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Personalised measures of obesity using waist to height ratios from an Australian health screening program

Herbert F Jelinek[1], Andrew Stranieri[2], Andrew Yatsko[2] and Sitalakshmi Venkatraman[3]

Abstract

Objectives: The aim of the current study is to generate waist circumference to height ratio cut-off values for obesity categories from a model of the relationship between body mass index and waist circumference to height ratio. We compare the waist circumference to height ratio discovered in this way with cut-off values currently prevalent in practice that were originally derived using pragmatic criteria.

Method: Personalized data including age, gender, height, weight, waist circumference and presence of diabetes, hypertension and cardiovascular disease for 847 participants over eight years were assembled from participants attending a rural Australian health review clinic (DiabHealth). Obesity was classified based on the conventional body mass index measure (weight/height^2) and compared to the waist circumference to height ratio. Correlations between the measures were evaluated on the screening data, and independently on data from the National Health and Nutrition Examination Survey that included age categories.

Results: This article recommends waist circumference to height ratio cut-off values based on an Australian rural sample and verified using the National Health and Nutrition Examination Survey database that facilitates the classification of obesity in clinical practice. Gender independent cut-off values are provided for waist circumference to height ratio that identify healthy (waist circumference to height ratio $\geq$0.45), overweight (0.53) and the three obese (0.60, 0.68, 0.75) categories verified on the National Health and Nutrition Examination Survey dataset. A strong linearity between the waist circumference to height ratio and the body mass index measure is demonstrated.

Conclusion: The recommended waist circumference to height ratio cut-off values provided a useful index for assessing stages of obesity and risk of chronic disease for improved healthcare in clinical practice.

Keywords

Obesity, body mass index, waist circumference to height ratio, data mining, personalised healthcare, National Health and Nutrition Examination Survey

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Introduction

Changes in lifestyle have led to an increase in chronic disease including obesity with numbers more than doubling in the USA from 15% in 1980 to 34% in 2006.[1,2] Worldwide, the proportion of the population being overweight or obese is reaching 40%, further leading to a rise in comorbidities.[2,3] Accurate measurement and

[1]Charles Sturt University, Australia
[2]Federation University, Australia
[3]Melbourne Polytechnic, Australia

Corresponding author:
Sitalakshmi Venkatraman, Melbourne Polytechnic, 144 High Street, Prahran, VIC 3181, Australia.
Email: SitaVenkat@melbournepolytechnic.edu.au

individual tracking of obesity is essential for managing risks of chronic disease[4,5] and evaluating prevention programs.[6–8] Body mass index (BMI), waist circumference (WC), and waist circumference to height ratio (WCHR) are the main clinical measures to classify obesity and assess the risk of hypertension, cardiovascular disease, and diabetes. Although BMI is commonly used, WCHR is independent of gender and has been shown to perform well, given age and ethnicity differences.[9–12] WCHR cut-off values for healthy, overweight, and obese categories proposed by Ashwell are 0.4, 0.5, and 0.6.[12] These values were set following analyses from a small dataset using pragmatic criteria aimed at arriving at boundaries that were simple to deploy in practice. A review confirmed that WCHR was a better measure for predicting conditions and the Ashwell cut-off values were broadly confirmed.[9,12,14]

The aim of the current study was to generate WCHR cut-off values for obesity categories from a model of the relationship between BMI and WCHR. By doing this, we expect to inspire confidence in the WCHR cut-off values discovered because the BMI has been taken into account in their generation. The methods section below describes regression equations relating WHCR to BMI and the solution of co-efficient and error terms using data from an Australian rural sample. The regression equations were verified using the US National Health and Nutrition Examination Survey (NHANES) dataset. This contributes to the growing body of evidence suggesting that WCHR-based classification of obesity in clinical practice can be adopted more widely.

