To Construct A Forecasting Model of the Anthropometric Chronic Disease Risk Factor Score

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Background: Many health indices have a relationship with anthropometric indices. This research attempts to provide a new measurement: a chronic disease risk factor score built into the regression model. This new model will help people visualize their health status and get multiple information during the process of the healthy examination.

Methods: Data from 8,034 subjects were collected from the data bank of the Health Examination Center in Chang Gung Memorial Hospital. Related anthropometric indices and biochemical factors were selected and used to construct a regression model. The anthropometric indices used were body mass index, waist hip ratio, waist hip area ratio, health index, waist leg ratio and trunk leg ratio. Biochemical data included blood pressure, glucose, triglyceride, cholesterol and uric acid, combined to form an anthropometric chronic disease risk factor score.

Results: Subjects under 45 years of age had the highest chronic disease risk factor score, and were selected to construct a regression model. The R-square of this model is 0.355; its predictive error is near 12%. After verification with a testing group, the regression model could be used to predict health status.

Conclusion: The purpose of this study was to develop a new anthropometric chronic disease risk factor score by combining anthropometric indices and biochemical data. A multiple regression model was used to illustrate health status via anthropometric chronic disease risk factor scores for the subjects participating in the health examination. The results show that the chronic disease risk factor score is useful for prescribing relevant medical treatment as well as for other research.

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Key words: chronic disease risk factor score, anthropometric chronic disease risk factor score (ACDRFS), waist hip ratio (WHR), body mass index (BMI), whole body scanner.

An important public health issue is the increasing number of people who are overweight and obese due to changes of lifestyle and diet. This phenomenon has been getting serious attention in developed countries. Many diseases are related to obesity including cardiovascular and cerebrovascular dis-

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eases. “Metabolic syndrome” is a typical characteristic in the primary stage of these diseases. Metabolic syndrome or syndrome X is defined as a clustering of cardiovascular disease risk factors comprising hyperinsulinemia, hypertension, hyperlipidemia, obesity and glucose intolerance.[1-3]

Free fatty acids, cortisol and testosterone have powerful combined effects, resulting in insulin resistance and increased hepatic gluconeogenesis. All these factors promoting insulin resistance are active in abdominal visceral obesity, which is closely associated with insulin resistance, non-insulin-dependent diabetes mellitus (Type 2 DM) and metabolic syndrome.[4]

Type 2 DM is the disease that is most consistently associated with obesity as defined by indicators such as body mass index (BMI).[5-6] Some researchers have shown that a high proportion of abdominal fat, particularly visceral fat, is a major risk factor for Type 2 DM and coronary heart disease.[7-8]

Obesity, with high waist circumference to hip circumference ratio (WHR), is deemed to be one of the important causes of syndrome X.[9] Waist circumference (WC) and WHR are frequently used to estimate the amount of abdominal adipose tissue. WHR provides an index relative to the accumulation of abdominal fat. Although advanced imaging techniques, such as computer tomography and magnetic resonance, can distinguish visceral fat from subcutaneous fat, they are too costly to apply in the clinical setting as a screening tool for patients.[10-11] Although indicators, such as BMI, WC and WHR, are frequently used by doctors to make a judgment on a patient’s health, many studies have shown that the cutoff points of these anthropometrical measures vary across ethnic groups and further revisions are necessary.[12-13]

Measurements of visceral fat, such as WC, WHR and WTR, were shown to be closely associated with Type 2 DM when compared with BMI.[14-17]

A study was conducted to investigate whether WHR and BMI influence glucose tolerance, blood pressure and serum lipids in middle-aged Japanese men. It concluded that both BMI and WHR were independently and positively associated with impaired glucose tolerance to almost the same degree. An adjusted mean blood pressure, total cholesterol and triglycerides were almost linearly increased with increased levels of both BMI and WHR, and was progressively decreased with high-density lipoprotein cholesterol.[18]

Many prediction equations are revised from anthropometry for use in health promotion and disease prevention. BMI has been used to estimate body fat by regression formulas either separately or in combination with other factors. BMI was chosen because of its independence from body fat distribution and its high correlation with body fat.[19]

