx.

[10] Hanley J, McNeil B. The meaning and use of the area under a Receiver Operating Characteristic (ROC) curve. Radiology 1982;143:29–36.

[11] Gray N, Picone G, Sloan F, Yashkin A. Relation between BMI and diabetes mellitus and its complications among US older adults. South Med J 2015;108(1):29–36.

[12] Janiszewski PM, Janssen I, Ross R. Does waist circumference predict diabetes and cardiovascular disease beyond commonly evaluated cardiometabolic risk factors? Diabetes Care 2007 Dec 1;30(12):3105–9.

[13] Wei M, Gaskill SP, Haffner SM, Stern MP. Waist circumference as the best predictor of noninsulin dependent diabetes mellitus (NIDDM) compared to body mass index, waist/hip ratio and other anthropometric measurements in Mexican Americans-A 7-year prospective study. Obes Res 1997 Jan 1;5(1):16–23.

[14] Lee DH, Giovannucci EL. Body composition and mortality in the general population: a review of epidemiologic studies, vol. 243. Experimental Biology and Medicine. SAGE Publications Inc.; 2018. p. 1275–85.

[15] Fawcett T. An introduction to ROC analysis. Pattern Recogn Lett 2006 Jun 1;27(8):861–74.

[16] Metz CE. Basic principles of ROC analysis. Semin Nucl Med 1978 Oct 1;8(4):283–98.

[17] Juel K, Sørensen J, Brønnum-Hansen H. Restorer og folkesundhed i Danmark. Sundhedsstyrelsen; 2006. p. 346.

[18] Kalyani RR, Corriere M, Ferrucci L. Age-related and disease-related muscle loss: the effect of diabetes, obesity, and other diseases. Lancet Diabetes Endocrinol 2014;2(10):819–29.

[19] Bosy-Westphal A, Müller MJ. Identification of skeletal muscle mass depletion across age and BMI groups in health and disease - there is need for a unified definition. Int J Obes 2015;39(3):379–86.

[20] Cruz-Jentoft AJ, Bahat G, Bauer J, Boirie Y, Bruyère O, Cederholm T, et al. Sarcopenia: revised European consensus on definition and diagnosis, vol. 48. Age and Ageing. Oxford University Press; 2019. p. 16–31.

[21] Browning LM, Hsieh SD, Ashwell M. A systematic review of waist-to-height ratio as a screening tool for the prediction of cardiovascular disease and diabetes: 05 could be a suitable global boundary value. Nutr Res Rev 2010;23:247–69.