Related work

BMI is a widely used statistic for classifying obesity stages and assessing the risk of type two diabetes mellitus (T2DM), cardiovascular disease (CVD) and hypertension (HT). BMI is calculated using the ratio of weight to the square of height as illustrated in Equation 1:

$$BMI = \frac{[weight\ (kg)]}{\left[height\ (m)^2\right]} \tag{1}$$

The BMI categories recommended for a Caucasian population are: 18.5–24.9 regarded as healthy; 25–29.9 as overweight; and 30 kg/m^2 or more as obese.[13] Treatment guidelines and treatment options tend to be based on the obesity category rather than on a specific BMI value.[4,5,13] For example, lifestyle modifications for weight loss are recommended for those classified as obese with a BMI generally above 30 kg/m^2. BMI levels of 30, 35, and 40 kg/m^2 signify the onset of stage one (I), two (II) and three (III) of obesity respectively and require different interventions. A BMI over 35 kg/m^2 often requires pharmacotherapy, whereas once the BMI has reached 40 kg/m^2, bariatric surgery is a possible option.[4,5] Increased BMI not only increases the risk of chronic disease but is also associated with a notable increase in all-cause mortality once stage II obesity (BMI>35 kg/m^2) is reached.[14]

A determination of the obesity category is currently based on BMI cut-off values or on WC.[15] Cut-off thresholds of WC for healthy, overweight, and obese categories differ for men and women. The standard overweight/oversize WC range for men is 94–102 cm, and for women 80–88 cm. Recent studies have reported a preference for WC measures as BMI may change within a short timeframe such as a day or week due to food intake or other factors.[16] However, care is required when placing the measuring tape for determining WC.[16,17] The WCHR represents central (visceral) adipose tissue accumulation[11] and is depicted in Equation 2. An advantage of WCHR as an alternative measure of obesity is that it is independent of gender and has been shown to conform well to age and ethnicity differences.[11,12]

$$WCHR = \frac{[WC\ (cm)]}{[height\ (cm)]} \tag{2}$$

WCHR cut-off values for healthy, overweight, and obese categories proposed by Ashwell[12] are 0.4, 0.5, and 0.6, respectively. However, cut-off values for WCHR that correspond to the obesity stages (I, II, III) used for determining interventions as described above, have not been reported. In addition, how WCHR corresponds to BMI has not been assessed in a large clinical dataset. Previously, a different dataset was considered for model generation and explored various age frames with results that were not universal for adulthood.[18,19] This study advances further the establishment of a clinical relevant scale for WCHR and indicates the correspondence to BMI for clinical use. While the previous related work has used bootstrapping, in this work we employ n-fold validation which is a less biased method.

Materials and methods

The dataset used in this research derives from a health screening program offered in rural Australia that has collected data on height, weight, WC, age, gender, and chronic disease status.[20] The dataset for 847 participants over eight years consisted of 57% women and 43% men. In addition to the Australian data, the publicly available US ongoing NHANES was used to evaluate associations between BMI and WCHR.[21] This is a well-known dataset with a plethora of work extensively covering various health aspects and more details are available in the literature.[18–21] Variations have been reported in the measurement of WC by different practitioners using different protocols.[9,17] The protocol for measuring WC according the NHANES anthropometry manual[22] can be presumed to have been used for all NHANES measures and some but not all of the Australian measurements. This introduces the possibility of error, though the influence of this source of error was assumed to be small and unlikely to influence regression coefficients. In both datasets no more than 5% of the data was identified as outliers and discarded. The parameters in both datasets are the actual measurements following well-established standards. In other words, these are not self-reported data and no data imputation was performed in these datasets. Table 1 provides the overall means and standard deviations of the data subset pertaining to the demographics such as age, height, weight, WC for each gender used for this study.

We applied regression for prediction as well as for WCHR threshold learning by setting up equations that related WCHR to BMI (Equations 3 and 4).

$$WCHR = \omega_0 + \omega_1 \cdot (BMI - \beta_0) \tag{3}$$

$$BMI = \beta_0 + \beta_1 \cdot (WCHR - \omega_0) \tag{4}$$

where ω_0 and β_0 represent the population WCHR and BMI means, respectively. Note that the two equations, although similar, are not equivalent in that ω_1 cannot be expressed via β_1. The methodological approach used to determine the WCHR cut-off values involves evaluation of the standard linear regression equations (Equations 3 and 4) between WCHR and BMI using the least squares method.[23] In previous work,[19] this technique was not used for WCHR obesity threshold learning from the data. The regression analysis was performed separately for men and women.

The regression equations were also used to identify outliers. These were defined as entries that fell more than 3 standard deviations from the mean. The procedure was applied to subsets of data arising from the data partitioning, as explained below. The measure of goodness of the linear fit to the data was determined by the correlation coefficient (Pearson):

$$r = \sqrt{\omega_1 \cdot \beta_1} \tag{5}$$

Table 1. Means and standard deviations for data subset with all-known anthropometric features.