Dezenberg et al. developed a prediction equation for total body fat in African-American and white children. However, this equation has not been tested in Latino children and no prediction equation is currently available for Latino children. Hence, it is the intention to evaluate the precision and accuracy of the previously developed equation by Dezenberg et al. in Latino children with a wide range of body fat, and to develop new equations using demographic and anthropometric measurements to predict total body fat specifically in Latino children.[20] However, there are age-related and racial differences in the application of these equations.[21]

Most of the previous research focused on the relationship between BMI and biochemical indices. However, there are few predictive models for chronic disease risk factors by anthropometric indices.

The purpose of this study is to find the correlation between chronic disease risk factor scores and anthropometric indices for Taiwanese adults. A chronic disease risk factor prediction equation was provided for metabolic disease by a 3-D anthropometric database.[14] Some anthropometric data was also used to test the performance (accuracy) of the prediction equation. This approach is helpful for making relevant diagnoses and consequential medical treatment.

METHODS

A cross-sectional population-based sample of 8,034 Taiwanese adults was collected from Chang Gung Memorial Hospital. Of these, a total of 1,037 subjects were under 45 years of age, 4,737 were between 45 and 64 years of age, and 2,233 subjects were 65 years of age or older. Most of the subjects were from the Health Examination Center; the rest were selected from patients who had some risk factors, such as being overweight. In order to assess the

accuracy of our investigation, we divided the 1,042 subjects who were under 45 years of age into two groups. After our systematic sampling, the two groups had 912 and 130 cases, respectively. Using data from the 912 cases, this research attempted to construct a forecast model by regression equation, to test the model by comparing it with the 130 cases for errors, and to assess accuracy and factors that affect accuracy.

Whole body 3D laser scans were used to obtain anthropometric measurements. This is a new scanning technology using high resolution 3D data points that measure the human body surface in 12 seconds. There are many advantages in using this technology over previous approaches to measurement, such as tape measures: (1) it reduces guess work, which makes data much easier to use in computer-aided design and rapid prototyping; (2) it alleviates dependency of measurements on the subject's position when measured, allowing the extraction of an almost infinite number and variety of measurements long after the subject has moved on; (3) it provides the first viable method for capturing human models in their clothing, equipment and workspace, and in realistic postures; (4) being a non-contact system, it reduces measuring differences between measures, making data sets collected by different groups more comparable.[21]

The subject's body was segmented into head, chest, waist, hips, trunk, upper-arm, forearm, leg, calf, upper-limb and lower-limb volume. Each segment's volume and surface area were calculated. HI was defined by the equation $HI = (body\ weight * 2 * waist\ profile\ area) / (body\ height^2 * (chest\ profile\ area + hip\ profile\ area))$. BMI was calculated as weight divided by height squared (kg/m^2). Chest profile area was measured at the maximal circumference around the chest. Waist profile area was measured at a level midway between the lower rib margin and the iliac crest. Hip profile area was measured at the maximal circumference over the buttocks. WHR was defined as waist circumference divided by hip circumference. WHAR was defined as waist profile area divided by hip profile area. WLR was the ratio of waist circumference to leg circumference. TLR was the ratio of the volume of the trunk to the volume of the leg.

The five biochemical risk factors selected were hypertension, blood sugar, heart disease factors, triglyceride and uric acid. We divided these factors into three levels: normal (score = 1.0), borderline (score = 0.5) and abnormal (score = 0). Related criteria were as follows: blood pressure (SDP/DBP), normal (1.0): SDP < 120 & DBP < 80, borderline (0.5): other, and abnormal (0): SDP > 140 or DBP > 90. Blood sugar (F/A glucose), normal (1.0): Glucose-AC < 110 and Glucose-PC < 140, borderline (0.5): other, and elevated/abnormal (0): Glucose-AC > 125 or Glucose-PC > 200. Triglyceride (TG), normal (1.0): TG < 150, borderline (0.5): other, elevated/abnormal (0): TG > 200. Heart disease risk factors (TC/HDL), normal (1.0): TC/HDL < 5, borderline (0.5): other, elevated/abnormal (0): TC/HDL > 7. Uric acid, normal (1.0): uric acid < 6, borderline (0.5): other, elevated/abnormal (0): uric acid > 8. Next, we defined the mean score, which is a combination of the five original scores; we called this the chronic disease risk factor score. Subjects with normal chronic disease risk factors had mean scores approaching 5. Subjects with abnormal chronic disease risk factors had mean scores approaching 0. Finally, all five scores were combined and divided by five; the chronic disease risk factor score represented the degree of health.

RESULTS

The correlations between chronic disease risk factor scores and anthropometric indices are shown in Table 1. All are significant ($p < 0.001$). However, there was lowest correlation between TLR and the chronic disease risk factor score. Based on these, five anthropometric indices (HI, BMI, WHR, WHAR and WLR) were selected for analysis. The correlation between anthropometric indices and chronic disease risk factor scores had higher correlation than the biochemical indices.

Table 2 presents a summary of the dependent and independent variables from three groups (under 45, 45 to 64 and over 64 years of age). All the independent variables (HI, BMI, WHR, WHAR, WLR and TLR) showed that the values of older subjects were greater than younger ones. Except for HI, it seems that there is little difference between the independent variables. As for the eight dependent variables, the results were the same as for the independent variables. More subjects over 64 years of age have elevated Glucose-AC or Glucose-PC than sub-

Table 1. Pearson's Correlation of Laboratory Data with Anthropometric Measurements

	HI	BMI	WHR	WHAR	WLR	TLR
Glucose-AC (mg/dl)	0.23*	0.17*	0.23*	0.26*	0.27*	0.10*
Glucose-PC (mg/dl)	0.24*	0.16*	0.25*	0.27*	0.29*	0.07*
Uric acid (mg/dl)	0.32*	0.29*	0.29*	0.32*	0.33*	0.16*
Triglyceride (mg/dl)	0.30*	0.28*	0.27*	0.29*	0.27*	0.10*
Chol/HDL	0.38*	0.36*	0.34*	0.37*	0.36*	0.23*
SBP (mmHg)	0.34*	0.30*	0.30*	0.32*	0.31*	0.11*
DBP (mmHg)	0.28*	0.29*	0.23*	0.24*	0.20*	0.15*
Chronic Disease Risk						
Factor Score	-0.46*	-0.41*	-0.41*	-0.46*	-0.44*	-0.23*
95% CI	(-0.48~-0.44)	(-0.43~-0.39)	(-0.43~-0.39)	(-0.48~-0.44)	(-0.46~-0.42)	(-0.25~-0.21)

Abbreviations: HI: Health index; BMI: Body mass index; WHR: Ratio of waist circumference to hip circumference; WHAR: Ratio of waist area to hip area; WLR: Ratio of waist circumference to leg circumference; TLR: Ratio of the volume of the trunk to the volume of the leg; Glucose AC: Fasting blood glucose; Glucose PC: Two hours post-prandial blood glucose; SBP: Systolic blood pressure; DBP: Diastolic blood pressure; TG: Triglyceride; Chol/HDL: Ratio of total cholesterol to high density lipoprotein.
*$p < 0.001$