WC, height and weight all known ($n = 3213$)			
	Gender		
Feature	Female (57%)	Male (43%)	Either
Age (years)	64 ± 12	66 ± 12	65 ± 12
Height (cm)	162 ± 7	176 ± 7	168 ± 10
Weight (kg)	75 ± 16	87 ± 14	80 ± 17
WC (cm)	93 ± 15	103 ± 14	97 ± 15
BMI (kg/m^2)	28 ± 6	28 ± 4	28 ± 5
WCHR	0.58 ± 0.10	0.59 ± 0.08	0.58 ± 0.09

BMI: body mass index; WC: waist circumference; WCHR: waist circumference to height ratio.

The confidence to magnitude ratio (C/M) can also be used to assess the linear model fitting of the data. The ratio is calculated as follows:

$$\frac{C}{M} = 2 \cdot \frac{CI_2 - CI_1}{(|CI_2| + |CI_1|)} \tag{6}$$

where CI_1 and CI_2 denote the 'from' and 'to' bounds of the applicable confidence interval, and $|\cdot|$ stands for absolute values.

To estimate the confidence intervals, mean values for regression coefficients and the coefficient of correlation between BMI and WCHR, all available data were randomly distributed into two equally sized groups proportional to gender. This was repeated five times to obtain 10 measurements for each coefficient.[24] The '5×2' re-sampling procedure was performed separately for each year of the data to prevent a possible bias due to missing values for some patients. Thus, for each parameter, 80 estimates were obtained. We employed simulated re-sampling via the n-fold validation here. The software packages used were mainly to perform the *t*-test and graphics that were rendered in Excel.

The current results have advanced further from the previous study[19] where bootstrapping was employed rather than n-fold validation. Outliers were identified and removed from each of the resulting samples. Besides, these arrangements were applied to a number of static subsets which formed historical layers of the data. Thus, accumulated statistical information was the basis for final characterization of our model. Additionally, our method for evaluation of agreement