Table 2. Summary of Dependent and Independent Variables from Three Age Groups

	Under 45	45~64	Over 64	All
HI	18.54 ±5.04*	20.84 ± 4.85	22.85 ±5.06	21.10 ± 5.11
BMI	23.76 ±3.76	25.05 ± 3.24	25.31 ±3.25	24.95 ± 0.08
WHR	0.86 ±0.07	0.89 ± 0.08	0.93 ±0.08	0.90 ± 0.08
WHAR	0.75 ±0.11	0.81 ± 0.12	0.89 ±0.14	0.83 ± 0.13
WLR	1.54 ±0.16	1.65 ± 0.19	1.81 ±0.19	1.68 ± 0.20
TLR	1.36 ±0.24	1.46 ± 0.24	1.53 ±0.24	1.47 ± 0.24
Glucose-AC (mg/dl)	90.22 ±12.31	97.14 ± 20.80	102.08 ±22.32	97.59 ± 20.64
Glucose-PC (mg/dl)	91.92 ±21.62	104.85 ± 36.60	117.49 ±41.81	106.62 ± 37.38
Uric acid (mg/dL)	6.13 ±1.73	6.16 ± 1.67	6.37 ±1.73	6.21 ± 1.70
Triglyceride (mg/dL)	112.20 ±83.29	131.98 ± 87.01	137.44 ±77.34	130.95 ± 84.29
Chol/HDL	3.58 ±1.14	3.91 ± 1.11	4.11 ±1.08	3.93 ± 1.12
SBP (mmHg)	113.00 ±15.851	119.06 ± 18.01	127.55 ±18.68	120.68 ± 18.55
DBP (mmHg)	73.10 ±10.84	76.04 ± 11.12	76.79 ±10.55	75.88 ± 10.98
ACDRFS	0.84 ±0.17	0.78 ± 0.19	0.72 ±0.19	0.77 ± 0.19

Abbreviations: HI: Health index; BMI: Body mass index; WHR: Ratio of waist circumference to hip circumference; WHAR: Ratio of waist area to hip area; WLR: Ratio of waist circumference to leg circumference; TLR: Ratio of the volume of the trunk to the volume of the leg; Glucose AC: Fasting blood glucose; Glucose PC: Two hours post-prandial blood glucose; SBP: Systolic blood pressure; DBP: Diastolic blood pressure; TG: Triglyceride; Chol/HDL: Ratio of total cholesterol to high density lipoprotein; ACDRFS: Anthropometric chronic disease risk factor score.
*mean ± SD

jects who are under 45 years. The triglyceride levels of those over 64 are higher than the other groups. Rates of cholesterol and high blood pressure are similar. As expected, subjects under 45 years of age had the highest chronic disease risk factor scores (0.84).

Next, we divided the subjects into three groups based on their chronic disease risk factor scores. Table 3 shows the results and percentages between the chronic disease risk factor scores and age. As expected, the chronic disease risk factor scores of younger subjects are higher and the scores of the older subjects are lower.

Consequently, all subjects in different ages were divided to modeling and testing groups. Table 4 shows the summary of regression results in each group. The regression model of the group who are under 45 years of age had the best performance, including higher R-square and lower predictive error.

Table 3. Distribution of ACDRFS in Different Age Groups

Age	ACDRFS			
	High risk (a)	Median (b)	Low risk (c)	Total
Under 45	13 (1.25%)	241 (23.24%)	783 (75.51%)	1037 (100%)
45~64	128 (2.70%)	1611 (34.01%)	2998 (63.29%)	4737 (100%)
Over 64	87 (3.90%)	1005 (45.01%)	1141 (51.10%)	2233 (100%)
Total	228 (2.85%)	2857 (35.68%)	4922 (61.47%)	8007 (100%)

Table 4. Summary of Regression Results in Each Group

Age	Modeling Group (n1)	R-Square	Testing Group (n2)	Chronic Disease Risk Factor Score	Predictive Error
Under 45	912	35.50%	130	0.84	12%
45~64	4156	28.70%	595	0.77	18%
Over 64	1960	13.20%	281	0.72	19%
Total	7028	27.20%	1006	0.77	17%

The last model, aged over 64, did not have a good performance. As a result, the first model for subjects who are under 45 was selected to build the regression model.

According to the above statement, the independent variables, including BMI, WHR, WHAR, HI, WLR, TLR, and the dependent variable, i.e. the chronic disease risk factor score, were used to build a regression model as follows. It's R-square is 35.5% and predictive error is 12%. ACDRFS stands for Anthropomorphic Chronic Disease Risk Factor Score.

ACDRFS = 1.8444-0.02827*BMI+0.5598*WHR-0.8*WHAR+0.0186*HI-0.3209*WLR-0.0483*TLR

Furthermore, Table 5 shows that there is no difference between the three different testing groups. Finally, we used the 130 subjects in the testing group to verify the regression model. The mean and standard deviation of each dependent variable is shown in Table 5. The predictive error values are given. Multiple range tests showed that the predictive errors of subjects with normal chronic disease risk factors are lower than median groups and disease groups. Dependent variables, glucose and chronic disease risk factor scores have no data in disease groups.

DISCUSSION

In this study, we presented a concept concerning the ACDRFS constructed by anthropometric measurements, including HI, BMI, WHR, WHAR, WLR and TLR. Those measurements were determined by the correlation between them and related biochemical variables, including blood pressure, uric acid, triglycerides, cholesterol and blood sugar. We divided all the subjects into three groups, high risk, median and low risk, using the chronic disease risk factor scores 1.0, 0.5 and 0, respectively. As expected, the group who were less than 45 years of age had the best ACDRFS (0.84), compared to the other groups (0.77 and 0.72). In the regression models, the R-square or predictive error of the group less than 45 years of age was also better than the two other groups. The model for those less than 45 years was significantly better. So, the regression of ACDRFS could be used to predict chronic disease factors with anthropometric measurements. ACDRFS is especially good for the younger group in helping to prevent chronic disease.

Many researchers have shown that BMI is a

Table 5. Mean and Standard Deviation of the Error of Dependent Variables in Different Groups (mean ± SD (n))

Variables	Disease (a)	Median (b)	Subjects with normal chronic disease risk factors (c)	Post hoc
BP	0.21 ± 0.18 (60)	0.11 ± 0.09 (34)	0.12 ± 0.09 (12)	a > b = c*
Glucose		0.30 ± 0.00 (1)	0.11 ± 0.10 (124)	
Triglyceride	0.30 ± 0.16 (12)	0.10 ± 0.07 (17)	0.09 ± 0.07 (96)	a > b = c
Chol/HDL	0.34 ± 0.00 (1)	0.18 ± 0.16 (11)	0.11 ± 0.09 (113)	b > c
Uric acid	0.25 ± 0.15 (16)	0.11 ± 0.09 (50)	0.09 ± 0.07 (60)	a > b = c
ACDRFS		0.22 ± 0.15 (27)	0.09 ± 0.06 (99)	b > c

* $p < 0.01$

good index for predicting body fat.[5-6] They also presented correlation between diseases and BMI in different groups. This study also verifies this point. However, some researchers felt that BMI was not a good index.[11,22-25] In their experience, BMI does not represent the body size of some persons because they are tall but not heavy or vice versa. As their clinical experiment showed, other measurements, including waist or hip, are better. They indicated that the hip and waist have the highest percentage of fat within the body. People developed more visceral fat as they aged. Also, people with more fat are more likely to easily develop certain diseases, including cardiovascular and cerebrovascular diseases. Therefore, waist, hip and thigh are important points to measure and compare. These indices combined as WHA, WHAR, WLR, TLR were considered in this study. We also found correlations, with the exception of TLR, that were significant in this population. It seems that TLR is not a good index for predicting chronic disease risk factors. The ACDRFS not only uses BMI but also combines other anthropometric measurements to predict chronic diseases.

Furthermore, many subjects influenced the value of our model to predict ACDRFS. All models with an accuracy of more than 80% can provide a good way of predicting ACDRFS. Thus, when we get a new subject, we can calculate the ACDRFS based on our predictive model and consequential treatment. In other words, when a new subject goes to the Health Examination Center, he can get a simple report of his health status with a score from 0 to 1, and his doctor can prescribe his related medical treatment based on this score. The ACDRFS will provide doctors with suggestions for patients regarding chronic disease prevention, and the patients will receive a greater consultation via the anthropometric measurements showing their health situation. The ACDRFS will provide a new predictive model for chronic disease by anthropometric measurements.