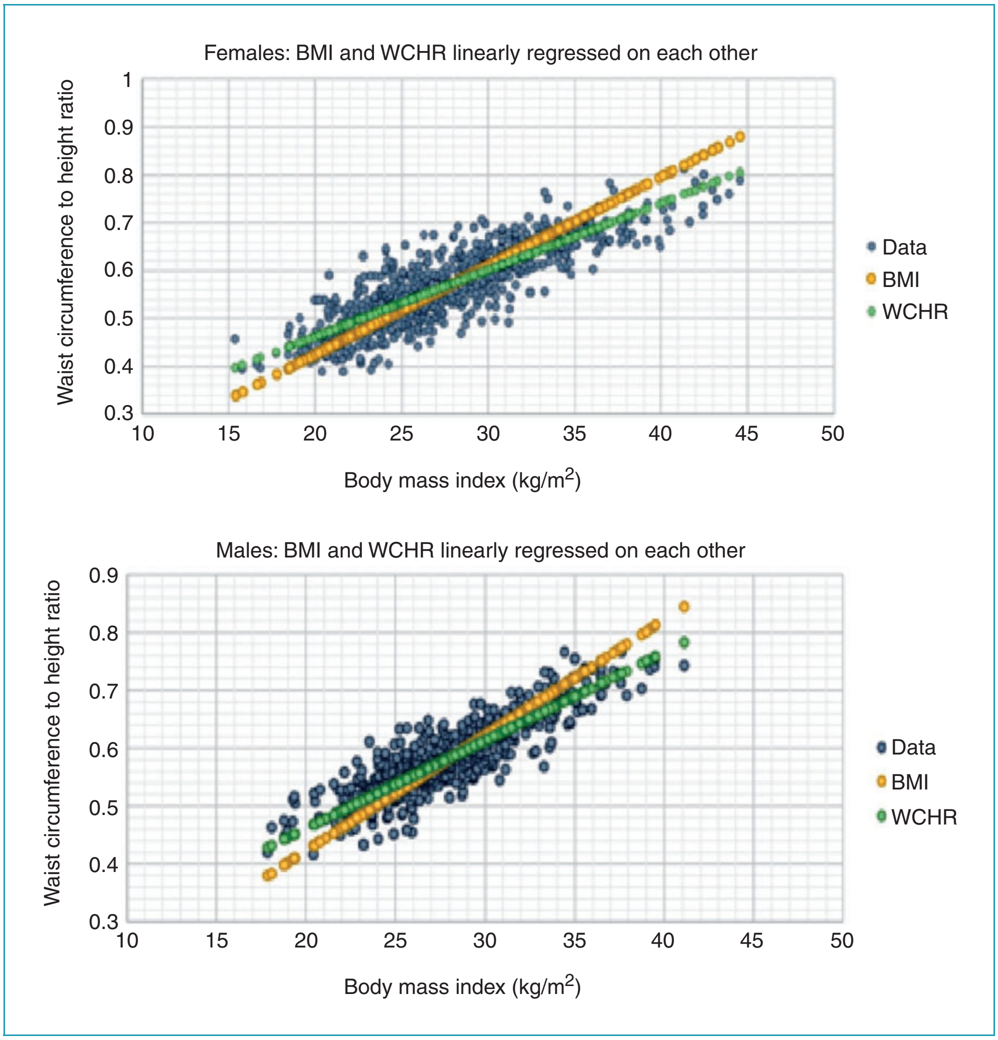

Figure 1. Evaluated linear dependences between waist circumference (WC) to height ratio (WCHR) and body mass index (BMI) for males and females.

between different obesity indices helps in easy understanding of the result by the end-user.

Results

WCHR vs BMI

The data points in the WCHR – BMI plane for female and male participants are plotted in Figure 1 (graphic image rendered in Excel spreadsheet). The regression coefficients (Equations 3 and 4) and the correlation coefficient (Equation 5) are listed separately for women and men in Table 2, where the confidence interval (CI) spans two standard deviations and is given by its bounds CI_1 and CI_2. The confidence to magnitude ratio C/M (Eq. 6), expressed as a percentage, is also shown in Table 2.

As seen from Table 2, the correlation coefficient approaches unity $r \approx 0.9$ and is at least 0.8 for either gender, indicating that the relationship between WCHR and BMI is close to linear. All regression coefficients were statistically distinct for men and women ($p < 0.001$) under the paired two-tailed *t*-test (Excel).

The WCHR and the BMI levels with respect to the current obesity classification are provided in Table 3. Despite the regression coefficients being statistically different for men and women, the confidence intervals (Table 2) overlap for all coefficients making it possible to introduce a WCHR-based index of obesity, which is gender independent. The proposed WCHR thresholds to classify obesity are also shown in Table 3.

Overweight is defined as WCHR of 0.525 or more, and obesity as WCHR of 0.6 or more, with morbid, stage III obesity set at WCHR of 0.75 for the gender-independent classification. WCHR of 0.6 was

Table 2. Waist circumference to height ratio (WCHR) vs body mass index (BMI) regression coefficients.

Coefficient	Mean	CI_1	CI_2	C/M (%)
Women				
β_0	27.83	26.63	29.04	9
β_1	53.83	45.52	62.13	31
ω_0	0.5702	0.5499	0.5905	7
ω_1	0.01397	0.01215	0.01579	26
r	0.8655	0.8044	0.9266	14
Men				
β_0	28.16	26.75	29.58	10
β_1	50.14	43.19	57.09	28
ω_0	0.5860	0.5682	0.6038	6
ω_1	0.01523	0.01306	0.01740	28
r	0.8722	0.8219	0.9226	12

CI: confidence interval; C/M: confidence to magnitude ratio.

Table 3. Calculated waist circumference to height ratio (WCHR) for women and men corresponding to body mass index (BMI) levels and proposed WCHR levels.

Category	BMI (kg/m^2) standard	WCHR women	WCHR men	WCHR gender independent
Healthy weight (official)	18.5	0.4399	0.4389	
Healthy weight (conventional)	20	0.4608	0.4617	0.450
Overweight	25	0.5307	0.5379	0.525
Obese I	30	0.6005	0.6140	0.600
Obese II	35	0.6704	0.6902	0.675
Obese III	40	0.7402	0.7663	0.750

previously suggested by comparing obese population prevalence by BMI and WCHR, whereas the overweight WCHR was set at 0.5 adhering to the consensus existing in literature, and therefore the normal WCHR was defined as 0.4.[12]

Obesity index

The goal of this work was to estimate obesity category cut-off thresholds for WCHR corresponding to the standard BMI-based categories. One problem with evaluating the correspondence between different measures is posed by borderline instances that can be classified into different categories depending on the measure applied.[19] The improvement in this study is that in order to avoid "bracket creep," half-intervals for any measure were introduced. For instance, in the case of BMI, various levels from 20–40 by increments of 2.5 were deployed. Thus for each index, 10 discrete obesity levels (from 0–9) were defined. By running a pair of indices through the data the discrepancies in classification between these can then be accounted for. To calculate the correspondence rate between indices, the absolute differences between their discrete values were found and those with magnitude of more than one were deemed as misclassifications.