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REFERENCES

1. Garaulet M, Perex-Llamas F, Fuente T, Zamora S, Tebar FJ. Anthropometric, computed tomography and fat cell data in an obese population: relationship with insulin, leptin, tumor necrosis factor-alpha, sex hormone-binding globulin and sex hormones. Eur J Endocrinol 2000;143:657-66.
2. Modan M, Halkin H. Hyperinsulinemia or increased sympathetic drive as links for obesity and hypertension. Diabetes Care 1991;14:470-87.
3. Reaven GM, Lithell H, Landsberg L. Hypertension and associated metabolic abnormalities--the role of insulin resistance and the sympathoadrenal system. N Engl J Med 1996;334:374-81.
4. Bjorntorp P. Metabolic implications of body fat distribution. Diabetes Care 1991;14:1132-43.
5. McNeely MJ, Boyko EJ, Shofer JB, Newell-Morris L, Leonetti DL, Fujimoto WY. Standard definitions of overweight and central adiposity for determining diabetes risk in Japanese Americans. Am J Clin Nutr 2001;74:101-7.
6. Nagaretani H, Nakamura T, Funahashi T, Kotani K, Miyanaga M, Tokunaga K, Takahashi M, Nishizawa H, Kishida K, Kuriyama H, Hotta K, Yamashita S, Matsuzawa Y. Visceral fat is a major contribution for multiple risk factor clustering in Japanese men with impaired glucose tolerance. Diabetes Care 2001;24:2127-33.
7. Sparrow AD, Borkan GA, Gerzof SG, Wisniewski C, Silbert CK. Relationship of fat distribution to glucose tolerance. Results of computed tomography in male participants of the Normative Aging Study. Diabetes 1986;35:411-5.
8. Bergstrom RW, Newell-Morris LL, Leonetti DL, Shuman WP, Wahl PW, Fujimoto WY. Association of elevated fasting C-peptide level and increased intra-abdominal fat distribution with development of NIDDM in Japanese-American men. Diabetes 1990;39:104-11.
9. Bacha F, Saad R, Gungor N, Janosky J, Arslanian SA. Obesity, regional fat distribution, and syndrome X in obese black versus white adolescents: race differential in diabetogenic and atherogenic risk factors. J Clin Endocrinol Metab 2003;88:2534-40.
10. Kissebah AH, Freedman DS, Peiris AN. Health risks of obesity. Med Clin North Am 1989;73:1111-38.
11. Pouliot MC, Despres JP, Lemieux S, Moorjani S, Bouchard C, Tremblay A, Nadeau A, Lupien PJ. Waist circumference and abdominal sagittal diameter: best simple anthropometric indexes of abdominal visceral adipose tissue accumulation and related cardiovascular risk in men and women. Am J Cardiol 1994;73:460-8.
12. Deurenberg-Yap M, Schmidt G, van Staveren WA, Deurenberg P. The paradox of low body mass index and high body fat percentage among Chinese, Malays and Indians in Singapore. Int J Obes Relat Metab Disord 2000;24:1011-7.