The correspondence rate as a percentage of a matching classifications by BMI and WCHR for the prototypical Australian screening data was 84% for females, 86% for males, and 85% for either gender. For the data from NHANES, the correspondence rate between BMI and WCHR is shown in Table 4 by gender for different age frames: older adults (frame 2), younger adults (frame 1), and youth (frame 0).

The older adults were identified here as respondents aged 40 years or older ($n = 3443$, 52% female) to match the age range of the Australian data. For age frame 2 in Table 3, it is evident that the indices work on the independent data at accuracy levels similar to those obtained for the prototypical dataset. However, WCHR consistently assigns a higher obesity category among females than BMI but the female WCHR-to-BMI correspondence remained high. This inconsistency is difficult to explain and may be due to NHANES data being modelled on the US population whereas the Australian diabetic health data reflects the participants who volunteered to attend the screening clinic in a rural community.

The results for NHANES younger adult respondents (here from 20 up to 39 years old, $n = 1813$, 51% female) are shown in Table 4 for age frame 1. It is evident that the WCHR and BMI indices are very well matched to each other and do not differ for gender. However, the WCHR and BMI indices for youth (children and adolescents up to 19 years old, $n = 3384$, 49% female), as seen for age frame 0 from Table 4, have a lower correspondence than for the older age categories. The poor correspondence between WCHR and BMI for youth does not imply that WCHR is unsuited for this age frame as an obesity measure. In fact, it is BMI that is unsuitable to measure

Table 4. National Health and Nutrition Examination Survey (NHANES) data obesity index correspondence rates (%).

	Gender		
Age Frame	Female	Male	Either
2	76	87	81
1	88	88	88
0	72	73	72

Table 5. National Health and Nutrition Examination Survey (NHANES) data alternative waist circumference to height ratio (WCHR) and body mass index (BMI) obesity index correspondence rates (%).

	Gender		
Age Frame	Female	Male	Either
2	73	85	79
1	85	92	88
0	54	56	55

body fat in this young cohort and needs to be adjusted for age in clinical practice. Despite being somewhat different for males and females, the age charts are designed so that for adults the standard BMI classification would apply.[9] However, the alternative WCHR levels of 0.4, 0.5, 0.6 suggested by Ashwell[16] and extended here with 0.7 and 0.8 to enable a comparison with the respective BMI levels of 20, 25, 30, 35, and 40 kg/m^2, perform less well than the proposed WCHR levels (Table 3) as evident from Table 5. Yet, the calculation for age frame 0 ignores the dependence of BMI on age in youth.

The alternative WCHR indexing, based in part on the system advocated by Ashwell,[16] provides similar, albeit not as accurate, results for older adults and is also gender-imbalanced for younger adults (Table 5, age frames 2 and 1), compared to the proposed WCHR indexing. The reason for this is that the obesity point of 0.6 is central within the indexing spectrum after inclusion of the obesity subcategories. This point is the same in the proposed and the alternative indices. It is of interest that the proposed WCHR classification is characterized by narrower intervals between levels of 0.075 compared to the alternative Ashwell classification of 0.1, suggesting better discriminatory power. Performance of the proposed and alternative WCHR-based obesity indices is compared in Table 6 relative to BMI by category for the older adults from the NHANES.

Table 6. National Health and Nutrition Examination Survey (NHANES) older adult proposed and alternative waist circumference to height ratio (WCHR) correspondence to body mass index (BMI) rates (%).

	Proposed			Alternative		
Obesity Category	F	M	F/M	F	M	F/M
Underweight	83	92	86	34	54	41
Healthy	69	86	77	51	70	60
Overweight	71	86	80	76	90	84
Obese I	77	87	82	92	96	94
Obese II	85	92	87	87	90	88
Obese III	98	94	98	85	63	82

F: female; M: male; F/M: female or male (either).