13. Lin JD, Chiou WK, Weng HF, Tsai YH, Liu TH. Comparison of three-dimensional anthropometric body surface scanning with waist-hip ratio and body mass index in correlation with metabolic risk factors. J Clin Epidemiol 2002;55:757-66.
14. Lin JD, Chiou WK, Weng HF, Fang JT, Li TH. Application of three-dimensional body scanner: observation of prevalence of metabolic syndrome. Clin Nutr 2004;23:1313-23.
15. Despres JP. Health consequences of visceral obesity. Ann Med 2001;33:534-41.
16. Wang J. Waist circumference: a simple, inexpensive, and reliable tool that should be included as part of physical examinations in the doctor's office. Am J Clin Nutr 2003;78:902-3.
17. Snijder MB, Dekker JM, Visser M, Bouter LM, Stehouwer CD, Yudkin JS, Heine RJ, Nijpels G, Seidell JC: Hoorn study. Trunk fat and leg fat have independent and opposite associations with fasting and post load glucose levels: the Hoorn study. Diabetes Care 2004;27:372-7.
18. Sakurai Y, Kono S, Shinchi K, Honjo S, Todoroki I, Wakabayashi K, Imanishi K, Nishikawa H, Ogawa S, Katsurada M. Relation of waist-hip ratio to glucose tolerance, blood pressure, and serum lipids in middle-aged Japanese males. Int J Obes Relat Metab Disord 1995;19: 632-7.
19. Gallagher D, Heymsfield SB, Heo M, Jebb SA, Murgatroyd PR, Sakamoto Y. Healthy percentage body fat ranges: an approach for developing guidelines based on body mass index. Am J Clin Nutr 2000;72:694-701.
20. Dezenberg CV, Nagy TR, Gower BA, Johnson R, Goran MI. Predicting body composition from anthropometry in pre-adolescent children. Int J Obes Relat Metab Disord 1999;23:253-9.
21. Brandon LJ. Comparison of existing skinfold equations for estimating body fat in African American and white women. Am J Clin Nutr 1998;67:1155-61.
22. Snijder M. B, Dekker J. M, Visser M, Yudkin JS, Stehouwer CD, Bouter LM, Heine RJ, Nijpels G, Seidell JC. Larger thigh and hip circumferences are associated with better glucose tolerance: the Hoorn study. Obes Res 2003;11:104-11.
23. Dobbelsteyn CJ, Joffres MR, Maclean DR, Flowerdew G. A comparative evaluation of waist circumference, waist-to-hip ratio and body mass index as indicators of cardiovascular risk factors. The Canadian Heart Health Surveys. Int J Obes Relat Metab Disord 2001;25:652-61.
24. Han TS , Williams K, Sattar N, Hunt KJ, Lean ME, Haffner SM. Analysis of obesity and hyperinsulinemia in the development of metabolic syndrome: San Antonio Heart Study. Obes Res 2002;10:923-31.
25. Warne DK, Charles MA, Hanson RL, Jacobsson LT, McCance DR, Knowler WC, Pettitt DJ. Comparison of body size measurements as predictors of NIDDM in Pima Indians. Diabetes Care 1995;18:435-9.

慢性病體型風險預測模式之建構

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背 景： 許多健康指數與體型有相當程度的關聯。本研究透過迴歸方程式，提出一個新的心血管風險因子分數預測模式，此模式將在進行健康檢查時，提供受檢者在慢性病預防醫學的多元診斷選擇及資訊。

方 法： 透過長庚紀念醫院健康檢查中心的 3D 體型銀行資料庫，篩選 8,034 例受檢者的體型資料，選擇六項體型指數及七項生化資料，以建構迴歸方程式。體型指數包含身體質量指數 (body mass index, BMI)、腰臀比 (wait hip ratio, WHR)、腰臀面積比 (wait hip area ratio, WHAR)、健康指數 (health index, HI)、腰腿比 (waist leg ratio, WLR) 及軀腿比 (trunk leg ratio, TLR) 等。生化資料包含收縮壓、舒張壓、飯前血糖、飯後血糖、三酸甘油脂、尿酸、心臟病變危險因子等，透過這七項慢性病的生化資料，計算出本研究新創的慢性病體型風因子分數 (anthropometric chronic disease risk factors score, ACDRFS)。

結 果： 三組年齡層中，年齡在 45 歲以下這組比起 45-64 歲組或 64 歲以上組，其迴歸方程模式準確度與健康分數，都高出甚多。45 歲以下這組的判定係數 (R-square) 值爲 0.355，其預測誤差約爲 12%，透過測試組的驗證，顯示具有體型與慢性疾病風險因子分數預測能力。

結 論： 本研究透過體型及生化資料結合，發展一個新的慢性病體型風險預測模式，初期適用於年齡在 45 歲以下的受檢者，未來將朝中高齡與高齡者，繼續發展適用的慢性病體型風險預測模式。慢性病體型風險預測模式不僅有益於健康檢查項目的設定，同時亦有益於其他相關研究的應用，值得體型資料繼續發展與應用。

(長庚醫誌 2006;29:135-42)

關鍵字： 人體計測，腰臀比，身體質量指數，慢性病體型風險因子分數，三次元人體掃瞄儀。

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