WCHR cut-off values for healthy, overweight, and obese categories (0.4, 0.5, and 0.6, respectively) proposed by Ashwell[16] loosely correspond to BMI levels of 20, 25, and 30 kg/m^2. However, this data distribution leads to incorrect results in the underweight and healthy (females) categories. With added levels of 0.7 and 0.8, the loss of precision is also observed towards the high end of the spectrum. The proposed WCHR indexing is not as different between categories and exhibits a steady tendency to better align with BMI for higher obesity categories.

Discussion

Our results indicate that there is a close link between the proposed WCHR and the traditional BMI categories. The main advantage of WCHR over BMI is that while weight and height can be precisely measured given a moment of time, the weight, and so BMI, constantly change. Particularly, weight is regulated by the cycles of digestion, and its measurement is affected by the type of clothes worn. Also, with age people tend to gain weight and become shorter,[24] which needs to be taken into consideration when older data is substituted for new one. One possible explanation why height is squared in the standard BMI (Equation 1) is that this reduces the effect of weight variation.

The current view of obesity is that it contributes cardiometabolic disorders such as T2DM, cardiovascular disease, and hypertension, but there is no reverse causation, although some medication may have beneficial effects.[5] To understand the impact of obesity on chronic diseases better, cut-off levels of obesity measures need to be considered. Previous research estimated the optimal WCHR value for predicting T2DM derived from a selection of studies as 0.56, and 0.58 was reported recently by us.[14,17] Both cut-off values are higher than the overweight level of 0.525 and approach the obesity level of 0.6 suggested by the current research. They are also between the values of 0.5 and 0.6 advocated by Ashwell.[11,12] Our results lead to further questions on how well can obesity be aligned with diabetes at the onset, and measures of overweight be stated as part of the metabolic syndrome in a general classification and what are optimal cut-off values that indicate chronic conditions from the existing BMI or WCHR scales?

These are some of the questions that require further investigation, providing directions for future work. The current research can be considered as directly related towards investigating how WCHR can be used to predict chronic diseases such as diabetes and hypertension. This is currently outside the scope of the article and is being considered for future research. Also, examining the potential influence of socioeconomic transition over the time-span of data collection as well as possible socioeconomic differences between the two populations (rural Australia versus USA) where the datasets were generated. However, there are inherent limitations in drawing the training and validation datasets from two different populations as the two populations were inherently different in many respects, in particular, the differences in the age spectrum. The results apply to adults of either sex but are dominated by older adults. While gender differences can be further explored, the existing BMI classification does not differentiate on this parameter. Ethnic or racial differences are more difficult to capture and require comparable populations in the training and validation sets. Although it is feasible to compare rural and urban populations in different countries, this was not possible with the available data: the Australian population is rural while the US population is largely urban.

In summary, previous studies have used data mining to discover variables, and their threshold, that lead to an assessment of the risk of chronic diseases such as T2DM.[17,26] This article recommends WCHR cut-off values that facilitate the classification of obesity in clinical practice. Our experimental results have been consistent with the reporting that WCHR is more relevant to obesity than BMI. The proposed WCHR-based obesity index is gender-independent and universally applicable for the adult population. It improves findings from previous work[19] by adopting a simulated resampling using n-fold validation rather than bootstrapping. While previous work relied on a single source of data, in this study a different data source was used for model generation and the results obtained demonstrate the applicability to another unrelated representative dataset. In addition, the universal WCHR thresholds for adulthood were explored for the first time in this work, Further, the accumulated statistical information forming the basis for final characterisation of the model is effective for evaluation of agreement between different obesity indices. This facilitates a better understanding of the result by the end-user, making it more useful for clinical practice.

Conclusions

The classification of obesity is currently based on BMI cut-off values or on WC. It is much preferable to use WC over BMI as BMI changes within a short timeframe based on food intake or other factors. Also, the standard overweight/oversize WC range varies based on gender, age, and other ethnicity differences. WCHR represents an alternative measure of obesity which is largely independent of gender age and ethnicity. The current cut-off values for obesity though originally determined for simplicity have been widely used and validated.

This study generated WCHR cut-off thresholds by solving regression equations that acted as a model of the relationship between WCHR and BMI. Cut-off values for WCHR that distinguished stage (I, II, III) obesity were found for each gender and three age groups. The cut-off values were similar to those common in clinical practice but accommodated personal differences better. This adds to the growing momentum toward the use of WCHR to classify obesity in clinical practice.

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Guarantor: Herbert F. Jelinek

ORCID iD

Sitalakshmi Venkatraman http://orcid.org/0000-0002-2772-133X

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